ENERGY MARKET AND ENERGY TRANSITION: DYNAMICS AND PROSPECTS

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ENERGY MARKET AND ENERGY TRANSITION: DYNAMICS AND PROSPECTS

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Editorial: Energy Market and Energy Transition: Dynamics and Prospects

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Editorial on the Research Topic

Energy Market and Energy Transition: Dynamics and Prospects

To mitigate the impact of climate change, the worldwide transition from fossil fuels to renewable energy is inevitable and the trend is irreversible. As a consequence of both a strong push from governments and technological progress, the global energy mix has experienced a significant shift toward renewables in the last decade. Transition is progressing, and a lot of changes have been seen in the global energy markets. While some of these changes may facilitate energy transition, others can bring forward challenges to the transition process. For example, the recent epidemic of COVID-19 has brought plenty of uncertainties and changes in the global market (Zhang et al., 2020). Its impacts on the global economy are profound, which have also spread to the energy markets. It has shrunk global energy demand and collapsed fossil fuel prices. Therefore, renewable energy projects are relatively losing their competitiveness that is making the energy transitions more difficult (Yoshino et al., 2020).

At the national level, the dynamics of the energy market and transition process differ greatly from one to the other, partly due to national policy frameworks (Liu et al., 2019a) and partly because of the level of economic development. Each country's ability to cope with the market dynamics and maintain a smooth energy transition process is, therefore, varying. Additional complexity is at the firm level, whereas large multinational energy companies operating in many countries have diversified products, spanning conventional and renewable energy (Geng et al., 2021). Their decision-making process tends to be affected by many, often non-market factors (Zhang et al., 2020; Zhao et al., 2020).

Under the current circumstance, exploring global energy market dynamics and unfolding challenges toward broader energy transition are equally important. Answers to relevant questions can bring forward critical information to both policymakers and corporate leaders. They can also lead to intensive academic debates and general interests to further exploring this exciting area. The current collection of research covers 21 papers looking into the dynamics of fossil fuel markets, renewable energy markets, and electricity markets. Notably, one-third of these papers address renewable energy issues in China. This is not entirely surprising as China is the leader of renewable energy investment in the world and its policies on renewable energy development are dynamic and especially interesting to many emerging economies (Wang et al., 2020). The second most popular topic is oil prices. It is an old topic but constantly attracts new attention. The international crude oil markets have been extremely dynamic since the shale revolution (Chen et al., 2020). During the COVID-19 pandemic, the oil prices shocked the world again and again, with the most astonishing one, in the end, that is the negative WTI price. These events demonstrate that much more about oil price shocks are yet to find out. Behavior economics,

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an emerging subject in energy and environmental studies (e.g., Liu et al., 2019b; Li et al., 2021), is also heavily investigated in this special issue.

Now, let's go briefly over each of the contributing papers:

Starting from Guo et al., which simulate the impacts of different renewable energy subsidies on China's energy transition. Subsidies are often considered critical driving factors to renewable energy development, their results, however, show that even with fewer subsidies, the Chinese government's 2030 targets on total energy consumption and carbon emission intensity can be achieved. Liang et al. evaluated the overall efficiency score of hydropower electricity generation in the three main regions of China. Using the Epsilon-based Measure model with the Data Envelopment Analysis method, they found that the western region has the highest efficiency, followed by the central region and then the eastern region. Efficiency level is mainly determined by natural water resources and geographical advantages, but little to do with economic development.

Bu and Zhang assess the completion pressure of a newly modified quota in 30 provinces under China's new renewable portfolio standard policy issued in 2019. They find that 17 provinces face significant challenges, while ten other provinces have no difficulty in achieving the target. Furthermore, Zhang et al. propose a comprehensive model for the allocation of China's total renewable electricity consumption (REC) targets to sub-national levels. Their analysis shows that China's existing REC policy is still conservative. The total achievable REC under China's current REC guarantee mechanism can be further increased by 15.36–20.25%.

Three provincial case studies are presented to investigate the different topics pertaining to renewable energy development in China. In a case study of the photovoltaic (PV) system in Beijing, China's capital, Zhang et al. estimate the deployment potential of rooftop PV in Beijing. It is found to be about 11.47 GW and the large-scale commercial rooftop PV is approaching grid parity. With the consideration of expanding renewable energy on the generation mix, Lv et al. propose a generation expansion planning method in the case of Jiangsu Province in China. The results show that the province could achieve a renewable energy share from 17.9 to 53.7% and the required flexibility can be achieved with the existing technologies. Liu et al. analyze renewable energy in the electricity market with China's Guangdong province as a case study. They find that a competitive electricity market is conducive to renewable penetration, but the economic viability of renewables still needs the support of feed-in-tariff.

The oil market is the second most popular subject in this special issue, with four papers devoted to studying the dynamic behaviors of the international oil market and the impact of such behaviors on the macro-economy or firms. Chen et al. (2020) examine how global oil prices had affected China's consumer and producer prices. They reveal a non-linear effect of oil prices on consumer/producer prices and find the non-linear effect is different between the Brent and West Texas Intermediate (WTI) crude oil prices. Li and Su investigate the time-frequency dynamics of stochastic volatility spillovers between international crude oil markets and China's commodity sectors. The results suggest that international crude oil markets have significant volatility spillover effects on China's bulk commodity markets, and the volatility spillovers are sensitive to extreme geopolitical or financial events. Cao et al. find that the coefficient of oil price uncertainty negatively affects corporate investment and its efficiency. Regarding the emerging benchmark prices in East Asia, Liu et al. find that China's crude oil futures market (INE market) has been well integrated with traditional benchmarks, such as WTI and Brent despite its recent launch in March 2018.

Three papers study the energy transition directly. Taghizadeh-Hesary and Rasoulinezhad investigate how energy transition patterns were affected by economic variables in 45 Asian economies. They find that economic growth and CO_2 emissions have opposite effects on the energy transition, with the former being positive. To deepen the understanding of energy transition, Wei et al. explore the evolution of national and global energy consumption structure (ECS) with the distribution dynamics approach. They find that while the relative consumption of coal and oil may be reduced, the oil will remain the most common form of energy source, while natural gas has a significant variability. As fuel switching between coal and natural gas is an effective strategy to mitigate the emissions and environmental pollutions of other forms of fossil fuel energy, Hao et al., quantify the role of natural gas in achieving urban Ecological Civilization in China using a case study.

Three papers exploring behavioral issues. Zhao et al. analyze the crucial influencing factors of governments' and manufacturers' strategies. They set up a theoretical model that governments' subsidy policies, manufacturers' environmental quality measures, and customer environmental awareness (CEA) are modeled in a game. Their analysis reveals that increases in penalties, the subsidy coefficient, environmental quality, and CEA can promote manufacturers' integrity. Baek et al. study how Kenyan households choose their lighting fuels using survey data. They confirm the energy ladder hypothesis and find that modern fuels are more likely to be chosen by households with a female head, higher income, more wealth, and higher levels of education. Zhou et al., investigate the effect of provincial social capital on environmental performance in China and find a heterogeneous relationship between social capital and environmental performance in different regions. The relationship is more consistent in the eastern and southwest regions than in other regions.

The rest four papers address a mix of compelling issues. Raath and Ensor explore the time-varying relationship between energy and water commodities with the application of the wavelet technique. They demonstrate that during specific localized economic events, water prices lead to energy prices at certain time horizons. Their findings suggest that reforming energy markets and gas prices are conducive to promote the use of natural gas for lower emissions. Gong et al. conceptualize an energy-economic resilience concept to evaluate the economic recovery ability of an economy. They test their model in a preliminary empirical analysis of 14 countries after the 2007–2008 global financial crisis. Li and Liao examine the heterogeneous impact of financial development on green total factor productivity for 40 countries. An inverted U-shaped relationship between financial development and green total factor productivity is found in developing countries. In developed countries, the development of bank and insurance tends to undermine green total factor productivity, while the development of securities has the opposite effect. With a proposed green mining efficiency, Wang et al. employ a two-stage combination Data Envelopment Analysis examined to assess some coal mines in China.

In the end, we would like to thank all the contributing authors, anonymous reviewers for their invaluable thoughts and insightful discussions. We also appreciate the journal editors and publication team behind it. Their hard work makes this collection possible.

AUTHOR CONTRIBUTIONS

XS has drafted the text and all authors listed have made a substantial, direct, and intellectual contribution to the work, and approved it for publication.

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REFERENCES

Chen, D., Yu, J., Shi, X., and Zhang, D. (2020). How does the Chinese economy react to uncertainty in international crude oil prices? *Int. Rev. Econ. Finance.* 64, 147–164. doi:10.1016/j.iref.2019.05.008

Geng, J.-B., Du, Y.-J., Ji, Q., and Zhang, D. (2021). Modeling return and volatility spillover networks of global new energy companies. *Renew. Sustain. Energy Rev.* 135, 110214. doi:10.1016/j.rser.2020.110214

Li, X., Zhang, D., Zhang, T., Ji, Q., and Lucey, B. (2021). Awareness, energy consumption and pro-environmental choices of Chinese households. *J. Clean. Prod.* 279, 123734. doi:10.1016/j.jclepro.2020.123734

Liu, J., Zhang, D., Cai, J., and Davenport, J. (2019a). Legal systems, national governance and renewable energy investment: evidence from around the world. *Br. J. Manag.* 1–32. doi:10.1111/1467-8551.12377

Liu, Y., Sun, X., Sun, T., Shi, X., and Liu, J. (2019b). Promoting green residential buildings by increasing homebuyers' willingness to pay: evidence from Sino-Singapore Tianjin Eco-city in China. *J. Clean. Prod.* 238, 117884. doi:10.1016/j.jclepro.2019.117884

Wang, Y., Zhang, D., Ji, Q., and Shi, X. (2020). Regional renewable energy development in China: a multidimensional assessment. *Renew. Sustain. Energy Rev.* 124, 109797. doi:10.1016/j.rser.2020.109797

Yoshino, N., Taghizadeh-Hesary, F., and Otsuka, M. (2020). Covid-19 and optimal portfolio selection for investment in sustainable development goals. *Finance Res. Lett.* 101695. doi:10.1016/j.frl.2020.101695

Zhang, D., Hu, M., and Ji, Q. (2020). Financial markets under the global pandemic of COVID-19. *Finance Res. Lett.* 36, 101528. doi:10.1016/j.frl.2020.101528

Zhao, Y., Shi, X., and Song, F. (2020). Has Chinese outward foreign direct investment in energy enhanced China's energy security? *Energy Pol.* 146, 111803. doi:10.1016/j.enpol.2020.111803

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Revisiting the Integration of China Into the World Crude Oil Market: The Role of Structural Breaks

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The China's crude oil futures market (INE market), as it was first launched in late March of 2018, quickly draws much attention from global investors. In reference to the high frequency data, this research explores how well this new product reacts efficiently to international influences and to what extent it can be integrated with traditional benchmarks, such as WTI and Brent. The multivariate GARCH models are employed to capture the cross-market time-varying correlations, return and volatility spillovers, which are modified by incorporating the detected structural breaks in the return dynamics to improve the accuracy of model estimates. Empirical results indicate a strong integration of INE market with these international benchmarks. A high but time-varying correlation is observed with recurring highs around 0.7. Spillover effects have included significant bidirectional return and volatility spillovers between the INE and the international benchmark markets. Secondly, INE market appears to interact better with the Brent market than with the WTI market. Thirdly, structural breaks can influence correlations, the portfolio weights and hedge ratios. Lastly, the correlation between crude oil futures markets decreases significantly during the periods when structural breaks caused by economic and/or geopolitical events are identified. These findings have important implications in policy makings and economic decisions on portfolio management and hedging strategies.

Keywords: crude oil, integration, structural breaks, dynamic correlation, volatility transmission

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INTRODUCTION

Crude oil is not only a crucial source of energy resource for economic growth and national security, but also one of the most valuable assets traded in the international commodity markets (Ding et al., 2017; Ma et al., 2019; Xu et al., 2019). In retrospect, reference benchmarks for crude oil prices have been dominated by the West Texas Intermediate (WTI) and the European Brent markets (Mensi et al., 2014). The lack of an effective benchmark market in Asia is responsible for the well-known "Asian premium" (AlKathiri et al., 2017; Shen et al., 2018). Although China has become the largest oil importer and the seventh major producer of crude oil in the world[1], the Chinese crude oil market can only passively follow the pricing mechanisms of these international markets and cannot reliably reflect its own supply and demand information in domestic markets (Shi and Sun, 2017).

[1] https://www.eia.gov/todayinenergy/detail.php?id=34812 (accessed September 15, 2019).

Consequently, the RMB-denominated crude oil futures of China was launched in the Shanghai International Energy Exchange (INE) in late March of 2018. As the first international futures product induced in China, the INE futures is traded to overseas investors and has attracted much attention by overseas institutions and investors. The success of this international product will depend on how well it will integrate with existing international crude oil futures markets. The present paper aims to model the Chinese newly introduced crude oil futures under global influence and assess the extent to which this product integrates with international benchmark markets, namely WTI and Brent.

The extent to which the Chinese crude oil futures market links to the international markets has great implications for the domestic energy security and overseas investors. China has actually surpassed the U.S. to become the largest net importer of crude oil in the world (EIA, 2018). The country's oil import dependency is expected to rise (Wang and Wei, 2016; Wang et al., 2017; Cheng et al., 2019), implying that China's oil market and oil security may be vulnerable to fluctuations in oil prices from the international oil markets. If the crude oil futures market in China is highly integrated into the international benchmark markets, the expected returns of China's crude oil futures will mainly be determined by the world's undiversifiable risk which further deteriorate energy security concerns over the country. Meanwhile, the conditions of oil demand and supply in China will likely substantially influence the international oil markets (Li and Leung, 2011). Given other things remaining unchanged, China will be more influential as the degree of integration into the international markets increases. If, on the contrary, the crude oil futures market in China is only weakly integrated into the world markets, international economic conditions will have less influence on the Chinese market. If the returns of the Chinese market do not move together with those of international markets, then global investors may benefit from the reduction of diversifiable risk (i.e., portfolio risk) by diversification that includes the Chinese crude oil futures. Moreover, the level of integration could insightfully reflect the position and power of China's newly introduced crude oil futures market in the global oil market.

Furthermore, the success of China's crude oil futures has important implications for introduction of additional advanced financial derivative products. International institutions are interested in such opportunities in China's opening financial markets (Shi et al., 2018). This is a critical issue for investors to realize potential gains from diversifying their international portfolio, and for policy makers to make proper market policies and deal with contagion risks as a result of international shock transmissions (Jouini, 2015). In the foreseeable future, Shanghai crude oil futures are likely to remain as the only financial product on which investors can hedge against or speculate on China's crude oil market. The interactions between the Chinese and the international crude oil futures markets may directly influence the investment decisions and profitability of those market participants who heavily rely on the signs and directions of information flow.

Research on the integration among oil markets in the world dates back to the 1980s, Adelman (1984) argued that the oil markets around the world were highly integrated and thus there is a global market for crude oil like "one great pool." This globalization hypothesis indicates that changes in oil prices in a regional oil market will spread to the other markets, which has been verified in subsequent empirical studies (see Rodriguez and Williams, 1993; Hammoudeh et al., 2008; Fattouh, 2010; Ji and Fan, 2016; Kuck and Schweikert, 2017; Klein, 2018, among others). Although there is no unanimously agreeable definition of market integration, following Bhar and Nikolova (2009), markets are considered to be integrated when assets in different locations or markets but with identical risk have the same expected return. Related to this definition, this paper focuses on two types of integration: the commonality of oil return movements over time among different markets and cross-market information transmission that measures through return and volatility spillovers.

In this paper, using intraday 5 min data for April 26, 2018, to July 23, 2019, we investigate the level of integration of the China's crude oil futures market with international benchmark markets by examining their time-varying correlations, return and volatility spillovers, with the VAR-DCC-GARCH and the VAR-BEKK-GARCH models. The DCC model measures the variation of the conditional correlations over time. The BEKK model captures the effects of past innovations and variance on the current conditional variance as well as the cross-market shocks and volatility transmission. The information obtained from these models can be used to computing optimal asset allocation and developing global hedging policies. In addition, the Bai and Perron (2003) test is applied to detect structural breaks in the crude oil futures return series, the detected breaks are then incorporated into the VAR-GARCH-type models to improve the accuracy of model estimates and examine the influence of structural breaks on cross-market relationships.

In this way, the contributions of our study are 3-fold. First, to the best of our knowledge, it is the first study to explore time-varying correlation and information transmission between China's newly crude oil futures market and the international markets. Although some stylized facts of the Chinese new crude oil futures have been reported in a pioneer work by Ji and Zhang (2018), they did not emphasize the cross-market relationships. Our empirical results reveal a strong evidence for integration of China's crude oil futures market with international benchmarks. For each pair, we find a high but time-varying correlations with recurring highs around 0.7 within the sample period. In particular, the INE market integrates better with the Brent market than with the WTI market. Although international benchmark markets play a dominate role in cross-market information transmission, the shocks of the INE market will have an impact on the volatility of the international markets.

Second, unlike previous studies using monthly data (Weiner, 1991; Rodriguez and Williams, 1993), weekly data (Reboredo, 2011; Liu et al., 2013; Ji and Fan, 2016; Kuck and Schweikert, 2017), or daily data (Zhang and Wang, 2014; Chan and Woo, 2015; Jiang et al., 2017; Scheitrum et al., 2018), we employ intraday data in examining correlation and information transmission among crude oil futures markets. In the financial market, the discrete collection of data will inevitably result in a loss of information. Since the crude oil market has become an important part of the global financial market, it has strong liquidity and can reflect more new information according to price dynamics within minutes (Liu and Wan, 2012; Elder et al., 2013; Wang et al., 2019). Studies based on low-frequency data cannot incorporate information implied in intraday price movements (Phan et al., 2016). Moreover, the economic benefits of using intraday data in modeling volatility and analyzing cross-market relationships among different financial markets have been explained in the literature (Wu et al., 2005; Rittler, 2012; Yang et al., 2012; Huo and Ahmed, 2018).

Third, we will detect structural breaks in crude oil futures price movements and incorporate them into the analytical procedures to improve the accuracy of volatility estimates. It has been acknowledged that certain economic and/or geopolitical events may cause structural changes in crude oil price dynamics (Zhang, 2008; Broadstock et al., 2016; Liu et al., 2019). The persistence of the volatility may be overestimated when the structural breaks are ignored (Lamoureux and Lastrapes, 1990). Several studies give further theoretical background and empirical evidences, documenting that structural breaks should be considered when modeling financial market volatility (see Mikosch and Stărică, 2004; Charles and Darné, 2014; Ewing and Malik, 2017, among others). In this study, structural breaks are found to influence the performance of the modeling estimates, and further have an impact on cross-market correlations, the portfolio weights and hedge ratios.

The remainder of this paper is structured as follows. The econometric methodology in this paper is explained in section related literature. Then section Methodology reviews related literature. Section Data Description describes the data and reports preliminary analyses. The empirical results are presented in section Empirical Results and section Discussion and Economic Significance of the Results includes the discussion and economic significance of the results. Section Conclusions and Policy Implications provides the concluding remarks and policy implications.

RELATED LITERATURE

Oil Market Integration

The question whether different crude oil markets located in various countries or regions are integrated has long been focused on in energy related literature. This can date back to the 1980s, when Adelman (1984) argued that the oil market around the world were highly integrated and thus there is a global market for crude oil like "one great pool." By contrast, Weiner (1991) supports the regionalization hypothesis across oil markets, claiming that the movements of oil prices depend on the local factors, e.g., government's energy policy and regional shocks and thus oil prices vary in an independent way.

More modern studies provide empirical evidence in favor of the assumption articulated by Adelman (1984) that oil markets in the world behave in a similar way and can be seen as one common market. "One great pool" hypothesis is also supported by Rodriguez and Williams (1993) and Hammoudeh et al. (2008). Using weekly data of crude oil spot prices for 24 major producers and consumers around the world, Ji and Fan (2016) further verify that the global crude oil markets are integrated. In a recent study, Kuck and Schweikert (2017) investigate long-term equilibrium relationships across five major crude oil spot prices, namely WTI, Brent, Bonny Light, Dubai, and Tapis, from 1987 to 2015. They find strong evidences to support that the crude oil markets are globally integrated, and the relationship between crude oil markets changes dynamically over time. Klein (2018) surveys the interconnectedness of WTI and Brent markets on different resolutions of price movements. Long-term movements of WTI and Brent confirm "one-great-pool" hypothesis.

The increasing degree of integration of global crude oil futures markets enable information transmission across markets that can be captured by return and variance spillovers. Lin and Tamvakis (2001) investigate variance spillovers across crude oil futures in New York Mercantile Exchange and London's International Petroleum Exchange, the authors find the existence of substantial spillover effects when both markets are traded simultaneously. Similarly, Kang et al. (2011) explore information transmission and volatility spillover between WTI and Brent market. Chang et al. (2010) reveal variance spillovers and asymmetric effects on conditional volatilities for most of the world oil markets. Magkonis and Tsouknidis (2017) find significant spillover effects across commodities based on petroleum and among their spot-future markets variances. As China has become the leading importer of crude oil in the world, its oil import dependence continues to rise. The interaction between Chinese and the international crude oil markets has recently attracted more attention in the literature. Li and Leung (2011) and Song and Li (2015) show that China's oil market is integrated into the international oil market. Liu et al. (2013) investigate volatility spillovers between China's crude oil spot price and four major crude oil spot prices in the world market from 2001 to 2011 with weekly data, their empirical results provide evidence for unidirectional risk spillover from the international benchmark markets to the oil market in China. The authors attribute the dominance of international benchmark markets over domestic market to the absence of China's crude oil futures market.

Intraday Periodicity

The ubiquitous intraday periodicity in the return volatility in financial markets may exert a significant influence in the statistical features of high-frequency returns (Andersen and Bollerslev, 1997). This issue can be addressed by standardizing the return series through the average absolute returns as well as the flexible Fourier form (FFF) first proposed by Andersen and Bollerslev (1997)[2]. Indeed, modern research draws attention to employ the framework combining high frequency data and GARCH-type models to analyze volatility spillovers across different financial markets (see Rittler, 2012; Yang et al., 2012; Nishimura et al., 2015; Huo and Ahmed, 2018, among others).

[2]For more details on comparison between the two seasonal adjustment methods, see Martens et al. (2002).

In a pioneer work, Ji and Zhang (2018) find that intraday periodicity indeed exists in high-frequency returns of China's crude oil futures, which is described as a multi-U-shape pattern. Thus, it is necessary to take account of intraday periodicity in order to reveal the complex intraday return dynamics across oil futures markets.

Structural Breaks

Lamoureux and Lastrapes (1990) prove that, the volatility persistence obtained from the standard GARCH model may be overestimated if the structural breaks are ignored. Mikosch and Stărică (2004) provide further theoretical explanations that structural breaks should be considered when modeling financial market volatility, which has been verified by following empirical research (see Stărică and Granger, 2005; Charles and Darné, 2014; Ewing and Malik, 2017, among others). In recent studies, Lee et al. (2010), Ewing and Malik (2017), and Liu et al. (2019) reveal that certain economic and/or geopolitical events may cause structural changes in crude oil dynamics. Although some studies have considered structural changes in analyzing oil markets, these studies use structural breaks only as the basis for dividing the sample periods; they do not incorporate structural breaks into the used empirical models (Gülen, 1999; Chen et al., 2015; Ji and Fan, 2015). One exception is Kang et al. (2011), who examine the volatility spillover between WTI and Brent by using a bivariate GARCH model with and without dummies accounting for structural changes. The authors conclude that the directions of information flows and volatility spillovers across crude oil markets may be distorted if structural changes are ignored. In the GARCH-type model, the conditional variance relies on the estimates of conditional mean process. Unlike Kang et al. (2011) considering structural changes in the conditional variance estimates, in a recent study, Tule et al. (2017) endogenously and sequentially detect structural breaks in return series with Bai and Perron (2003) test and modify the VARMA-AGARCH model by incorporating break points into conditional mean equation, to investigate information transmission between world oil markets and the sovereign bond market of Nigerian. Their results indicate that volatility spillover between markets is sensitive to structural breaks.

METHODOLOGY

The purpose of this study is to examine the time-varying correlations and spillover effects between China's crude oil futures market and international benchmark markets. The research framework includes (a) detection of structural breaks in the crude oil futures return series using the Bai and Perron (2003) test, (b) inclusion of structural breaks as dummy variables into the mean equation of the VAR model to determine the cross-market return spillovers, and (c) use of DCC-GARCH and BEKK-GARCH models to calculate the dynamic conditional correlations and volatility spillovers between the crude oil futures markets. Although the VAR model can reasonably estimate return spillovers, incorporating structure breaks into the VAR model can help improve the estimates of volatility.

Structural Break Test

Ignoring structural breaks in the financial time series may lead to bias in the estimation of the GARCH model due to overestimates of volatility persistence (Lamoureux and Lastrapes, 1990; Mikosch and Stărică, 2004; Charles and Darné, 2014; Tule et al., 2017). Several methods are available to detect structural breakpoints in financial time series, such as the Chow test (Chow, 1960), the cumulative sum (CUSUM) test (Brown et al., 1975), and the Bai and Perron (2003) test. However, the Chow test requires a priori knowledge of the exact data points of the structural breaks (McLeod and Haughton, 2018; Taghizadeh-Hesary et al., 2019). The CUSUM test cannot provide information on the number of breakpoints and their corresponding dates (Mensi et al., 2016). Therefore, the Bai and Perron (2003) test is employed in this paper. This test can detect multiple breakpoints in a time series based on least squares techniques and endogenously locate the date on which a breakpoint occurred. If the number of structural breakpoints detected is m, the full sample period can be divided into $m + 1$ regimes. This test can be expressed by the following linear regression equation:

$$y_t = \delta_j z_t + \gamma \varphi_t + \epsilon_t \ \ for \ \ t = T_{j-1} + 1, \cdots, T_j, \\ j = 1, \cdots, m+1 \tag{1}$$

In Equation (1), y_t denotes the dependent variable at time t; z_t is a constant term; φ_t is the independent variable; δ_j and γ are the corresponding coefficients; and ϵ_t is the disturbance at time t. $T_1, \cdots, T_m$ are indices that represent the break points, which by assumption are unknown. In this study, we use the sequential test developed by Bai and Perron (2003).

VAR Model for the Conditional Mean Specification

The VAR model can be used to forecast interconnected time series systems, analyze the dynamic shocks of random disturbances on variable systems, and assess the impact of economic shocks or events on economic variables (Zhang and Sun, 2016). In this study, we use the VAR model to examine the return spillover between crude oil futures markets. We choose the VAR (1) model based on the principle of minimum Akaike information criterion (AIC) values. The bivariate VAR model with structural break dummy variables is shown in Equations (2) and (3).

$$r_t^c = \mu^c + a^c r_{t-1}^c + b^c r_{t-1}^g + d_1 D_1 + \cdots + d_p D_p + \varepsilon_t^c \tag{2}$$

$$r_t^g = \mu^g + a^g r_{t-1}^g + b^g r_{t-1}^c + e_1 D_1 + \cdots + e_q D_q + \varepsilon_t^g \tag{3}$$

where r_t^c and r_t^g are the logarithmic returns of China's crude oil futures price (INE) and the international crude oil futures prices (WTI and Brent), respectively, calculated by $r_t = 100^* \ln\left(\frac{P_t}{P_{t-1}}\right)$; P_t is the closing price of each crude oil futures market at time t; μ^c and μ^g are the conditional mean series; and a^c and a^g can measure the return spillover of each market on their own, whereas b^c and b^g measure the return spillover across markets. ε_t^c and ε_t^g are the residual series of the VAR (1) model. p and

q, respectively, represent the number of structural breakpoints in INE return and WTI (Brent) return series; $D_i (i = p, q)$ denote the dummy variables corresponding to structural breaks, in line with Tule et al. (2017), and $D_i = 1$ *if* $t \geq$ *break dates*; otherwise, $D_i = 0$.

MGARCH Models for the Conditional Variance Specification

Two multivariate GARCH-type models are employed to examine the dynamic correlation and volatility spillovers between different crude oil futures markets. The first is the DCC-GARCH model proposed by Engle (2002), which not only measures the volatility persistence of each market but also flexibly models the variance-covariance matrix to describe the time-varying linkages between markets[3]. Although the rolling window approach can estimate the time-varying correlation coefficients, the time-varying results can be affected by the selection of the window length to allow a trade-off between noisy and smooth data for small and large window widths, respectively. The DCC-GARCH model can address the disturbance of window length selection (Ji and Fan, 2016). The second is a full BEKK-GARCH model defined in Engle and Kroner (1995), which measures the volatility spillover effects of the two markets on their own and across markets.

(1) DCC-GARCH model

The DCC-GARCH model is estimated in two stages. The first is to perform a series of univariate GARCH estimates, and the second is to compute the dynamic conditional correlations based on the first stage.

First, a typical univariate GARCH (1,1) model can be described as follows:

$$\varepsilon_t \left| \Omega_{t-1} \right. \sim N\left(0, H_t\right), \quad \varepsilon_t = \begin{bmatrix} \varepsilon_t^c \\ \varepsilon_t^g \end{bmatrix}, H_t = \begin{bmatrix} h_t^{cc} & h_t^{cg} \\ h_t^{gc} & h_t^{gg} \end{bmatrix} \tag{4}$$

$$h_t = \omega + \alpha \varepsilon_{t-1}^2 + \beta h_{t-1} \tag{5}$$

where ε_t is a 2×1 vector of residuals obtained from the VAR (1) model, and Ω_{t-1} is the information set available up to time $t-1$. H_t is the conditional variance-covariance matrix of residuals. h_t^{cg} and h_t^{gc} are the covariance between the INE and WTI (Brent) returns. h_t^{cc} and h_t^{gg} are derived from the univariate GARCH process and are conditional variances of the INE and WTI (Brent) returns series. $\omega > 0$, $\alpha \geq 0$, and $\beta \geq 0$ ensure the positive definite of the conditional variance (h_t). ω is a constant term, while the sum of α and β measures the volatility persistence of a given shock.

Second, DCC coefficients for the two markets are estimated. The conditional variance-covariance matrix of the residuals can be described as follows:

$$H_t = D_t R_t D_t \tag{6}$$

$$D_t = diag\left(\sqrt{h_t^{cc}}, \sqrt{h_t^{gg}}\right) \tag{6a}$$

$$R_t = diag\left(Q_t\right)^{-\frac{1}{2}} Q_t diag\left(Q_t\right)^{-\frac{1}{2}} \tag{6b}$$

$$Q_t = \left(1 - \theta_1 - \theta_2\right) \overline{Q_t} + \theta_1 \left(z_{t-1} z_{t-1}'\right) + \theta_2 Q_{t-1} \tag{6c}$$

$$z_t = \left(\varepsilon_t^c, \varepsilon_t^g\right)' \tag{6d}$$

where R_t is the dynamic conditional correlation (DCC) coefficient matrix; D_t is a 2×2 diagonal matrix of the conditional standard deviation of the residuals; Q_t is the 2×2 conditional variance-covariance matrix, with its unconditional variance-covariance matrix Q_t; and z_t is a 2×1 standardized residual matrix. θ_1 and θ_2 denote the short-term and long-term persistence of shocks to the DCC, respectively. θ_1 and θ_2 are both non-negative and satisfy $\theta_1 + \theta_2 < 1$.

The parameters of the DCC-GARCH model are estimated using the quasi-maximum likelihood method, where the conditional distribution of ε_t is assumed to follow a joint Gaussian log-likelihood function for a sample of T observations and $k = 2$ in a bivariate model, as in Equation (7).

$$\text{Log Likelihood} = -\frac{1}{2} \sum_{t=1}^{T} \left[k \log(2\pi) + 2 \log|D_t| + \log|R_t| + \varepsilon'_t R_t^{-1} \varepsilon_t\right] \tag{7}$$

(2) BEKK-GARCH model

Note that different specifications of H_t will lead to different multivariate GARCH models. Engle and Kroner (1995) introduce the BEKK representation of the multivariate GARCH models by specifying the positive definite covariance matrix. Specifically, the bivariate full BEKK-GARCH for INE and WTI (Brent) returns takes the following form.

$$H_t = CC' + A' \varepsilon_{t-1} \varepsilon'_{t-1} A + B' H_{t-1} B \tag{8}$$

$$C = \begin{bmatrix} c^{cc} & 0 \\ c^{cg} & c^{gg} \end{bmatrix}, A = \begin{bmatrix} a^{cc} & a^{cg} \\ a^{gc} & a^{gg} \end{bmatrix}, B = \begin{bmatrix} b^{cc} & b^{cg} \\ b^{gc} & b^{gg} \end{bmatrix} \tag{9}$$

where C is a 2×2 lower triangular matrix of constants, and C' is a transposed matrix of C. a^{cg} and b^{cg} capture short-term and long-term volatility spillover from INE to WTI (Brent) returns, respectively; a^{gc} and b^{gc} capture short-term and long-term volatility spillover from WTI (Brent) to INE returns, respectively. a^{cc} and a^{gg} capture the impacts of past shocks of INE to WTI (Brent) returns on their own current volatility, respectively; b^{cc} and b^{gg} capture the impacts of past volatility of INE to WTI (Brent) returns on their own current volatility, respectively.

Similarly, the parameters of the BEKK-GARCH model are estimated by the quasi-maximum likelihood method in Equation (10):

$$\text{Log Likelihood} = -\frac{1}{2} \sum_{t=1}^{T} \left[k \log(2\pi) + \ln|H_t| + \varepsilon_t' H_t^{-1} \varepsilon_t\right] \tag{10}$$

DATA DESCRIPTION

Data

In financial markets, sampling frequency has an important impact on the estimation of volatility. Several studies suggest

[3] We leave the application of fractionally integrated specifications allowing for long memory in the variance equation (see Conrad et al., 2011) for future research.

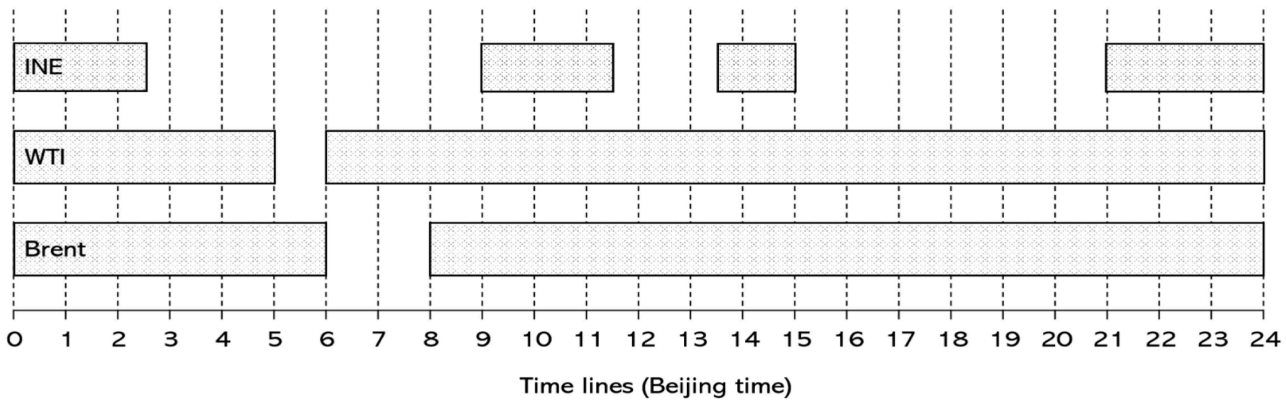

FIGURE 1 | INE, WTI, and Brent trading sessions.

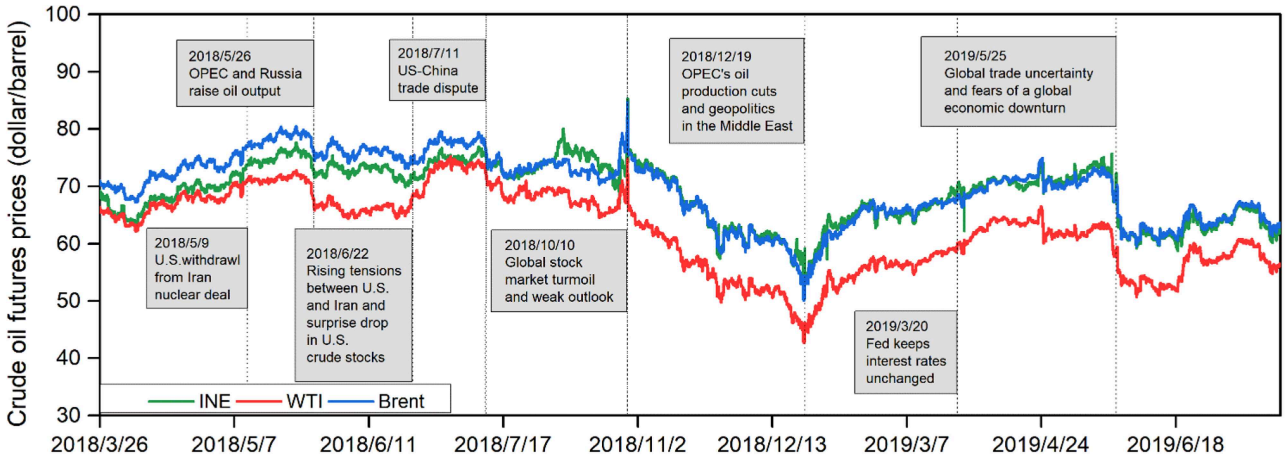

FIGURE 2 | INE, WTI, and Brent price series.

that the 5-min interval is short enough that most of the volatility information in a day is guaranteed, and long enough that the confounding effects from market microstructure noise are not overwhelming (Andersen, 2000; Gong and Lin, 2018). Following the works of Liu and Wan (2012), Rosa (2014), and Wen et al. (2016), we choose a 5-min sampling frequency. For China's crude oil futures market, we include prices for the nearby month contract on INE. For the international benchmark markets, we include prices for the nearby month contract on the New York Mercantile Exchange (NYMEX) and the London Intercontinental Exchange (ICE). The 5 min high-frequency data were collected from Bloomberg and cover the period from March 26, 2018, to July 23, 2019. Price records of the INE crude oil futures in the first month of futures trading (i.e., from March 26, 2018, to April 25, 2018) were excluded from the sample because this period is regarded as the learning stage where the market is not stable (Hou and Li, 2016). To facilitate data screening, we convert the trading hours of WTI and Brent crude oil futures to Beijing time for a typical day (see **Figure 1**). Additionally, INE crude oil futures priced in RMB (yuan) are converted into US dollars. After removing periods with either a shortened trading session or too few transactions, we obtain 20,701 5 min high-frequency observations. From the econometric point of view, 5 months of intraday 5 min data (a total of 20,701 observations) are long enough to yield meaningful estimation results without a serious small sample bias issue (Yang et al., 2012; Huo and Ahmed, 2018).

Figure 2 shows the trend of INE, WTI and Brent crude oil futures prices, in which the prices of the three crude oil futures markets tend to move similarly. This implies that crude oil futures prices are largely driven by common fundamental factors, such as the conditions of supply and demand, geopolitics, economic growth and financial markets (Ji and Fan, 2016; Zhang et al., 2019). The common trend for the price dynamics of these crude oil futures markets can initially indicate that there may be shock and volatility correlations between markets; hence, multivariate methods are needed to further reveal the correlation and spillover effects between markets.

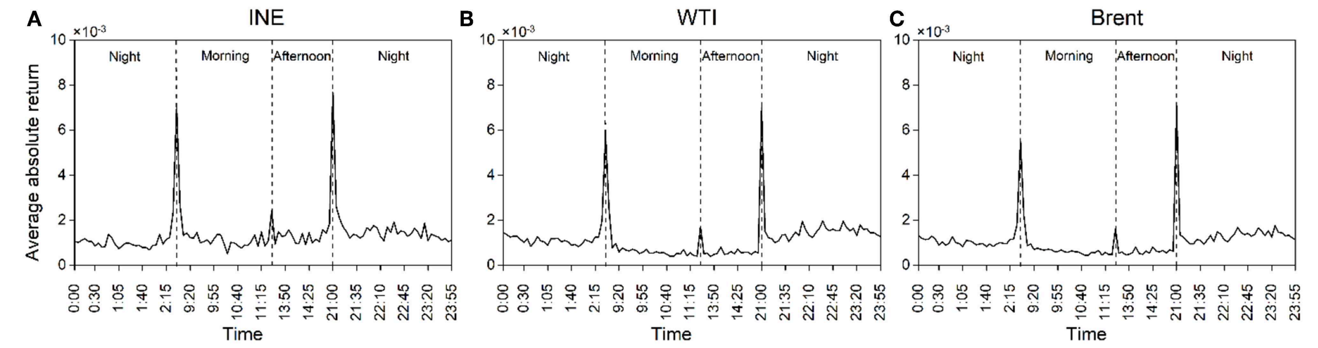

FIGURE 3 | Intraday average absolute returns at 5 min intervals during a trading day. **(A)** INE, **(B)** WTI, **(C)** Brent. The absolute values of original 5 min returns are averaged across days over the entire sample period. There are 112 such values per day.

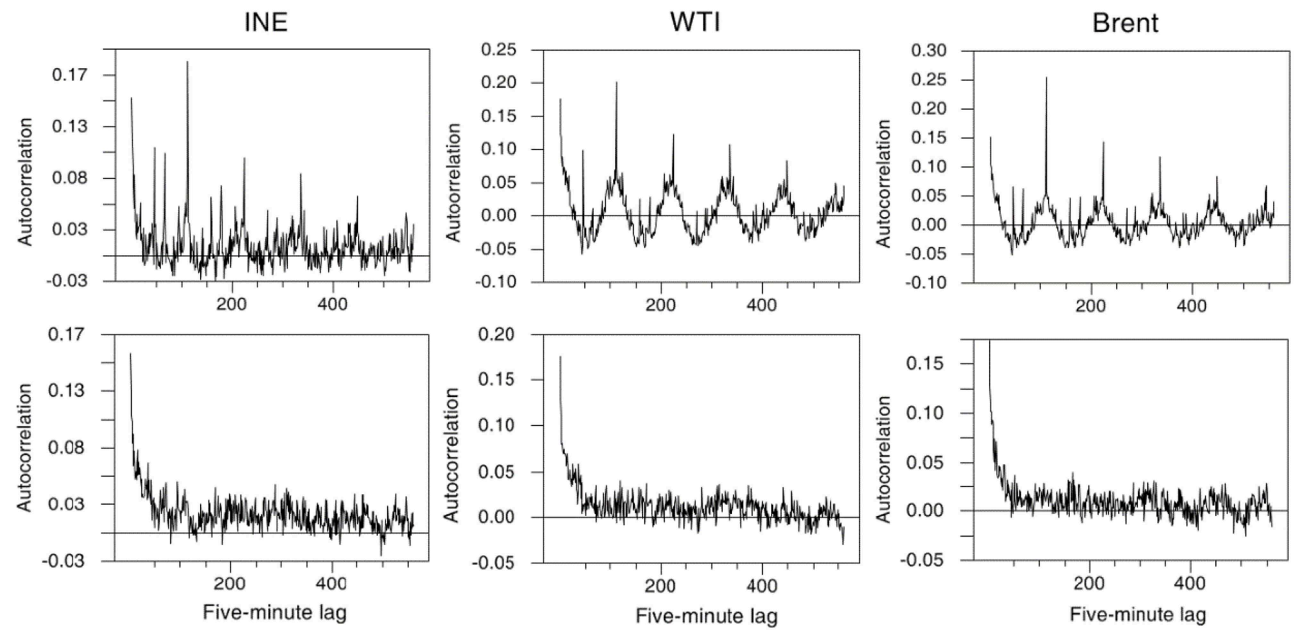

FIGURE 4 | Autocorrelation coefficients of intraday absolute returns. Autocorrelation coefficients of the absolute values of original 5 min returns are displayed by the upper figure and those of the filtered values by the lower figure. The horizontal axis measures lags up to 560 (5 days times 112 per day).

Removal of Intraday Periodicity

A well-known stylized fact about the intraday dynamic characteristics of many financial markets is that return volatility follows a U-shaped pattern (Tse, 1999). **Figure 3** plots the average absolute returns, $f_k = \frac{1}{T}\sum_{t=1}^{T}\left|r_{t,k}\right|,\ t = 1,\cdots,T\ and\ k = 1,\cdots,\ K$, where $r_{t,k}$ denotes the percentage returns for each crude oil futures at the end of the kth interval at day t. T is the total number of trading days and K is the number of equidistant intervals during a trading day. As evident from **Figure 3**, the usual U-shaped patterns in return volatility of all crude oil futures are observed. Taking the INE crude oil futures as an example, significantly higher return volatility can be observed in each starting period of morning hours (9:00–11:30), afternoon hours (13:30–15:00), and night trading sessions (21:00–2:30). These results parallel the study of Ji and Zhang (2018), they reveal that intraday periodicity indeed exists in high-frequency returns of China's crude oil futures and it can be described as a multi-U-shaped pattern.

Figure 4 presents the pattern of the autocorrelation of absolute crude oil futures returns at 5 min intervals for five consecutive days, that is a lag of 560 5 min intervals. The sample autocorrelations exhibit a declining U-shaped pattern, though somewhat distorted, across each day. As shown, each short-term cycle of the autocorrelations is spaced a day (i.e., 112 5-min intervals) apart. The same periodicity pattern is observed for the following days. Hence, one urgent problem in using high-frequency data is that such ubiquitous intraday periodicity in the return volatility in financial markets may have a significant

TABLE 1 | Statistical properties of 5 min filtered returns.

Variables	INE returns	WTI returns	Brent returns
Mean	0.0017	0.0053	0.0070
Standard deviation	2.2492	1.7620	1.7404
Skewness	1.7131	1.6522	2.1941
Kurtosis	200.1113	130.9842	142.8540
Jarque-Bera	3.4547E+07***	1.4806E+07***	1.7617E+07***
Q (10)	1260.0240***	91.724***	90.303***
Q^2 (10)	9137.7050***	3465.7010***	4121.7880***
ADF	−122.4840***	−103.5710***	−104.5520***
PP	−186.0730***	−140.0410***	−142.3940***
KPSS	0.0874	0.0654	0.0720
ARCH-LM test	5686.3500***	2562.0600***	3106.3720***

*The Jarque-Bera tests for normal distribution. The Ljung-Box Q^2 (10) statistic checks for the presence of serial correlation in squared returns up to the 10th order. The ARCH-LM test refers to the Engle (1982) test for conditional heteroscedasticity. The asterisks *** denote the rejection of the null hypothesis at the 1% significance levels.*

TABLE 2 | Unconditional correlations among crude oil futures returns.

	INE returns	WTI returns	Brent returns
INE returns	1.0000		
WTI returns	0.4908***	1.0000	
Brent returns	0.5109***	0.8961***	1.0000

*The asterisks *** denote the rejection of the null hypothesis at the 1% significance level.*

impact on the dynamic features of high-frequency returns; Only taking account of intraday periodicity is it possible to reveal the complex intraday return dynamics across financial markets (Andersen and Bollerslev, 1997).

However, there are several ways to address the issue for the intraday periodicity (see e.g., Martens et al., 2002). Following Conrad et al. (2012), we employ a simple but very effective method is to remove the intraday periodicity by standardizing $r_{t,k}$ according to the following rule:

$$R_{t,k} = \frac{r_{t,k}}{f_k}.$$

The standardization simply scales each return $r_{t,k}$ by the average absolute return of the interval k. **Figure 4** displays the effect of filtering by depicting the sample autocorrelation function of $|R_{t,k}|$ for five consecutive days. As shown, the recurring intraday periodical patterns indeed disappear, implying that the filtering method is quite effective in removing the intraday periodic pattern.

The above results indicate that the clear intraday periodicity has a significant impact on the autocorrelation patterns of intraday returns. Thus, distortion in the GARCH modeling of the high-frequency return volatility is likely to occur when the intraday periodicity is ignored (Andersen and Bollerslev, 1997).

Descriptive Statistics for Filtered Data

Table 1 demonstrates the descriptive statistics of filtered returns on the different crude oil futures prices under investigation. The INE return is more volatile than the WTI and Brent return, as supported by their corresponding standard deviations. All skewness coefficients are significantly different from 0, and the kurtosis coefficients are higher than 3, implying that each return series has a leptokurtic distribution with asymmetric tails. The Jarque-Bera test provides further evidence that the data do not satisfy the normality assumption. The Ljung-Box Q and Ljung-Box Q^2 statistics confirm the presence of serial autocorrelations in both returns and squared returns series. Augmented Dickey-Fuller (ADF) (Dickey and Fuller, 1979), Kwiatkowski-Phillips-Schmidt-Shin (KPSS) (Kwiatkowski et al., 1992) and Phillips-Perron (PP) (Phillips and Perron, 1988) unit root tests are employed in this paper. The results suggest that all return series are stationary at the 1% significance level. Finally, the results of the ARCH-LM test (Engle, 1982) provide evidence of the ARCH effect for these return series, which leads us to employ the GARCH-type models to investigate the dynamic correlation and volatility spillovers among markets.

Next, we take a glance at unconditional correlations among returns of these crude oil futures, as shown in **Table 2**. It can be found that the INE market is positively correlated with WTI and Brent markets, indicating that the trends of different oil futures markets are relatively consistent on the whole. Moreover, the INE market is more correlated with the Brent market than with the WTI market.

EMPIRICAL RESULTS

In this section, we present the results of structural breakpoints detected in the crude oil futures return series using the Bai and Perron (2003) test as well as the estimates of dynamic conditional correlations and volatility spillovers between markets without and with structural breaks.

Structural Break Tests: Bai and Perron (2003)

The results of Bai and Perron (2003) tests for structural break, including the number of breakpoints and their corresponding dates, are collected in **Table 3**. The Bai and Perron (2003) test determines five structural breaks for each of the INE, WTI, and Brent returns. One interesting finding is that the dates of the detected structural breakpoints are very close, indicating a timely flow of information among the crude oil futures markets. Moreover, the break dates coincide with economic events, geopolitics and energy policies that have great impacts on the supply and demand of crude oil. The first structural break in the crudes occurred in June 2018 may be attributed to rising tensions between U.S. and Iran and surprise drop in U.S. crude stocks; these factors add to fears of a deepening conflict and potential disruption to oil supplies[4]. The second structural break occurred in October 2018 is related to financial markets and economic conditions. More specifically, during this period, the

[4]https://www.nytimes.com/2018/07/04/business/energy-environment/oil-prices-opec.html (accessed October 31, 2019).

TABLE 3 | Results of structural break tests and related events.

Series	Breakpoints	Locations	Break dates (Beijing)	Related events
INE returns	5	4,549	2018/06/30 02:15	Rising tensions between U.S. and Iran and surprise drop in U.S. crude stocks.
		8,136	2018/10/17 22:05	Global stock market turmoil and weak demand.
		11,324	2018/12/19 21:25	OPEC's oil production cuts and geopolitics in the Middle East.
		14,428	2019/03/19 23:40	Fed keeps interest rates unchanged.
		17,536	2019/05/25 00:50	Global trade uncertainty and fears of a global economic downturn.
WTI returns	5	3,676	2018/06/19 22:40	Rising tensions between U.S. and Iran and surprise drop in U.S. crude stocks.
		8,126	2018/10/10 00:55	Global stock market turmoil and weak demand.
		11,303	2018/12/19 10:00	OPEC's oil production cuts and geopolitics in the Middle East.
		14,483	2019/03/21 09:40	Fed keeps interest rates unchanged.
		17,595	2019/05/31 23:25	Global trade uncertainty and fears of a global economic downturn.
Brent returns	5	3,968	2018/06/22 22:25	Rising tensions between U.S. and Iran and surprise drop in U.S. crude stocks.
		8,126	2018/10/10 00:55	Global stock market turmoil and weak demand.
		11,303	2018/12/19 10:00	OPEC's oil production cuts and geopolitics in the Middle East.
		14,409	2019/03/19 21:50	Fed keeps interest rates unchanged.
		17,550	2019/05/28 11:00	Global trade uncertainty and fears of a global economic downturn.

global stock markets suffer worst losing streak for the last 5 years and economic data weakens demand outlook[5], as Zhang (2017) and Zhang and Wang (2019) argue that there is a significant risk transmission between oil market and stock market. Thus, the fear sentiment in financial markets quickly spreads to the oil market, leading to a sharp decline in crude oil prices. The third structural break occurred in December 2018 is caused by OPEC's oil production cuts and geopolitics in the Middle East threatened to hurt oil supply[6]. As a result, these three crude oil markets prices rise simultaneously. The fourth structural break occurred in March 2019 is related to the announcement that Fed keeps interest rates unchanged, this economic policy plays a role in supporting oil prices. The last structural break occurred in May 2019 can be attributed to global trade uncertainty and fears of a global economic downturn, especially the trade conflict between the two major economies, the US and China, which brings more uncertainty to the global trade[7]. The trade war environment pushes expectations for global growth to lower levels, thus pressing oil price movements. Consequently, INE crude falls by $12, or 16% within 10 days, WTI crude and Brent crude fall by $7 (12%) and $8 (12%), respectively. This decline is the biggest drop since December 2018.

Dynamic Conditional Correlations Without and With Structural Breaks

We estimate the dynamic conditional correlation coefficients between China's crude oil futures market and the international benchmark markets using a bivariate VAR-DCC-GARCH model without and with dummy variables accounting for structural breaks. The results are compiled as **Table 4**. In this subsection, we first report the estimates when the structural breaks are ignored and then report the results after incorporating structural breaks.

The estimated results of the conditional mean equation (**Table 4** panel A) show that returns of all the three markets are related to their own past returns (a^c and a^g), implying that these market returns are predictable in the short term. In terms of cross-market return spillovers, there is a significant bidirectional positive return spillover (b^c and b^g) between the INE market and Brent market, indicating that the rise of Brent oil futures prices will increase INE market returns and vice versa. However, there is unidirectional positive return spillover running from the WTI market to the INE market (b^c). The findings show that the interaction of the INE market with the Brent market is stronger than that with the WTI market at the return level.

The variance equation estimates (**Table 4** panel B) show that all crude oil futures return series have ARCH and GARCH effects that are statistically significant. For each return series, the sum of the coefficients on the lagged innovation (α) and the lagged condition volatility (β) is close to 1, which implies that shocks to the conditional volatility are highly persistent. In addition, β is significantly larger than α, indicating that past volatility is more important than past shocks for forecasting future market volatility.

Panel C of **Table 4** summarizes the resulting DCC coefficients for crude oil futures returns. The short-term (θ_1) and long-term (θ_2) persistence of shocks on the DCC are statistically significant in all cases. This suggests that the correlations between markets are time-varying. With θ_2 close to unity, the long-term persistence of the shock plays an important role in predicting the DCC coefficients. More importantly, as displayed in **Figure 5**, the plots of the DCCs for the INE market and each of the international market pairs exhibit significant variability in the conditional correlations across the full sample period, with important phases of decreases and increases. For example, the decrease of the conditional correlations across markets is more apparent starting from August 7, 2018,

[5]https://edition.cnn.com/2018/10/31/investing/stocks-markets-october/index.html (accessed October 31, 2019).
[6]https://www.cnbc.com/2018/12/07/opec-meeting-saudi-arabia-and-russia-look-to-impose-production-cuts.html (accessed October 31, 2019).
[7]https://ihsmarkit.com/research-analysis/crude-oil-trade-uncertainty-causing-pressure-on-oil-prices.html (accessed October 31, 2019).

TABLE 4 | Estimation results of the bivariate VAR-DCC-GARCH model for crude oil futures price returns without and with structural breaks.

Variables	INE and WTI returns		INE and Brent returns	
	Without breaks	With breaks	Without breaks	With breaks
PANEL A: MEAN EQUATION				
μ^c	0.0062 (0.0055)	0.0208*** (0.0065)	0.0057 (0.0055)	0.0229** (0.0099)
μ^g	0.0104 (0.0064)	0.0104 (0.0065)	0.0115* (0.0062)	0.0256** (0.0113)
a^c	−0.1151*** (0.0075)	−0.1156*** (0.0059)	−0.1366*** (0.0081)	−0.1370*** (0.0072)
a^g	−0.0741*** (0.0078)	−0.0744*** (0.0069)	−0.0855*** (0.0084)	−0.0857*** (0.0074)
b^c	0.0403*** (0.0066)	0.0402*** (0.0062)	0.0607*** (0.0072)	0.0605*** (0.0061)
b^g	0.0080 (0.0070)	0.0078 (0.0067)	0.0175** (0.0075)	0.0172*** (0.0065)
PANEL B: VARIANCE EQUATION				
ω^c	0.0755*** (0.0056)	0.0755*** (0.0053)	0.0753*** (0.0051)	0.0753*** (0.0055)
ω^g	0.0790*** (0.0062)	0.0790*** (0.0060)	0.0893*** (0.0061)	0.0894*** (0.0061)
α^c	0.1589*** (0.0073)	0.1587*** (0.0071)	0.1516*** (0.0064)	0.1513*** (0.0062)
α^g	0.1425*** (0.0073)	0.1422*** (0.0072)	0.1492*** (0.0069)	0.1489*** (0.0060)
β^c	0.8208*** (0.0066)	0.8209*** (0.0061)	0.8196*** (0.0063)	0.8198*** (0.0064)
β^g	0.8426*** (0.0067)	0.8428*** (0.0062)	0.8290*** (0.0063)	0.8291*** (0.0059)
PANEL C: CORRELATION PARAMETERS				
θ_1	0.0639*** (0.0041)	0.0644*** (0.0040)	0.0659*** (0.0035)	0.0659*** (0.0034)
θ_2	0.9339*** (0.0044)	0.9333*** (0.0042)	0.9319*** (0.0036)	0.9318*** (0.0036)
PANEL D: RESIDUAL DIAGNOSTIC TESTS				
Q_c^2 (10)	8.3141	8.2737	8.0385	8.0115
Q_g^2 (10)	4.3831	4.3567	7.4098	7.3833
$ARCH_c$ (10)	8.2600	8.2200	8.0000	7.9700
$ARCH_g$ (10)	4.5000	4.4700	7.6300	7.6000
PANEL E: MODEL SELECTION CRITERIA				
AIC	5.4360	5.4357	5.3460	5.3450
SBC	5.4460	5.4420	5.3560	5.3510
Log likelihood	−56240.6675	−56228.6179	−55304.4703	−55295.9425

*The figures in parentheses are standard errors. The asterisks *, **, and *** denote significance at the 10, 5, and 1% levels, respectively.*

which may be related to the prospect of lower exports from Iran due to American sanctions and uncertainty about Saudi Arabia's oil output strategy; these events have increased market uncertainty. These findings have important implications for energy risk management. Specifically, using constant conditional correlations to compute optimal portfolio weights and hedge ratios can lead to biased estimates. Energy investors should be aware that correlations change dynamically over time, and therefore, portfolios should be dynamically adjusted (Mensi et al., 2015). Additionally, we find high degree of co-movements between the INE market and the international markets. For each pair, the time-varying cross-market correlation coefficient reverts to the mean of 0.7. The results of the diagnostic test (**Table 4** panel D) reveal that the residuals of the VAR-DCC-GARCH model estimates are free of serial correlation and the ARCH effect, indicating that the VAR-DCC-GARCH model is correctly specified.

Modeling volatility by ignoring the structural breaks in the time series may result in spurious regressions due to overestimation of volatility (Lamoureux and Lastrapes, 1990). Therefore, we incorporate the structural break dummy variables into the mean equation to more accurately estimate the conditional volatility of crude oil price returns and the DCCs across crude oil futures markets. Model selection criteria can determine whether the modified model optimizes model estimates. These model selection criteria include the AIC, the Schwarz Bayesian criterion (SBC), and log likelihood. By looking at the results of the model selection criteria in panel E of **Table 4**, we conclude that the bivariate VAR-DCC-GARCH model with structural breaks is superior to the same model without structural breaks.

The empirical results show that the estimates of cross-market return spillovers are similar to those of the case without structural breaks. However, it is worth mentioning that the significance level for parameter b^g–denoting the return spillover from the INE market to the Brent market—has changed from 5% without breaks to 1% with breaks. This finding indicates that structural breaks have an impact on modeling cross-market return spillovers.

The estimating results of variance equations (**Table 4** panel B) show that the volatility persistence of all crude oil futures return series decreases after the structural breaks are included, which indicates that ignoring these structural changes in return series may distort the degree of volatility persistence in each market

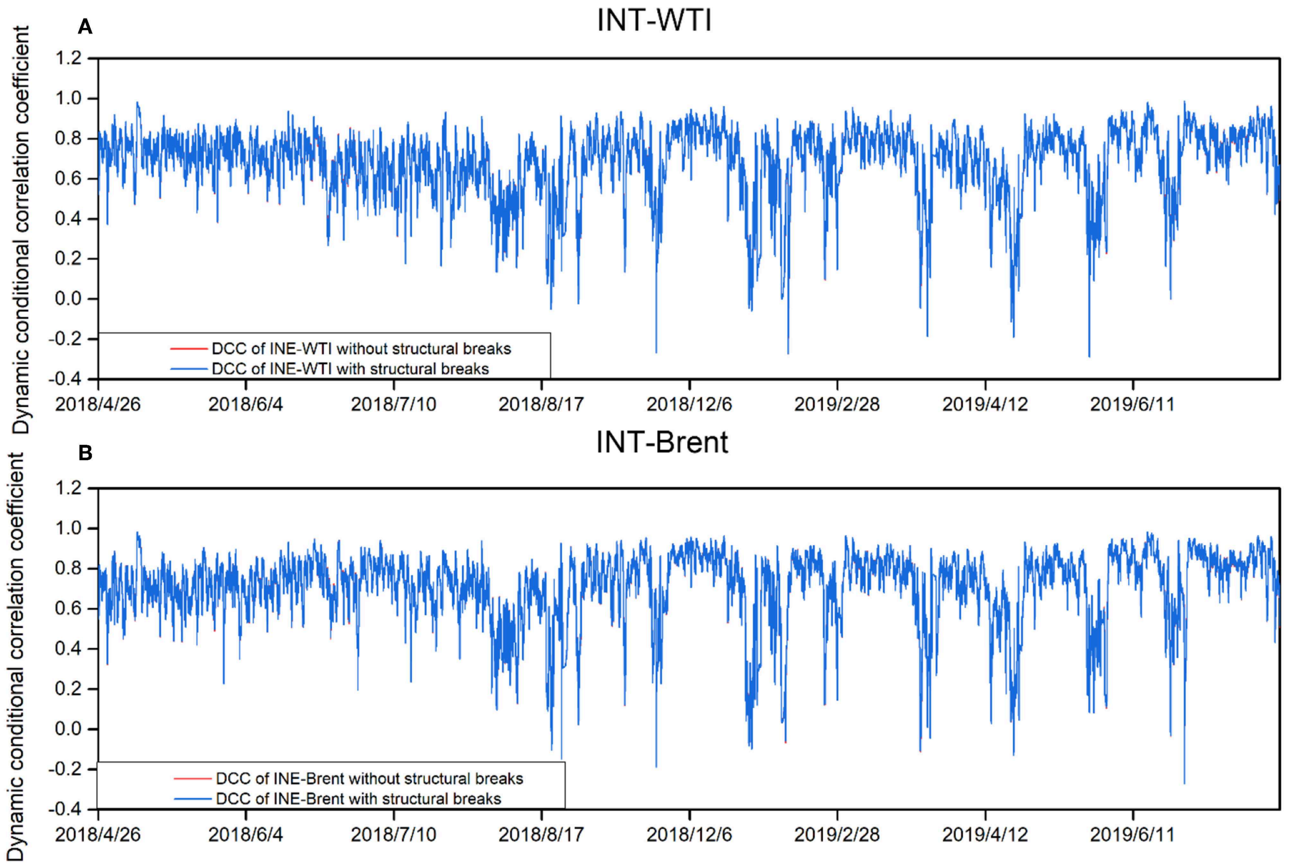

FIGURE 5 | DCCs between crude oil futures returns without and with structural breaks. **(A)** INT-WTI, **(B)** INT-Brent.

TABLE 5 | Descriptive statistics of correlation coefficients for crude oil futures returns without and with structural breaks.

Descriptive statistics	DCC between INE and WTI returns		DCC between INE and Brent returns	
	Without breaks	With breaks	Without breaks	With breaks
Mean	0.6852	0.6849	0.7111	0.7109
Median	0.7253	0.7247	0.7562	0.7560
Maximum	0.9861	0.9864	0.9835	0.9836
Minimum	−0.2845	−0.2873	−0.2632	−0.2694
Standard deviation	0.1737	0.1739	0.1774	0.1774

and volatility spillovers across markets. This finding is consistent with those of Kang et al. (2011) and Ewing and Malik (2016). More interestingly, **Figure 5** shows that the correlation between the INE market and each of the international benchmark markets decreases significantly for each period when structural breaks are identified. This result implies that, energy policy, economic and geopolitical events that cause structural breaks, will significantly reduce the correlation between the crude oil futures markets.

Table 5 summarizes the descriptive statistics of the DCC coefficients between the INE market and each of the international benchmark markets. As shown, the mean value of the DCC coefficients between the INE market and the Brent market is greater than that of the DCC coefficients between the INE market and the WTI market, regardless of whether the structural breaks are included. **Figure 5** also shows that the conditional correlation between the INE market and the Brent market is higher than that between the INE market and the WTI market for most of the sample period. These findings indicate a stronger linkage between the INE market and the Brent market. This is consistent with Song et al. (2019), who use the crude oil spot price to examine the linkage between the Chinese crude oil market and the international crude oil markets during the period 1997–2011. They find that the correlation between the Chinese crude oil market and the Brent crude oil market is significantly higher than that between the Chinese crude oil market and the WTI crude oil market after 2003. Two main reasons for this can be summarized as follows. First, although both WTI and Brent crudes are international benchmark crude oil prices, the WTI crude mainly reflects the supply and demand of the crude oil market in the United States, whose crude oil mainly comes from Canada and Mexico. Meanwhile, the Brent crude mainly reflects the supply and demand in the European crude oil markets, whose crude oil

TABLE 6 | Results of paired *t*-tests.

Variables	Conditional correlations		Portfolio weight		Hedge ratio	
	INE-WTI	INE-Brent	INE-WTI	INE-Brent	INE-WTI	INE-Brent
Without breaks	0.6852	0.7111	0.5955	0.6329	0.6871	0.7090
With breaks	0.6849	0.7109	0.5962	0.6331	0.6868	0.7088
Difference	0.0003	0.0002	−0.0007	−0.0002	0.0003	0.0002
T-test	16.2161***	15.0242***	−9.7088***	−3.5111***	6.5554***	6.6865***
Observations	20,698	20,698	20,698	20,698	20,698	20,698

*This table reports the paired t-test results on the conditional correlations, portfolio weight and hedge ratio of INE-WTI and INE-Brent. The paired t-test performs t-tests on the equality of means of two samples, assuming paired data and constant variance. For example, in the case of conditional correlation of INE-WTI, it tests that the estimated conditional correlations between INE and WTI returns from the VAR-DCC-GARCH models without and with breaks have the same mean. The asterisks *** denote significance at the 1% level.*

comes mainly from the Middle East and North Africa. As most of China's crude oil is imported from the Middle East, Africa, and Russia (BP, 2018), whose oil pricing mainly refers to the Brent crude oil price, China's crude oil market is more correlated with the Brent market. Second, in recent years, the United States has implemented an independent energy strategy and is vigorously developing alternative energy sources, such as shale gas; this has resulted in a decline in oil demand, which weakens the leading role of the WTI crude in global benchmark crude oil markets. However, the Brent crude oil price is more sensitive to changes in fundamentals; it can more directly represent the trend of global oil prices. In particular, WTI behaved as the price setter before 2010, while Brent has played the leading role in the crude oil market since 2011 (Ji and Fan, 2015).

In addition, following Yin et al. (2018), we employ a paired *t*-test to measure whether there is a significant difference in DCC coefficients between crude oil futures markets without and with structural breaks. The results of the paired *t*-test shown in **Table 6** provide evidence that the difference between the estimated mean values of conditional correlation coefficients is significant at the 1% level.

Volatility Spillovers Without and With Structural Breaks

Analysis of volatility spillovers between crude oil futures markets helps improve the understanding of information and risk transmission across markets as well as the computation of optimal portfolio weights and hedge ratios. Therefore, we further analyze the volatility spillover effect between the INE market and each of the international benchmark markets by using the bivariate full VAR-BEKK-GARCH model, and the estimated results are reported in **Table 7**. The estimates of the mean equation are similar to those of the VAR-DCC-GARCH model, we will not interpret them here. The results of the conditional variance equation (**Table 7** panel B) show that the volatility of these crude oil markets in the current period depends on the past shocks and their past volatilities. These findings indicate that unexpected events in the oil market can increase the volatility of their own markets; current volatility in the oil market has the potential to drive higher volatility in subsequent periods.

Results pertaining to cross-market volatility spillover indicate that there are significant bidirectional short-term and long-term volatility spillovers between the INE market and each of the international benchmark crude oil markets. These results indicate significant bidirectional volatility transmission between the INE market and the international oil markets; the shocks of the INE market will have an impact on the volatility of the international markets. Part of our results differ from Liu et al. (2013), who use weekly data for crude oil spot prices to examine volatility spillovers between China's crude oil market (Daqing) and four international crude oil markets (WTI, Brent, Dubai and Sandi Arabia's Medium) during the period of 2001–2011. They find that there is only unidirectional volatility spillover from the international markets to China's crude oil market. The main reason for these differences is that on the one hand, the crude oil futures market plays an important role in price discovery; on the other hand, China's crude oil futures market shows a certain influence in the world oil market.

After incorporating structural breaks, the estimates of cross-market volatility spillovers are similar to those of the case without structural breaks. Thus, we will not interpret them here. The results of the diagnostic test (**Table 7** panel C) reveal that the residuals are free of serial correlation and the ARCH effect, indicating that the employed model is correctly specified. Finally, as evidenced from the model selection criteria (**Table 7** panel D), the VAR-BEKK-GARCH model with structural breaks is superior to the same model without structural breaks.

DISCUSSION AND ECONOMIC SIGNIFICANCE OF THE RESULTS

Our empirical results have important economic implications because decisions regarding asset allocation and portfolio risk management require accurate estimations of conditional volatility (Ewing and Malik, 2013). The overall essence of portfolio management is to show how an investor can potentially benefit from portfolio diversification between the two asset markets (Tule et al., 2017). In portfolio management, the inherent uncertainties can be mitigated by considering the following two important indicators: (i) the optimal portfolio weight and (ii) the hedge ratio. In this section, we present estimates of these

TABLE 7 | Estimation results of the bivariate BEKK-GARCH model for crude oil futures returns without and with structural breaks.

Variables	INE and WTI returns		INE and Brent returns	
	Without breaks	With breaks	Without breaks	With breaks
PANEL A: MEAN EQUATION				
μ^c	0.0084 (0.0070)	0.0312** (0.0137)	0.0056 (0.0073)	0.0204 (0.0135)
μ^g	0.0073 (0.0075)	0.0104 (0.0140)	0.0101 (0.0083)	0.0119 (0.0147)
a^c	−0.0980*** (0.0095)	−0.0997*** (0.0093)	−0.1180*** (0.0098)	−0.1189*** (0.0096)
a^g	−0.0444*** (0.0092)	−0.0448*** (0.0087)	−0.0656*** (0.0092)	−0.0661*** (0.0092)
b^c	0.0876*** (0.0090)	0.0888*** (0.0084)	0.1098*** (0.0086)	0.1099*** (0.0086)
b^g	0.0266 (0.0081)	0.0263 (0.0083)	0.0443*** (0.0087)	0.0440*** (0.0088)
PANEL B: VARIANCE EQUATION				
c^{cc}	0.1829*** (0.0061)	0.1830*** (0.0058)	0.1613*** (0.0065)	0.1611*** (0.0065)
c^{cg}	0.0796*** (0.0077)	0.0786*** (0.0076)	0.0770*** (0.0081)	0.0769*** (0.0081)
c^{gg}	−0.1158*** (0.0046)	−0.1159*** (0.0046)	−0.1089*** (0.0053)	−0.1090*** (0.0048)
a^{cc}	0.4386*** (0.0089)	0.4424*** (0.0092)	0.4545*** (0.0081)	0.4549*** (0.0082)
a^{cg}	0.0303*** (0.0064)	0.0307*** (0.0066)	0.0262*** (0.0064)	0.0266*** (0.0062)
a^{gc}	−0.1491*** (0.0104)	−0.1541*** (0.0104)	−0.1733*** (0.0078)	−0.1738*** (0.0080)
a^{gg}	0.2476*** (0.0080)	0.2467*** (0.0077)	0.2226*** (0.0071)	0.2226*** (0.0071)
b^{cc}	0.9009*** (0.0037)	0.8993*** (0.0039)	0.8951*** (0.0032)	0.8949*** (0.0033)
b^{cg}	−0.0174*** (0.0025)	−0.0178*** (0.0025)	−0.0183*** (0.0023)	−0.0184*** (0.0023)
b^{gc}	0.0511*** (0.0037)	0.0529*** (0.0037)	0.0605*** (0.0028)	0.0606*** (0.0029)
b^{gg}	0.9744*** (0.0024)	0.9748*** (0.0023)	0.9814*** (0.0020)	0.9815*** (0.0020)
PANEL C: DIAGNOSTIC TESTS				
Q_c^2 (10)	13.9458	13.9764	15.3284	15.3668
Q_g ^{2} (10)	5.2156	5.3180	14.9008	14.7545
$ARCH_c$ (10)	13.6600	13.6900	15.0800	15.1100
$ARCH_g$ (10)	5.1300	5.2300	14.6600	14.5300
PANEL D: MODEL SELECTION CRITERIA				
AIC	5.8990	5.8980	5.7600	5.7600
SBC	5.9090	5.9050	5.7710	5.7670
Log likelihood	−61029.3500	−61007.8397	−59597.2190	−59583.4394

*The figures in parentheses are standard errors. The asterisks *, **, and *** denote significance at the 10, 5, and 1% levels, respectively.*

indicators and provide several economic implications for asset allocation and risk management.

Optimal Portfolio Weights and Hedge Ratios

To manage crude oil risks more efficiently, we compute the optimal portfolio weights and hedge ratios for designing the optimal hedging strategies based on the estimates of our bivariate VAR-BEKK-GARCH with and without structural breaks.

We consider a portfolio that can minimize risk without lowering expected returns. We assume that an investor is holding INE crude oil and hope to hedge against the adverse effects of price changes in the international crude oil markets. Following Kroner and Ng (1998), the portfolio weight is expressed as

$$w_t = \frac{h_{22,\,t} - h_{12,t}}{h_{11,t} - 2h_{12,t} + h_{22,t}} \tag{11}$$

$$w_t = \begin{cases} 0 & if\ w_t < 0 \\ w_t & if\ 0 \le w_t \le 1 \\ 1 & if\ w_t > 1 \end{cases} \tag{12}$$

where w_t is the weight of INE crude oil in a \$1 portfolio of two asset holdings, INE and WTI (Brent), at time t; $h_{11,t}$ and $h_{22,t}$ denote the conditional volatility of the INE and WTI (Brent) market, respectively; and $h_{12,t}$ represents the conditional covariance between the returns of the INE and WTI (Brent) markets. Therefore, the weight of the WTI (Brent) in the considered portfolio is $1 - w_t$.

For the hedge ratio, this paper follows Kroner and Sultan (1993) and assumes that to minimize the risk of a portfolio, an investor should short \$$B$ of the WTI (Brent) oil portfolio that is \$1 long in the INE portfolio, where "risk minimizes hedge ratio" B is expressed as.

$$B_t = \frac{h_{12,t}}{h_{22,t}} \tag{13}$$

Economic Implications for Portfolio Management

The computed optimal portfolio weights and hedge ratios from the VAR-BEKK-GARCH model without and with structural

TABLE 8 | Summary statistics for the portfolio weights and the hedge ratios.

	Portfolio weight				Hedge ratio			
	Mean	**Std. Dev.**	**Min**	**Max**	**Mean**	**Std. Dev.**	**Min**	**Max**
PANEL A: VALUES ARE CALCULATED USING ESTIMATES OF THE BIVARIATE VAR-BEKK-GARCH MODEL WITHOUT STRUCTURAL BREAKS								
INE-WTI	0.5955	0.3211	0.0000	1.0000	0.6871	0.2468	−1.5130	6.3417
INE-Brent	0.6329	0.3217	0.0000	1.0000	0.7090	0.2250	−0.8781	6.2538
PANEL B: VALUES ARE CALCULATED USING ESTIMATES OF THE BIVARIATE VAR-BEKK-GARCH MODEL WITH STRUCTURAL BREAKS								
INE-WTI	0.5962	0.3208	0.0000	1.0000	0.6868	0.2466	−1.5419	6.3689
INE-Brent	0.6331	0.3217	0.0000	1.0000	0.7088	0.2249	−0.8808	6.2329

breaks are presented in **Table 8**. From the table, we find a difference in the portfolio weights after the inclusion of the structural breaks. Specifically, in the portfolio of INE and WTI, the average optimal weight of INE increases from 0.5955 without structural breaks to 0.5962 with breaks. A portfolio weight of 0.5962 implies that an investor who is willing to invest $100 should have optimal holdings of $59.62 in INE oil and $40.38 in WTI oil. As for the portfolio of INE and Brent, the average portfolio weight of INE increases from 0.6329 when the structural breaks are ignored to 0.6331 after controlling for the breaks. These results indicate that (1) ignoring the structural breaks in the crude oil futures return series may lead to bias in the estimation of the optimal portfolio weights, and (2) overall, investors tend to invest in more INE crude oil futures in their portfolio, which indicates more potential gains in the Chinese newly launched crude oil futures market.

As for the hedge ratios, the mean values of the hedge ratio between the INE and WTI (Brent) markets are 68.71% (70.90%) without structural breaks and 68.68% (70.88%) with breaks. This implies that an investor who is holding a long position of $100 in the INE oil will short sell WTI (Brent) for $68.71 ($70.90) without structural breaks and short sell $68.68 ($70.88) with breaks. The minimum and maximum values indicate that each of the hedge ratios shows considerable variability. Therefore, investors must frequently adjust their hedging strategies.

With reference to **Table 6** for robustness test, we can reject the null hypothesis that the portfolio weight and the hedge ratio series without and with structural breaks have the same mean values since those differences are statistically significant at the 1% level.

CONCLUSIONS AND POLICY IMPLICATIONS

The integration between crude oil futures markets can provide several interrelated benefits for energy risk management, such as risk sharing and diversification, as well as better allocation of assets. In this paper, we use intraday 5 min data to investigate the dynamic conditional correlations, information transmission and time-varying hedging strategies between China's crude oil futures market and the international benchmark markets (WTI and Brent). Moreover, structural breaks in the crude oil futures markets are detected and incorporated into the models to provide more accurate empirical results.

The results of the Bai and Perron (2003) test show a strong evidence for the presence of structural breaks in all crude oil futures return series. The correlation between crude oil futures markets exhibits significant time-varying characteristics, which indicates that portfolios should be dynamically adjusted over time. In particular, the correlation between crude oil futures markets decreases significantly during the periods when structural breaks caused by economic and/or geopolitical events are identified.

Our empirical results reveal strong evidence for the integration of China's newly crude oil futures market into the international benchmark markets. On the one hand, the mean values of the time-varying conditional correlations among the INE market and the two international markets are both around 0.7, regardless of whether the structural breaks are included. On the other hand, there are significant bidirectional return and volatility spillovers between the INE market and the international benchmark crude oil markets. These findings indicate that China's crude oil futures market exhibits a certain influence on the world's oil markets. Another finding is that the INE market integrates better with the Brent market than with the WTI market, which confirms the leading role of Brent in the world crude oil futures market in recent years (Ji and Fan, 2015). In addition, we further compute the optimal portfolio weights and time-varying hedge ratios for investors who aim to efficiently reduce the investment risk by implementing asset allocations and hedging strategies, by which we highlight the economic significance of our empirical results. The results show that a $100 long position in INE can be hedged for $68.68 ($70.88) with a short position in the WTI (Brent) market, implying that hedging long INE positions by shorting the WTI is cheaper than shorting Brent. The paired t-test results show that the mean values of the DCCs, portfolio weights and hedge ratios estimated from the models without and with structural breaks are statistically significantly different at the 1% level. In summary, introducing dummy variables into the models to account for structural breaks improves our understanding of the correlations and volatility spillovers between crude oil futures markets.

The policy implications of our empirical evidences are 3-fold. First, portfolio managers should possess important information about the directions of spillovers among markets when they allocate assets across crude oil futures markets to take preventive measures to handle sudden events, especially major economic events that may induce risk contagion across markets. Second, investors can dynamically adjust their asset allocation and hedging strategies based on time-varying correlations between crude oil futures markets to maximize benefits and minimize risks. Third, for policy makers, the uncertainty information contained in the market can be obtained from the volatility transmission between the markets, which can be used to forecast future market volatility.

DATA AVAILABILITY STATEMENT

The datasets generated for this study are available on request to the corresponding author.

AUTHOR CONTRIBUTIONS

ZL, ZD, and PZ: conceptualization and writing—original draft. ZL and PZ: data curation, methodology, and software. ZD, TL, JW, and KZ: supervision. ZL, PZ, and JW: writing—review and editing. All authors read and approved this version.

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REFERENCES

Adelman, M. A. (1984). International oil agreements. *Energy J.* 5, 1–9. doi: 10.5547/ISSN0195-6574-EJ-Vol5-No3-1

AlKathiri, N., Al-Rashed, Y., Doshi, T. K., and Murphy, F. H. (2017). "Asian premium" or "North Atlantic discount": does geographical diversification in oil trade always impose costs? *Energy Econ.* 66, 411–420. doi: 10.1016/j.eneco.2017.07.005

Andersen, T. G. (2000). Some reflections on analysis of high-frequency data. *J. Bus. Econ. Stat.* 18, 146–153. doi: 10.1080/07350015.2000.10524857

Andersen, T. G., and Bollerslev, T. (1997). Intraday periodicity and volatility persistence in financial markets. *J. Empir. Finance* 4, 115–158. doi: 10.1016/S0927-5398(97)00004-2

Bai, J., and Perron, P. (2003). Computation and analysis of multiple structural change models. *J. Appl. Econom.* 18, 1–22. doi: 10.1002/jae.659

Bhar, R., and Nikolova, B. (2009). Return, volatility spillovers and dynamic correlation in the BRIC equity markets: an analysis using a bivariate EGARCH framework. *Glob. Finance J.* 19, 203–218. doi: 10.1016/j.gfj.2008.09.005

BP (2018). *BP Energy Outlook Country and Regional Insights–China*. London. Available online at: https://www.bp.com/content/dam/bp/en/corporate/pdf/energy-economics/energy-outlook/bp-energy-outlook-2018-country-insight-china.pdf (accessed September 1, 2019).

Broadstock, D. C., Fan, Y., Ji, Q., and Zhang, D. (2016). Shocks and stocks: a bottom-up assessment of the relationship between oil prices, gasoline prices and the returns of Chinese firms. *Energy J.* 37, 55–86. doi: 10.5547/01956574.37.SI1.dbro

Brown, R. L., Durbin, J., and Evans, J. M. (1975). Techniques for testing the constancy of regression relationships over time. *J. Royal Stat. Soc. Ser. B* 37, 149–192. doi: 10.1111/j.2517-6161.1975.tb01532.x

Chan, H. L., and Woo, K.-Y. (2015). An investigation into the dynamic relationship between international and China's crude oil prices. *Appl. Econ.* 48, 2215–2224. doi: 10.1080/00036846.2015.1117046

Chang, C.-L., McAleer, M., and Tansuchat, R. (2010). Analyzing and forecasting volatility spillovers, asymmetries and hedging in major oil markets. *Energy Econ.* 32, 1445–1455. doi: 10.1016/j.eneco.2010.04.014

Charles, A., and Darné, O. (2014). Volatility persistence in crude oil markets. *Energy Policy* 65, 729–742. doi: 10.1016/j.enpol.2013.10.042

Chen, W., Huang, Z., and Yi, Y. (2015). Is there a structural change in the persistence of WTI–Brent oil price spreads in the post-2010 period? *Econ. Model.* 50, 64–71. doi: 10.1016/j.econmod.2015.06.007

Cheng, D., Shi, X., Yu, J., and Zhang, D. (2019). How does the Chinese economy react to uncertainty in international crude oil prices? *Int. Rev. Econ. Finance* 64, 147–164. doi: 10.1016/j.iref.2019.05.008

Chow, G. C. (1960). Tests of equality between sets of coefficients in two linear regressions. *Econometrica* 28, 591–605. doi: 10.2307/1910133

Conrad, C., Karanasos, M., and Zeng, N. (2011). Multivariate fractionally integrated APARCH modeling of stock market volatility: a multi-country study. *J. Empir. Finance* 18, 147–159. doi: 10.1016/j.jempfin.2010.05.001

Conrad, C., Rittler, D., and Rotfuß, W. (2012). Modeling and explaining the dynamics of European Union Allowance prices at high-frequency. *Energy Econ.* 34, 316–326. doi: 10.1016/j.eneco.2011.02.011

Dickey, D. A., and Fuller, W. A. (1979). Distribution of the estimators for autoregressive time series with a unit root. *J. Am. Stat. Assoc.* 74, 427–431. doi: 10.1080/01621459.1979.10482531

Ding, Z., Liu, Z., Zhang, Y., and Long, R. (2017). The contagion effect of international crude oil price fluctuations on Chinese stock market investor sentiment. *Appl. Energy* 187, 27–36. doi: 10.1016/j.apenergy.2016.11.037

EIA (2018). *China Surpassed the United States as the World's Largest Crude Oil Importer in 2017*. Available online at: https://www.eia.gov/todayinenergy/detail.php?id=34812 (accessed September 1, 2019).

Elder, J., Miao, H., and Ramchander, S. (2013). Jumps in oil prices: the role of economic news. *Energy J.* 34, 217–237. doi: 10.5547/01956574.34.3.10

Engle, R. (2002). Dynamic conditional correlation: a simple class of multivariate generalized autoregressive conditional heteroskedasticity models. *J. Bus. Econ. Stat.* 20, 339–350. doi: 10.1198/073500102288618487

Engle, R. F. (1982). Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation. *Econometrica* 50, 987–1007. doi: 10.2307/1912773

Engle, R. F., and Kroner, K. F. (1995). Multivariate simultaneous generalized ARCH. *Econom. Theory* 11, 122–150. doi: 10.1017/S0266466600009063

Ewing, B. T., and Malik, F. (2013). Volatility transmission between gold and oil futures under structural breaks. *Int. Rev. Econ. Finance* 25, 113–121. doi: 10.1016/j.iref.2012.06.008

Ewing, B. T., and Malik, F. (2016). Volatility spillovers between oil prices and the stock market under structural breaks. *Glob. Finance J.* 29, 12–23. doi: 10.1016/j.gfj.2015.04.008

Ewing, B. T., and Malik, F. (2017). Modelling asymmetric volatility in oil prices under structural breaks. *Energy Econ.* 63, 227–233. doi: 10.1016/j.eneco.2017.03.001

Fattouh, B. (2010). The dynamics of crude oil price differentials. *Energy Econ.* 32, 334–342. doi: 10.1016/j.eneco.2009.06.007

Gong, X., and Lin, B. (2018). Structural breaks and volatility forecasting in the copper futures market. *J. Futures Markets* 38, 290–339. doi: 10.1002/fut.21867

Gülen, S. G. (1999). Regionalization in the world crude oil market: further evidence. *Energy J.* 20, 125–139. doi: 10.5547/ISSN0195-6574-EJ-Vol20-No1-7

Hammoudeh, S. M., Ewing, B. T., and Thompson, M. A. (2008). Threshold cointegration analysis of crude oil benchmarks. *Energy J.* 29, 79–95. doi: 10.5547/ISSN0195-6574-EJ-Vol29-No4-4

Hou, Y., and Li, S. (2016). Information transmission between U.S. and China index futures markets: an asymmetric DCC GARCH approach. *Econ. Model.* 52, 884–897. doi: 10.1016/j.econmod.2015.10.025

Huo, R., and Ahmed, A. D. (2018). Relationships between Chinese stock market and its index futures market: evaluating the impact of QFII scheme. *Res. Int. Bus. Finance* 44, 135–152. doi: 10.1016/j.ribaf.2017.07.049

Ji, Q., and Fan, Y. (2015). Dynamic integration of world oil prices: a reinvestigation of globalisation vs. regionalisation. *Appl. Energy* 155, 171–180. doi: 10.1016/j.apenergy.2015.05.117

Ji, Q., and Fan, Y. (2016). Evolution of the world crude oil market integration: a graph theory analysis. *Energy Econ.* 53, 90–100. doi: 10.1016/j.eneco.2014.12.003

Ji, Q., and Zhang, D. (2018). China's crude oil futures: introduction and some stylized facts. *Finance Res. Lett*. 28, 376–380. doi: 10.1016/j.frl.2018.06.005

Jiang, M., An, H., Jia, X., and Sun, X. (2017). The influence of global benchmark oil prices on the regional oil spot market in multi-period evolution. *Energy* 118, 742–752. doi: 10.1016/j.energy.2016.10.104

Jouini, J. (2015). New empirical evidence from assessing financial market integration, with application to Saudi Arabia. *Econ. Model.* 49, 198–211. doi: 10.1016/j.econmod.2015.04.010

Kang, S. H., Cheong, C., and Yoon, S.-M. (2011). Structural changes and volatility transmission in crude oil markets. *Physica A* 390, 4317–4324. doi: 10.1016/j.physa.2011.06.056

Klein, T. (2018). Trends and contagion in WTI and Brent crude oil spot and futures markets—the role of OPEC in the last decade. *Energy Econ.* 75, 636–646. doi: 10.1016/j.eneco.2018.09.013

Kroner, K. F., and Ng, V. K. (1998). Modeling asymmetric comovements of asset returns. *Rev. Financ. Stud.* 11, 817–844. doi: 10.1093/rfs/11.4.817

Kroner, K. F., and Sultan, J. (1993). Time-varying distributions and dynamic hedging with foreign currency futures. *J. Financ. Quant. Anal.* 28, 535–551. doi: 10.2307/2331164

Kuck, K., and Schweikert, K. (2017). A Markov regime-switching model of crude oil market integration. *J. Commodity Markets* 6, 16–31. doi: 10.1016/j.jcomm.2017.03.001

Kwiatkowski, D., Phillips, P. C. B., Schmidt, P., and Shin, Y. (1992). Testing the null hypothesis of stationarity against the alternative of a unit root: how sure are we that economic time series have a unit root? *J. Econ.* 54, 159–178. doi: 10.1016/0304-4076(92)90104-Y

Lamoureux, C. G., and Lastrapes, W. D. (1990). Persistence in variance, structural change, and the GARCH model. *J. Bus. Econ. Stat.* 8, 225–234. doi: 10.1080/07350015.1990.10509794

Lee, Y.-H., Hu, H.-N., and Chiou, J.-S. (2010). Jump dynamics with structural breaks for crude oil prices. *Energy Econ.* 32, 343–350. doi: 10.1016/j.eneco.2009.08.006

Li, R., and Leung, G. C. K. (2011). The integration of China into the world crude oil market since 1998. *Energy Policy* 39, 5159–5166. doi: 10.1016/j.enpol.2011.05.048

Lin, S. X., and Tamvakis, M. N. (2001). Spillover effects in energy futures markets. *Energy Econ.* 23, 43–56. doi: 10.1016/S0140-9883(00)00051-7

Liu, L., Chen, C.-C., and Wan, J. (2013). Is world oil market "one great pool"?: an example from China's and international oil markets. *Econ. Model.* 35, 364–373. doi: 10.1016/j.econmod.2013.07.027

Liu, L., and Wan, J. (2012). A study of Shanghai fuel oil futures price volatility based on high frequency data: long-range dependence, modeling and forecasting. *Econ. Model.* 29, 2245–2253. doi: 10.1016/j.econmod.2012.06.029

Liu, Z., Ding, Z., Lv, T., Wu, J. S., and Qiang, W. (2019). Financial factors affecting oil price change and oil-stock interactions: a review and future perspectives. *Nat. Hazards* 95, 207–225. doi: 10.1007/s11069-018-3473-y

Ma, Y. r., Ji, Q., and Pan, J. (2019). Oil financialisation and volatility forecast: evidence from multidimensional predictors. *J. Forecast.* 38, 564–581. doi: 10.1002/for.2577

Magkonis, G., and Tsouknidis, D. A. (2017). Dynamic spillover effects across petroleum spot and futures volatilities, trading volume and open interest. *Int. Rev. Financ. Anal.* 52, 104–118. doi: 10.1016/j.irfa.2017.05.005

Martens, M., Chang, Y.-C., and Taylor, S. J. (2002). A comparison of seasonal adjustment methods when forecasting intraday volatility. *J. Financ. Res.* 25, 283–299. doi: 10.1111/1475-6803.t01-1-00009

McLeod, R. C. D., and Haughton, A. Y. (2018). The value of the US dollar and its impact on oil prices: evidence from a non-linear asymmetric cointegration approach. *Energy Econ.* 70, 61–69. doi: 10.1016/j.eneco.2017.12.027

Mensi, W., Hammoudeh, S., Nguyen, D. K., and Kang, S. H. (2016). Global financial crisis and spillover effects among the U.S. and BRICS stock markets. *Int. Rev. Econ. Finance* 42, 257–276. doi: 10.1016/j.iref.2015.11.005

Mensi, W., Hammoudeh, S., Nguyen, D. K., and Yoon, S.-M. (2014). Dynamic spillovers among major energy and cereal commodity prices. *Energy Econ.* 43, 225–243. doi: 10.1016/j.eneco.2014.03.004

Mensi, W., Hammoudeh, S., and Yoon, S.-M. (2015). Structural breaks, dynamic correlations, asymmetric volatility transmission, and hedging strategies for petroleum prices and USD exchange rate. *Energy Econ.* 48, 46–60. doi: 10.1016/j.eneco.2014.12.004

Mikosch, T., and Stărică, C. (2004). Nonstationarities in financial time series, the long-range dependence, and the IGARCH effects. *Rev. Econ. Stat.* 86, 378–390. doi: 10.1162/003465304323023886

Nishimura, Y., Tsutsui, Y., and Hirayama, K. (2015). Intraday return and volatility spillover mechanism from Chinese to Japanese stock market. *J. Jpn. Int. Econ.* 35, 23–42. doi: 10.1016/j.jjie.2014.11.005

Phan, D. H. B., Sharma, S. S., and Narayan, P. K. (2016). Intraday volatility interaction between the crude oil and equity markets. *J. Int. Financ. Market. Inst. Money* 40, 1–13. doi: 10.1016/j.intfin.2015.07.007

Phillips, P. C. B., and Perron, P. (1988). Testing for a unit root in time series regression. *Biometrika* 75, 335–346. doi: 10.1093/biomet/75.2.335

Reboredo, J. C. (2011). How do crude oil prices co-move? *Energy Econ.* 33, 948–955. doi: 10.1016/j.eneco.2011.04.006

Rittler, D. (2012). Price discovery and volatility spillovers in the European Union emissions trading scheme: a high-frequency analysis. *J. Banking Finance* 36, 774–785. doi: 10.1016/j.jbankfin.2011.09.009

Rodriguez, A. E., and Williams, M. D. (1993). Is the world oil market 'one great pool'? a test. *Energy Stud. Rev.* 5, 121–130. doi: 10.15173/esr.v5i2.302

Rosa, C. (2014). The high-frequency response of energy prices to U.S. monetary policy: understanding the empirical evidence. *Energy Econ.* 45, 295–303. doi: 10.1016/j.eneco.2014.06.011

Scheitrum, D. P., Carter, C. A., and Revoredo-Giha, C. (2018). WTI and Brent futures pricing structure. *Energy Econ.* 72, 462–469. doi: 10.1016/j.eneco.2018.04.039

Shen, Y., Shi, X., and Variam, H. M. P. (2018). Risk transmission mechanism between energy markets: a VAR for VaR approach. *Energy Econ.* 75, 377–388. doi: 10.1016/j.eneco.2018.08.027

Shi, X., Ji, Q., and Zhang, D. (2018). Evolution of international crude oil pricing mechanism and its implications to China's crude oil futures. *J. Environ. Econ.* 3, 121–134. doi: 10.19511/j.cnki.jee.2018.03.009

Shi, X., and Sun, S. (2017). Energy price, regulatory price distortion and economic growth: a case study of China. *Energy Econ.* 63, 261–271. doi: 10.1016/j.eneco.2017.02.006

Song, C., and Li, C. (2015). Relationship between Chinese and international crude oil prices: a VEC-TARCH approach. *Math. Probl. Eng.* 2015, 1–10. doi: 10.1155/2015/842406

Song, M., Fang, K., Zhang, J., and Wu, J. (2019). The co-movement between Chinese oil market and other main international oil markets: a DCC-MGARCH approach. *Comput. Econ.* 54, 1303–1318. doi: 10.1007/s10614-016-9564-5

Stărică, C., and Granger, C. (2005). Nonstationarities in stock returns. *Rev. Econ. Stat.* 87, 503–522. doi: 10.1162/0034653054638274

Taghizadeh-Hesary, F., Yoshino, N., Rasoulinezhad, E., and Chang, Y. (2019). Trade linkages and transmission of oil price fluctuations. *Energy Policy* 133:110872. doi: 10.1016/j.enpol.2019.07.008

Tse, Y. (1999). Price discovery and volatility spillovers in the DJIA index and futures markets. *J. Futures Markets* 19, 911–930. doi: 10.1002/(SICI)1096-9934(199912)19:8<911::AID-FUT4>3.0.CO;2-Q

Tule, M. K., Ndako, U. B., and Onipede, S. F. (2017). Oil price shocks and volatility spillovers in the Nigerian sovereign bond market. *Rev. Financ. Econ.* 35, 57–65. doi: 10.1016/j.rfe.2017.03.003

Wang, K., and Wei, Y.-M. (2016). Sources of energy productivity change in China during 1997–2012: a decomposition analysis based on the Luenberger productivity indicator. *Energy Econ.* 54, 50–59. doi: 10.1016/j.eneco.2015.11.013

Wang, Q., Zhang, C., and Cai, W. (2017). Factor substitution and energy productivity fluctuation in China: a parametric decomposition analysis. *Energy Policy* 109, 181–190. doi: 10.1016/j.enpol.2017.07.003

Wang, T., Zhang, D., and Clive Broadstock, D. (2019). Financialization, fundamentals, and the time-varying determinants of US natural gas prices. *Energy Econ.* 80, 707–719. doi: 10.1016/j.eneco.2019.01.026

Weiner, R. J. (1991). Is the world oil market "one great pool"? *Energy J.* 12, 95–107. doi: 10.5547/ISSN0195-6574-EJ-Vol12-No3-7

Wen, F., Gong, X., and Cai, S. (2016). Forecasting the volatility of crude oil futures using HAR-type models with structural breaks. *Energy Econ.* 59, 400–413. doi: 10.1016/j.eneco.2016.07.014

Wu, C., Li, J., and Zhang, W. (2005). Intradaily periodicity and volatility spillovers between international stock index futures markets. *J. Futures Markets* 25, 553–585. doi: 10.1002/fut.20155

Xu, X., Yu, J., Zhang, D., and Ji, Q. (2019). Energy insecurity, economic growth and the role of renewable energy: a cross-country panel analysis. *Singapore Econ. Rev.* 1–21. doi: 10.1142/S021759081943001X

Yang, J., Yang, Z., and Zhou, Y. (2012). Intraday price discovery and volatility transmission in stock index and stock index futures markets: evidence from China. *J. Futures Markets* 32, 99–121. doi: 10.1002/fut.20514

Yin, S., Mazouz, K., Benamraoui, A., and Saadouni, B. (2018). Stock price reaction to profit warnings: the role of time-varying betas. *Rev. Quant. Finance Account.* 50, 67–93. doi: 10.1007/s11156-017-0623-3

Zhang, B., and Wang, P. (2014). Return and volatility spillovers between china and world oil markets. *Econ. Model.* 42, 413–420. doi: 10.1016/j.econmod.2014.07.013

Zhang, D. (2008). Oil shock and economic growth in Japan: a nonlinear approach. *Energy Econ.* 30, 2374–2390. doi: 10.1016/j.eneco.2008.01.006

Zhang, D. (2017). Oil shocks and stock markets revisited: measuring connectedness from a global perspective. *Energy Econ.* 62, 323–333. doi: 10.1016/j.eneco.2017.01.009

Zhang, D., Ji, Q., and Kutan, A. M. (2019). Dynamic transmission mechanisms in global crude oil prices: estimation and implications. *Energy* 175, 1181–1193. doi: 10.1016/j.energy.2019.03.162

Zhang, Y.-J., and Sun, Y.-F. (2016). The dynamic volatility spillover between European carbon trading market and fossil energy market. *J. Clean. Prod.* 112, 2654–2663. doi: 10.1016/j.jclepro.2015.09.118

Zhang, Y.-J., and Wang, J.-L. (2019). Do high-frequency stock market data help forecast crude oil prices? Evidence from the MIDAS models. *Energy Econ.* 78, 192–201. doi: 10.1016/j.eneco.2018.11.015

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Subsidy-Related Deception Behavior in Energy-Saving Products Based on Game Theory

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The appropriate use of subsidies is the key to promote the development of energy-saving products (ESPs). However, subsidy-related deception behavior frequently occurs. Considering the relevant stakeholders, a game model including governments' subsidy policies, manufacturers' environmental quality measures, and customer environmental awareness (CEA) was constructed. We analyzed the crucial influencing factors of governments' and manufacturers' strategies. Quantitative analyses were performed to verify the modeling analyses and to demonstrate the influence of the game parameters. The results indicate that government regulation is necessary to keep manufacturers honest. Increases in penalties, the subsidy coefficient, environmental quality, and CEA all promoted manufacturer integrity. The results further reveal that the equilibrium probability of manufacturer's integrity decreased with both the sales price of ESPs and the cost of government inspections. Moreover, as the cost coefficient of ESPs increased, the government enhanced the relevant regulations. Collectively, these results suggest strategies to reduce subsidy-related deception behavior and improve the effectiveness of government regulations.

Keywords: government regulation, energy-saving product, subsidy policy, deception behavior, payoff matrix, game model

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INTRODUCTION

Products with energy-saving and carbon emissions-reducing features, such as those that cover the hourly electricity consumption of household appliances and electric vehicles with low carbon emissions, can be referred to as energy-saving products (Ji and Zhang, 2019; Li et al., 2019). In this paper, we discuss the carbon emissions attribute of ESPs. Due to the growing ecological problems associated with environmental deterioration, resource depletion, and energy shortages, ESPs are now receiving significant attention from governments, consumers, and manufacturers worldwide (Zhang D. Y. et al., 2019). To stimulate the development of ESPs, a series of government regulation policies, such as tax reduction, subsidies, and cap and trade, have been issued to manufacturers and consumers (Liu and Yu, 2019). Indeed, financial subsidies directly offered by governments play a critical role in the stimulation of ESP manufacturing (Tang and Zhou, 2012; Song et al., 2018). In the United States, for example, the federal government has regulated the emissions of automobiles for decades, and in December 2015, the State Council of the People's Republic of China announced that 33.4 billion CNY had been earmarked to subsidize the production of vehicles with low carbon emissions. In addition, the Chinese government also invested 26.5 billion CNY in financial subsidies, which successfully promoted energy-saving household appliances. Similar subsidy schemes have also been implemented by European governments. Due to increasing customer environmental awareness

(CEA), customers are now more familiar with low carbon emission products, and they are willing to pay extra for ESPs (Paksoy and Ozceylan, 2014; Chander and Muthukrishnan, 2015). Therefore, many manufacturers actively seek to improve their economic and environmental performance, and they engage in the ESP market to gain a competitive advantage.

The current trend in ESP development is not without obstacles and risks. It is well known that both the design and the production of ESPs bear high levels of risk and uncertainty. Research and development of low carbon technologies are often extremely costly. Subsidy policies that intend to reduce production costs lead to subsidy-related deception behavior (Bonroy and Constantatos, 2015). To attract the growing environmentally aware consumer segment and to obtain the huge financial subsidies offered by governments, some manufacturers promote their products as green products, but such claims may be false or misleading (Nyilasy et al., 2014). The products in question may not reflect the attributes or performance associated with ESPs, such as quality and safety. In 2016, the Ministry of Finance of the People's Republic of China conducted a special inspection of automobile manufacturers and discovered that the production of 76,000 new and supposedly energy-saving automobiles was associated with the fraudulent payment of up to 9.27 billion CNY. In 2015, the US Environmental Protection Agency announced that Volkswagen had installed exhaust emission detection software in its vehicles that violated government regulations, which resulted in daily emissions of nitrogen oxides that were approximately 40 times higher than the statutory standard.

It is clear that subsidy-related deception behaviors, such as those described above, can seriously harm society, and consumers. Such behaviors lead to a loss of competitive advantage for manufacturers that adhere to the requirements to receive subsidies. Governments cannot afford to support high-level manufacturers due to subsidies paid to fraudulent manufacturers. Additionally, these types of deception behaviors can cause consumers to question manufacturer integrity (Parguel et al., 2015; Paul et al., 2016). Therefore, the issue of subsidy-related deception behaviors requires urgent attention. To reduce the incidence of deception behaviors and to stabilize the development of ESPs, the present paper aimed to answer the following research questions.

1. With respect to financial intervention by governments to promote the development of ESPs, what factors motivate manufacturers to fraudulently obtain subsidies?
2. How do manufacturers respond to the punishments and increased subsidy standards instituted by governments?
3. Will greater CEA and environmental quality reduce manufacturer subsidy-related deception behaviors?

Considering the interactions that occur among CEA, product environmental quality, and government subsidy policies, a game model involving manufacturers and governments was constructed to answer these questions. Furthermore, to better understand the relationship between the manufacturer and government equilibrium probabilities, simulations and sensitivity analyses of the model were performed. This paper also examines how governments should set subsidies considering manufacturer subsidy-related deception behaviors. From the Nash equilibrium probabilities of the players, we determined that punishment, environmental quality, subsidies, and CEA are all key influencing factors for manufacturer and government strategy selection.

The remainder of this paper is organized as follows. After a review of the relevant literature in section Literature Review, the model formulation and solution procedure are described in section Problem Assumptions and Model Development. Section Numerical Examples presents quantitative analyses of the equilibrium probabilities. Finally, section Conclusions and Suggestions for Future Research describes the conclusions of the research and the implications of the findings.

LITERATURE REVIEW

The literature reviewed here primarily relates to three research streams: the effect of regulation policies on ESPs, the dishonest behaviors of manufacturers, and CEA of manufacturer production. Key studies from the different research streams are briefly reviewed in the following subsections.

Government Regulations on ESPs

As increasingly more regulations to protect the environment are issued, much research has been performed on how these regulations affect manufacturers' environmental performance and operations management (Song et al., 2019; Xia et al., 2019). Regulations such as carbon taxes, subsidies, and cap and trade certainly provide substantial motivation for manufacturers to curb emissions (Chen, 2001; Kroes et al., 2012; Gong and Zhou, 2013; Liao and Shi, 2018; Liu C. Y. et al., 2019). The authors of some studies sought to identify optimal operations decisions and to analyze the impact of regulation policies on production decisions. Xue et al. (2019) examined centralized and decentralized decision-making models within a green supply chain for ESPs with government subsidies. Tao et al. (2014) discussed the effective quantitative evaluation of energy-saving and emission-reducing production.

More recently, game theory has been used to model manufacturers' responses to emissions regulations (Liu and Yu, 2015; Xu L. et al., 2019; Xu X. F. et al., 2019). Huang et al. (2019) analyzed a government subsidy scheme that encouraged manufacturers to optimize price and energy efficiency. Barari et al. (2012) used an evolutionary game method to analyze the mechanisms of competition and cooperation between manufacturers and retailers and to identify the ideal balance between net profit and low carbon production. Zhou and Huang (2016) discussed fixed-type contracts and discount-type contracts for ESPs in a monopoly with the government's subsidy budget constraints. Hafezalkotob (2015) explored three-level game theory to demonstrate how the government acts as a Stackelberg leader by offering subsidies and tax strategies for green supply chains. Madani and Rasti-Barzoki (2017) and Zhang et al. (2018) developed game models to determine the effect of governmental fixed and discounted subsidies on ESP manufacturers.

Manufacturers' Dishonest Behavior

Manufacturers may engage in multiple dishonest behaviors, which primarily include fraud, the misuse of eco-labels, and the use of counterfeit products. These issues are the subject of long-term research, as the problem is global (Hamilton and Zilberman, 2006; Lee et al., 2018). Ibanez and Grolleau (2008) proposed that a polluting firm may also claim eco-labels by paying a fee because consumers cannot observe production technology or pollution related to production. Lyon and Montgomery (2015) explained that greenwashing is a broad term that encompasses many forms of misleading environmental communications. Zu et al. (2018) used a Stackelberg game to examine a two-echelon supply chain consisting of one manufacturer and one supplier and compared the sustainable profits of efforts to reduce CO_2 emissions in environmental regulation. Jin et al. (2018) proposed that enterprises should be supervised and regulated after certification. Without effective supervision and regulations, enterprises may cease to implement standards after being certified. Goh and Balaji (2016) used structural equation modeling to investigate the role of skepticism in green purchase behaviors and emphasized that skepticism reduced consumers' knowledge and environmental concerns, which then decreased their intention to purchase green products.

Customer Environmental Awareness

Another relevant research stream is the CEA of manufacturers' product design and pricing. Most studies on these topics have revealed that CEA influences manufacturers' carbon reduction strategies (Liao et al., 2019; Liu Y. X. et al., 2019). For example, Yalabik and Fairchild (2011) discovered that when there are environmentally sensitive customers, manufacturers are incentivized to reduce carbon emissions through investment in green technology. Liu et al. (2012) investigated the impact of CEA on supply chain players and manufacturer competition. Zhang et al. (2015) also considered the impact of CEA on firms' operations decisions, such as optimal ordering policies and coordination contracts, and firms' economic and environmental performance. Li and Li (2016) analyzed consumers' preferences for low carbon products and concluded that retailers are motivated to promote low carbon products whether or not manufacturers are incentivized to produce them. Hammami et al. (2018) studied the effect of CEA on emission intensity and product price and discovered that CEA efficiently drives better environmental performance. Zhang Y. X. et al. (2019) identified the influencing factors for products, consumers, and regulations based on energy-saving appliances. There is evidence that manufacturers are willing to invest in green technology and reduce carbon emissions when they realize that consumers prefer environmentally friendly products (Sengupta, 2015; Xu and Wang, 2018).

Based on the existing research, we made conclusions about the relationships among governments, manufacturers, and consumers of ESPs, which are illustrated in **Figure 1**. During the entire production of ESPs, governments, manufacturers, and consumers were key influencing factors. Therefore, we considered the effect of CEA on the joint environmental quality of ESPs and governmental subsidies. Most of the previous studies on ESPs focused on how to design contracts to encourage stakeholders. However, the prevention of deceptive behaviors to obtain subsidies, which is a severe problem in practice, was rarely discussed in depth. In this paper, we used game theory to discuss the crucial influencing factors of manufacturer subsidy-related deception behaviors.

PROBLEM ASSUMPTIONS AND MODEL DEVELOPMENT

Problem Assumptions

Several model assumptions have been used to analyze manufacturers' attempts to fraudulently obtain government subsidies. We assumed that a monopolist provides two kinds of durable products with different carbon emissions: ESPs and traditional products (TRPs). Both of these types of products emit carbon dioxide when they are used. Carbon emission is

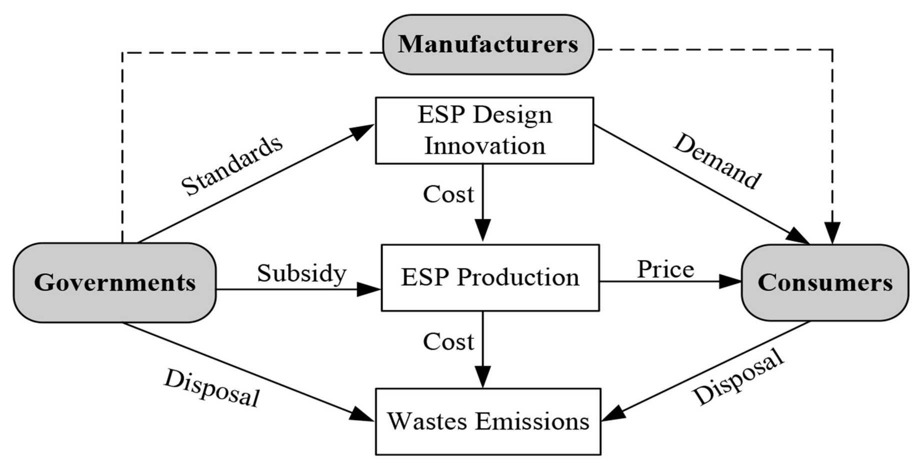

FIGURE 1 | The relationships among governments, manufacturers, and consumers of ESPs.

denoted by M ($M > 0$). Herein, M_E and M_T represent the carbon emissions of ESPs and TRPs, respectively. ESPs have lower carbon emissions, that is, $M_E < M_T$. For example, the choice to drive an electric vehicle rather than a traditional fuel vehicle can help reduce carbon emissions by approximately 30 tons per year (Sulman et al., 2009).

The market demand for ESPs is denoted by D and expressed by the following equation: $D = a - bp + \xi e$ ($a > 0, b > 0$). In this equation, a is the primary demand for ESPs; p is the product's sale price; b is the sensitivity to the sale price; e is environmental quality; ξ is CEA; and $a - bp > 0$. Market demand increases with CEA and with the environmental quality of ESPs, and it decreases as price increases (Liu et al., 2012).

The manufacturer can only receive governmental subsidies when a product's carbon emissions meet certain energy-saving standards. The carbon emissions standard is expressed by $\left[\underline{M}, M_0\right]$. If $M < M_0$, the manufacturer can receive the subsidy. In this paper, we define environmental quality, e, as $e = \frac{M_0 - M}{M_0}$. In contrast to ESPs, TRPs do not have environmental quality, and higher values of e demonstrate better environmental quality.

The subsidy coefficient is φ, and the subsidy for manufacturers that produce ESPs is φe. Government budgets are limited, so the upper bound of the subsidy is Λ. If $M < \underline{M}$, the total subsidy cannot exceed Λ. The subsidy is calculated using the following equation.

$$f(\varphi, e) = \begin{cases} 0 & M \geq M_0 \\ \varphi \dfrac{M_0 - M}{M_0}\left(a - bp + \xi \dfrac{M_0 - M}{M_0}\right) & \underline{M} \leq M < M_0 \\ \Lambda & M < \underline{M} \end{cases}$$

Similar to the model by Gouda et al. (2016), the production cost in our model was calculated using a quadratic function, $\frac{1}{2}ce^2$. This function is independent of production volume, and c is a strictly positive cost coefficient.

Governments aim to improve environmental performance, so the government's objective is to minimize total carbon emissions. The benefit coefficient is k, and the government's profit is $k(M_0 - M_E)D$. The cost of supervision and inspection is denoted by C_g, and special inspections of manufacturers are conducted after obtaining subsidies.

If the manufacturer fraudulently obtains government subsidy, the government's loss is $s(M_T - M_E)D$; s represents the loss coefficient. The government will then impose penalties of $(1 + f)\varphi eD$ on the manufacturer. For example, a bus company in China received 519 million CNY in financial subsidies in 2015. Fifty percent of this amount was fined a total 800 million CNY based on irregularities. The major parameters of the game model are summarized in **Table 1**.

An optional set of strategies for the government is (a_1, a_2) = (regulation, non-regulation). Under the conditions of government regulation and market demand, the set of strategies for manufacturers is (b_1, b_2) = (integrity, fraud). The probability of government regulation is $y(0 \leq y \leq 1)$, and the probability of non-regulation is $1 - y$. The probability of manufacturer integrity is $x(0 \leq x \leq 1)$, and the probability that manufacturers will obtain subsidies through fraud is $1 - x$.

According to the model assumptions, two players simultaneously choose one of the two possible strategies, and there are four combinations of strategies for the government and the manufacturer. The payoff matrix of the government–manufacturer game is shown in **Table 2**.

Model Analysis

In this section, we review the equilibrium probability calculated for this game and analyze the factors influencing manufacturers' and governments' strategy choices.

The Nash Equilibrium Probability of Manufacturer

Theorem 1. The Nash equilibrium probability of manufacturer integrity is x^* and is expressed by the following equation: $x^* = 1 - \frac{C_g}{(1+f)\varphi e(a-bp+\xi e)}$.

Proof of Theorem1: The expected utility of government regulation and non-regulation are denoted by V_{g1} and V_{g2}, respectively, and are expressed by the following equations.

$$\begin{aligned} V_{g1} &= x\left\{\left[k(M_0 - M_E) - \varphi e\right](a - bp + \tau e) - C_g\right\} \\ &\quad + (1 - x)\left\{\left[(1 + f)\varphi e - s(M_T - M_E)\right](a - bp + \xi e) - C_g\right\} \\ V_{g2} &= x\left\{\left[k(M_0 - M_E) - \varphi e\right](a - bp + \xi e)\right\} \\ &\quad + (1 - x)\left[-s(M_T - M_E)(a - bp + \xi e)\right] \end{aligned}$$

TABLE 1 | The parameters of the game model.

Parameters	Description
e	Environmental quality
φ	Coefficient of the manufacturer subsidy
M_E, M_T	Carbon emissions of ESPs and TRPs, respectively
M_0	Subsidy standard for carbon emissions
p	Product sales price
c	Cost coefficient of ESPs
f	Government penalty coefficient
k	Government benefit coefficient
s	Government loss coefficient
C_g	Cost of supervision and inspection
a	Primary demand for ESPs
b	Coefficient for the sensitivity of demand to price
ξ	Consumer environmental awareness

TABLE 2 | The payoff matrix for the government and the manufacturer.

		Government	
		Regulation, y	**Non-regulation, 1 − y**
Manufacturer	Integrity, x	$(p + \varphi e)(a - bp + \xi e) - \frac{1}{2}ce^2$ $[k(M_0 - M_E) - \varphi e]$ $(a - bp + \xi e) - C_g$	$(p + \varphi e)(a - bp + \xi e) -$ $\frac{1}{2}ce^2$ $[k(M_0 - M_E) - \varphi e]$ $(a - bp + \xi e)$
	Fraud, $1 - x$	$[p - (1 + f)\varphi e]$ $(a - bp + \xi e)$ $[(1 + f)\varphi e - s(M_T - M_E)]$ $(a - bp + \xi e) - C_g$	$(p + \varphi e)(a - bp + \xi e) -$ $s(M_T - M_E)(a - bp + \xi e)$

When $V_{g1} = V_{g2}$, we calculated that $x^* = 1 - \frac{C_g}{(1+f)\varphi e(a-bp+\xi e)}$. Therefore, the Nash equilibrium probability of fraud can be expressed as $1 - x^* = \frac{C_g}{(1+f)\varphi e(a-bp+\xi e)}$.

Theorem 1 presents the Nash equilibrium probability of manufacturer integrity. This probability is determined by the cost of supervision and inspection, government penalty coefficient, environmental quality, manufacturer subsidy coefficient, and demand for the product.

The probability of manufacturer integrity is expressed by $x^* = 1 - \frac{C_g}{(1+f)\varphi e(a-bp+\xi e)}$. When $x > x^*$, the government's optimal strategy is non-regulation. When $x < x^*$, the government's optimal strategy is regulation. When $x = x^*$, it does not matter which strategy the government chooses.

Proposition 1: The probability of manufacture integrity, x^*, decreases as supervision cost, C_g, and sale price, p, increase.

Since $x^* = 1 - \frac{C_g}{(1+f)\varphi e(a-bp+\xi e)}$, the first derivative of the probability of manufacture integrity on C_g and p is as follows:

$$\frac{\partial x^*}{\partial C_g} = -\frac{1}{(1+f)\varphi e(a-bp+\xi e)} < 0;$$
$$\frac{\partial x^*}{\partial p} = \frac{-C_g b(1+f)\varphi e}{\left[(1+f)\varphi e(a-bp+\xi e)\right]} < 0.$$

Proposition 1 shows that the Nash equilibrium probability of manufacture integrity decreases when the government spends substantial funds on supervision. In other words, the higher the cost of regulation, the less likely it is that governments will be willing to make regulations. Manufacturers will recognize this scenario, which reduces the necessity to obtain subsidies honestly and decreases the integrity of manufacturers.

The higher the sale price of the ESPs, the more likely manufacturers are to commit fraud. ESP manufacturers who have the potential to gain more profits are more motivated to fraudulently obtain government subsidies.

Proposition 2: The Nash equilibrium probability of manufacture integrity, x^*, increases as the penalty coefficient, f, environmental quality, e, the subsidy coefficient, φ, and CEA, ξ, increase.

The first derivative of the Nash equilibrium probability of the manufacturer in terms of f, e, φ, and ξ was obtained as follows:

$$\frac{\partial x^*}{\partial f} = \frac{C_g\varphi e(a-bp+\xi e)}{\left[(1+f)\varphi e(a-bp+\xi e)\right]^2} > 0;$$
$$\frac{\partial x^*}{\partial e} = \frac{C_g\left[(1+f)\varphi(a-bp+2\xi e)\right]}{\left[(1+f)\varphi e(a-bp+\xi e)\right]^2} > 0;$$

$$\frac{\partial x^*}{\partial \varphi} = \frac{C_g(1+f)e(a-bp+\xi e)}{\left[(1+f)\varphi e(a-bp+\xi e)\right]^2} > 0; \text{ and}$$
$$\frac{\partial x^*}{\partial \xi} = \frac{C_g(1+f)\varphi e^2}{\left[(1+f)\varphi e(a-bp+\xi e)\right]^2} > 0.$$

Proposition 2 shows that if the penalty, the subsidy coefficient, environment quality, and CEA increase, the Nash equilibrium probability of manufacture integrity improves.

The higher the penalty, the lower the probability the manufacturer will fraudulently obtain the subsidy. We also demonstrated that improving environment quality increases the Nash equilibrium probability of manufacture integrity. Since $e = \frac{M_0 - M}{M_0}$, if the government enhances the subsidy standard, M_0, for ESPs, environment quality will improve, and the Nash equilibrium probability of manufacturer integrity will increase.

If CEA is high, ESP demand is also high. If manufacturers do not produce qualified ESPs, consumer complaints will increase. Therefore, honest efforts to obtain government subsidies are the manufacturer's optimal strategy.

The Nash Equilibrium Probability of the Government

Theorem 2. The Nash equilibrium in governmental regulatory strategies is y^* and is expressed by the following equation: $y^* = \frac{ce}{(4+2f)\varphi(a-bp+\xi e)}$.

Proof of Theorem 2: The expected utility of integrity is V_{m1} and is expressed by the following equation:

$$V_{m1} = y\left[(p+\varphi e)(a-bp+\xi e) - \frac{1}{2}ce^2\right] + (1-y)\left[(p+\varphi e)(a-bp+\xi e) - \frac{1}{2}ce^2\right]$$

The expected utility of fraud to the manufacturer is V_{m2} and is expressed by the following equation:

$$V_{m2} = y\left\{\left[p-(1+f)\varphi e\right](a-bp+\xi e)\right\} + (1-y)\left[(p+\varphi e)(a-bp+\xi e)\right]$$

When $V_{m1} = V_{m2}$, we can calculate the Nash equilibrium probability of the government's strategy, y^*, using the following equation: $y^* = \frac{ce}{(4+2f)\varphi(a-bp+\xi e)}$.

The equilibrium probability of the government depends on the production cost coefficient, c, environmental quality, e, the penalty coefficient, f, the subsidy coefficient, φ, and the demand for ESPs.

The probability of government regulation of manufacturers is expressed by the following equation: $y^* = \frac{ce}{(4+2f)\varphi(a-bp+\xi e)}$. When $y > y^*$, the manufacturer's optimal strategy is to adhere to government regulations. When $y < y^*$, the manufacturer's optimal strategy is fraud. If $y = y^*$, it makes no difference which strategy the manufacturer selects.

Proposition 3: The equilibrium probability of government regulation, y^*, decreases as the manufacturer penalty, f, the subsidy coefficient, φ, and CEA, ξ, increase.

The solutions for f, φ, and ξ for the first derivatives of y^* are as follows:

$$\frac{\partial y^*}{\partial f} = \frac{-2ce\varphi(a-bp+\xi e)}{\left[(4+2f)\varphi(a-bp+\xi e)\right]^2} < 0;$$
$$\frac{\partial y^*}{\partial \varphi} = \frac{-(4+2f)ce(a-bp+\xi e)}{\left[(4+2f)\varphi(a-bp+\xi e)\right]^2} < 0;$$

and

$$\frac{\partial y^*}{\partial \xi} = \frac{-(4+2f)c\varphi e^2}{\left[(4+2f)\varphi(a-bp+\xi e)\right]^2} < 0$$

Proposition 3 demonstrates that as the subsidy, CEA, and the penalty for fraud increase, the probability of government regulation decreases. The reverse is also true.

The higher the penalty, the more the government deters manufacturers from committing fraud. This phenomenon reduces the need for government supervision and reduces the probability of quality supervision. The reverse is true as well.

As the government subsidy coefficient increases, subsidy expenditures increase as well. Furthermore, as supervision cost increases, the intensity of government supervision decreases.

When CEA is high, the need for government supervision decreases. Therefore, improving CEA can effectively reduce the pressure to implement government supervision.

Proposition 4: The probability of government regulation y^*, increases as the production cost coefficient, c, the price of ESPs, p, and environmental quality, e, increase.

The solutions for the first derivative of y^* for c, p, and e are as follows:

$$\frac{\partial y^*}{\partial c} = \frac{e}{(4+2f)\varphi(a-bp+\xi e)} > 0;$$

$$\frac{\partial y^*}{\partial p} = \frac{(4+2f)ce\varphi b}{\left[(4+2f)\varphi(a-bp+\xi e)\right]^2} > 0;$$

and

$$\frac{\partial y^*}{\partial e} = \frac{(4+2f)c\varphi(a-bp)}{\left[(4+2f)\varphi(a-bp+\xi e)\right]^2} > 0$$

Proposition 4 shows that the higher the production cost, the sale price, and environmental quality of ESPs, the greater the probability of government regulation.

This finding shows that when the cost and price of ESPs are higher, manufacturers are more likely to fraudulently obtain subsidies to increase their profits, and the government is more likely to supervise manufacturers. When government subsidy standards for ESPs are higher, the government is more likely to supervise manufacturers to prevent substandard manufacturers from fraudulently obtaining subsidies.

The changes in equilibrium probability as the model parameters increase are presented in **Table 3**.

Table 3 displays that the penalty coefficient, f, environmental quality, e, the subsidy coefficient, φ, CEA, ξ, and the ESPs price, p, influence both governments and manufacturers. Therefore, to reduce fraudulent efforts to obtain subsidies, these critical factors should be adjusted to support the desired strategic choice. Furthermore, high penalties, high subsidies, and high CEA benefit both manufacturers and governments. Therefore, penalties and subsidies should be increased, and governments should invest in improving CEA.

TABLE 3 | Changes in equilibrium probability as model parameters increase.

	Parameters	f	e	φ	ξ	p	C_g	c
Manufacturer's integrity equilibrium probability	x^*	+	+	+	+	–	–	0
Government's regulation equilibrium probability	y^*	–	+	–	–	+	0	+

+, Increase; –, Decrease; 0, No effect.

NUMERICAL EXAMPLES

To illustrate these conclusions more intuitively, quantitative analyses are presented. Simulations explore the effect of the penalty coefficient, environmental quality, the subsidy coefficient, CEA, and price on the manufacturer and government equilibrium probabilities. This section also further describes the effect of inspection costs on the manufacturer's equilibrium probability and the effect of the ESPs cost coefficient on the government equilibrium probability. For each scenario, a quantitative example is provided to illustrate the change.

For this quantitative demonstration, we assigned values to each parameter based on the assumptions described in the previous sections and the practical implications. The parameters $a = 20$ and $b = 1$ were used.

The Impact of the Penalty Coefficient, *f*, on Equilibrium Probability

In this example, $C_g = 1$, $\varphi = 0.5$, $e = 0.5$, $p = 10$, $\xi = 0.5$, and $c = 24$. Herein, we explored the change in both game members' equilibrium probabilities as the government penalty coefficient, f, changed. **Figure 2** shows that the equilibrium probability of manufacturers increases with f and the government's equilibrium probability decreases as f increases. These results are in accordance with propositions 2 and 3.

As shown in **Figure 2**, government penalties can effectively control manufacturer dishonesty and ensure the stable development of ESPs. Higher penalties also reduce the probability of regulation, which can decrease the cost of

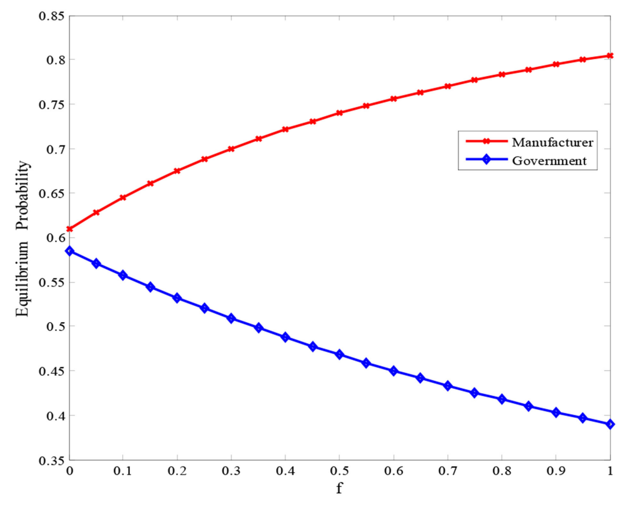

FIGURE 2 | Game members' equilibrium probabilities as a function of f.

government regulation. This relationship reveals the key to increasing penalties for manufacturer fraud.

The Influence of Environmental Quality, *e*, on Equilibrium Probability

This section examines the effect of environmental quality, $\boldsymbol{e}$, on equilibrium probability. Herein, $C_g = 0.5, \varphi = 0.5, p = 6, f = 0.5, \xi = 0.5$, and $c = 24$. **Figure 3** shows that the manufacturer's and the government's equilibrium probabilities increase with $\boldsymbol{e}$. This result is in accordance with propositions 2 and 4.

Figure 3 shows that improving environmental quality can benefit the manufacturer. It is optimal to produce products that meet the standard defined in the subsidy declaration.

The Impact of the Subsidy Coefficient, φ, on Equilibrium Probability

The parameters were assumed as follows: $C_g = 0.5$, $e = 0.5$, $p = 6, f = 0.5, \xi = 0.5$, and $c = 4$. **Figure 4** shows that the manufacturer's equilibrium probability increases with φ, and the government's equilibrium probability decreases as φ increases. This result is in accordance with propositions 2 and 3.

Figure 4 demonstrates that when government subsidies increase, manufacturers' dishonest behavior increases as well. Because government budgets are limited, extremely high subsidies affect the regulation cost. Therefore, increased subsidies also decrease the government's motivation to regulate manufacturers.

The Impact of CEA, ξ, on Equilibrium Probability

In this subsection, $C_g = 0.5, \varphi = 0.5, p = 18, f = 0.5, \varphi = 0.5$, and $c = 24$. This section explores the effect of CEA, ξ, on equilibrium probability. **Figure 5** shows how CEA, ξ, impacts the game members' strategies. The manufacturer's equilibrium probability increases with ξ, while the government's equilibrium probability decreases as ξ increases. This result is in accordance with propositions 2 and 3.

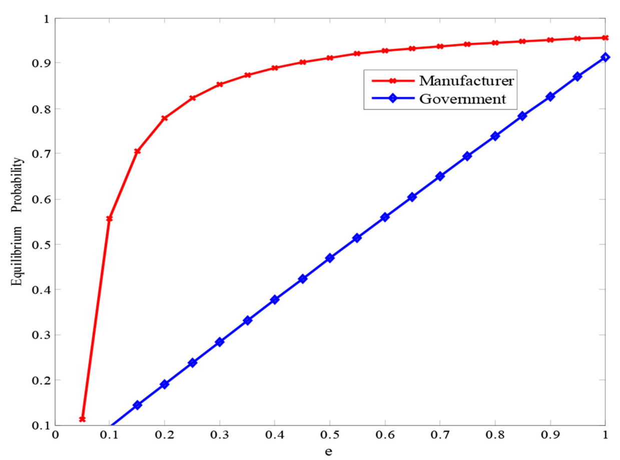

FIGURE 3 | Game members' equilibrium probabilities as a function of *e*.

As shown in **Figure 5**, when CEA increases, the probability of manufacturer integrity increases as well. The government benefits from this phenomenon. Therefore, it is a good strategy for the government to improve CEA.

The Impact of Sale Price, *p*, on Equilibrium Probability

We set the following parameters: $C_g = 0.5$, $e = 0.5$, $\varphi = 0.5$, $f = 0.5$, $\xi = 0.5$, and $c = 60$. **Figure 6** shows how price, p, impacts game members' strategies. The manufacturer's equilibrium probability decreases as p increases, while the government's equilibrium probability increases with p. This result is in accordance with propositions 1 and 4.

Figure 6 shows that as the ESPs sale price increases, manufacturer dishonesty increases. When the ESP price is

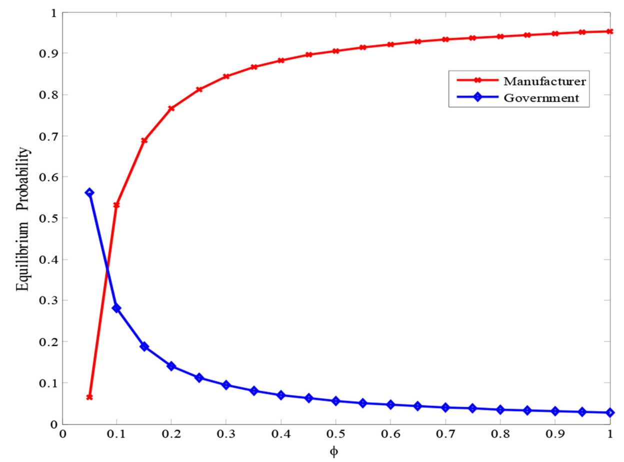

FIGURE 4 | Game members' equilibrium probabilities as a function of φ.

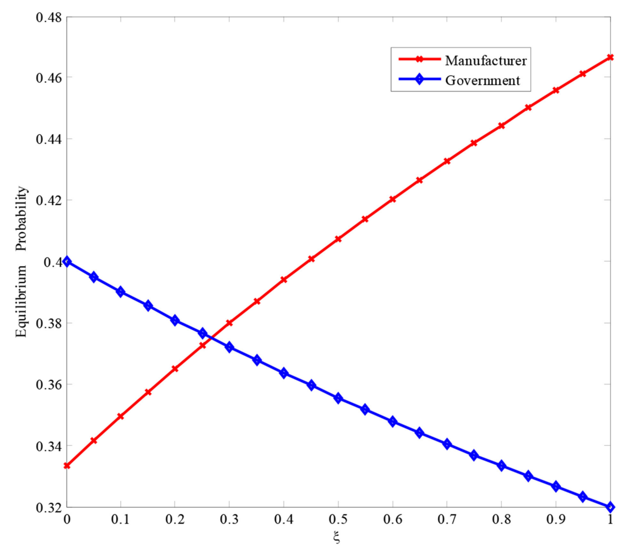

FIGURE 5 | Game members' equilibrium probabilities as a function of ξ.

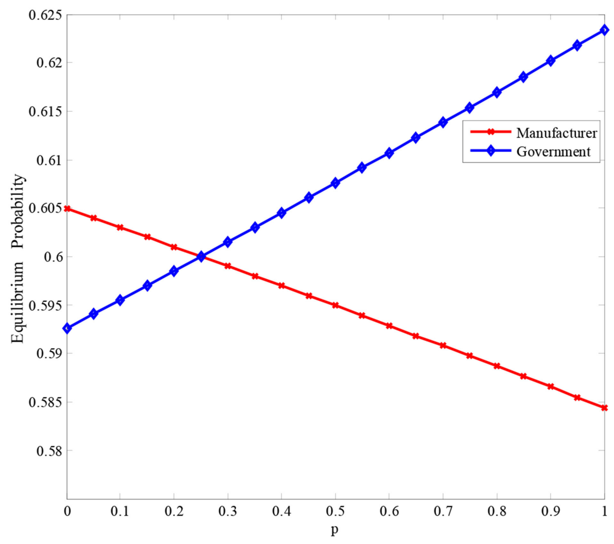

FIGURE 6 | Game members' equilibrium probabilities as a function of *p*.

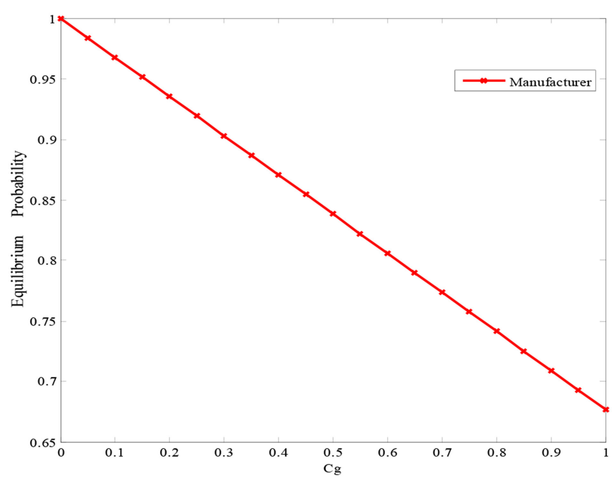

FIGURE 7 | The manufacturer's equilibrium probability as a function of C_g.

high, the manufacturer is more likely to take the risk of fraudulently obtaining subsidies to gain market share and increase profits.

The Impact of Inspection Cost, C_g, on the Manufacturer's Equilibrium Probability

Here $\varphi = 0.5$, $p = 12$, $f = 0.5$, and $e = 0.5$. **Figure 7** shows that the manufacturer's equilibrium probability decreases as the government inspection cost, C_g, decreases.

Figure 7 shows that if government inspection costs are high, the probability of manufacturer integrity decreases. Therefore, the government should take measures to detect manufacturer subsidy fraud and reduce regulatory costs in this scenario.

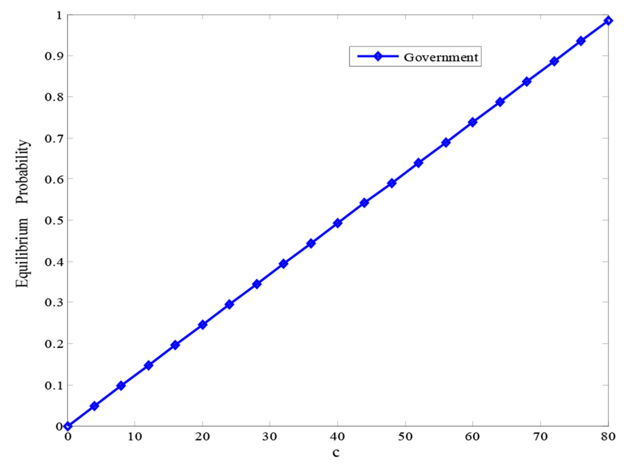

FIGURE 8 | The government's equilibrium probability as a function of *c*.

The Impact of the Cost Coefficient, *c*, on the Government's Equilibrium Probability

Here $e = 0.5$, $\varphi = 0.5$, $f = 0.5$, $p = 4$, and $\xi = 0.5$. **Figure 8** shows that as *c*increases, the government's equilibrium probability increases as well. In other words, if the production cost of ESPs is extremely high, the probability of government regulation increases.

CONCLUSIONS AND SUGGESTIONS FOR FUTURE RESEARCH

To improve manufacturers' environmental performance, governments offer financial subsidies to enhance ESP development. This paper discussed the issue of manufacturer fraud to obtain government subsidies. We used theoretical analyses and simulations to identify the factors that impact strategic choices. Considering CEA, environmental quality, and government subsidy policies, a game model was developed to discuss the relationship between governments and manufacturers. The Nash equilibrium probability demonstrates that the penalty coefficient, environmental quality, the subsidy coefficient, the sale price, and CEA were the primary factors influencing players' behavioral strategies. We further used quantitative examples to analyze the change in these parameters. Based on the equilibrium probability, this study can help governments further develop and implement appropriate environmental policies. The following regulation policies are recommended.

First, increased penalties for manufacturer fraud and CEA not only increase the probability of manufacturer integrity but also decrease the probability of government regulation. Therefore, increasing penalties and CEA is beneficial to both players and presents a win-win situation. However, penalties affect manufacturer strategies. It is better for the government to impose penalties on dishonest manufacturers. Manufacturers make greater efforts to reduce emissions when CEA is high.

The government can also promote greater CEA, which can increase manufacturer integrity and reduce the probability of government regulation.

Second, improving the environmental quality of ESPs can increase manufacturer integrity. Therefore, the standards for carbon reduction affect manufacturers. When subsidies are high, manufacturers are more likely to honestly apply for subsidies. Considering the need for environmental protection and budgetary concerns, therefore, is crucial for governments to set proper standards and subsidy amounts to balance the environment and the economy.

Third, the government's inspection cost is critical to manufacturers' decisions. To reduce the cost and the pressure on government regulation, a multi-stakeholder supervision system that includes the government, the public, and the media should be established to monitor subsidy fraud.

To simplify the problem, we only analyzed the manufacturer and the government and did not consider the supply chain. Future research should address the following aspects: (1) A competitive game, including manufacturers and retailers, and a game model of multi-party participation could be constructed. (2) Although we analyzed CEA, manufacturer product quality, and government subsidy policies, the game model was constructed with complete information. The construction of a dynamic game model with incomplete information will be a direction of further research. (3) It would also be interesting to use relevant cases to conduct an empirical application and analysis of the game models.

DATA AVAILABILITY STATEMENT

All datasets generated for this study are included in the article/supplementary material.

AUTHOR CONTRIBUTIONS

All authors contributed to the study conception and design.

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REFERENCES

Barari, S., Agarwal, G., Zhang, W. J., Mahanty, B., and Tiwari, M. K. (2012). A decision framework for the analysis of green supply chain contracts: an evolutionary game approach. *Expert Syst. Appl.* 39, 2965–2976. doi: 10.1016/j.eswa.2011.08.158

Bonroy, O., and Constantatos, C. (2015). On the economics of labels: how their introduction affects the functioning of markets and the welfare of all participants. *Am. J. Agric. Econ.* 97, 239–259. doi: 10.1093/ajae/aau088

Chander, P., and Muthukrishnan, S. (2015). Green consumerism and pollution control. *J. Econ. Behav. Organ.* 114, 27–35. doi: 10.1016/j.jebo.2015.02.013

Chen, C. L. (2001). Design for the environment: a quality-based model for green product development. *Manage. Sci.* 47, 250–263. doi: 10.1287/mnsc.47.2.250.9841

Goh, S. K., and Balaji, M. S. (2016). Linking green skepticism to green purchase behavior. *J. Clean. Prod.* 131, 629–638. doi: 10.1016/j.jclepro.2016.04.122

Gong, X. T., and Zhou, S. X. (2013). Optimal production planning with emissions trading. *Oper. Res.* 61, 908–924. doi: 10.1287/opre.2013.1189

Gouda, S. K., Jonnalagedda, S., and Saranga, H. (2016). Design for the environment: impact of regulatory policies on product development. *Eur. J. Oper. Res*. 248, 558–570. doi: 10.1016/j.ejor.2015.07.043

Hafezalkotob, A. (2015). Competition of two green and regular supply chains under environmental protection and revenue seeking policies of government. *Comput. Ind. Eng.* 82, 103–114. doi: 10.1016/j.cie.2015.01.016

Hamilton, S. F., and Zilberman, D. (2006). Green markets, eco-certification, and equilibrium fraud. *J. Environ. Econ. Manage.* 52, 627–644. doi: 10.1016/j.jeem.2006.05.002

Hammami, R., Nouira, I., and Frein, Y. (2018). Effects of customers' environmental awareness and environmental regulations on the emission intensity and price of a product. *Decis. Sci.* 49, 1116–1155. doi: 10.1111/deci.12302

Huang, W. X., Zhou, W. H., Chen, J. G., and Chen, X. (2019). The government's optimal subsidy scheme under Manufacturers' competition of price and product energy efficiency. *Omega-Int. J. Manage. Sci.* 84, 70–101. doi: 10.1016/j.omega.2018.04.006

Ibanez, L., and Grolleau, G. (2008). Can ecolabeling schemes preserve the environment? *Environ. Resour. Econ.* 40, 233–249. doi: 10.1007/s10640-007-9150-3

Ji, Q., and Zhang, D. Y. (2019). How much does financial development contribute to renewable energy growth and upgrading of energy structure in China? *Energy Policy* 128, 114–124. doi: 10.1016/j.enpol.2018.12.047

Jin, J., Zhuang, J., and Zhao, Q. H. (2018). Supervision after certification: an evolutionary game analysis for chinese environmental labeled enterprises. *Sustainability* 10:1494. doi: 10.3390/su10051494

Kroes, J., Subramanian, R., and Subramanyam, R. (2012). Operational compliance levers, environmental performance, and firm performance under cap and trade regulation. *Manuf. Serv. Oper. Manage.* 14, 186–201. doi: 10.1287/msom.1110.0357

Lee, H. C. B., Cruz, J. M., and Shankar, R. (2018). Corporate social responsibility (CSR) issues in supply chain competition: should greenwashing be regulated? *Decis. Sci.* 49, 1088–1115. doi: 10.1111/deci.12307

Li, J. J., Zhang, J., Zhang, D. Y., and Ji, Q. (2019). Does gender inequality affect household green consumption behaviour in China? *Energy Policy* 135:111071. doi: 10.1016/j.enpol.2019.111071

Li, X., and Li, Y. J. (2016). Chain-to-chain competition on product sustainability. *J. Clean. Prod.* 112, 2058–2065. doi: 10.1016/j.jclepro.2014.09.027

Liao, X. C., Shen, S. V., and Shi, X. P. (2019). The effects of behavioral intention on the choice to purchase energy-saving appliances in China: the role of environmental attitude, concern, and perceived psychological. *Energy Effic.* 1–17. doi: 10.1007/s12053-019-09828-5

Liao, X. C., and Shi, X. P. (2018). Public appeal, environmental regulation and green investment: evidence from China. *Energy Policy* 119, 554–562. doi: 10.1016/j.enpol.2018.05.020

Liu, C. Y., and Yu, T. (2015). Study on the tripartite game in quality regulation of green products. *China Popul. Resour. Environ.* 25, 170–175. doi: 10.3969/j.issn.1002-2104.2015.10.023

Liu, C. Y., and Yu, T. (2019). The regulatory warning model of regional product quality based on the back-propagation artificial neural network. *Neural Comput. Appl.* 1–10. doi: 10.1007/s00521-019-04188-8

Liu, C. Y., Yu, T., and Ma, Y. H. (2019). Game of government, enterprise and consumer based on product quality regulation perspective. *Chin. J. Manage. Sci.* 27, 128–130. doi: 10.3724/SP.J.1042.2019.00646

Liu, Y. X., Sun, X., Sun, T., Shi, X. P., and Liu, J. M. (2019). Promoting green residential buildings by increasing homebuyers' willingness to pay: evidence from Sino-Singapore Tianjin Eco-city in China. *J. Clean. Prod.* 238, 24–30. doi: 10.1016/j.jclepro.2019.117884

Liu, Z. G., Anderson, T. D., and Cruz, J. M. (2012). Consumer environmental awareness and competition in two-stage supply chains. *Eur. J. Oper. Res.* 218, 602–613. doi: 10.1016/j.ejor.2011.11.027

Lyon, T. P., and Montgomery, A. W. (2015). The means and end of greenwash. *Organ. Environ.* 28, 223–249. doi: 10.1177/1086026615575332

Madani, S. R., and Rasti-Barzoki, M. (2017). Sustainable supply chain management with pricing, greening and governmental tariffs determining strategies: a game-theoretic approach. *Comput. Ind. Eng.* 105, 287–298. doi: 10.1016/j.cie.2017.01.017

Nyilasy, G., Gangadharbatla, H., and Paladino, A. (2014). Perceived greenwashing: the interactive effects of green advertising and corporate environmental performance on consumer reactions. *J. Bus. Ethics* 125, 693–707. doi: 10.1007/s10551-013-1944-3

Paksoy, T., and Ozceylan, E. (2014). Environmentally conscious optimization of supply chain networks. *J. Oper. Res. Soc.* 65, 855–872. doi: 10.1057/jors.2012.95

Parguel, B., Benoit-Moreau, F., and Russell, C. A. (2015). Can evoking nature in advertising mislead consumers? The power of 'executional greenwashing'. *Int. J. Advert.* 34, 107–134. doi: 10.1080/02650487.2014.996116

Paul, J., Modi, A., and Patel, J. (2016). Predicting green product consumption using theory of planned behavior and reasoned action. *J. Retail. Consum. Serv.* 29, 123–134. doi: 10.1016/j.jretconser.2015.11.006

Sengupta, A. (2015). Competitive investment in clean technology and uninformed green consumers. *J. Environ. Econ. Manage.* 71, 125–141. doi: 10.1016/j.jeem.2015.03.001

Song, X. N., Lu, Y. J., Shen, L. Y., and Shi, X. P. (2018). Will China's building sector participate in emission trading system? Insights from modelling an owner's optimal carbon reduction strategies. *Energy Policy* 118, 232–244. doi: 10.1016/j.enpol.2018.03.075

Song, Y. J., Ji, Q., Du, Y. J., and Geng, J. B. (2019). The dynamic dependence of fossil energy, investor sentiment and renewable energy stock markets. *Energy Econ.* 84:104564. doi: 10.1016/j.eneco.2019.104564

Sulman, B. N., Desai, A. R., Cook, B. D., Saliendra, N. Z., and Mackay, D. S. (2009). Contrasting carbon dioxide fluxes between a drying shrub wetland in Northern Wisconsin, USA, and nearby forests. *Biogeosciences* 6, 1115–1126. doi: 10.5194/bg-6-1115-2009

Tang, C. S., and Zhou, S. (2012). Research advances in environmentally and socially sustainable operations. *Eur. J. Oper. Res.* 223, 585–594. doi: 10.1016/j.ejor.2012.07.030

Tao, F., Zuo, Y., and Xu, L. D. (2014). Internet of things and BOM-based life cycle assessment of energy-saving and emission-reduction of products. *IEEE Trans. Ind. Inform.* 10, 1252–1254. doi: 10.1109/TII.2014.2306771

Xia, Y., Kong, Y. S., Ji, Q., and Zhang, D. Y. (2019). Impacts of China-US trade conflicts on the energy sector. *China Econ. Rev.* 58:101360. doi: 10.1016/j.chieco.2019.101360

Xu, L., and Wang, C. X. (2018). Sustainable manufacturing in a closed-loop supply chain considering emission reduction and remanufacturing. *Resour. Conserv. Recycling* 131, 297–304. doi: 10.1016/j.resconrec.2017.10.012

Xu, L., Zhang, Q., and Shi, X. P. (2019). Stakeholders strategies in poverty alleviation and clean energy access: a case study of China's PV poverty alleviation program. *Energy Policy* 135:111011. doi: 10.1016/j.enpol.2019.111011

Xu, X. F., Wei, Z. F., Ji, Q., Wang, C. L., and Guo, G. W. (2019). Global renewable energy development: influencing factors, trend predictions and countermeasures. *Resour. Policy* 63. doi: 10.1016/j.resourpol.2019.101470

Xue, J., Gong, R. F., Zhao, L. J., Ji, X., and Xu, Y. (2019). A green supply-chain decision model for energy-saving products that accounts for government subsidies. *Sustainability* 11, 2–17. doi: 10.3390/su11082209

Yalabik, B., and Fairchild, R. J. (2011). Customer, regulatory, and competitive pressure as drivers of environmental innovation. *Int. J. Prod. Econ.* 131, 519–527. doi: 10.1016/j.ijpe.2011.01.020

Zhang, D. Y., Zhao, R., and Ji, Q. (2019). Green innovation and firm performance: evidence from listed companies in China. *Resour. Conserv. Recycling.* 144, 48–55. doi: 10.1016/j.resconrec.2019.01.023

Zhang, L. H., Wang, J. G., and You, J. X. (2015). Consumer environmental awareness and channel coordination with two substitutable products. *Eur. J. Oper. Res.* 241, 63–73. doi: 10.1016/j.ejor.2014.07.043

Zhang, L. H., Xue, B. W., and Liu, X. Y. (2018). Carbon emission reduction with regard to retailer's fairness concern and subsidies. *Sustainability* 10, 1–28. doi: 10.3390/su10041209

Zhang, Y. X., Xiao, C. C., and Zhou, G. H. (2019). Willingness to pay a price premium for energy-saving appliances: role of perceived value and energy efficiency labeling. *J. Clean. Prod.* 33, 1–10. doi: 10.1016/j.jclepro.2019.118555

Zhou, W. H., and Huang, W. X. (2016). Contract designs for energy-saving product development in a monopoly. *Eur. J. Oper. Res.* 250, 902–913. doi: 10.1016/j.ejor.2015.10.024

Zu, Y. F., Chen, L. H., and Fan, Y. (2018). Research on low-carbon strategies in supply chain with environmental regulations based on differential game. *J. Clean. Prod.* 177, 527–546. doi: 10.1016/j.jclepro.2017.12.220

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Strategic Research on the Urban Natural Gas Energy System Under the Path to Ecological Civilization: Fuyang City Case Study

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To help meet the strategic development needs of urban energy systems today and reduce carbon emissions, natural gas can play a pivotal transition role, especially in a country such as China, which has relied very heavily on coal for decades. Though making significant progress toward the maximum possible use of clean, renewable forms of energy, such as hydro, thermal, solar, and wind power, it will take a long time before China can completely abandon the use of fossil fuels. In this paper, using Fuyang City in Anhui Province as a case study, a four-dimensional differential equation model, based on the consumption, price, economic growth, and "ecological civilization construction" of natural gas energy, is developed, which incorporates concepts and calculations of natural gas energy intensity, "natural gas ecological civilization intensity," and "economic ecological civilization intensity." It is the first attempt ever made to quantify the construction of urban ecological civilization and discuss the evolutionary relationship among the internal variables of the system. Regression analysis, data fitting, neural network, and other methods are used to confirm the parameters of the system model. Through Matlab simulation of each variable and using an evolution map, a quantitative understanding of the role of natural gas is generated. The research findings reveal that paying attention to the environmental aspects of energy consumption is beneficial to economic growth. The paper concludes that, at present, the best ways for China to reduce its carbon emissions are to implement a market price and peak–valley prices for natural gas, improve the tiered price mechanism, appropriately reduce the economic growth rate, continue to adjust the industrial structure away from heavy industry, and scientifically manage the natural gas energy system. These reforms are of great practical significance in working toward a sustainable development path for the city.

Keywords: natural gas, differential equation, natural gas energy intensity, natural gas ecological civilization intensity, economic ecological civilization intensity

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INTRODUCTION

After more than 30 years of rapid economic development, China has created considerable material wealth. However, the country's enormous resource consumption has resulted in severe pollution of the atmosphere, soil, and water, leading to increasingly serious ecological problems. There is an urgent need to protect the ecological environment, by greatly reducing environmental pollution, strengthening the importance of "ecological civilization construction" (described below), and creating a good working and living environment for the people (Zhang et al., 2018).

In 1978, the reform and opening up of China established "economic construction" as the central task of the whole nation. However, economic development led to rapid deterioration of the ecological environment. Therefore, in 1983, the central government established environmental protection as a fundamental national policy for China and enacted many relevant laws (Wang and Gao, 2017). With the introduction of the concept of "sustainable development" by the United Nations, the Central Committee of the Communist Party of China (CPC) proposed a sustainable development strategy. Under the guidance of the "scientific concept of development," the 16th National Congress of the CPC formed the strategic concept called "building an ecological civilization" (Du, 2015). The report of the 17th National Congress of the CPC provides a clear definition and explains the connotations of ecological civilization, and lists "constructing ecological civilization" as the new requirement for building a well-off society in a comprehensive manner (Zeng and Liang, 2018). The Third Plenary Session of the 18th CPC Central Committee pointed out that: "To build an ecological civilization, we must establish a systematic and complete ecological civilization system, and use this system to protect the ecological environment. Use natural resource assets to determine the red line of ecological protection. Use system and ecological compensation system [to reform] the ecological environmental protection management system." In addition, at the Fifth Plenary Session of the 18th CPC Central Committee, "Green Development" was promoted to become one of the "five major development" concepts. "Beautiful China" was first written into the 13th Five-Year Plan, and the construction of ecological civilization was ranked as an even higher priority than it had been before (Xiao, 2008). At the 19th National Congress of the CPC, the Party proposed a comprehensive plan for the construction of ecological civilization (Yu, 2018), put forward the concept of "the harmonious coexistence of man and nature," and proposed a new development direction, the road to sustainable development (Jiang et al., 2019).

In recent years, China has made remarkable achievements in resource conservation and effective resource use, but there is still a large gap between China and the world's advanced countries (Hansen et al., 2018). China must incorporate ecological science in its development instead of endlessly pursuing blind growth. It must vigorously implement green environmental protection work, promote sustainable development, establish awareness of the green economy, and ensure a healthy lifestyle for its inhabitants (Xie et al., 2019). Other countries have also adopted the concept of "construction of ecological civilization" and are likewise striving for the same goals (Zhu, 2016; Zhang and Yang, 2019).

Fuyang City is a third-tier city (according to the size of the city, population, level of economic development, and the total economic value) situated in China's Anhui Province, with a population density of 850 people per square kilometer and a total population of over 10 million, comparable to that of the nation's capital, Beijing. In recent years, the economy has grown at an average rate of 9.5%, with gross domestic product (GDP) reaching 170 billion yuan in 2018, making Fuyang one of the wealthiest of China's third-tier cities. However, there is a shortage of energy and there are few coal resources nearby. Thus, Fuyang depends on the surrounding cities for electricity and energy sources. With the expansion of the city, the demand for natural gas has been increasing. Fortunately, the natural gas input channels are abundant and excellent. In recent years, the government of Fuyang City has placed great importance on the construction of ecological civilization. It has formulated plans and implementation measures focusing on the prevention of atmospheric, water, and soil pollution, hiring environmental protection inspectors to provide feedback, and ensuring that the environmental issues are rectified as quickly as possible. The central goals are to increase accountability in the field of ecological environmental protection, improve the long-term supervision mechanisms, and continue promoting awareness about environmental protection.

As the world's largest emitter of CO_2, China faces an enormous challenge in reducing these emissions quickly. Natural gas is a high-heat energy source that emits far less CO_2 than coal (or fuel oil). Generating electricity from natural gas does not completely eliminate CO_2 emissions (Zhou et al., 2018). However, expanding its use across the country will help meet the growing demand for energy and also improve the current energy consumption structure (Xu and Lin, 2019). While many advanced countries abandoned the use of coal and fuel oil decades ago, in favor of natural gas, China is now adopting this "transition" fuel as rapidly as it can while concomitantly developing the various forms of renewable energy it has available, such as hydro, thermal, solar, and wind power, to the greatest extent possible. Indeed, given that China has a large and increasing population, and that the economic growth rate is relatively high, it has become a very urgent task to develop the natural gas industry in order to protect the fragile the ecological environment and strive for a more sustainable path toward modernization development (Tanaka, 2015; Wang et al., 2018).

Urban energy consumption accounts for two thirds of the total global energy consumption, and carbon emissions mainly come from cities. Yet, urban development connotes modern social progress (van Ruijven and van Vuuren, 2009; Emma and John, 2013). By 2030, it is predicted that 76% of the world's CO_2 emissions from energy consumption will come from cities (Ji et al., 2014). China is at the stage of industrialization and urbanization in which emissions and the urban evaporation rate are expected to rise significantly higher until they finally peak. One-time energy consumption will continue to grow rapidly and place tremendous pressure on China's energy supply capacity and environmental protection policies. Though still not a completely clean form of energy, natural gas is an available, easily usable, and economical energy alternative with which to generate a large share of the huge amounts of electricity that the country requires, and is thus pivotal in China's goal to achieve the construction of a comprehensive ecological civilization (He and Lin, 2017; Mark et al., 2017; Liu et al., 2018; Li et al., 2019).

To date, there have been many qualitative studies on natural gas consumption, but few quantitative studies in China. Based on the logistic theory of energy consumption, Tian Lixin, Fang Guochang et al. (Fang et al., 2012, 2017, 2018a; Wang et al., 2015; Zhang and Tian, 2016) established a differential equation model for quantitative analysis of energy systems using chaos theory. Differential equations have great advantages in dealing with non-linear problems in many respects. Many studies have been conducted pertaining to energy conservation and emission reductions. This paper uses the differential equation method to establish a model to study the natural gas energy system of Fuyang City (Fang et al., 2013; Hao et al., 2019). In the past, Fuyang was a poor and densely populated city, with a backward economy, energy shortages, and a deteriorating environment. In recent years, however, it has ranked second and third in terms of economic growth and economic aggregate, respectively, in Anhui province (Hao et al., 2019), and ranked in the top 10 of third-tier cities in China. Over the past decade, it has invested significant funding toward sustainable development.

To purify the environment and create an ecological and modern city, the government of Fuyang in 2000 year issued a directive prohibiting the use of coal, upon which it has always relied almost entirely throughout its history. Arguably the most viable solution to its immediate energy and pollution problems is to raise the proportion of natural gas in its energy mix as rapidly as possible while also harnessing as much solar power as practical in the local conditions.

In this paper, the concept of "urban ecological civilization construction" is integrated into a mathematical model for the first time, and natural gas energy intensity, as well as the concepts of natural gas ecological civilization intensity and economic ecological civilization intensity are proposed. Studying an urban natural gas energy system under a path to ecological civilization can assist the government in formulating the most appropriate policies to improve the efficiency of energy utilization, quantify the construction of ecological civilization, strengthen the reform of the natural gas market, and enhance the development of tertiary industries. This study simulates and analyzes the market administrative measures that are most beneficial in achieving a more sustainable development strategy for the city. Its results are applicable not only to Fuyang, but also to many other cities in China.

ESTABLISHMENT OF URBAN NATURAL GAS ENERGY MODEL

The consumption of natural gas is influenced by the environment, government policies, and its price (Fang et al., 2018b; Ji et al., 2018). Existing research indicates that its consumption and price, along with economic growth (mainly measured in terms of GDP) form a complex system consisting of many elements (Ji and Zhang, 2018; Cheng et al., 2019), and that the relationships among these elements are nonlinear and complex in nature (Fang et al., 2012, 2017, 2018b; Wang et al., 2015). Exploring these relationships can assist the government of Fuyang City in its quest to reduce the pollution in and around the city.

Using a logistic model of energy consumption (Shi and Sun, 2017; Shia and Shi, 2019) as a basis, the specific models for urban natural gas consumption, natural gas prices, and economic growth are formulated as follows:

$$\begin{cases} \dfrac{dx}{dt} = a_1 x\,(M-x) + a_2\left(1-\dfrac{y}{N}\right)x - a_3 y + a_4 z \\ \dfrac{dy}{dt} = b_1 x + b_2 y\left(1-\dfrac{y}{L}\right) + b_3\,(z-K) \\ \dfrac{dz}{dt} = c_1 x\left(\dfrac{x}{Q}-1\right) - c_2 z \end{cases} \tag{1}$$

where $x\,(t)$ represents natural gas consumption over time; $y\,(t)$ represents gas prices over time; $z\,(t)$ represents economic growth over time, and GDP. a_1, a_2, a_3, a_4, b_1, b_2, b_3, c_1, c_2, M, N, L, k, and Q are the normal numbers. $t \in I$, I is an economic period. The term a_1 is the development coefficient of natural gas consumption; a_2 is the influence coefficient of the price on the natural gas consumption; a_3 is the inhibition coefficient of the price on the natural gas consumption; a_4 is the development coefficient of economic growth on the natural gas consumption; b_1 is the development coefficient of natural gas consumption on the price; b_2 is the intrinsic growth coefficient of the natural gas price; b_3 is the influence coefficient of economic growth on the natural gas price; c_1 is the influence of natural gas consumption on economic growth; c_2 is the inhibition factor of natural gas investment, technology, and research and development on the economy; M is the peak value of natural gas consumption in a city in an economic period; N is the threshold value of the urban natural gas price in relation to natural gas consumption; L is the peak value of the urban natural gas price; k is the peak value of urban economic growth; and Q is a turning point for natural gas consumption in relation to economic growth.

The first formula in Equation (1) states that, over time, the demand for natural gas as a share of urban energy sources increases gradually until it reaches the peak value of M, when it gradually slows; namely, at $M - x > 0$, the demand for natural gas increases, whereas following this, the demand for natural gas slows down. When the price is below the threshold of N, that is, $1 - y/N > 0$, the price stimulates the consumption of natural gas. When $1 - y/N < 0$, the price exceeds this threshold, and it has an inhibitory effect on the consumption of natural gas. The term $a_3 y$ indicates that natural gas consumption is inversely proportional to the natural gas price in the market. Hence, economic development results in increased consumption of natural gas.

The second formula in Equation (1) indicates that the consumption of natural gas has a positive effect on the price. The term $b_2 y(1 - y/L)$ indicates that many factors can impact the price of natural gas, such as geographical restrictions, the prices of electricity and oil, the peak and valley periods of gas demand, and the economic development of the city. When the natural gas price does not exceed the threshold L, which is determined by these factors, then the natural gas price can continue to increase. In contrast, when the price exceeds the threshold, the natural gas price will decrease. The term $b_3\left(z - k\right)$ indicates that economic development will increase the consumption of natural gas. When the growth rate of the economy is low, i.e., $z - k < 0$, the market demand for natural gas is low, which means that natural gas prices remain low. However, when the growth rate of the economy has reached a certain point, i.e., $z - k > 0$, the demand for natural gas energy, and thus prices, will both increase.

In the third formula in Equation (1), $c_1 x (x/Q - 1)$ refers to the natural gas consumption. During the early stages of development, namely, at $x/Q - 1 < 0$, the cost of natural gas consumption is high because the natural gas management system is not well-developed. There are also limitations arising from the immature technical conditions in the early stages of natural gas exploration. At this time, the effect of natural gas consumption on economic growth is limited, which is a negative growth state. When the consumption of natural gas is more than Q, namely, when $x/Q - 1 > 0$, it will have positive effects on economic development. The term $c_2 z$ indicates that the development of natural gas will involve economic costs due to the development costs, technical research, transportation, and other factors.

ESTABLISHMENT OF AN ENERGY SYSTEM MODEL OF ECOLOGICAL CIVILIZATION

After adding the variable of ecological civilization to model (1) of the urban natural gas energy system, the new model is as follows:

$$\begin{cases} \dfrac{dx}{dt} = a_1 x (M - x) + a_2 \left(1 - \dfrac{y}{N}\right) x - a_3 y + a_4 z + a_5 w \\ \dfrac{dy}{dt} = b_1 x + b_2 y \left(1 - \dfrac{y}{L}\right) + b_3 (z - K) \\ \dfrac{dz}{dt} = c_1 x \left(\dfrac{x}{Q} - 1\right) - c_2 z + c_3 w \\ \dfrac{dw}{dt} = k_1 x + k_2 w \left(1 - \dfrac{z}{H}\right) \end{cases} \tag{2}$$

Here, $w(t)$ represents the amount of ecological civilization, a_5 is the development coefficient of urban ecological civilization on natural gas energy, c_3 is the influence coefficient of ecological civilization construction on economic growth, k_1 is the development coefficient of natural gas consumption on ecological civilization construction, k_2 is the influence coefficient of economic development on ecological civilization, and H is the peak value of economic development on ecological civilization construction.

Equation (2) in the fourth formula states that the use of the various forms of clean energy and natural gas has a significant positive effect on the construction of ecological civilization. $(1 - z/H) < 0$ indicates that excessive levels of economic inputs hinder the development of ecological civilization, whereas $(1 - z/H) > 0$ indicates that appropriate economic inputs have positive effects on ecological civilization.

The energy consumption system reflects the interdependence among natural gas consumption, the natural gas price, and economic growth in a certain economic period. The power system represented by Formula (1) can derive the following energy consumption of natural gas in a given period of time:

$$\phi_1 \left(x, y, z, w, R, t\right) = \int_0^T x^* (t) dt, x^* (t) = \varphi (x, t) \tag{3}$$

Economic growth during this period can be expressed as follows:

$$\phi_2 \left(x, y, z, w, S, t\right) = \int_0^T z (t) dt \tag{4}$$

The construction of ecological civilization in this period is as follows:

$$\phi_3 \left(x, y, z, w, V, t\right) = \int_0^T w (t) dt \tag{5}$$

When T is a given period, R, S, and V are constants. Thus, the energy intensity of natural gas can be expressed as:

$$U_1 = \phi_1 \left(x, y, z, w, R, t\right) / \phi_2 \left(x, y, z, w, S, t\right) \tag{6}$$

The intensity of natural gas energy ecological civilization is as follows:

$$U_2 = \phi_1 \left(x, y, z, w, R, t\right) / \phi_3 \left(x, y, z, w, V, t\right) \tag{7}$$

TABLE 1 | Overview of the natural gas system in Fuyang City from 2007 to 2016.

Year	Natural gas consumption (thousands of cubic meters)	Pipe length (km)	Gas population (thousands)
2007	626	200	4.2
2008	2764	265	21.5
2009	4870	380	23.95
2010	6460	425	37.26
2011	7300	458.1	45.5
2012	8700	483	46.08
2013	9260	502	48.68
2014	6938	585	49
2015	7040	585.4	49.5
2016	10405	637.4	54.5

TABLE 2 | Regression analysis of *a* and *r* in Fuyang City for the next 10 years.

K (10,000 cubic meters)	R^2	*a*	*r*
10,500	0.6974	2.2546	0.5376
11,000	0.7104	1.9832	0.4311
12,000	0.6927	1.9524	0.3702
13,000	0.6785	1.9981	0.3402
14,000	0.6677	2.0591	0.3209
15,000	0.6591	2.1232	0.3071
16,000	0.6523	2.1867	0.2966
17,000	0.6466	2.2482	0.2883
18,000	0.6418	2.3071	0.2815
19,000	0.6377	2.3635	0.2759
20,000	0.6341	2.4173	0.2711
25,000	0.6218	2.6527	0.2551
30,000	0.6144	2.8449	0.2459

The intensity of economic and ecological civilization is:

$$U_3 = \phi_2\left(x, y, z, w, S, t\right) / \phi_3\left(x, y, z, w, V, t\right) \tag{8}$$

SYSTEM PHASE DIAGRAM AND PARAMETER DETERMINATION

To determine the model's coefficients accurately, data collected from the statistical yearbooks of Fuyang City and Anhui Province were utilized (see **Table 1**).

Fuyang's natural gas consumption was analyzed using regression analysis (see **Table 2**).

Regression analysis shows that the fit is best when consumption reaches 110 million cubic meters, so we select $M = 1.1$.

Given the investments made in Fuyang's natural gas infrastructure from 2007 to 2016 (**Table 3**), the coefficient of Fuyang's total natural gas investment was obtained by fitting the data curve: the error is less than 10^{-5}, and the result is $c_2 = 0.0089$.

From Hao et al. (2019) we know that $c_1 = 0.00416$ has a parameter value k_1. The econometric regression and empirical analysis of the development of ecological civilization and the evolution of energy consumption in the major developed countries in the world indicate that the growth rate of energy consumption in a developed country has an elastic impact on the growth rate of ecological civilization. In particular, there is evidence that this elasticity coefficient is 0.006. In other words, a unit of growth in the energy consumption level results in 0.006 units of growth in the ecological civilization construction level. The meaning of parameters k_2 and c_3 is mutual influence and dialectical unity of interaction. Thus, their values are the same. The statistical yearbooks of Fuyang City provide the economic value and ecological civilization construction fund value of Fuyang City over the last 10 years. We obtained $k_2 = c_3 = 0.776$ by curve-fitting, and the other parameters were optimized by the neural network model. The results are shown in **Table 4**.

Taking the data of Fuyang City in 2000 as the initial value (0.0034, 0.19, 2.0, 0.0012), and using numerical simulations, it can be seen from **Figure 1** that the system is stable.

As shown in **Figure 2**, the development value of ecological civilization in Fuyang City is about 0.005125, which is much lower than that in developed cities such as Paris (0.02115) and Seoul (0.01323) (Zhu, 2016). This reflects the fact that there have been some initial achievements in Fuyang's ecological civilization construction in recent years, but that there is still quite a ways to go. At present, natural gas accounts for a very low proportion of energy consumption at less than 10% of total energy consumption. Thus, it can be inferred that the development value of ecological civilization of the disposable energy is about 0.05125, which is close to the national average of 0.054043 (Zhu, 2016). The use of the various clean and sustainable forms of energy must be increased while coal consumption is steadily reduced.

It can be seen from **Figure 3** that the natural gas energy intensity is smaller and fluctuates less than does the construction of ecological civilization. However, following the introduction of the concept of construction of ecological civilization to the people of Fuyang, and the strengthening of the relevant institutions and the cultivation of awareness, the intensity of natural gas energy in the city began to decline. The red line in the chart shows that, over time, the intensity of natural gas energy has fluctuated very little and decreased gradually.

TABLE 3 | Overview of natural gas investment in Fuyang City from 2007 to 2016.

Year	GDP in Fuyang (10^4 yuan)	Natural gas investment (10^4 yuan)
2007	1,130,000	13,791.66
2008	1,125,000	24,106.33
2009	1,128,000	24,016.66
2010	7,215,298	50,961.33
2011	8,532,068	33,440
2012	9,625,290	35,501.66
2013	10,997,133	39,102
2014	11,889,663	72,424
2015	12,674,500	99,332
2016	14,019,000	240,884.33

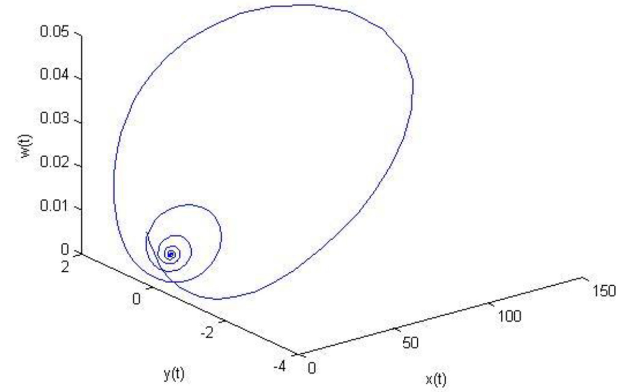

FIGURE 1 | System phase diagram.

TABLE 4 | System coefficients after model optimization.

a_1	a_2	a_3	a_4	a_5	b_1	b_2	b_3	c_1	c_2
0.028	0.961	0.055	1.87	16.7	0.316	0.205	0.15	0.00416	0.0089
c_3	M	N	L	K	Q	k_1	k_2	H	
0.0776	1.1	0.13	0.11	28	7.7	0.006	0.0776	0.018	

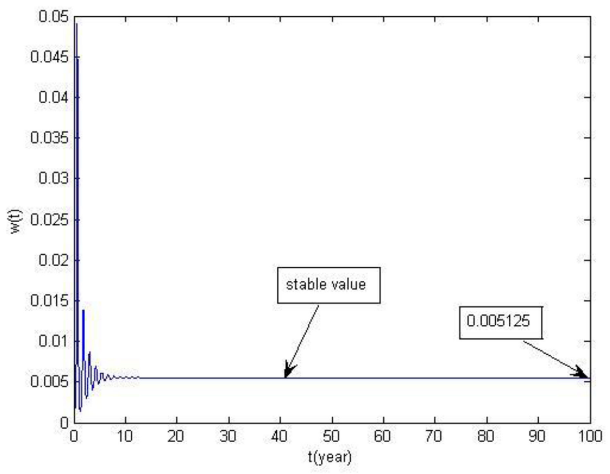

FIGURE 2 | Simulation value of variable ecological civilization.

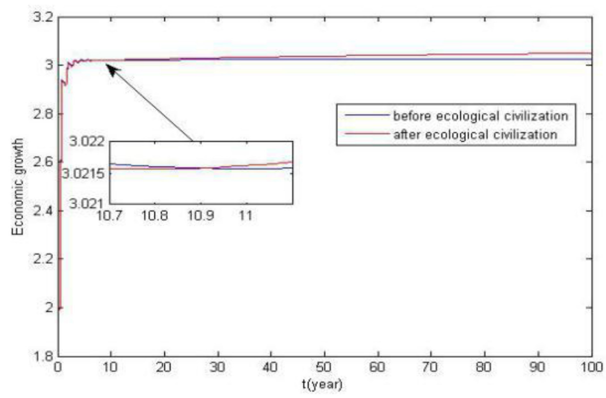

FIGURE 4 | Comparison of economic growth.

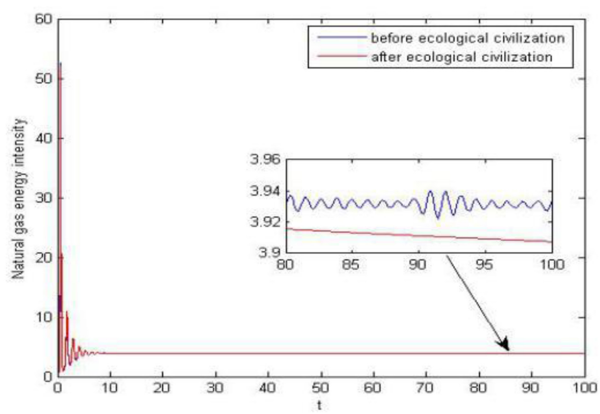

FIGURE 3 | Comparison of natural gas energy intensity.

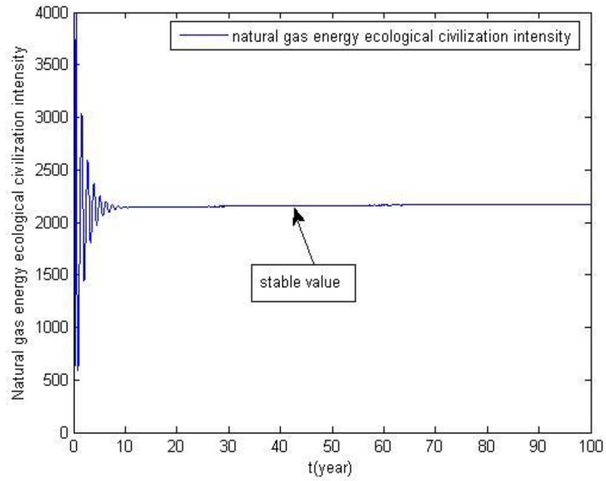

FIGURE 5 | Natural gas energy ecological civilization ecological construction intensity chart.

In December 2017, Fuyang City was issued with (trial) detailed rules for the investigation of leading cadres of the Party and Government of Anhui Province who have caused ecological environmental damage. The municipal government attaches great importance to this. It studied and communicated the rules, formulated implementation measures, and planned and implemented measures focused on the prevention and control of air, water, and soil pollution. It also collated the feedback gathered by the environmental protection inspectors and imposed serious discipline and accountability measures to rectify the environmental problems. As its next steps, the government should implement its policies vigorously, increase accountability in the field of ecological environmental protection, improve long-term regulatory mechanisms, and continue its efforts to promote the construction of ecological civilization and environmental protection. It should also advocate less materialistic lifestyles in favor of healthier ones, and foster green and low carbon mainstream values. The intensity of natural gas energy use in Fuyang City has gradually begun to decline. In the longer term, the implementation of ecological civilization will promote economic growth (**Figure 4**).

The intensity of natural gas energy is about 2,160,000 cubic meters/10,000 yuan (**Figure 5**). At present, there is almost no renewable energy utilization in Fuyang City. This demonstrates that the ecological civilization construction requires a great deal of effort. Switching from coal to natural gas is not enough alone; the use of renewable green energy sources is also required (Zhang et al., 2018). In 2017, the proportion of natural gas in total energy consumption in Fuyang City was only 6.41%, which was lower than the national average level. Hence, there is still much room for improvement in ecological civilization construction.

It can be seen from **Figure 6** that future economic and ecological civilization of Fuyang City is stable at 541. Drawing on the calculation method of Shanghai's ecological civilization with land use as the research object (Shi and

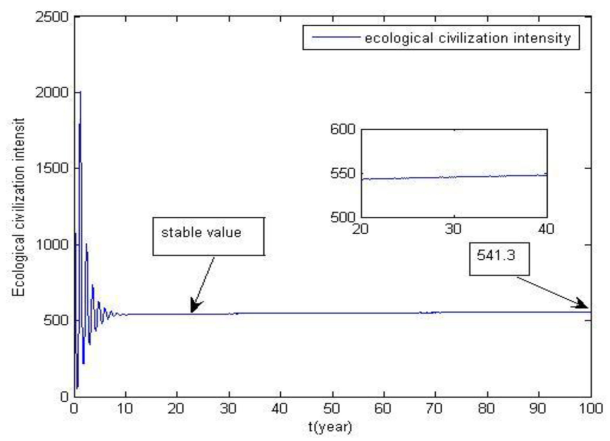

FIGURE 6 | Chart of the intensity of economic and ecological construction progress.

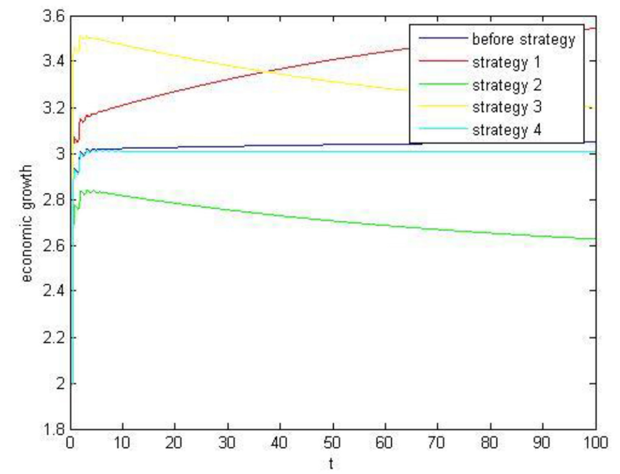

FIGURE 7 | Economic growth strategy chart.

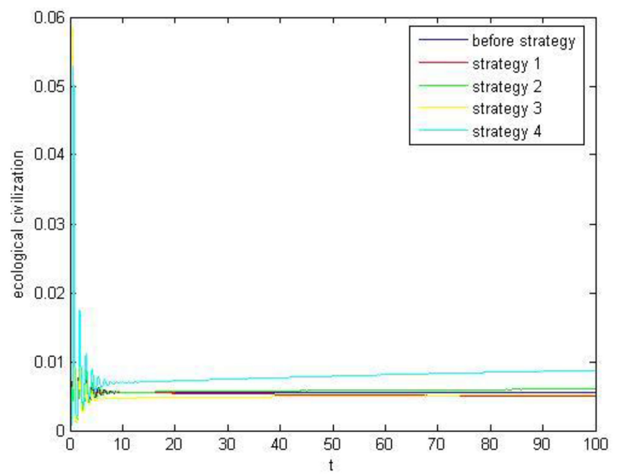

FIGURE 8 | Strategy map of ecological civilization variables.

Sun, 2017), the urban area of Fuyang City is 200 km^2, with an average annual expenditure of 1.32 million yuan and an intensity of 660 ten thousand yuan/km^2, reflecting the fact that Fuyang City has matured after implementation of the ecological civilization system. The strength of the economic and ecological civilization is stable at a value of 541. It is also very likely to serve as a reference for future ecological civilization investment.

PROMOTION OF THE HEALTHY DEVELOPMENT OF URBAN ENERGY ECOLOGICAL CIVILIZATION CONSTRUCTION

To meet the increasingly stiff environmental requirements stipulated by the local and central governments, all cities are actively upgrading their energy structures. The use of natural gas is gradually penetrating all of the urban energy systems. Government regulation and control in the early stages of natural gas development is required, through strategies for adjustment, regulation, and control of the natural gas market. The goal is to achieve a healthy, sustainable, and stable development strategy for the natural gas market, improve its structure, and promote balanced social development. In the next section, we identify and analyze several effective regulatory strategies to stabilize China's natural gas market.

STRATEGY 1: DEEPEN THE NATURAL GAS MARKET REFORMS AND VIGOROUSLY ADVOCATE THE DEVELOPMENT OF NATURAL GAS

In China, especially in third-tier cities such as Fuyang, the proportion of natural gas consumption in total energy consumption is not large. To build clean and environmentally friendly cities, China must increase the proportion of natural gas in its urban energy systems as quickly as possible, deepen the relevant market reforms, and increase imports of natural gas. These actions will increase the system model coefficient a_1. To avoid excessive wastage of natural gas and control the increase of coefficient a_1, it is necessary to not only increase natural gas consumption but also ensure price stability. Price increases should be restrained in order to increase coefficient K and also increase natural gas consumption, resulting in economic growth. When a_1 increases from 0.028 to 0.048 and K increases from 28 to 30, other parameters remain unchanged, as shown in **Figures 7–11**, for economic growth, ecological civilization construction, natural gas energy ecological civilization intensity, economic ecological civilization intensity, and natural gas energy intensity.

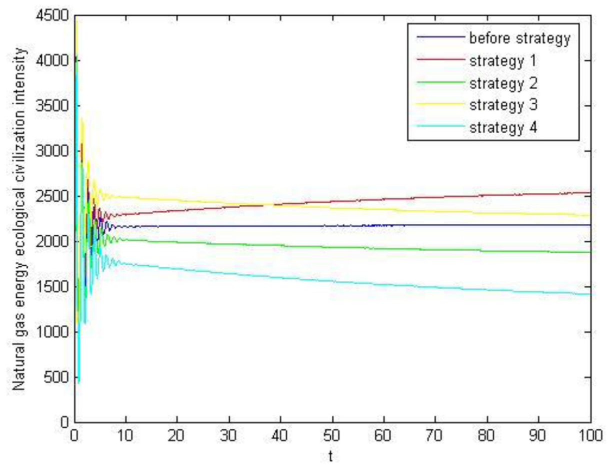

FIGURE 9 | Intensity of natural gas energy.

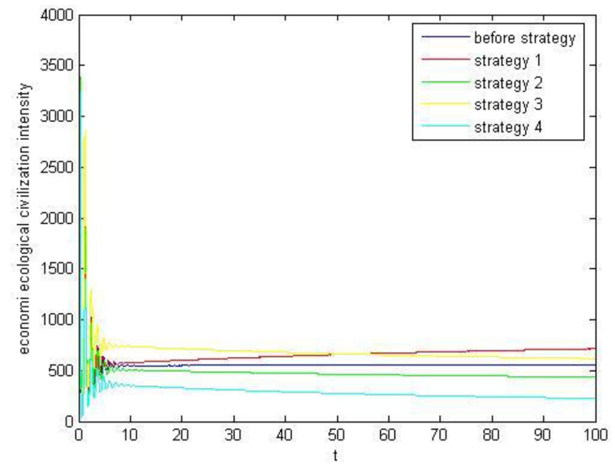

FIGURE 10 | Intensity of economic ecological civilization.

STRATEGY 2: IMPLEMENT HIGH AND LOW PRICES

The second recommended strategy is to implement gas peak–valley pricing and improve the step price mechanism. This can effectively avoid the peak load of natural gas consumption by gradually making demand stable. In terms of the model, the parameter a_4 would decrease. At the same time, these reforms can assist in reducing the influence of the natural gas price on consumption, so that model parameter b_3 would be reduced. When the system state a_4 is reduced from 1.87 to 1.77, and when b_3 is reduced from 0.15 to 0.14, other parameters remain unchanged (as above, see **Figures 7–11**).

STRATEGY 3: TAKE APPROPRIATE ADMINISTRATIVE MEASURES

Appropriate administrative measures should be taken to adjust the inherent growth rate parameter b_2 and the natural gas price peak value L. By loosening the price controls on natural gas, the government can ensure that the supply and consumption of natural gas in the natural gas market is balanced and that the price remains within a reasonably acceptable range for consumers. This will also promote the market allocation of resources and ensure economic growth and sustainable development. In terms of the model, the specific measures recommended are to adjust the price parameters b_2 and L. When parameter b_2 increases from 0.205 to 0.215 and parameter L decreases from 0.11 to 0.10, other parameters remain unchanged (as above, see **Figures 7–11**).

STRATEGY 4: INDUSTRIAL STRUCTURE ADJUSTMENT

An effective strategy to strengthen the scientific management of the natural gas energy system is to stabilize the natural gas price. What is needed is a transformation from high natural gas consumption at low efficiency, to low consumption at high efficiency. Economic growth is restrained by reducing the economic growth coefficient c_1 and increasing the science and technology investment coefficient c_2 for natural gas development. When c_1 decreases from 0.00416 to 0.00406 and parameter c_2 increases from 0.0089 to 0.0093, the other parameters remain unchanged (as above, see **Figures 7–11**).

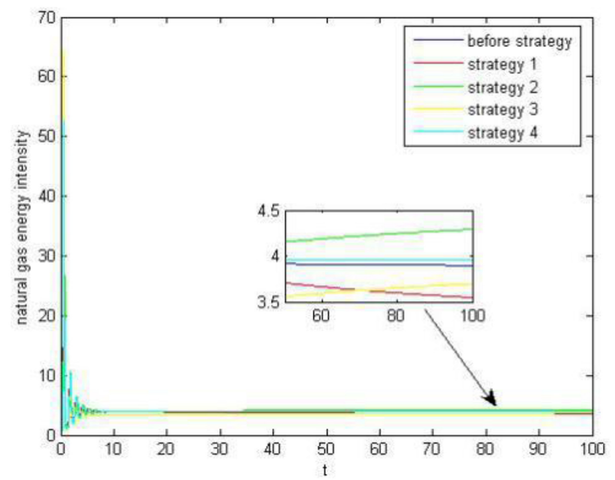

FIGURE 11 | Natural gas energy intensity diagram.

As we know from **Figure 4**, the construction of ecological civilization will make economic growth decline in the short term, but thereafter the economy will grow smoothly. From **Figure 7**, we can see that among the four strategies, only Strategy 4 causes a short-term decline in economic growth (followed by resumption of smoother growth), in line with the results shown in **Figure 4**. In contrast, the other strategies result in economic growth declining and fluctuating greatly.

From **Figure 8**, we can see that the construction of ecological civilization is further enhanced under Strategies 2 and 4. Strategy 2 aligns with the state policy to liberalize the price of the competitive link. The way for the state to liberalize the price of the competitive link is to take appropriate measures to liberalize the price of natural gas, implement peak and valley prices for natural gas, perfect the ladder price mechanism, and guide the rationalization of natural gas consumption. The government should establish a natural gas supervision system covering the whole industrial chain and the whole process, and strengthen government supervision over market access (Dou et al., 2013), trading behavior, monopoly links, prices and costs, quality, safety, environmental protection, and other key links. In addition, it should hasten the improvement of the natural gas industry standardization system and undertake other administrative measures. The adjustment of the industrial structure is a fundamental condition for realizing the stable and sustainable development of China's economy (Shen and Shi, 2018; Wang et al., 2019). It is the main way to create economic benefits by effectively promoting the transformation of the mode of economic growth. In addition, it is an important condition for reducing energy consumption and environmental pollution and improving the ecological environment. Blind pursuit of high economic growth is not conducive to promoting the adjustment of industrial structures; rather, it aggravates the imbalances in the industrial structures.

It can be seen from **Figures 9**, **10** that Strategy 4 minimizes the intensity of natural gas energy ecological civilization and economic ecological civilization, which are the best ways to achieve urban construction of ecological civilization at present. **Figure 11** shows that Strategy 4 does not minimize natural gas energy intensity. Strategy 1 is the lowest, indicating that the construction of urban ecological civilization should be achieved with a combination of Strategies 1, 2, and 4, or other methods to supervise the construction of urban ecological civilization. According to the above analysis, to improve the development of Fuyang's natural gas energy and ecological civilization, and to actively deepen the reform of the natural gas market (Shi and Padinjare, 2017), the government should implement peak and valley real-time prices and ladder prices, vigorously develop the tertiary industry, and strengthen the industrial structure adjustments. To date, Fuyang City has implemented ladder prices for natural gas, but has not implemented real-time peak–valley prices. The value of the tertiary industry has increased year by year. The government of Fuyang is planning to implement real-time peak and valley prices for natural gas and hasten the development of the tertiary industry.

Urban ecological civilization construction is a systematic project requiring the government to consider the development of the economy and environmental optimization, and determine which are the relevant departments to integrate natural gas resources, undertake coordinated development planning, publicity and education, policies and measures, and pay attention to new energy factors (Li et al., 2018; Wang et al., 2018; Xu et al., 2019). In addition, to realize the rapid development of ecological civilization and sustainable development of cities, it is necessary to coordinate the construction of propaganda software and policy hardware.

CONCLUSIONS

This paper marks the first attempt ever made to quantify the construction of urban ecological civilization and promotes an urban natural gas production and consumption revolution from the perspective of ecological civilization. Ecological civilization is conducive to enhancing energy security and support capabilities, improving the quality and efficiency of economic development, strengthening urban sustainable development, and proactively responding to global climate change. Comprehensively promoting the construction of ecological civilization has important practical significance and far-reaching strategic significance for accelerating the construction of a modernized country. By adhering to the promotion of industrial restructuring, deepening the reform of the natural gas market, and liberalizing the natural gas price market mechanism, the government can promote a natural gas revolution as a national policy for building urban energy systems development, energy security, efficient energy consumption, supply diversification, and technological innovation. If Fuyang City and indeed all cities in China are to develop in a healthy and sustainable manner, the deepening of reforms and fundamental transformation of energy production and consumption patterns are imperative.

DATA AVAILABILITY STATEMENT

The datasets generated for this study are available on request to the corresponding author.

AUTHOR CONTRIBUTIONS

YH completed the simulations and experimental research, and wrote the manuscript. SL and QX completed the experimental research and revised the article.

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REFERENCES

Cheng, D., Shi, X., and Yu, J. (2019). How does the Chinese economy react to uncertainty in international crude oil prices?. *Int. Rev. Econ. Finan.* 64, 147–164. doi: 10.1016/j.iref.2019.05.008

Dou, X., Li, S., and Wang, J. (2013). Ecological strategy of city sustainable development. *APCBEE Proc.* 5, 429–434. doi: 10.1016/j.apcbee.2013.05.074

Du, X. (2015). Analysis of energy development and reform in China under the background of ecological civilization (in Chinese). *Chinese Eng. Sci.* 17, 46–53. doi: 10.3969/j.issn.1009-1742.2015.08.008

Emma, S., and John, S. (2013). Price discovery in European natural gas markets. *Energy Policy* 61, 628–634. doi: 10.1016/j.enpol.2013.06.080

Fang, G., Tian, L., and Fu, M. (2012). Analysis and application of a novel three-dimensional energy-saving and emission- dynamic evolution system. *Energy* 40, 291–299. doi: 10.1016/j.energy.2012.01.071

Fang, G., Tian, L., and Fu, M. (2018b). How to promote the development of energy-saving and emission-reduction with changing economic growth rated A case study of China. *Energy* 143, 732–745. doi: 10.1016/j.energy.2017.11.008

Fang, G., Tian, L., Fu, M., Sun, M., Du, R., Lu, L., et al. (2017). The effect of energy construction adjustment on the dynamical evolution of energy-saving and emission-reduction system in China. *Appl. Energy* 196, 180–189. doi: 10.1016/j.apenergy.2016.11.049

Fang, G., Tian, L., Liu, M., Fu, M., and Sun, M. (2018a). How to optimize the development of carbon trading in China—Enlightenment from evolution rules of the EU carbon price. *Appl. Energy* 211, 1039–1049. doi: 10.1016/j.apenergy.2017.12.001

Fang, G., Tian, L., and Sun, M. (2013). The impacts of carbon tax on energy intensity and economic growth – A dynamic evolution analysis on the case of China. *Appl. Energy* 110, 17–28. doi: 10.1016/j.apenergy.2013.04.041

Hansen, M. H., Li, H., and Svarverud, R. (2018). Ecological civilization: interpreting the Chinese past, projecting the global future. *Glob. Environ. Change* 53, 195–203. doi: 10.1016/j.gloenvcha.2018.09.014

Hao, Y., Han, X., and Wang, M. (2019). Study on natural gas energy system model of fuyang city (in Chinese). *Energy Energy Conserv.* 4, 43–45. doi: 10.3969/j.issn.2095-0802.2019.04.021

He, Y., and Lin, B. (2017). The impact of natural gas price control in China: a computable general equilibrium approach. *Energy Policy* 107, 524–531. doi: 10.1016/j.enpol.2017.05.015

Ji, Q., Fan, Y., and Troilo, M. (2018). China's natural gas demand projections and supply capacity analysis in 2030. *Energy J.* 30, 53–70. doi: 10.5547/01956574.39.6.qji

Ji, Q., Geng, J., and Fan, Y. (2014). Separated influence of crude oil prices on regional natural gas import prices. *Energy Policy* 70, 96–105. doi: 10.1016/j.enpol.2014.03.019

Ji, Q., and Zhang, H. (2018). What drives natural gas prices in the United States? A directed acyllic graph approach. *Energy Econ.* 69, 79–88. doi: 10.1016/j.eneco.2017.11.002

Jiang, B., Bai, Y., and Wong, C. (2019). China's ecological civilization program – Implementing ecological redline policy. *Land Use Policy* 81, 111–114. doi: 10.1016/j.landusepol.2018.10.031

Li, J., Zhang, D., and Su, B. (2019). The impact of social awareness and lifestyles on household carbon emissions in China. *Ecol. Econ.* 160, 145–155. doi: 10.1016/j.ecolecon.2019.02.020

Li, Z., Shao, S., and Shi, X. (2018). Structural transformation of manufacturing, natural resource dependence, and carbon emissions reduction: evidence of a threshold effect from China. *J. Cleaner Prod.* 206, 920–927. doi: 10.1016/j.jclepro.2018.09.241

Liu, G., Dong, X., Jiang, Q., Dong, C., and Lia, J. (2018). Natural gas consumption of urban households in China and corresponding T influencing factors. *Energy Policy* 122, 17–26. doi: 10.1016/j.enpol.2018.07.016

Mark, A., Peter, H., Kenneth, M. III., and Ted, T. (2017). Employment impacts of upstream oil and gas investment in the United States. *Energy Econ.* 62, 171–180. doi: 10.1016/j.eneco.2016.12.012

Shen, Y., and Shi, X. (2018). Risk transmission mechanism between energy markets: a VAR for VaR approach. *Energy Econ.* 75, 377–388. doi: 10.1016/j.eneco. 2018. 08.027

Shi, X., and Padinjare, H. M. (2017). Global impact of uncertainties in China's gas market. *Energy Policy* 104, 382–394. doi: 10.1016/j.enpol.2017.02.015

Shi, X., and Sun, S. (2017). Energy price, regulatory price distortion and economic growth: a case study of China. *Energy Econ.* 63, 261–271. doi: 10.1016/j.eneco.2017.02.006

Shia, Y., and Shi, S. (2019). Relationship between social civilization forms and carbon emission intensity: a study of the Shanghai metropolitan area. *J. Cleaner Prod.* 228, 1552–1563. doi: 10.1016/j.jclepro.2019.04.356

Tanaka, S. (2015). Environmental regulations on air pollution in China and their impact on infant mortality. *J. Health Econ.* 42, 90–103. doi: 10.1016/j.jhealeco.2015.02.004

van Ruijven, B., and van Vuuren, D. P. (2009). Oil and natural gas prices and greenhouse gas emission mitigation. *Energy Policy* 37, 4797–4808. doi: 10.1016/ j.enpol.2009.06.037

Wang, H., Fang, H., Yu, X., and Wang, K. (2015). Development of natural gas vehicles in China: an assessment of enabling factors and barriers. *Energy Policy* 85, 80–93. doi: 10.1016/j.enpol.2015.05.012

Wang, K., Wu, M., Sun, Y., and Shi, X. (2019). Resource abundance, industrial structure, and regional carbon emissions efficiency in China. *Resour. Policy* 60, 203–214. doi: 10.1016/j.resourpol.2019.01.001

Wang, L., and Gao, J. (2017). China's road to ecological civilization (in Chinese). *Wisdom China* 14, 4–5. doi: 10.3969/j.issn.1009-5349.2017.18.119

Wang, Q., Su, B., and Zhou, P. (2018). Contributions to sector-level carbon intensity change: an integrated decomposition analysis. *Energy Econ.* 70, 12–25. doi: 10.1016/j.eneco.2017.12.014

Xiao, J. (2008). Ecological energy construction in ecological civilization construction (in Chinese). *J. Beijing Petrol. Manage. Cadre Inst.* 1, 4–9. doi: 10.3969/j.issn.1008-4576.2008.01.001

Xie, L., Flynn, A., May, T. M., and Ali, C. (2019). The making and remaking of ecological space in China: the political ecology of Chongming Eco-Island. *Polit. Geogr.* 69, 89–102. doi: 10.1016/j.polgeo.2018.12.012

Xu, B., and Lin, B. (2019). Can expanding natural gas consumption reduce China's CO_2 emissions? *Energy Econ.* 81, 393–407. doi: 10.1016/j.eneco.2019.04.012

Xu, X., Wei, Z., and Ji, Q. (2019). Global renewable energy development: influencing factors trend predictions and countermeasures. *Resour. Policy* 63, 1–15. doi: 10.1016/ j.resourpol.2019.101470

Yu, Y. (2018). Environmental catching-up, eco-innovation, and technological leadership in China's pilot ecological civilization zones (in Chinese). *Technological* 7, 32–37.

Zeng, J., and Liang, Q. (2018). Research and enlightenment on ecological civilization and energy consumption evolution of major developed countries in the world (in Chinese). *J. Econ. Res.* 36, 25–127.

Zhang, L., and Yang, J. (2019). Evaluation of the ecological civilization index of China based on the bouble benchmark progressive method. *J. Cleaner Prod.* 222, 511–519. doi: 10.1016/j.jclepro.2019.02.173

Zhang, M., Liu, Y., and Wu, J. (2018). Index system of urban resource and environment carrying capacity based on ecological civilization. *Environ. Impact Assess. Rev.* 68, 90–97. doi: 10.1016/j.eiar.2017.11.002

Zhang, W., and Tian, L. (2016). The evolution model of electricity market on the stable development in China and its dynamic analysis. *Energy* 114, 344–359. doi: 10.1016/j.energy.2016.08.015

Zhou, B., Zhang, C., and Wang, Q. (2018). How does emission trading reduce China's carbon intensity? An exploration using a decomposition and difference-in-differences approach. *Sci. Total Environ.* 676, 514–523. doi: 10.1016/j. scitotenv.2019.04.303

Zhu, Z. (2016). *Assessment of the Impact of Energy Utilization on Ecological Civilization in Major Developed Countries and Its Implications for China* (in Chinese). Nanjing: East China Institute of Technology.

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Developing Distributed PV in Beijing: Deployment Potential and Economics

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The building sector consumed a total of 580 million tons-coal equivalent (Mtce) terminal energy in China in 2018 including 1,888 terawatt-hours (TWh) electricity, accounting for 20.2% of total terminal energy consumption in this country. As the capital of China, Beijing is striving to improve the air quality while ensuring power and heat supply due to heavy reliance on electricity intake from other energy-rich provinces. The distributed photovoltaic, as a flexible application of renewable energy systems in urban and rural regions, can contribute to the power supply for rapid urbanization and mitigate the negative environmental impact of fossil energy use. In the context of grid parity, this article provides a systematic analysis of solar resource potential, power generation economics and policy support for the rooftop photovoltaic (PV) system in Beijing. The deployment potential of rooftop PV is estimated to be 11.47 GW and the large-scale commercial rooftop PV is approaching grid parity. Furthermore, this article discusses the feasibility of large-scale distributed PV deployment in Beijing by considering distributed electricity trade envisioned the ongoing power market reform in China.

Keywords: rooftop PV, deployment potential, economics, environmental value, Beijing

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INTRODUCTION

Solar PV and wind power are currently obtaining great opportunity for installation expansion and technological innovation around the world. Renewables are becoming an excellent option for many countries in the transition toward a secure, cost-effective and low-carbon energy supply system, while simultaneously combating climate change and local air pollution (IRENA, 2019). Current energy policies regard the development of renewables as a fundamental action plan to meet the immediate rise in energy demands expected in the coming decades. Moreover, solar PV is more universal and feasible for end-use sectors than clean energy such as hydropower, wind power, and biomass, because the rooftop PV can be installed on the demand side (IRENA, 2019). In this context, solar PV is one of the most promising options with an infinite sunlight resource and environmental sustainability to cover the evolving landscape for the integration of variable renewable power (Chitra and Himavathi, 2013; Bye et al., 2018).

The modularity of solar PV systems allows the universal deployment of modern energy across urban, rural, and suburban areas. Driven by the environmental policies and the sharp decline in renewable power costs, in particular the cost of PV falling by almost 75% between 2009 and 2018 (IRENA, 2018), the solar PV gains impressive growth with the installed capacity reaching 397 gigawatts (GW), comprising 17% of total renewable energy capacity and 5.78% of total power generating capacity (IEA, 2018). The power supply from distributed photovoltaic (DPV) and small solar devices, such as commercial park PV and solar home systems, is growing especially fast. New data from IRENA shows that about 25 million people obtain a higher level of renewable energy services through solar home systems or connection to a solar mini-grid (IRENA, 2016). International experiences may provide insight that the successful applications of solar PV contribute energy supply and conservation in the building sector (Bansal and Goel, 2000; Radhi, 2010; Sadineni et al., 2012; Emziane and Al Ali, 2015).

Assessment of the deployment potential of rooftop PV systems has been an expansive area for research scholars. Taking advantages of developing geospatial technology and efficient computational methods, several methodologies based on Geographic Information System (GIS) techniques are more accurate than the constant value method (making a number of assumptions to calculate the utilizable rooftop area) and manual based selection (using remote sensing techniques such as high-resolution satellite images to evaluate the available rooftop areas) in evaluating the potential of building rooftop PV installation (Dehwah et al., 2018). Literature summarizes several generic GIS-based toolkits including Feature Analyst tool (Wiginton et al., 2010), Light Detection and Ranging (LiDAR) (Jacques et al., 2014; Gooding et al., 2015; Lingfors et al., 2017) and Digital Surface Model (DSM) (Buffat et al., 2018). An alternative to DSM is 3D building models created from aerial photos, as Google Maps demonstrates, which will be available in the foreseeable future. Digital Elevation Model (DEM) and DSM are both the branches of the Digital Terrain Model. DEM represents the topographic surface of the terrain. This article uses DEM supported by Platform for Geographical Situation Monitoring of China to identify the rooftop geometries and compute the PV installed potential in Beijing. Thus, the process of DEM assessments is further elaborated in the sections below.

The economic evaluation metrics of a power generation project comprise various technical indicators of engineering economics, including net present value (NPV), life-cycle costing, levelized cost of electricity (LCOE), internal rate of return (IRR) and payback period, etc. Short et al. (1995) presented a comprehensive and detailed review of economic evaluation modeling. NPV index, as a profitability indicator used in capital budgeting, refers to the present value of cash inflows minus the present value of cash outflows. Li and Liu (2018) integrated NPV analysis with a developed pixel-based method to estimate the revenue of potential building PV projects. IRR is defined as the discount rate when the NPV equals zero, that is, the total present value of inflows equals the total present value of outflows. IRR method integrates the project returns during its lifespan with its total investment and provides a benchmark metric to determine whether the project is worth investing (Zhao et al., 2017). This merits the attention that, when evaluating independent projects, NPV, and IRR yield the same decision. Unfortunately, NPV intrinsically necessitates an appropriate discount rate that is the focus of controversy. Thus, IRR analysis is generally preferred other than NPV. The LCOE methodology is extensively applied when mentioning generation competitiveness of various power technologies options or considering grid parities for emerging technologies (Branker et al., 2011; Congedo et al., 2013; Larsson et al., 2014). The rationale for LCOE analysis is to consider lifetime generation and costs to evaluate the tariff per unit of electricity by minimizing the biases between diverse generating technologies (Yuan et al., 2014). Therefore, this article applies the LCOE method and IRR analysis to appraise the rooftop PV system in Beijing.

The combustion of fossil fuels predominately causes deterioration of the atmospheric environment by releasing sulfur dioxide (SO_2), nitrogen oxides (NO_X), particulate matter (PM), and carbon dioxide (CO_2). In China, the coal-fired power issued severe regional pollution. Beijing and its surrounding areas explicitly prohibit captive coal power plants for coal capping and air quality improvement (NDRC and NEA, 2017). The DPV deployment will contribute to this process. Jones and Gilbert (2018) used the life cycle assessment (LCA) to assess the greenhouse gases (GHG) emissions for PV generation at the aggregated distribution network scale. Wang et al. (2018) estimated the potential of life cycle CO_2 emissions reduction for three different patterns in Beijing. Allouhia et al. (2019) illustrated the environmental impact of PV systems by evaluating the potential of carbon emissions reduction, assuming that the energy generated by PV installations substitutes that by thermal power. The aforementioned literature conducted environmental impact analysis by employing a single factor of carbon emissions, which underestimates the environmental value without considering SO_2, NO_X, and PM. Thus, this article will consider all of the emissions mitigation fees to explore the real environmental value of rooftop PV.

Compared with previous studies, this article contributes a more comprehensive and comprehensive analysis of the potential and value of photovoltaic development. This article employs DEM technology to explore the precise potential of rooftop PV deployment, reconciles LCOE and IRR theories to appraise the appealing economics, and further considers the environmental value through mitigating emissions from coal-fired power generating.

This study unfolds as follows. Section A Development Briefing of Beijing presents a brief overview of power development in Beijing. Section Methodology introduces the methodology of potential estimation and economic analysis. Section Results and Discussion illuminates the empirical results and discussion on rooftop PV development in Beijing. Finally, section Conclusion and policy implications concludes the article with implications. The abbreviation for manuscript is depicted in **Appendix I**, and supporting policies and governmental subsidies for DPV power are described in **Appendix II**.

A DEVELOPMENT BRIEFING OF BEIJING

Beijing, as the capital of China, covers 6,410 square kilometers with 27.1 million permanent residents. The capital city provides a massive daily energy consumption of 195,000 tce with daily GDP (Gross Domestic Product) of 767.5 million Chinese Yuan (CNY) in 2017. In order to optimize the energy structure and improve the environment, the government has formulated a large number of regulations to restrain the utilization of coal. Typically, from 2013, Beijing committed to phasing out all coal-fired generation fleets and installing alternative gas power plants. By the end of 2017, the energy mix of 71.33 Mtce in Beijing comprised coal (5.65%), petroleum (33.8%), natural gas (31.8%), external transmitted electricity (25.99%), and others (2.77%) (Beijing Municipal Bureau of Statistics, 2018). One of

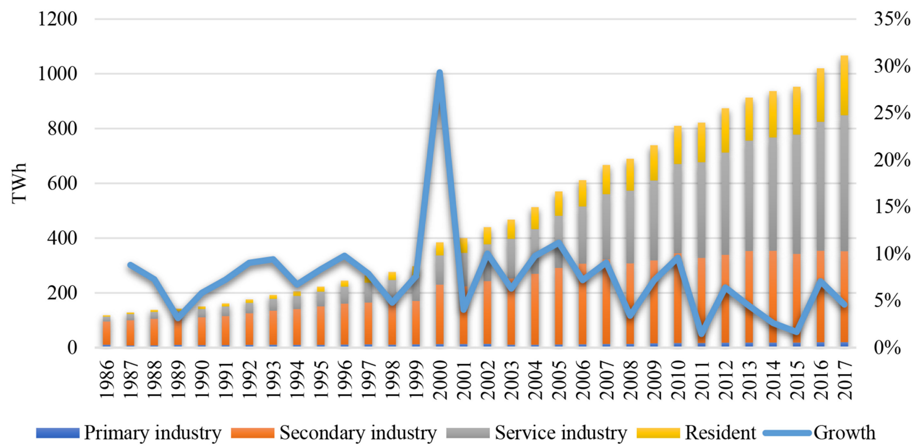

FIGURE 1 | Electric power consumption and annual growth of total power consumption in Beijing, 1986–2017. Primary industry refers to agriculture, forestry, animal husbandry, and fishery and services in support of these industries. Secondary industry refers to mining and quarrying, manufacturing, production, and supply of electricity, water and gas, and construction. The tertiary industry, namely service industry, refers to other industries except the primary industry and the secondary industry. Resident refers to the household. The annual growth is calculated compared to the previous year.

the remarkable performances is that from 2000 to 2017, the daily average concentration of SO_2 has dropped from 71 to 8 mg/m^3. The average concentration of Particulate Matters 2.5 (PM2.5) in Beijing drops from 104 μg/m^3 in 2010 to 50.9 μg/m^3 in 2018, ranking 8th in the global capital city in 2018 (AirVisual, 2018). The improvement of environmental performance in Beijing benefits from the cleaner energy and power supply.

As shown in **Figure 1**, the total electric power consumption in Beijing has increased to 1,067 TWh by the end of 2017. The development process characterizes several following marked features: (a) the sharp growth in 2000 derives from the compression of the coal utilization in terminal energy consumption to mitigate the severe environmental pollution, with the proportion of coal in terminal energy consumption falling from 70% in 1978 to 43% in 2000 (Beijing Municipal Bureau of Statistics, 2017); (b) the power consumption of service industry exceeded that of secondary industry in 2011, indicating the strong growth of real economic in service industry; (c) residential power consumption remains a fairly rapid increasing, 44 times higher in 2017 than in 1986; (d) the rebound of electricity consumption growth in 2016 is partially driven by the clean heating policy of coal-to-electricity transformation. Simultaneously, in 2017, the household electricity consumption in Beijing reached 1004 kWh/p which is equivalent to the level in Germany, Korea and Italy in 2011 (IEA Statistics, 2018).

The solar PV resource in Beijing is pretty abundant. The annual solar radiation in Beijing is about 4,600–5,700 MJ/m^2, located in the Class-II resource areas of China[1]. The annual average generation hours of DPV system may reach 1,214 h[2] in Beijing. PV systems can be classified into grid-connected and standalone systems based on their operational and functional requirements (Chitra and Himavathi, 2013). This article conducts a comparative economic evaluation of grid-connected and standalone rooftop PV systems for commerce and household.

Beijing pioneers in the full supply of clean electric power because there are no local coal-fired power plants. In 2017, the bulk of electric power was local gas power generation (34.7%) and renewable power generation (1.57%), as well as external electricity (63.7%) transmitted from vicinal provinces. By the end of 2018, the DPV installed capacity is 350 MW, occupying 87.5% of total solar PV installation, and the recently installed capacity accounts for 42.85% of the total. Until now, the government has issued seven award lists of DPV generation projects, which includes 141 commercial DPV projects and 9,796 household PV projects connected to the grid (shown in **Table 1**). The solar PV market gained momentum due to electricity generation planning and financial support policy. Beijing government explicitly pledged to 1,000 MW installed

TABLE 1 | Beijing DPV power generation project award list.

Time	List	Commercial		Household	
		Number	Capacity (kW)	Number	Capacity (kW)
2016.03.14	1	7	4319.4	19	110.34
2016.09.18	2	11	14446.52	210	1758.875
2017.03.02	3	9	7986.3	1207	10074.5
2017.08.31	4	7	11038.1	2045	16869.32
2018.03.02	5	37	12500.6	2431	20342.375
2018.09.05	6	70	28265.92	3884	34230
2019.03.08	7	67	37343	2337	23546.24
Total		208	115909.84	12133	106931.65

Source: Compiled based on Award list of distributed photovoltaic power generation projects in Beijing (the 1–7th batches).

[1] http://guangfu.bjx.com.cn/news/20150401/604172.shtml
[2] https://news.solarbe.com/201801/11/123171.html

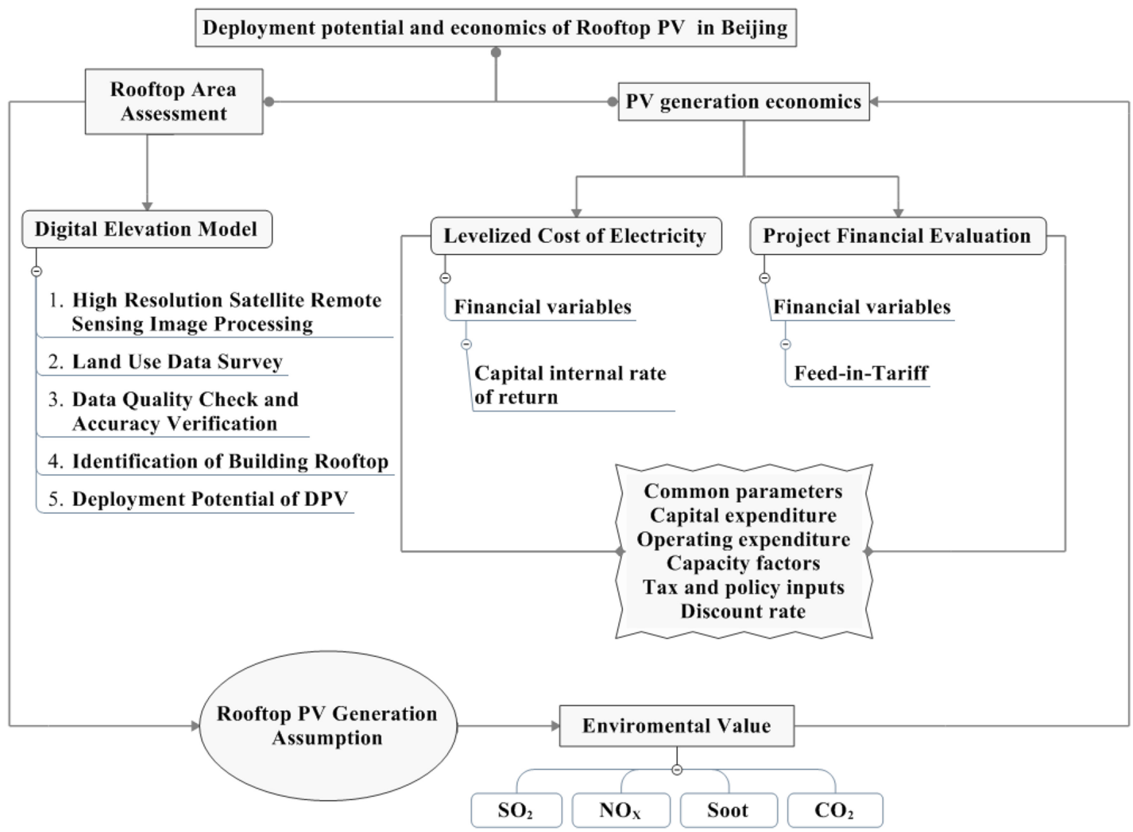

FIGURE 2 | Overall research methodology.

capacity by 2020. The concentrated PV will be hardly increased because it covers additional land resources instead of building roof resources like DPV. Thus, for the overcrowded capital city, the DPV installation is a more probable choice for the rest of the deployment.

METHODOLOGY

We devised a three-stage approach to calculate the deployment potential and economics of rooftop PV in Beijing. The three research blocks comprise rooftop area assessment, PV generation economic appraisal and environmental value (depicted in **Figure 2**). In this article, the deployment potential of rooftop PV depends on the available roof of commercial and residential buildings, which is evaluated by DEM based on advanced digital and spatial techniques coupled with distinct building roof features. Then, the financial appraisal methods of engineering projects, including LCOE and Project Financial Evaluation, are employed to quantify the investment attraction. Finally, the environmental value assessment can provide insight into the positive impact on pollutant emission reduction in Beijing.

Digital Elevation Model

DEM realizes the digital simulation of terrain (i.e., the digital representation of terrain surface morphology) through limited terrain elevation data. It is an entity terrain model that represents terrain elevation in the form of a set of ordered numerical arrays. The technology map of DEM is presented in **Figure 3**.

DEM database supported by Platform for Geographical Situation Monitoring of China adopts a rapid extraction method of full digital human-computer interaction remote sensing to establish a spatial dataset for construction land and simultaneously make raster data of multiple scales. The high-quality DEM data with a spatial resolution of 30, 90 m and 1 km covers urban land use, rural residential area and other construction lands, etc. Then, the building area suitable for rooftop PV deployment is capable to be screened out from the massive land utilization data.

LCOE

LCOE refers to the tariff when the present value of the total revenues is equivalent to the present value of the total cost during the project lifespan. In this context, we employ the analytical approach proposed by Yuan et al. (2014) to evaluate the LCOE of rooftop PV systems in Beijing. The formula for calculation is shown as follows:

$$LCOE = \left(\sum_{n=0}^{N} \frac{Cost_n}{(1+r)^n}\right) / \left(\sum_{n=0}^{N} \frac{E_n}{(1+r)^n}\right) \tag{1}$$

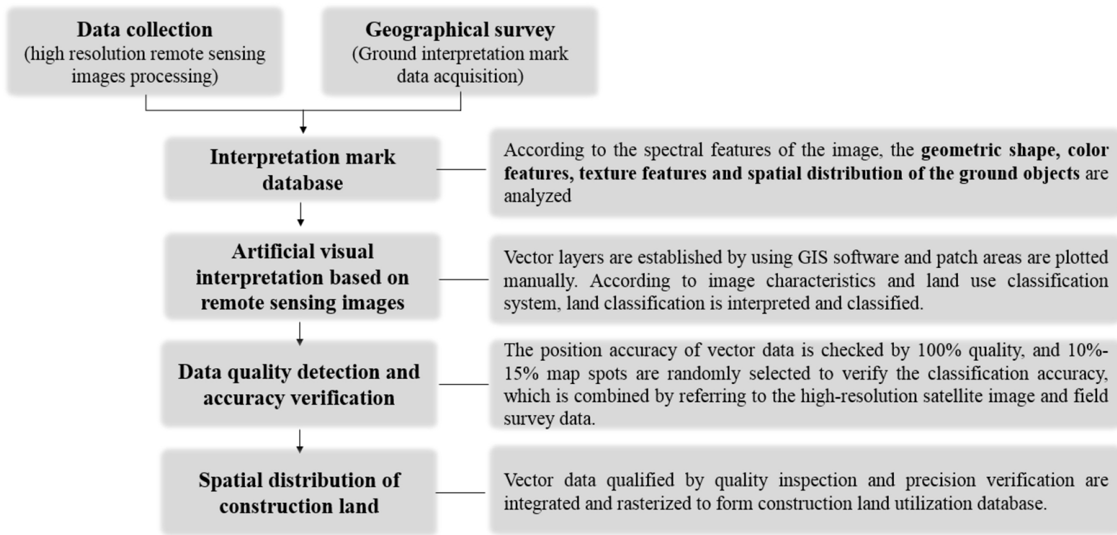

FIGURE 3 | DEM technology map. Source: Platform for geographical situation monitoring of China.

$$LCOE = \frac{C + \sum_{n=1}^{N} \frac{(OPEX+I)\times C + TAX_n + C_i + R}{(1+r)^n}}{\sum_{n=1}^{N} \frac{H\times S\times \eta \times (1-d)^n}{(1+r)^n} + \frac{365-a}{365} \times H \times S \times \eta} \quad (2)$$

where E_n is the annual PV generation, C is the unit investment cost of the system, OPEX is the rate of operation and maintenance (O & M) cost, and I is the rate of insurance cost, TAX_n is annual tax, C_i is interest rate of the loan, R is roof renting cost, H is annual utilization hours, S is generating capacity, d is the annual degradation rate of PV system, η is the performance factor of the system, r is discount rate and a stands for the construction period.

Project Financial Appraisal

The financial appraisal analysis of engineering projects involves a comprehensive evaluation of profitability, solvency and financial viability through integrating investment, costs, revenues, taxes and profits under a certain system of accounting, tax and price (Fu and Quan, 1996). The source of funds and the repayment of loan funds will affect the cash flow, then affect the economic performance of an enterprise. Thus, the economic appraisal covers two assessments: (a) "full investment" financial analysis regards all funds as own funds to examine the economic effects within the scope of enterprises; (b) "proprietary funds" financial analysis considers all factors including financial conditions to investigate the profitability of enterprises. In this article, we appraise the economics of engineering projects, not the profitability of own investment. Thereby, the full investment assessment matches the purpose. IRR, as already noted, is a rational metric to determine whether the project is worthy of investment (Yuan et al., 2014). IRR is generally considered to reflect the investing efficiency. Thus, we employ full investment IRR as an economic indicator.

LCOE analysis and project financial appraisal share many common variables and parameters that can be integrated into four categories: technical and economic variables, taxes and charges, operation expenditure and financial variables (**Figure 4**). **Table 2** reports a detailed description of the common parameters for LCOE and IRR estimation based on current PV investment market briefs (detailed in Yuan et al., 2014; Li et al., 2018).

RESULTS AND DISCUSSION

Deployment Potential of Rooftop PV in Beijing

The high-quality DEM data can categorize construction land area in Beijing into urban land, rural land, and industry and traffic land. In detail, the urban land includes commercial buildings, ancient buildings, office buildings (including government, hospital and education institutions), and urban residential buildings (including multi-family and detached house) with clear features and name identifications. The public facility consists of transportation, water conservancy and industrial land. This article identifies the commercial building, office building, and residential building as available blocks for the rooftop PV system.

The DEM data describes the land use of Beijing covers 16,411 km^2 (square kilometer) and the share of the building area is 19.7%. The building area suitable for rooftop PV is estimated at 241 km^2 in Beijing in 2018, accounting for 7.45% of the total building area. After estimating the rooftop areas available for PV installation, it also requires the information about land use for unit installation to calculate the deployment potential. The Ministry of Land and Resources (MLR) of China, now renamed the Ministry of Natural Resources (MNR), recommends that the average land use for the rooftop PV project is 21 m^2/kW in Beijing. Coupled with the estimated building roof area of

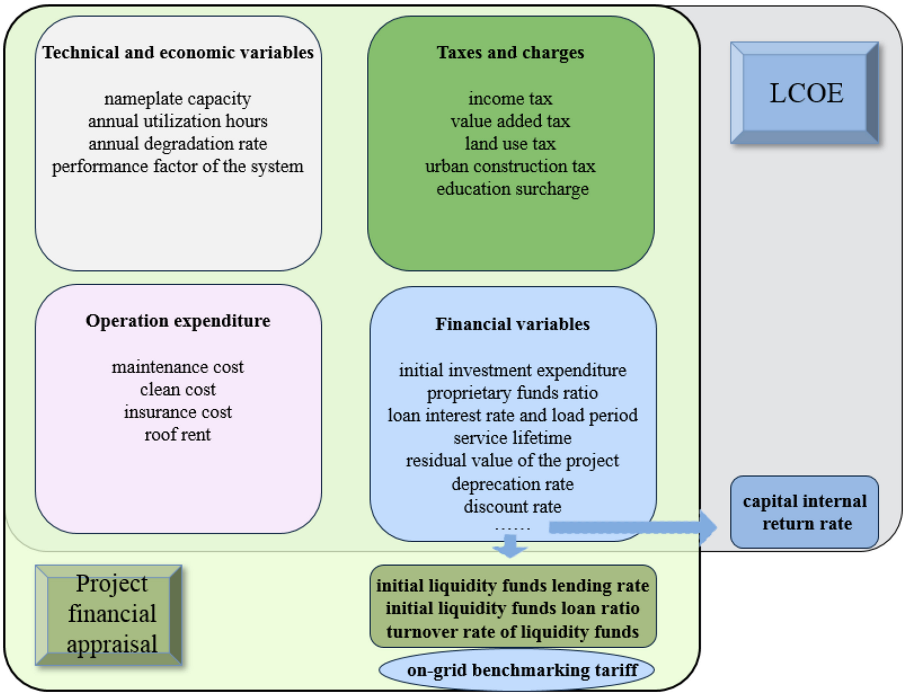

FIGURE 4 | Model variables and parameters.

241 km^2, the deployment potential of distributed PV in Beijing is determined to be 11.47 GW.

LCOE Results

By using the concise summaries of market findings, this article integrates the rooftop PV projects into six groups by generation capacity as the baseline levels of LCOE and IRR estimation. The distributed PV is defined as the station with generating capacity <6 MW in China (NEA, 2013). The large-scale rooftop PV more than 1 MW is appreciated to installation in the commercial zones and office buildings, and the small-scale DPV can be installed in residential buildings (apartment buildings and detached houses). The smallest-scale rooftop PV occupies the highest initial unit investment cost, that is, 9,000 CNY/kWh in the current market. In addition, the 2 kW-scale PV project rarely obtains a loan due to the tiny investment scale. The annual utilization hours of DPV derives from the annual valid data extraction of previous years. **Table 3** presents the baseline LCOE levels of rooftop PV projects in Beijing. The capacity of commercial rooftop PV is assumed as 6, 2, and 1 MW; for the residential rooftop PV projects, the capacity is set as 20, 10, and 2 kW. The unit investment costs decrease with the increase of installed capacity of DPV project. As mentioned above, the unit roof usage is set as 21 m^2/kW and the annual utilization hours is configured as 1,214 h/year. The baseline LCOE for diverse scales of rooftop PV projects ranges between 0.57 and 0.79 CNY/kWh. The result explored by Yuan et al. (2014) revealed that the LCOE of DPV ranged between 1.16 and 1.29 CNY/kWh, which is substantially more than our estimation. This disparity is due to the sharp decline in PV modules and an additional reduction of operation and maintenance cost.

IRR Appraisal

In the baseline scenario of IRR, for convenience sake, we made some assumptions: (a) the roof owner and the PV investor are the same and thus the rules of on-site own consumption and on-grid redundant sale can be approved, and then the savings for commercial electricity bills are equivalent to the revenue of DPV project; (b) the shares of on-grid electricity for commercial and residential rooftop PV are 50% and 20%, respectively[3]; (c) the benchmarking on-grid electricity for coal power is set to 0.36 CNY/kWh according to the market price in Hebei province (the district around Beijing), because there is no longer any coal power in Beijing[4]; (d) the average commercial and residential electricity prices are 1 and 0.5 CNY/kWh[5], respectively. **Table 4** reports the results of the baseline IRR of commercial and residential DPV in Beijing. We term 8% as the benchmarking IRR for the power industry (Beijing Municipal Commission of Development Reform, 2013; Yuan et al., 2014). Thus, the IRRs of residential rooftop PV yield of 10 and 2 kW installed capacity are less than industry reference profitability, implying the poor investment attraction even with government subsidies. For parts of the patch, feed-in-tariff (FiT) for renewable energy is equal to the benchmarking on-grid electricity price for coal power plus renewable energy price subsidy, and Beijing's subsidy for the first 5 years is additional (see **Appendix II** for details). Comparing

[3]https://www.sohu.com/a/158209384_752928
[4]http://www.hebei.gov.cn/hebei/11937442/10761139/13897734/index.html
[5]http://bj.bendibao.com/zffw/201374/109201.shtm

TABLE 2 | Common parameters for economic analysis of rooftop PV.

Common parameters	Value
Technical and economic variables	
Annual utilization hours (h)	1,300
Annual degradation rate (%)	0.6
Performance factor of the system (%)	75
Financial variables	
Unit investment costs (CNY/kW)	6,000–9,000
Proprietary funds ratio (%)	80
Loan investment rate (%)	6
Loan period (years)	15
Service period (years)	25
Residual rate of the project (%)	5
Deprecation years	15
Discount rate (%)	8
Operation expenditure	
Maintenance rate (%/decade)	8.56%
Clean cost rate (%)	1
Insurance rate (%)	0.25
Roof rent (CNY/m^2) (if valid)	2–4
Taxes and charges	
Income tax (%)	Full exemption of the first three operation years, and half exemption of the second three operation years, otherwise 15%
Value added tax (%)	17% with 50% exemption
Land use tax (%)	1.2% with 30% exemption of roof rent
Urban construction tax (%)	5
Education surcharge (%)	1

TABLE 3 | Baseline LCOE levels of rooftop PV projects at various scales.

PV project	Commercial rooftop PV			Residential rooftop PV		
Capacity	6 MW	2 MW	1 MW	20 kW	10 kW	2 kW
Unit investment costs (CNY/kW)	6,000	6,500	7,000	8,000	8,500	9,500
Own capital	80%	80%	80%	80%	80%	100%
Annual utilization hours (h/year)	1,214	1,214	1,214	1,214	1,214	1,214
Roof usage (m^2)	126,000	42,000	21,000	420	210	42
LCOE (CNY/kWh)	0.57	0.62	0.67	0.69	0.73	0.79

with residential DPV, the IRRs of large-scale commercial rooftop PV projects are higher than the sector's benchmarking return rate due to the low investment cost and high commercial electricity price.

Environmental Value Estimation

Although all the coal power plants have been eliminated, a large part of the power supply originates from the cross-regional transmission of coal power. This measure just shifts the pollution to other places rather than pollutants remission. Unlike the combustion of fossil fuels emitting various pollutants, the clean power generated by rooftop PV contributes to mitigating the environmental pressures. Lau et al. (2016) illustrated the emissions factors of different pollutants in China's regional power grids, and the sewage tax standard is the average charge of surrounding provinces (shown in **Table 5**) (Science Academy and Geography Institute of Henan Province, 2018). Then the total generation of rooftop PV could be 13924.58 GWh aligned with the deployment potential of 11.47 GW. Finally, the environmental value of rooftop PV in Beijing is estimated to be 1237.97 million CNY, which is a considerable social gain. Furthermore, DPV creates diverse implicit benefits, such as energy conservation, smart power and poverty alleviation, etc.

TABLE 4 | IRR of commercial and residential rooftop PV in the baseline scenario.

PV project	Commercial rooftop PV			Residential rooftop PV		
Capacity	6 MW	2 MW	1 MW	20 kW	10 kW	2 kW
Unit investment costs (CNY/kWh)	6,000	6,500	7,000	8,000	8,500	9,000
Own capital	80%	80%	80%	80%	80%	100%
Annual utilization hours (h/year)	1,214	1,214	1,214	1,214	1,214	1,214
On grid	50%	50%	50%	20%	20%	20%
Commercial/residential electricity price (CNY/kWh)	1	1	1	0.5	0.5	0.5
Benchmarking on-grid price for coal power (CNY/kWh)	0.36	0.36	0.36	0.36	0.36	0.36
National subsidy (CNY/kWh)	0.1	0.1	0.1	0.18	0.18	0.18
PV on-grid tariff (CNY/kWh)	0.46	0.46	0.46	0.54	0.54	0.54
Local subsidy by Beijing (for 5 years) (CNY/kWh)	0.3	0.3	0.3	0.3	0.3	0.3
IRR	14.4%	12.9%	11.7%	8.6%	7.9%	7.0%

TABLE 5 | Emissions factors and sewage tax for coal power and environmental value of DPV in Beijing.

Sewage emissions	CO_2	SO_2	NO_X	PM
Emissions factors (g/kWh)	987.23	1.37	4.07	0.11
Sewage tax (CNY/t)	80	1,260	2,000	550
Rooftop PV generation (GWh)	13924.58			
Emissions charge (million CNY)	1099.74	24.04	113.35	0.84
Environmental value (million CNY)	1237.97			

Environment value = total emissions charges = $\sum$*emissions factor × sewage tax × PV generation.*

Sensitivity Analysis and Discussions

The initial investment of power project usually has a crucial impact on the LCOE, especially for the renewable energy stations due to the no-fuel-cost feature. The progress of grid parity for wind and solar power mainly derives from the device's cost decline. In China, the lowest quotation for the DPV project is

TABLE 6 | The impact of initial investment on the LCOE and IRR of rooftop PV in Beijing.

PV project	Commercial rooftop PV			Residential rooftop PV		
Capacity	6 MW	2 MW	1 MW	20 kW	10 kW	2 kW
Unit investment costs (CNY/kW)	5,000	5,500	6,000	7,000	7,500	8,000
LCOE (CNY/kWh)	0.48	0.53	0.57	0.6	0.64	0.7
IRR	18.2%	16.1%	14.4%	10.5%	9.5%	8.5%

TABLE 7 | The impact of on-grid share on the LCOE and IRR of rooftop PV in Beijing.

PV project	Commercial rooftop PV			Residential rooftop PV		
Capacity	6 MW	2 MW	1 MW	20 kW	10 kW	2 kW
Unit investment costs (CNY/kW)	6,000	6,500	7,000	8,000	8,500	9,000
On grid	40%	40%	40%	10%	10%	10%
IRR	15.7%	14.2%	12.8%	8.9%	8.1%	7.3%
On grid	60%	60%	60%	30%	30%	30%
IRR	13.1%	11.7%	10.5%	8.4%	7.6%	6.8%

5,000 CNY/kWh in specific districts (ERI, 2019). Suppose other factors remaining the same, the impact of initial investment variations on LCOE and IRR is quantified in **Table 6**. Given 1,000 CNY/kWh reduction in unit investment cost of rooftop PV, the LCOE would drop by 0.09–0.1 CNY/kWh and the IRR would rise by 1.5–3.8 percentage points. If the unit investment cost of 2 kW residential rooftop PV became, the IRR would be higher than the benchmarking return rate.

For IRR of a rooftop PV project, another influencing factor is the share of on-grid electricity. As shown in **Table 7**, the share of on-grid electricity has a significant impact on the IRR of rooftop PV. For example, the IRR of 6 MW rooftop PV is 13.1, 14.4 and 15.7% when the share is 60, 50 and 40%, respectively. In simple terms, IRR is negatively correlated with the share of on-grid electricity, because the commercial/residential electricity price is higher than FiT.

The subsidy for renewable energy still boosts the rooftop PV industry, whereas the government has promulgated subsidy retreat policy. Given that the national subsidy is halted and local subsidy remains the same, the IRRs of rooftop PV at various scales in Beijing would fall by a fraction as reported in **Table 8**. By then, the IRRs of commercial rooftop PV would remain higher than 8%, but residential rooftop PV gains a poor return rate. We can conclude that the grid parity of large-scale distributed PV in Beijing is nearly feasible.

At the end of October 2017, NDRC and NEA jointly issued the "notice on the implementation of a market-oriented trading pilot program for distributed power generation," which put forward reform plans on the problems such as low degree of market-oriented trading, lagging public services and imperfect management system encountered in distributed power generation. Then in January 2018, NEA further clarified the

TABLE 8 | The impact of subsidy retreat on the LCOE and IRR of rooftop PV in Beijing.

PV project	Commercial rooftop PV			Residential rooftop PV		
Capacity	6 MW	2 MW	1 MW	20 kW	10 kW	2 kW
Unit investment costs (CNY/kW)	6,000	6,500	7,000	8,000	8,500	9,000
FiT (CNY/kWh)	0.36	0.36	0.36	0.46	0.46	0.46
IRR	12.3%	10.9%	9.8%	7.2%	6.5%	5.4%

market-oriented trading pilot requirements of distributed power generation in terms of detailed rules. Recently, NDRC announced the pilot list for market-oriented trading of distributed power generation including 26 programs with a total installed capacity 1.47 GW though not in the Beijing area. These distributed power programs as grid parity demonstration occupy a full-scale guaranteed acquisition and priority right for generating, which is pledged by long-term fixed-price electricity purchase contract (not <20 years) aligned with benchmarking tariff of coal power. The market-oriented transaction of DPV helps to form the mechanism of market-determined electricity price, construct the market transaction process and system, reflect the reasonable value of distributed power, realize the grid parity as soon as possible, and create a win-win situation for power enterprises and terminal consumers.

FiTs function in a similar way to a standardized, long-term power purchase agreement (PPA), usually signed with a utility or a network company and backed by the government, although the stability and consistency of the FiT depend on the durability of its supporting legislation. Full consumption of electricity production is the key prerequisite for realizing profitability. The long-term fixed-price electricity purchase contract is a virtual long-term PPA that can guarantee a stable revenue expectation and then lessen/share risks. Another shared-risk instrument is a variable premium system, including the United Kingdom's Contracts for Difference (CfDs) and the variable renewable premium in Germany, similar to FiTs in that they provide a standardized, long-term PPA for renewable energy (IEA, 2016). The long-term fixed-price electricity purchase contract would help rooftop PV projects weaken operation risk and then help cut down the loan threshold and interest rate, which is a strong incentive to deploy rooftop PV extensively in Beijing.

Furthermore, the pilots for DPV are exempted from policy cross-subsidies and transmission charges of the previous voltage level without being involved. In the policy context, the commercial DPV project in Beijing can be profitable without subsidies due to the high share of own-consumption or direct transaction with industrial and commercial consumers.

CONCLUSION AND POLICY IMPLICATIONS

The scope of this article is to estimate the deployment potential and economics of DPV in Beijing. The DEM identifies the roof area suitable for DPV installed in Beijing as 241 km^2, so the deployment potential is estimated to be 11.47 GW according to the occupation standard of 21 m^2/kW. Then, by employing the LCOE and project financial appraisal method, the rooftop PV can earn a profit under existing tariff and subsidy policy, except the 2 and 10 kW residential DPV projects. The reduction of initial investment cost and on-grid share both could improve the profitability of DPV. Moreover, if eliminating national subsidy but reserving local subsidy, the commercial rooftop PV still generates good returns, which reveals the feasibility of grid parity for large-scale DPV in Beijing.

Renewables are the rational choice to reconcile energy supply and environmental governance in Beijing. In the initial phase, DPV deployment in Beijing depends on the national and local preferential policies and financial incentives for promoting renewable energy, including FiT, tax breaks, on-grid priority, and pilot projects, etc. The favorable strength for DPV development in Beijing is to guarantee full-scale acquisition through the long-term fixed-price electricity purchase contract, which is in place to ensure stable market expectation and conducive to lowering the DPV project risks. Driven by policy stimulus and technology innovation, the rising profitability of DPV can motivate investors and even cause overheated investment without any guidance. DPV power generation project award list in Beijing and national DPV subsidy retreat can curb the excessive expansion momentum. Incidentally, excessive renewable subsidies will add to the public finance burden and drive up electricity prices. A sun-set mechanism in FiT and then integration with the market are the solution. Thus, in the development process, persistent adherence to progressive policies is crucial to readjust DPV deployment to rapidly evolving industrial landscape.

Aligned with ongoing power market reform, subsidy retreat indicates the upcoming grid parity of large-scale DPV. The pilots for nearby direct trading of DPV is gaining momentum without any subsidy in China. Meanwhile, to facilitate market-oriented transactions, the government issues a series of regulations involving reducing non-technical cost, equipping associated power network, and penalizing nonperformance. The non-technical cost dilemmas cover loan cost, land renting, and transmission-distribution price. From the perspective of policy innovation, China's new policies include implementing a long-term PPA system, reducing transmission-distribution fees, exempting cross-subsidies, and implementing green certificate schemes, as well as emphasizing and clarifying past policies such as classified subsidy system, full-scale guaranteed acquisition system, and priority scheduling scheme. It can be concluded that full interact with a market-driven and policy guarantee is crucial to achieving the benign development of DPV. Beijing's experience has a good reference for other cities to develop renewable energy.

DATA AVAILABILITY STATEMENT

The datasets generated for this study are available on request to the corresponding author.

AUTHOR CONTRIBUTIONS

XZ was responsible for the specific work of this paper. SF carried out some of the calculation work. HZ guided the work of this article. JY optimized the structure and tone of this article.

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REFERENCES

AirVisual (2018). *World Air Quality Report 2018*. Available online at: https://www.airvisual.com/world-most-polluted-cities

Allouhia, A., Saadanib, R., and Buker, M. S. (2019). Energetic, economic and environmental (3E) analyses and LCOE estimation of three technologies of PV grid-connected systems under different climates. *Sol. Energy* 178, 25–36. doi: 10.1016/j.solener.2018.11.060

Bansal, N. K., and Goel, S. (2000). Integration of photovoltaic technology in cafeteria building, at Indian Institute of Technology, New Delhi. *Renew. Energy* 19, 65–70. doi: 10.1016/S0960-1481(99)00017-8

Beijing Municipal Bureau of Statistics (2018). *Beijing Statistical Yearbook*. Beijing. Available online at: http://tjj.beijing.gov.cn/nj/main/2018-tjnj/zk/indexch.htm [in Chinese].

Beijing Municipal Bureau of Statistics (2017). *Beijing Statistical Yearbook*. Beijing. Available online: http://tjj.beijing.gov.cn/nj/main/2017-tjnj/zk/indexch.htm [in Chinese].

Beijing Municipal Commission of Development and Reform (2013). *How is 8% Decided as Reference Internal Return Rate*? Available online at: http://fgw.beijing.gov.cn/zwxx/ztzl/wzz/zcjd/201512/t9769937.htm (Cited July 31, 2013) [in Chinese].

Branker, K., Pathak, M., and Pearce, J. M. (2011). A review of solar photovoltaic levelized cost of electricity. *Renew. Sust. Energy Rev.* 15, 4470–4482. doi: 10.1016/j.rser.2011.07.104

Buffat, R., Grassi, S., and Raubal, M. (2018). A scalable method for estimating rooftop solar irradiation potential over large regions. *Appl. Energy* 216, 389–401. doi: 10.1016/j.apenergy.2018.02.008

Bye, B., Fæhn, T., and Rosnes, O. (2018). Residential energy efficiency policies: costs, emissions and rebound effects. *Energy* 143, 191–201. doi: 10.1016/j.energy.2017.10.103

Chitra, A., and Himavathi, S. (2013). "Modeling and experimental validation of solar PV system for cascade H-bridge multilevel inverter," in *International Conference on Power* (Dindigul: IEEE).

Congedo, P. M., Malvoni, M., Mele, M., and De Giorgi, M. G. (2013). Performance measurements of monocrystalline silicon PV modules in South-eastern Italy. *Energy Convers. Manage.* 68, 1–10. doi: 10.1016/j.enconman.2012.12.017

Dehwah, A. H. A., Asif, M., and Rahman, M. T. (2018). Prospects of PV application in unregulated building rooftops in developing countries: a perspective from Saudi Arabia. *Energy Build.* 171, 76–87. doi: 10.1016/j.enbuild.2018.04.001

Emziane, M., and Al Ali, M. (2015). Performance assessment of rooftop PV systems in Abu Dhabi. *Energy Build.* 108, 101–105. doi: 10.1016/j.enbuild.2015.08.057

ERI (2019). *Report on New Energy Power Generation in China*. Beijing: Energy Research Institute. [in Chinese]

Fu, J., and Quan, Y. (1996). *Industrial Technology Economics*. Beijing: Tsinghua University Press. [in Chinese]

Gooding, J., Crook, R., and Tomlin, A. S. (2015). Modelling of roof geometries from low-resolution lidar data for city-scale solar energy applications using a neighbouring buildings method. *Appl. Energy* 148, 93–104. doi: 10.1016/j.apenergy.2015.03.013

IEA (2016). *Re-Powering Markets: Market Design and Regulation During the Transition to Low-Carbon Power Systems*. Paris: International Energy Agency.

IEA (2018). *World Energy Outlook 2018*. Paris: OECD/IEA.

IEA Statistics (2018). Available online at: https://www.iea.org//statistics/

IRENA (2016). *Accelerating Off-grid Renewable Energy*. Abu Dhabi: International Renewable Energy Agency.

IRENA (2018). *Renewable Power Generation Costs in 2017*. International Renewable Energy Agency. Available online at www.irena.org/publications/2018/Jan/Renewable-powergeneration-costs-in-2017

IRENA (2019). *Innovation Landscape for a Renewable-Powered Future: Solutions to Integrate Variable Renewables*. Abu Dhabi: International Renewable Energy Agency.

Jacques, D. A., Gooding, J., Giesekam, J. J., Tomlin, A. S., and Crook, R. (2014). Methodology for the assessment of PV capacity over a city region using low-resolution lidar data and application to the city of Leeds (UK). *Appl. Energy* 124, 28–34. doi: 10.1016/j.apenergy.2014.02.076

Jones, C., and Gilbert, P. (2018). Determining the consequential life cycle greenhouse gas emissions of increased rooftop photovoltaic deployment. *J. Clean. Prod.* 184, 211–219. doi: 10.1016/j.jclepro.2018.02.140

Larsson, S., Fantazzini, D., Davidsson, S., Kullander, S., and Mikael, H. (2014). Reviewing electricity production cost assessments. *Renew. Sust. Energy Rev.* 30, 170–183. doi: 10.1016/j.rser.2013.09.028

Lau, K. Y., Muhamad, N. A., Arief, Y. Z., Tan, C. W., and Yatim, A. H. M. (2016). Grid-connected photovoltaic systems for Malaysian residential sector: effects of component costs, feed-in tariffs, and carbon taxes. *Energy* 102, 65–82. doi: 10.1016/j.energy.2016.02.064

Li, C., Zhou, D. Q., and Zheng, Y. (2018). Techno-economic comparative study of grid-connected PV power systems in five climate zones, *China. Energy* 165, 1352–1369. doi: 10.1016/j.energy.2018.10.062

Li, Y., and Liu, C. (2018). Revenue assessment and visualisation of photovoltaic projects on building envelopes. *J. Clean. Prod.* 182, 177–186. doi: 10.1016/j.jclepro.2018.01.128

Lingfors, D., Bright, J., Engerer, N., Ahlberg, J., Killinger, S., and Widén, J. (2017). Comparing the capability of low- and high-resolution LiDAR data with application to solar resource assessment, roof type classification and shading analysis. *Appl. Energy* 205, 1216–1230. doi: 10.1016/j.apenergy.2017.08.045

NDRC and NEA (2017). *Opinions on Promoting the Supply Side Reform to Prevent and Solve Overcapacity in the Coal-fired Power Generation Industry*. Beijing: NDRC, NEA. [in Chinese].

NEA (2013). *The Interim Procedures on the Management of Distributed PV Generation*. Available online at: http://zfxxgk.nea.gov.cn/auto87/201312/t20131211_1735.htm (Cited November 18, 2013) [in Chinese].

Radhi, H. (2010). Energy analysis of façade-integrated photovoltaic systems applied to UAE commercial buildings. *Sol. Energy* 84, 2009–2021. doi: 10.1016/j.solener.2010.10.002

Sadineni, S. B., Atallah, F., and Boehm, R. F. (2012). Impact of roof integrated PV orientation on the residential electricity peak demand. *Appl. Energy* 92, 204–210. doi: 10.1016/j.apenergy.2011.10.026

Science Academy and Geography Institute of Henan Province (2018). *Study on the Scheme and Policy of Coal Consumption Cap in Henan Province of China*. Zhengzhou: Science Academy and Geography Institute of Henan Province. [in Chinese]

Short, W., Packey, D., and Holt, T. (1995). *A Manual for Economic Evaluation of Energy Efficiency and Renewable Energy Technologies*. Golden, CO: National Renewable Energy Laboratory. doi: 10.2172/35391

Wang, M., Mao, X., Gao, Y., and He, F. (2018). Potential of carbon emission reduction and financial feasibility of urban rooftop photovoltaic power generation in Beijing. *J. Clean. Prod.* 203, 1119–1131. doi: 10.1016/j.jclepro.2018.08.350

Wiginton, L., Nguyen, H. T., and Pearce, J. M. (2010). Quantifying rooftop solar photovoltaic potential for regional renewable energy policy. *Comput. Environ. Urban Syst.* 34, 345–357. doi: 10.1016/j.compenvurbsys.2010.01.001

Yuan, J., Sun, S., Zhang, W., and Xiong, M. (2014). The economy of distributed PV in China. *Energy* 78, 939–949. doi: 10.1016/j.energy.2014.10.091

Zhao, C., Zhang, W., Wang, Y., Liu, Q., Guo, J., Xiong, M., et al. (2017). The economics of coal power generation in China. *Energy Policy* 105, 1–9. doi: 10.1016/j.enpol.2017.02.020

Conflict of Interest: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

APPENDIX I

Glossary table.

Term	Definition	Term	Definition
CNY	Chinese Yuan	LCA	Life cycle assessment
CfDs	Contracts for Difference	LiDAR	Light Detection and Ranging
CO_2	Carbon dioxide	LCOE	Levelized cost of electricity
DPV	Distributed photovoltaic	MLR	Ministry of Land and Resources
DEM	Digital Elevation Model	MNR	Ministry of Natural Resources
DSM	Digital Surface Model	MW	Megawatt
ERI	Energy Research Insititute	NEA	National Energy Agency
FiT	Feed-in-tariff	NDRC	National Development and Reform Council
GDP	Gross Domestic Product	NPV	Net present value
GW	Gigawatt	NO_X	Nitrogen oxides
GIS	Geographic Information System	PV	Photovoltaic
GHG	Greenhouse gases	PM	Particulate matter
IRENA	International Renewable Energy Agency	PPA	Power purchase agreement
IEA	International Energy Agency	SO_2	Sulfur dioxide
IRR	Internal rate of return	Mtce	Million tons-coal equivalent
kWh	Kilowatt-hours	TWh	Terawatt-hours

APPENDIX II

Supporting policies and governmental subsidies for DPV power.

Year	Policy	Main content	Source
2013	Opinions on promoting the healthy development of the PV industry	Prioritized supporting commercial DPV, encouraging public and household PV	State Council
2013	Notice on exerting price leverage to promote the healthy development of the PV industry	DPV subsidy of 0.42 CNY/kWh	National Development and Reform Commission (NDRC)
2015	Notice on the awarded funds of DPV power generation in Beijing	DPV subsidy of 0.3 CNY/kWh in the first 5 years	Beijing DRC
2018.01	Notice on price policy of PV power generation in 2018	DPV subsidy of 0.37 CNY/kWh	NDRC
2018.06	Notice on matters related to PV power generation in 2018	DPV subsidy of 0.32 CNY/kWh	NDRC
2019.05	Notice on Improving the Price Mechanism of PV Generation	DPV subsidy: 0.1 CNY/kWh for a commercial project and 0.18 CNY/kWh for a residential project	NDRC

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How Social Capital Affects Environmental Performance in China

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Chinese society's unique characteristics present challenges with regard to discovering new ways to tackle tremendous environmental problems. This paper examines the effect of provincial social capital on environmental performance in China. In the first stage of the analysis, we measured the environmental performance levels of the 2011–2017 panel data of 30 provinces in China. We did this using data envelopment analysis (DEA). After introducing the concept of social capital, we innovatively built the social capital index system based on China's national conditions and measured social capital data from three perspectives. Then, we used the Probit regression model to explore the effect of social capital on environmental performance. The results show that the environmental performance of the well-known and better developed regions of China (such as Beijing, Shanghai, etc.) is significantly higher than other regions. Social capital and environmental performance are related in general. However, the effect of social capital on environmental performance is heterogeneous in different regions. They are more consistent in the eastern and southwest regions but are less stable in other regions. Among the three types of social capital, structural capital has the most obvious benefits for environmental performance. This is followed by relational capital and innovative capital. Furthermore, it has been found that the proportion of the tertiary industry in GDP and the level of social trust are the largest indicators of the rates at which structural capital and relational capital contribute, respectively, to environmental performance.

Keywords: social capital, environmental performance, data envelopment analysis, China, innovative capital, structural capital, relational capital

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INTRODUCTION

China is currently facing tremendous environmental pressures (Liao, 2018; Hang et al., 2019; Zhang et al., 2019a). The government has tackled these in various ways, such as by promoting the use of clean energy and introducing tough policies (Zhang et al., 2019c), and have achieved good results (Zhang and Li, 2018; Zhang et al., 2019b). However, these methods often overlook Chinese society's specific characteristics and pose their own challenges. The trends of social space segmentation and structural solidification make protecting the environment difficult. For this reason, we start from the perspective of social capital to try and find new ways to solve environmental governance.

The concept "social capital" was first used by sociologists. Specifically, Granovetter was the first to conceptualize social capital. According to the World Bank's Social Capital Initiative, social capital refers to collective actions taken by the government and civil society for the mutual benefit of an organization. Similarly, according to the Organization for Economic Cooperation and Development (OECD) (Healy and Côté, 2001), social capital is a network that promotes cooperation within and among groups. This network contains norms, values, and understandings that are recognized by group members. Unfortunately, the multifaceted nature of social capital has meant that it has a wide range of definitions in the academic literature, with no consensus on how it should be measured (Svendsen and Svendsen, 2009). In general, social capital can be understood as an association between individuals or groups. It refers to the social networks, reciprocal norms, and resulting trust that people get from their positions in the social structure.

Putnam et al. (1994) and Knack and Keefer (1997) all found that there is a positive correlation between social capital and economic phenomena. Similarly, Pretty and Ward (2001) argue that social capital can increase cooperation and participation within a given community, resulting in greater collectivism and increased willingness to protect natural resources. Jones (2009) claims that social capital is positively related to the achievement of environmental goals because social capital is associated with the individual perceived costs and benefits of environmental policies. Moreover, Halkos and Jones (2012) show that certain forms of social capital, especially social norms and trust, are positively related to people's willingness to pay for environmental taxes. With adequate social capital, citizens are more inclined to protect their environment because they expect their peers to do the same. Similar conclusions were found by Polyzou et al. (2011), Liu et al. (2014), and Czajkowski et al. (2015).

Bjørnskov and Méon (2015) point out that social capital may also influence environmental behaviors depending on the quality of the government, the institutional framework, and the degree of corruption. Fredriksson et al. (2004) found a negative correlation between corruption and the outcomes of energy policies in a sample of OECD countries. Grafton and Knowles (2016), however, found no significant causal relationship between various elements of social capital and several indicators of environmental quality. That being said, they did acknowledge the complexity of social capital and suggest that it needed further research. Peiró-Palomino and Picazo-Tadeo (2018) analyzed the relationship between social capital and environmental performance in the European Union and they failed to reject the hypothesis that social capital has no effect on environmental performance.

At present, the Chinese government is yet to realize the importance of social for solving environmental problems. Starting from the unique perspective of social capital, therefore, this paper addresses it with respect to the characteristics of Chinese society. Based on original first-hand data from the Chinese Social Survey (CSS), we calculate the elements of social capital that are more in line with China's national conditions. On the basis of these results, the effect of social capital on environmental performance is studied. The results of the research highlight the heterogeneity of social capital in different regions and demonstrate how different types of social capital contribute to environmental performance. The results can provide a more powerful and China-oriented basis for the formulation of future policies.

The remainder of the paper is organized as follows: section Methodology and Data describes the methodology and data, section Results and Discussion presents the results, and the final section offers a summary and a conclusion.

METHODOLOGY AND DATA

Measurement of Environmental Performance

To measure environmental performance, we selected the method of data envelopment analysis (DEA). This method has been widely used in performance measurement and has proven effective for measuring energy efficiency (Blomberg et al., 2012; Wang et al., 2013, 2018; Wu et al., 2013; Blancard and Martin, 2014; Xue et al., 2015) and environmental performance (Zhou et al., 2006, 2007, 2008; Jin et al., 2014). However, real production processes often generate undesirable outputs; these should be reduced as much as possible in order to ensure optimal economic efficiency. DEA cannot handle this problem automatically. Tone (2001) established the slack-based measure (SBM) model as a way of addressing this limitation. Due to its ability to solve problems of input–output slack and avoid the influence of radial and oriented choice, the SBM model has become the most powerful and popular tool for evaluating efficiency. It has been successfully used to evaluate the performance of banks (Juo et al., 2012; Avkiran and Cai, 2014), airports (Yu, 2010), the environment (Na et al., 2017; Cecchini et al., 2018; Wang et al., 2019), and more. For this reason, the SBM model was chosen to measure environmental performance. The SBM model is shown below.

$$
\min \rho = \frac{1-\frac{1}{m}\sum_{i=1}^{m}\frac{s_i^{x-}}{x_{i0}}}{1+\frac{1}{s_d+s_u}\left(\sum_{d=1}^{d}\frac{s_d^{y+}}{y_{d0}}+\sum_{u=1}^{u}\frac{s_u^{b-}}{b_{u0}}\right)}
$$

$$
\begin{aligned}
s.t.\quad x_{i0} &= \sum_{j=1}^{n}\lambda_j x_{ij}+s_i^{x-} && i=1,2,\ldots,m\\
y_{d0} &= \sum_{j=1}^{n}\lambda_j y_{dj}-s_d^{y+} && d=1,2,\ldots,p\\
b_{u0} &= \sum_{j=1}^{n}\lambda_j b_{uj}+s_u^{b-} && u=1,2,\ldots,q\\
& \lambda \geq 0, s_i^{x-}\geq 0, s_d^{y+}\geq 0, s_u^{b-}\geq 0
\end{aligned}
$$

ρ represents the environmental performance; m represents the number of decision-making units (DMU); p represents the number of desirable outputs; q represents the number of undesirable outputs. The numerator in the ρ formula represents the ratio at which the amount actually invested by a given evaluation unit can be reduced relative to the average of the production front; that is, the input is invalid. The denominator indicates the actual output of the evaluated unit relative to the production. $x_{ij}\,(i = 1, 2, \ldots, m)$ represents the ith input indicator of DMU_j; $y_{dj}\,(d = 1, 2, \ldots, p)$ represents the dth desirable output indicator of DMU_j; $b_{uj}\,(u = 1, 2, \ldots, q)$ denotes

TABLE 1 | Statistical description of input and output variables.

			Mean	Max	Min	Std
Input	Labor	10^6 people	26.41	67.67	1.86	17.92
	Total social water consumption	10^4 million cubic meters	1.96	5.91	0.23	1.45
	Energy consumption	10^7 tons coal equivalent	14.27	38.72	0.44	8.38
Desirable output	GDP	10^7 RMB	22.02	84.05	0.61	17.36
Undesirable output	CO_2 emissions	10^8 tons	6.01	27.40	0.65	4.90
	Total industrial wastewater	10^8 tons	22.59	93.83	0.46	18.41
	Industrial sulfur dioxide pollutants	10^4 tons	55.29	182.74	0.35	40.23
	Industrial nitrogen oxides pollutants	10^4 tons	53.66	180.11	0.35	39.33
	Industrial smoke dust pollutants	10^4 tons	50.93	179.77	0.35	37.99

the undesirable output indicator of DMU_j; $s_i^{x-} \in R, s_d^{y+} \in R^d$, *and* $s_u^{b-} \in R^u$ represent the slack variable of the input, the desirable output, and the undesirable output.

We have selected the appropriate indicators and data sources based on this particular model. According to literature review (Zhou et al., 2006, 2007; Wang et al., 2013; Wu et al., 2013; Jin et al., 2014; Wang et al., 2019), we find that capital investment, labor input, social water consumption, energy consumption, GDP, carbon dioxide (CO_2) emissions, industrial wastewater, and industrial emissions are the most used indicators. However, capital investment is somewhat relevant to social capital, so we didn't choose it as our indicators. Starting with the 12th Five-Year Plan, data from 2011 to 2017 was selected. As there are no data for the Autonomous Region of Tibet, the DMUs add up to a total of 30 provincial administrative units. Each DMU has three types of inputs, one type of expected output, and five types of undesired outputs. The inputs are as follows: labor input (x_{1j}), total social water consumption (x_{2j}), and energy consumption (x_{3j}). The desirable output is GDP (y_{1j}). The five undesirable outputs are carbon dioxide (CO_2) emissions (b_{1j}), total industrial wastewater discharges (b_{2j}), industrial sulfur dioxide emissions (b_{3j}), industrial nitrogen oxides emissions (b_{4j}), and industrial smoke dust emissions (b_{5j}). The data sources used are the China Statistical Yearbook and the China Energy Statistics Yearbook.

From a geographic perspective and a convenient picture display, we divided 30 DMUs into six regions: Northeast China (Heilongjiang, Jilin, and Liaoning), North China (Beijing, Tianjin, Hebei, Shanxi, and Inner Mongolia), East China (Shanghai, Jiangsu, Zhejiang, Jiangxi, Anhui, Fujian, and Shandong), Central South (Henan, Hubei, Hunan, Guangdong, Guangxi, and Hainan), Northwest China (Shaanxi, Gansu, Qinghai, Ningxia, and Xinjiang), and Southwest China (Chongqing, Sichuan, Guizhou, and Yunnan).

The calculation of CO_2 emissions is based on the net calorific value and CO_2 emission factor data of various energy sources issued by the 2006 IPCC Guidelines (Eggleston et al., 2006) for National Greenhouse Gas Inventories. These data are combined with the regional energy balance sheets of each province in order to ensure that the calculation results are more realistic. The following energy varieties should be included as comprehensively as possible: raw coal, clean coal, other coal washing, coke, coke oven gas, crude oil, gasoline, diesel, kerosene, fuel oil, petroleum coke, natural gas, liquefied petroleum gas, and other petroleum products. This is a total of 14 kinds of energy varieties. The specific calculation based on the IPCC Guidelines is as follows:

$$\sum CO_2 = \sum C_{\mathrm{i}} \times NCV_i \times CEF_{\mathrm{i}} \times COF_{\mathrm{i}}$$

Where CO_2 is the carbon dioxide emission of energy, C_i is the actual consumption of the ith type of energy source, NCV_i is the net calorific value of the ith energy, CEF_i is the carbon dioxide emission factor of the ith energy, and COF_i is the carbon oxidation rate of the ith energy source. For ease of calculation, the COF_i is taken as 1. The statistical description of input and output variables are shown in **Table 1**.

Measurement of Social Capital

When it came to assessing the measurement of social capital, we referred to a wide range of studies. We found that scholars usually divide social capital into several categories in order to measure it. Based on their various categories and indicators (Putnam et al., 1994; Grootaert et al., 1999; Pretty and Ward, 2001; Villalonga-Olives and Kawachi, 2015) and considering China's special national conditions, we have identified three types of categories. These are innovative capital, structural capital, and relational capital. The evaluation indicators for each category are shown in **Table 2**.

Since CSS data are currently only available up until 2015, and as the Chinese government began to implement the Environmental Protection Law in 2015, when studying the effect of social capital on environmental performance, we only used data from 2015. This is to ensure that the research results are more instructive for future national policy developments.

We used the entropy method to process the data concerning social capital. In general, if the weight of an indicator is smaller, it demonstrates that the greater the degree of variation of the indicator value, the more information is provided, and the greater the role that this indicator should play in the comprehensive final evaluation.

The weights of the final calculated indicators are shown in **Table A1**. After measuring the index weights by using the entropy weight method, the data were synthesized into a comprehensive index.

TABLE 2 | The social capital indicator system.

Category	Variables	Data Sources
Innovative capital	The proportion of undergraduate education or above in scientific and technological activities	Regional statistical yearbook
	Number of patent applications	
	Number of people in R&D activities	
	Funding for R&D activities	
Structural capital	Age structure of permanent population (15–64 years old)	Regional statistical yearbook
	Proportion of women in the permanent population	
	The tertiary industry accounts for the proportion of GDP	
Relational capital	Social equity level	China Social Survey (2015)[a]
	Social participation willingness	
	Social trust level	
	Social security level	

[a]*The relational capital data used in this paper comes from the China Society of Social Sciences major project "China Social Survey (2015)" This survey was conducted by the Institute of Sociology of the Chinese Academy of Social Sciences, and the project leader is Li Pei-lin. Thanks to the above institutions and personnel for providing assistance with data.*

RESULTS AND DISCUSSION

The Results of Environmental Performance

According to the index system elaborated in section Methodology and Data, we collected and pre-organized the data before calculating the environmental performance level (EPL) of each province in 2011–2017 according to the SBM model. The final results are shown in **Figure 1**.

The above charts show the level of environmental performance in China's six major regions from 2011 to 2017. From the results of the EPL, it is not difficult to see that the best-performing provinces are Beijing, Tianjin, Shanghai, Jiangsu, Shandong, Guangdong, Inner Mongolia, Hainan, and Qinghai. Other provinces in these regions, as well as all the provinces in the Northeast and Southwest, have a performance level of <0.2. The most noteworthy province is Zhejiang, which has been technically effective since 2014. Our analysis suggests that the reason for this is related to Zhejiang Province's introduction of tough environmental regulations in early 2014.

It can also be seen from this analysis that the EPL of various provinces in China is improving year by year. Nonetheless, the eastern region still performs better than the central and western regions. Looking at these figures in more detail, it becomes clear that the EPL of the provinces other than those at the frontier are essentially not fluctuating. The EPL of the provinces in the northeastern regions has declined slightly in recent years, and the EPL of the provinces in other regions has increased slightly in recent years.

Social Capital Measurement Results

The final measurement results of social capital level (SCL) are shown in **Figure 2**. It can be seen from **Figure 2** that the eastern coastal areas and the Beijing province have the highest levels of social capital. The overall trend is a gradual decrease in social capital from east to west. The province with the highest SCL in 2015 was Jiangsu.

It can be seen from the above figure that the overall trend is for a high level of social capital in the east and a low level of social capital in the west. As far as the average level of the six regions is concerned, the social capital levels in the provinces of the eastern, northern, and central regions are heterogeneous. The heterogeneity in other regions is relatively small. From **Table A2**, we can see that the biggest gap between adjacent regions is Guangdong and Hainan in Central and South China. Guangdong ranks second whereas Hainan ranks second to the last. Both the northeast and northwest regions have very low levels of social capital.

In addition, by observing the SCL of Beijing-Tianjin-Hebei, the Yangtze River Delta, the Pearl River Delta, and the surrounding provinces, we can see that the deep red region of the Yangtze River Delta has the widest range. This means that, on average, it has the highest level of social capital. Therefore, we have reason to believe that the three provinces of Jiangsu, Zhejiang, and Shanghai have relatively good knock-on effects on their surrounding provinces.

If we look at the capital outcomes of the three categories separately, we note that the results of relational capital are interesting. It is not difficult to see from the bar chart below (**Figure 3**) that the relational capital levels of the regions with economies that are relatively more developed are lower. Xinjiang, for example, has the highest level of relational capital, whereas Beijing, Jiangsu, and Shanghai rank the bottom. We believe that this result is consistent with the current state of Chinese society.

In this regard, we speculate that the more developed the economy, the more atomized the people and the easier it is to be outside the social system. Furthermore, we speculate that this would lead to a decline of social relations capital and the emergence of a crisis of social trust. This, however, is not the main focus of this paper; the reasons for this phenomenon need further study.

The Contribution of Social Capital to Environmental Performance

To explore the effect of social capital on environmental performance, we first display the EPL and SCL of various provinces in China in 2015 on the maps that are shown in **Figure 4**. Comparing these two maps, we can see that the SCL and EPL are generally consistent. In other words, environmental performance is better in regions with higher social capital. There are, however, some provinces with abnormalities.

The environmental performance and social capital levels of the six regions in 2015 are plotted in more detail on the scatter chart in **Figure 5**. From this, it can be seen that social capital and environmental performance are more consistent in the eastern and southwest regions. The other regions are less stable.

From the above two figures, we can easily see that social capital and environmental performance are related in general. We have adopted Probit regression of the binary discrete selection model to help us reflect the impact of social capital on environmental performance more accurately.

Firstly, it is important to take the particularity of the results of environmental performance into account: that is, the

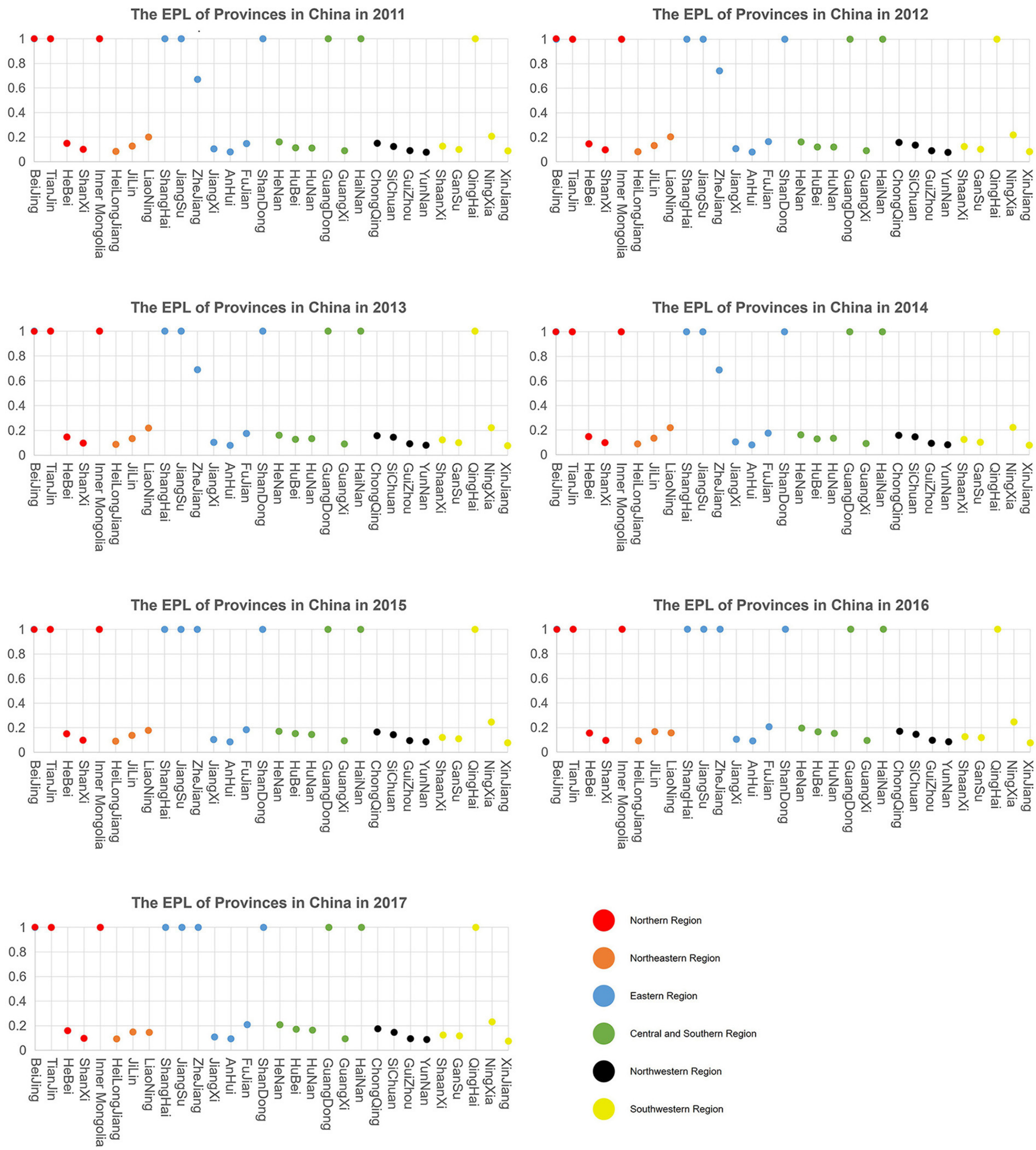

FIGURE 1 | EPL of various provinces in China by year.

performance at the frontier is 1 and the performance at the frontier is very small (performance is <0.25). This makes the general regression model difficult to portray the impact of social capital on environmental performance accurately. For the case where the environmental performance of this paper is either 1 or very small, we approximate it as the selection problem. In other words, the performance is at the frontier and is not at the frontier; the binary discrete selection model is selected. The original model is shown below:

$$\boldsymbol{Y_i = \alpha + \beta X_i + \mu_i,\ \ i = 1, 2, \cdots, 30}$$

Y_i represents the environmental performance level, X_i represents the social capital level, α is the drift, β is the slope, and μ_i is the error term.

The results of Probit regression are shown in **Table 3**.

From the above results, it can be seen that social capital has a significant effect on environmental performance. In areas with higher social capital, the environmental performance table is better. According to the Probit regression model, when the social capital of a province is known, the observations of the environmental performance of the province can be calculated. This observation highlights the possibility that the province's environmental performance is at the frontier.

Combined with the weights of the specific indicators obtained by the entropy method outlined in section Methodology and Data, it can be argued that structural capital in social capital contributes the most to environmental performance. This is followed first by relational capital and finally by innovation capital. The contribution of the tertiary industry to GDP is the largest contributing factor to structural capital. The indicator of social trust is the most relevant for relational capital.

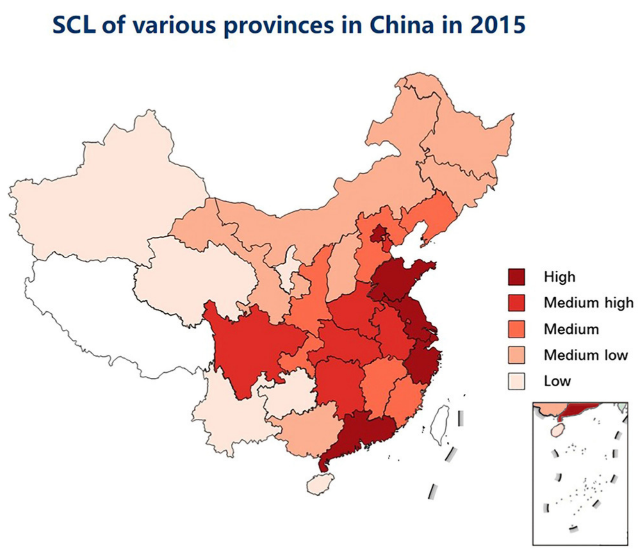

FIGURE 2 | SCL of various provinces in China in 2015.

The relatively unorthodox provinces are Inner Mongolia, Qinghai, Hainan, Anhui, and Ningxia. Inner Mongolia, Qinghai, Hainan, and Ningxia all have high levels of environmental performance and low levels of social capital. By multiplying the coefficients of three small indicators of innovation capital with the measurement model and the raw data of social capital for these four provinces, we can account for why the numerical results regarding social capital are so small. These three indicators are the number of patent applications, the number of people in R&D activities, and the funding for R&D activities. Anhui Province has high social capital, but a low environmental performance. This may be due to the fact that Anhui was affected by Jiangsu and Zhejiang; it received a certain degree of knock-on economic growth and also accepted the transfer of industrial enterprises. This resulted in more serious environmental pollution.

However, due to data sources, there are statistical yearbook data from various provinces in China and social capital data based on questionnaires published by CSS. In the data processing, we found that the statistical methods of the same indicator in the statistical yearbooks of different provinces are different. We try to select the original data of the same method when selecting the data. The questionnaires used to investigate social capital data have different ways of asking questions in different years, so the authenticity of the data will have an impact on the research results of this paper.

In response to the results, we believe that there are two ways to improve the levels of environmental performance.

Firstly, the proportion of the tertiary industry in GDP could be increased. The tertiary industry is a service industry, and its unique service functions promote the development of primary

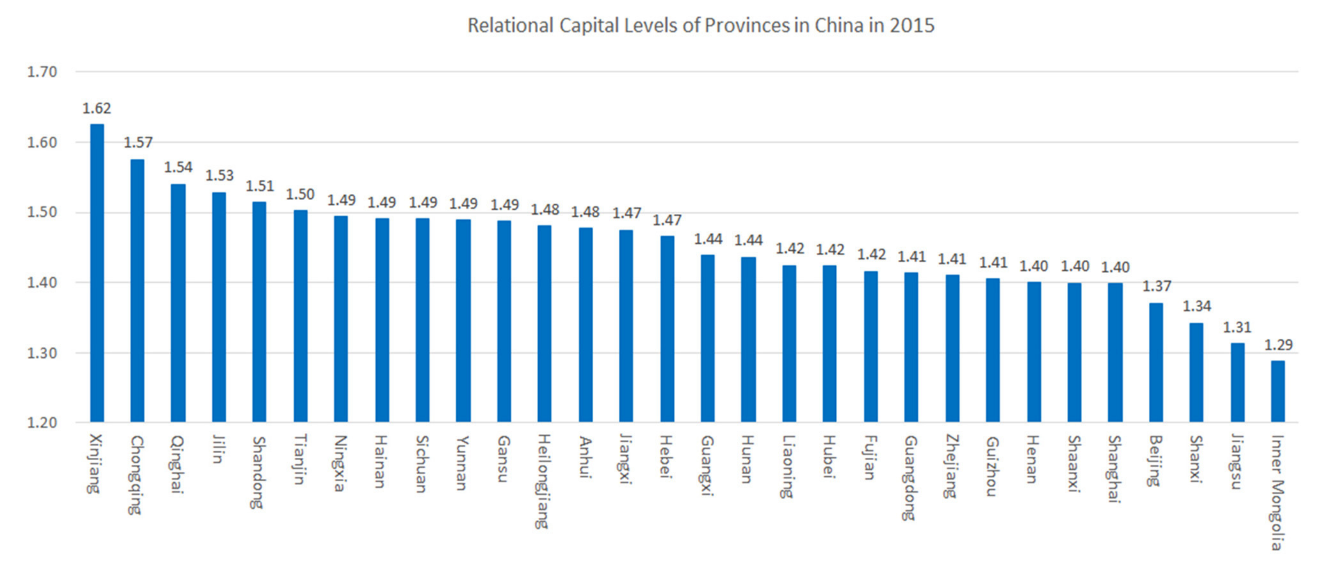

FIGURE 3 | Relational capital levels of provinces in China in 2015.

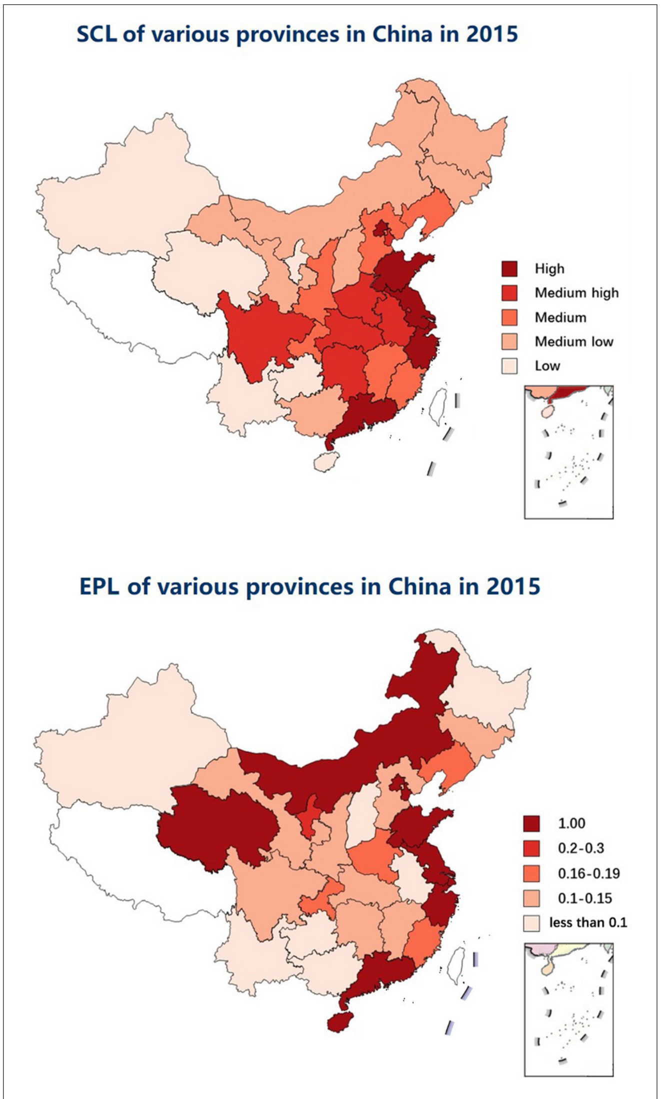

FIGURE 4 | Maps of SCL and EPL in China in 2015.

and secondary industries and the entire national economy. It also meets the needs of the nation for a better life in the future. For this reason, it is recommended that the government continue to support the development of the tertiary industry and formulate a more favorable policy environment. They could provide tax incentives, loan concessions, and talent introduction support.

In addition, according to the results that the Yangtze River Delta region has the best radiation effect, the government should strengthen economic cooperation among provinces to transform it into an intensive development model of "low consumption, low pollution and high output." At the same time, "the proportion of undergraduate education or above in scientific and technological activities" is the most important indicator of innovation capital. The government should vigorously develop higher education and cultivate high-quality talents. Increase investment in research funding and accelerate the flow and spread of energy-saving and emission reduction technologies between regions.

Secondly, they could increase the level of social trust. Bjørnskov (2006) finds that social polarization in the form of income inequality reduces social trust. Bjørnskov (2009) also argues that social trust affects both schooling and the rule of law directly. As demonstrated by the CSS questionnaire, social trust is mainly related to interpersonal relationships, the degree of government corruption, and the degree of citizenship. Social trust is related not only to culture and social systems, but also to individual objective factors such as age and education level.

From the perspective of macroeconomic policy, the government should strive to build a stable social norm and a good social trust system. It should also promote clean government and reduce corruption. It should promote equal opportunities, fair education, and fair income distribution. From a micro-psychological perspective, individuals should also give full play to their subjective initiative. They should actively participate in social activities, uphold the values of equality, and offer mutual assistance. They should be good neighbors and work to create a healthy and harmonious atmosphere.

CONCLUSION

This paper has taken the unique characteristics of Chinese society into account. It has looked at both the human society and the relationship society, and it has focused on the effect of China's provincial social capital on environmental performance.

In the first stage, we used the SBM model to measure the environmental performance level of the 2011–2017 panel data from 30 provinces in China. The results showed that the environmental performance levels of the more developed regions (such as Beijing, Shanghai, Jiangsu, and others) were significantly higher than the rest. As a whole, it can be seen that the environmental performance levels of various provinces in China are improving year by year, although the eastern region still performs better than both the central and the western region.

In the second stage of the research, we introduced the concept of social capital and divided it into three categories: innovation capital, structural capital, and relational capital. We used the Probit regression model to explore the effect of social capital on environmental performance. From the results, it is clear that the effect of social capital on environmental performance is significant. Structural capital has the most obvious impact on environmental performance. This is followed by relational capital. It was further found that the proportion of the tertiary industry in GDP and the level of social trust are the factors that contribute most to the rate of structural capital and relational capital, respectively.

Based on research results, we put forward two suggestions: increasing the proportion of the tertiary industry in GDP and increasing the level of social trust. We also put forward macro and micro specific measures for the two proposals. Overall, the results of this paper offer a new means for assessing the effect of social capital on environmental performance. However, the results also involve some limitations: whether or not there is a non-linear relationship between social capital and environmental performance, and how the economic meaning is represented at the inflection point is worth studying.

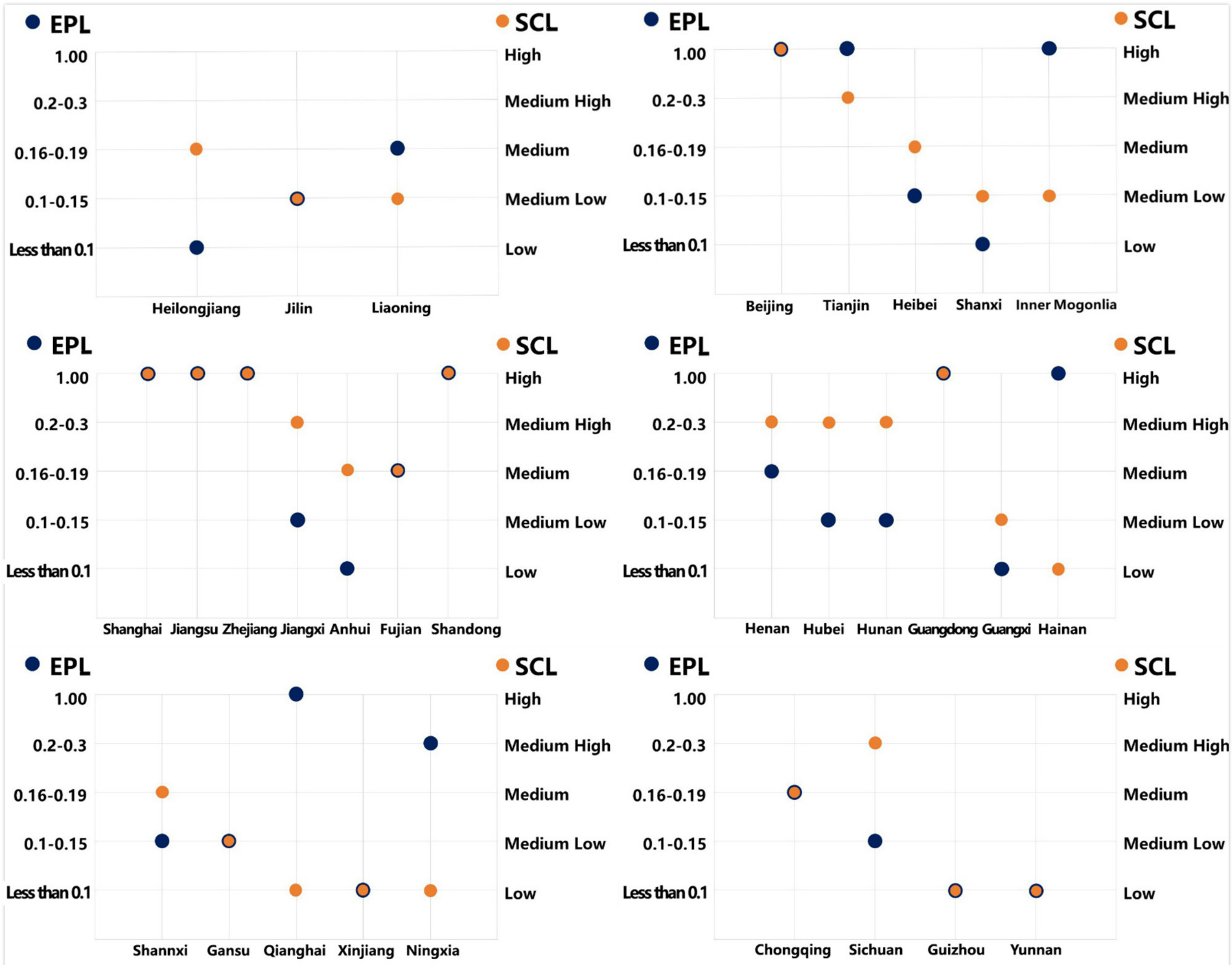

FIGURE 5 | Scatter plot of SCL and EPL in China in 2015.

TABLE 3 | The estimation result of Probit regression.

Coefficients	Estimate	Std.	Error z	value Pr (>|z|)
(Intercept)	−1.302e+00	4.014e−01	−3.244	0.00118**
SC	3.846e−06	1.447e−06	2.658	0.00787**

***99% confidence level.*

DATA AVAILABILITY STATEMENT

All datasets generated for this study are included in the article/supplementary material.

AUTHOR CONTRIBUTIONS

QW designed the paper framework. TL wrote the manuscript. DZ provided policy recommendations and data.

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REFERENCES

Avkiran, N. K., and Cai, L. (2014). Identifying distress among banks prior to a major crisis using non-oriented super-SBM. *Annu. Open Res.* 217, 31–53. doi: 10.1007/s10479-014-1568-8

Bjørnskov, C. (2006). Determinants of generalized trust: a cross-country comparison. *Public Choice* 130, 1–21. doi: 10.1007/s11127-006-9069-1

Bjørnskov, C. (2009). Social trust and the growth of schooling. *Econ. Educ. Rev.* 28, 249–257. doi: 10.1016/j.econedurev.2006.09.013

Bjørnskov, C., and Méon, P.-G. (2015). The productivity of trust. *World Dev.* 70, 317–331. doi: 10.1016/j.worlddev.2015.01.015

Blancard, S., and Martin, E. (2014). Energy efficiency measurement in agriculture with imprecise energy content information. *Energy Policy* 66, 198–208. doi: 10.1016/j.enpol.2013.10.071

Blomberg, J., Henriksson, E., and Lundmark, R. (2012). Energy efficiency and policy in Swedish pulp and paper mills: a data envelopment analysis approach. *Energy Policy* 42, 569–579. doi: 10.1016/j.enpol.2011.12.026

Cecchini, L., Venanzi, S., Pierri, A., and Chiorri, M. (2018). Environmental efficiency analysis and estimation of CO2 abatement costs in dairy cattle farms in Umbria (Italy): a SBM-DEA model with undesirable output. *J. Clean. Prod.* 197, 895–907. doi: 10.1016/j.jclepro.2018.06.165

Czajkowski, M., Hanley, N., and Nyborg, K. (2015). Social norms, morals and self-interest as determinants of pro-environment behaviours: the case of household recycling. *Environ. Resour. Econ.* 66, 647–670. doi: 10.1007/s10640-015-9964-3

Eggleston, S., Buendia, L., Miwa, K., Ngara, T., and Tanabe, K. (eds.). (2006). "Energy," in *2006 IPCC guidelines for national greenhouse gas inventories*. Vol. 2 (Hayama: Institute for Global Environmental Strategies), 2.6–2.23.

Fredriksson, P. G., Vollebergh, H. R. J., and Dijkgraaf, E. (2004). Corruption and energy efficiency in OECD countries: theory and evidence. *J. Environ. Econ. Manage.* 47, 207–231. doi: 10.1016/j.jeem.2003.08.001

Grafton, R. Q., and Knowles, S. (2016). Social capital and national environmental performance: a cross-sectional analysis. *J. Environ. Dev.* 13, 336–370. doi: 10.1177/1070496504271417

Grootaert, C., Oh, G.-T., and Swamy, A. V. (1999). *The Local Level Institutions Study: Social Capital and Development Outcomes in Burkina Faso,* Vol. 7. Washington, DC: World Bank, Social Development Family, Environmentally and Socially Sustainable Development Network, 1–54.

Halkos, G. E., and Jones, N. (2012). Modeling the effect of social factors on improving biodiversity protection. *Ecol. Econ.* 78, 90–99. doi: 10.1016/j.ecolecon.2012.04.003

Hang, Y., Wang, Q., Wang, Y., Su, B., and Zhou, D. (2019). Industrial SO2 emissions treatment in China: a temporal-spatial whole process decomposition analysis. *J. Environ. Manage.* 243, 419–434. doi: 10.1016/j.jenvman.2019.05.025

Healy, T., and Côté, S. (2001). *The Well-Being of Nations: The Role of Human and Social Capital.* Education and Skills, ERIC.

Jin, J., Zhou, D., and Zhou, P. (2014). Measuring environmental performance with stochastic environmental DEA: the case of APEC economies. *Econ. Model.* 38, 80–86. doi: 10.1016/j.econmod.2013.12.017

Jones, N. (2009). Investigating the influence of social costs and benefits of environmental policies through social capital theory. *Policy Sci.* 43, 229–244. doi: 10.1007/s11077-009-9107-1

Juo, J.-C., Fu, T.-T., and Yu, M.-M. (2012). Non-oriented slack-based decompositions of profit change with an application to Taiwanese banking. *Omega* 40, 550–561. doi: 10.1016/j.omega.2011.11.002

Knack, S., and Keefer, P. (1997). Does social capital have an economic payoff? A cross-country investigation. *Q. J. Econ.* 112, 1251–1288. doi: 10.1162/003355300555475

Liao, X. (2018). Public appeal, environmental regulation and green investment: evidence from China. *Energy Policy* 119, 554–562. doi: 10.1016/j.enpol.2018.05.020

Liu, J., Qu, H., Huang, D., Chen, G., Yue, X., Zhao, X., et al. (2014). The role of social capital in encouraging residents' pro-environmental behaviors in community-based ecotourism. *Tourism Manage.* 41, 190–201. doi: 10.1016/j.tourman.2013.08.016

Na, J.-H., Choi, A. Y., Ji, J., and Zhang, D. (2017). Environmental efficiency analysis of Chinese container ports with CO 2 emissions: an inseparable input-output SBM model. *J. Trans. Geogr.* 65, 13–24. doi: 10.1016/j.jtrangeo.2017.10.001

Peiró-Palomino, J., and Picazo-Tadeo, A. J. (2018). Is social capital green? Cultural features and environmental performance in the European union. *Environ. Res. Econ.* 72, 795–822. doi: 10.1007/s10640-018-0226-z

Polyzou, E., Jones, N., Evangelinos, K. I., and Halvadakis, C. P. (2011). Willingness to pay for drinking water quality improvement and the influence of social capital. *J. Socio. Econ.* 40, 74–80. doi: 10.1016/j.socec.2010.06.010

Pretty, J., and Ward, H. (2001). Social capital and the environment. *World Dev.* 29, 209–227. doi: 10.1016/S0305-750X(00)00098-X

Putnam, R. D., Leonardi, R., and Nanetti, R. Y. (1994). *Making Democracy Work: Civic Traditions in Modern.* New Jersey, NJ: Princeton University Press. doi: 10.1515/9781400820740

Svendsen, G. T., and Svendsen, G. L. H. (2009). *Handbook Of Social Capital: The Troika of Sociology, Political Science and Economics*. Cheltenham: Edward Elgar Publishing.

Tone, K. (2001). A slacks-based measure of efficiency in data envelopment analysis. *Eur. J. Oper. Res.* 130, 498–509. doi: 10.1016/S0377-2217(99)00407-5

Villalonga-Olives, E., and Kawachi, I. (2015). The measurement of social capital. *Gaceta Sanitaria* 29, 62–64. doi: 10.1016/j.gaceta.2014.09.006

Wang, K., Wu, M., Sun, Y., Shi, X., Sun, A., and Zhang, P. (2019). Resource abundance, industrial structure, and regional carbon emissions efficiency in China. *Res. Policy* 60, 203–214. doi: 10.1016/j.resourpol.2019.01.001

Wang, Q., Hang, Y., Su, B., and Zhou, P. (2018). Contributions to sector-level carbon intensity change: an integrated decomposition analysis. *Energy Econ.* 70, 12–25. doi: 10.1016/j.eneco.2017.12.014

Wang, Q., Zhao, Z., Zhou, P., and Zhou, D. (2013). Energy efficiency and production technology heterogeneity in China: a meta-frontier DEA approach. *Econ. Model.* 35, 283–289. doi: 10.1016/j.econmod.2013.07.017

Wu, A.-H., Cao, Y.-Y., and Liu, B. (2013). Energy efficiency evaluation for regions in China: an application of DEA and Malmquist indices. *Energy Efficien.* 7, 429–439. doi: 10.1007/s12053-013-9232-8

Xue, X., Wu, H., Zhang, X., Dai, J., and Su, C. (2015). Measuring energy consumption efficiency of the construction industry: the case of China. *J. Clean. Prod.* 107, 509–515. doi: 10.1016/j.jclepro.2014.04.082

Yu, M.-M. (2010). Assessment of airport performance using the SBM-NDEA model. *Omega* 38, 440–452. doi: 10.1016/j.omega.2009.11.003

Zhang, M., and Li, H. (2018). New evolutionary game model of the regional governance of haze pollution in China. *Appl. Math. Model.* 63, 577–590. doi: 10.1016/j.apm.2018.07.008

Zhang, M., Li, H., Song, Y., and Li, C. (2019a). Study on the heterogeneous government synergistic governance game of haze in China. *J. Environ. Manage.* 248:109318. doi: 10.1016/j.jenvman.2019.109318

Zhang, M., Li, H., Xue, L., and Wang, W. (2019b). Using three-sided dynamic game model to study regional cooperative governance of haze pollution in China from a government heterogeneity perspective. *Sci. Total Environ.* 694:133559. doi: 10.1016/j.scitotenv.2019.07.365

Zhang, M., Liu, X., Ding, Y., and Wang, W. (2019c). How does environmental regulation affect haze pollution governance?—An empirical test based on Chinese provincial panel data. *Sci. Total Environ.* 695:133905. doi: 10.1016/j.scitotenv.2019.133905

Zhou, P., Ang, B. W., and Poh, K.-L. (2008). A survey of data envelopment analysis in energy and environmental studies. *Eur. J. Oper. Res.* 189, 1–18. doi: 10.1016/j.ejor.2007.04.042

Zhou, P., Ang, B. W., and Poh, K. L. (2006). Slacks-based efficiency measures for modeling environmental performance. *Ecol. Econ.* 60, 111–118. doi: 10.1016/j.ecolecon.2005.12.001

Zhou, P., Poh, K. L., and Ang, B. W. (2007). A non-radial DEA approach to measuring environmental performance. *Eur. J. Oper. Res.* 178, 1–9. doi: 10.1016/j.ejor.2006.04.038

China Social Survey (2015). Institute of Sociology, Chinese Academy of Social Sciences. Available online at: http://css.cssn.cn/css_sy/zlysj/lnsj/201706/t20170615_3551582.html

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APPENDIX

Table A1 | The weight of the social capital indicator system.

Category	First-layer weight	Variables	Second-layer weight
Innovative capital	0.204	The proportion of undergraduate education or above in scientific and technological activities	0.405
		Number of patent applications	0.137
		Number of people in R&D activities	0.227
		Funding for R&D activities	0.231
Structural capital	0.415	Age structure of permanent population (15–64 years old)	0.427
		Proportion of women in the permanent population	0.098
		The tertiary industry accounts for the proportion of GDP	0.475
Relational capital	0.381	Social equity level	0.139
		Social participation willingness	0.279
		Social trust level	0.293
		Social security level	0.289

Table A2 | The SCL results of the provinces in China in 2015.

Provinces	SCL	Ranks	Provinces	SCL	Ranks
Jiangsu	2.64	1	Hebei	1.87	14
Guangdong	2.56	2	Chongqing	1.86	17
Shandong	2.52	3	Jiangxi	1.85	18
Beijing	2.43	4	Jilin	1.84	19
Zhejiang	2.23	5	Shanxi	1.81	20
Shanghai	2.18	6	Inner Mongolia	1.79	21
Hubei	2.04	7	Heilongjiang	1.78	22
Tianjin	2.00	8	Guangxi	1.78	22
Sichuan	1.97	9	Gansu	1.76	24
Henan	1.95	10	Guizhou	1.75	25
Anhui	1.94	11	Yunnan	1.74	26
Hunan	1.92	12	Xinjiang	1.71	27
Fujian	1.89	13	Ningxia	1.68	28
Shaanxi	1.87	14	Hainan	1.67	29
Liaoning	1.87	14	Qinghai	1.60	30

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Green Mining Efficiency and Improvement Countermeasures for China's Coal Mining Industry

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This study defines a green mining system as a synergetic operation system composed of a mining subsystem and an environmental governance subsystem. Through conducting a case study of China's coal enterprises, this study identifies the mining subsystem as the first production stage and the environmental governance subsystem as the second production stage. To evaluate green mining efficiency, an entire green mining efficiency indicator system was constructed by analyzing the main inputs and outputs of the two subsystems. Using the 2019 data collected from Chinese coal mining enterprises based on the constructed indicator system, this study presents a two-stage combination Data Envelopment Analysis model to assess green mining efficiency in terms of mining efficiency and environmental governance efficiency. According to this empirical study's results, there were four main findings. First, coal enterprises can be divided into three categories in accordance with the efficiency value ranking generated by the two-stage model and the corresponding synergetic development levels. Second, the percentage distribution of coal enterprises based on their green mining efficiency level embodies the attributes of a spindle structure. Third, the exported parameters information from the two-stage model supports green mining efficiency improvement as quantitative evidence. Fourth, the model results form the basis for policy proposals and improvement countermeasures.

Keywords: green mining, mining efficiency, environmental governance efficiency, two-stage combined DEA model, improvement countermeasure

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INTRODUCTION

In recent years, the imperative of low-carbon economic development has been acknowledged globally. Reducing the environmental impacts of mining activities is recognized as a key component of low-carbon economic development. Therefore, it is vital to conduct research on green mining efficiency and sustainable development strategies for the mining industry. Joshua Kirkey, Communications Advisor for Natural Resources Canada (NRC), defines green mining as "technologies, best practices and mine processes that are implemented as a means to reduce the environmental impacts associated with the extraction and processing of greenhouse gases, used water and minerals" (Kirkey, 2014). In short, the development of innovative green mining technologies aims to improve the mining sector's economic and environmental performance simultaneously.

Following decades of deep exploitation of resources, the associated environmental problems have become increasingly aggravated. The main environmental challenges associated with coal mining include the handling of coal gangue, the escape of coalbed methane (CBM), mine drainage, soil erosion, and land subsidence. The Chinese authorities have been seeking to establish more effective policy systems to propel the implementation of green mining technologies. The close coordination of coal mining and environment governance is of great significance for the sustainable development of China's mining industry (Shi, 2012; Nurmi, 2017).

The purpose of this study is to evaluate coal mining efficiency in China through the use of a creative Data Envelopment Analysis (DEA) model under the framework of green and sustainable growth. A key focus of attention in China's pursuit of a clean, sustainable environment is its coal industry. Indeed, it is regarded as a strategic objective. This study constructs an entire green mining efficiency indicator evaluation system and establishes a two-stage combined DEA model that reflects the real production condition of China's coal mining enterprises. Accordingly, the specific countermeasures and policy implications under the guidance of green mining are summarized based on the empirical study results.

The remainder of this paper is organized as follows. Literature Review presents a literature review. Materials and Methods develops a two-stage model that combines input- and output-oriented slack-based measures for green mining efficiency evaluation. It also outlines the two-stage evaluation indicator system of green mining. Empirical Study presents the empirical study of China's coal mining enterprises in 2019 and analyzes the empirical results. Conclusions outlines the main findings and policy implications for improving the ecological performance of China's coal industry.

LITERATURE REVIEW

Table 1 summarizes the main relevant literature carried out between 2006 and 2018. About a decade ago, Franks, Brereton, and Moran and Mamurekli evaluated the environmental cumulative effects of coal resource development and utilization and suggested that the authorities involved should play significant roles in improving impact assessment and institutional formulation (Franks et al., 2010; Mamurekli, 2010). Using evidence from China's coal sector, a recent study by Zhang et al. addressed the relationship of energy-price regulations and price fluctuations by building simultaneous equations for coal price and coal supply and constructing a forward-looking coefficient to evaluate different coal pricing policies from 2008 to 2016 (Zhang et al., 2019). Sueyoshi and Yuan focused on the unintended consequences of China's coal capacity cut policy and revealed that the capacity cut policy should be differentiated across regions due to the fragmentation of the coal markets, unbalanced distribution of resources, and a mismatch between production and demand centers (Sueyoshi and Yuan, 2018). These same researchers used the intermediate DEA innovation model to study the energy utilization efficiency and sustainable development of Asian countries (Sueyoshi and Yuan, 2015, 2018). Bi et al. used different DEA models to study the exploitation and utilization efficiency of coal resources in China and to make comparisons between China and the United States (Bi et al., 2014).

To date, little research has been carried out on mining efficiency and sustainable development countermeasures in China based on the concept of green mining. Hence, this study constructs an entire green mining efficiency indicator evaluation system and sets up a two-stage combined DEA model that reflects the real production conditions of coal mining enterprises. Specific countermeasures and strategies for sustainable development under the guidance of green mining are formulated on the basis of empirical study results.

Second, from the perspective of model establishment, the authors also tracked and analyzed the relevant research on DEA theory and its derivative models, which, in recent years, have been used to examine energy efficiency and environmental performance.

The classical DEA models and their extensions include the constant returns to scale model (CCR), variable returns to scale model (BCC), additive model, and slacks-based DEA models (Cook and Seiford, 2009). Yang and Pollitt simultaneously considered the undesirable outputs and uncontrollable variables to propose six DEA-based performance evaluation models based on research relating to Chinese coal-fired power plants (Yang and Pollitt, 2009). Scholars such as Sueyoshi and Goto have applied different DEA models to systematically evaluate the operational and environmental efficiency of the United States US coal-fired power plants. To examine the influence of the US Clean Air Act (CAA), they used a range-adjusted measure to examine the environmental and unified performance of United States coal-fired power plants. They discussed a combined use of DEA and Discriminant Analysis (DA) (DEA–DA) to determine the efficiency scores and ranks of the electric power industry (Sueyoshi and Goto, 2010, 2012b). Tao and Zhang applied two environmental DEA models incorporating undesirable outputs to measure the environmental efficiency of the electric power industry in the Yangtze River Delta from 2000 to 2010 (Tao and Zhang, 2013). Meanwhile, Xie et al. used a two-stage environmental network DEA model to compare the efficiency of 30 provincial administrative power systems in China (Xie et al., 2012). Zhou et al. proposed a non-radial DEA approach by integrating the entropy weight and a slacks-based model (SBM) to access the environmental efficiency of the Chinese power industry at the provincial level from 2005 to 2010 (Zhou et al., 2013). Using CCR and BCC models with advanced DEA linear programming, Fang et al. attempted to compare the relative technical efficiency performance of listed coal mining companies in China and the United States (Fang et al., 2009). Sing data spanning 2002–2010, Wang et al. put forward an innovative approach based on the meta-frontier DEA theory to conduct an empirical study on energy efficiency in the eastern, central, and western regions of China. They discovered the main factors that lead to inefficiency by taking the provincial heterogeneities of production technology into full consideration (Wang et al., 2013). Wang et al. established a method based on a meta-frontier function and a non-radial directional distance function to assess performance following the interconnection of energy-saving and emissions reduction. An empirical analysis was

TABLE 1 | Research carried out on this topic between 2009 and 2019.

Country	References	Research topic	Main conclusions
Australia	Franks et al. (2010)	Managing the cumulative impacts of coal mining on regional communities and environment in Australia	I. Governments can play a greater role in improving impact assessment through the provision of strategic assessments and explicit links between regional and land use planning and environmental information system. II. Cumulative impact management approaches represent a range of institutional forms from single company initiatives and programs, to cross-industry and multistake holder partnerships and networking.
Australia	Zhang et al. (2019)	Can energy-price regulations smooth price fluctuations? Evidence from China's coal sector	I. A methodological contribution is the building of simultaneous equations for coal price and coal supply and innovatively constructing a forward-looking coefficient to evaluate different coal pricing policies from 2008 to 2016. II. The government needs to coordinate the pricing policies with the policies for protecting economic growth and environmental development. III. Suggests that the government make efforts to improve market transparency by installing and implementing market rules. Other policies may have indirect impacts on coal prices, such as coal capacity cut policy.
Australia	Shi et al. (2018)	Unintended consequences of China's coal capacity cut policy	I. The capacity cut policy should be differentiated across regions due to the fragmented coal markets, unbalanced distribution of resources, and a mismatch between production and demand centers. II. Market approaches would be preferable to command-and-control instruments. III. Rather than focusing on overcapacity itself, the policies should target the underlying factors that distort the behavior of participants and investors. Potential measures may include strict enforcement of safety, environmental, and technological standards.
America	Sueyoshi and Yuan (2015)	China's regional sustainability and diversified resource allocation: DEA environmental assessment on economic development and air pollution	I. The Chinese government should distribute its economic resources to cities located in the northwest region. To improve the environment in major cities such as Beijing, Tianjin, Shanghai, and Chongqing, the government should also more strictly reinforce the regulation of energy consumption. II. Replacing China's economic growth policy to one of environmental protection is essential for the future of China.
America	Sueyoshi and Yuan (2018)	Measuring energy usage and sustainability development in Asian nations by DEA intermediate approach	I. A methodological contribution is that it newly proposes an "intermediate approach" between radial and unradial DEA for assessing a level of social sustainability. II. The Asian nations examined in this study were classified into four or five groups based upon their unified efficiency measures under natural disposability and managerial disposability in terms of the proposed approach.
Turkey	Mamurekli (2010)	Environmental impacts of coal mining and coal utilization in the UK	I. The most significant reductions in the environmental impacts from coal usage can be achieved through the adoption of higher efficiency combustion technologies in power generation. II. More modest improvements can be achieved by improving the efficiency of existing processes across the coal value chain.
China	Bi et al. (2014)	Does environmental regulation affect energy efficiency in China's thermal power generation? Empirical evidence from a slacks-based DEA model	I. Environmental efficiency plays a significant role in affecting the energy performance of China's thermal power generation sector. Decreasing the discharge of major pollutants can improve both energy performance and environmental efficiency. II. Three main findings: (1) Energy efficiency and environmental efficiency were relatively low. (2) Energy and environmental efficiency scores showed great variations among provinces. (3) Both energy efficiency and environmental efficiency were obvious geographical characteristics.

organized to examine the primary factors that cause performance loss in energy-saving and emissions reduction (Wang et al., 2015). Zhang et al. used dynamic SBM models to evaluate the overall efficiency of decision-making units (DMUs) for the whole term period, as well as the term period efficiencies in industrial water pollution (Zhang et al., 2019). This proposed dynamic DEA model incorporates carryover activities and helps measure a period's specific efficiency based on long-term optimization during the whole period. It can also calculate the system and period efficiencies under dynamic conditions. Patricija Bajec and Danijela Tuljak-Suban proposed an integrated analytic hierarchy process (AHP) as well as an SBM DEA model (Bajec and Tuljak-Suban, 2019). First, an AHP pairwise comparison was used to rank a set of criteria (inputs, outputs) according to their importance. Then, an SBM DEA model that evaluated both the undesirable and desirable outputs was used. Incorporating undesirable performance criteria, this combined model was employed to evaluate the efficiency of logistics service providers. Yang and Wei used the game cross-efficiency DEA model to study the urban total factor energy efficiency of China's 26 interprovincial cities from 2005 to 2015. They concluded that city-scale and economic development can improve the energy efficiency of a city, while investment and endowment will lower the urban energy efficiency (Yang and Wei, 2019). Wu et al.

divided 38 industries into four categories through cluster analysis and used a DEA model with non-homogeneous inputs and outputs to evaluate the energy and environmental efficiencies of 38 industries in China's industry from 2007 to 2011 (Wu et al., 2019). The results showed that the energy and environmental efficiency of China's industry is generally low, that the variation is large, and that efficiency increased over 5 years. Li Xie proposed a combined different DEA model using a Gini criterion to measure environmental efficiency (Xie et al., 2019). The authors used data for 36 Chinese industries spanning 2006–2015 and a multiple DEA with a Gini criterion as well as a systematic clustering approach. They first calculated the environmental efficiency score of Chinese industries, then identified the pollution sources based on a ranking and clustering analysis. The main conclusion was that the ranking of various industries' environmental efficiency varied greatly by time. Shao and Han proposed an SBM model to address the inefficiency of the production system after considering pollutant abatement technology heterogeneity for different kinds of pollutants (Shao and Han, 2019). The authors then employed the model to study the inefficiency of the Chinese industrial production system, analyzing the inefficiency in the stages of economic production and pollutant treatment. Sueyoshi et al. used DEA Window Analysis to evaluate the efficiency using moving averages (Sueyoshi et al., 2017). In other words, the analysis outcome focused on recent years by different windows. Therefore, the advantage of this study is that the policy implications are more accurate and credible. In their recent research on resource abundance, industrial structure, and regional carbon emissions efficiency in China, Wang and Shi et al. employed the SBM with window analysis approach to estimate the carbon emissions efficiency and abatement potential while applying the panel Tobit model to investigate the influencing factors of carbon emissions efficiency under the framework of DEA (Wang et al., 2019). Xian and Shi et al. constructed a non-parametric DDF model based on the DEA technique to measure carbon efficiency and productivity in the study of carbon emission intensity reduction targets for China's power industry (Xian et al., 2018). They determined that the nationwide 18% CO_2 reduction target is not feasible through improving the technical efficiency or an upgrading of technologies for electricity generation and carbon abatement in the short or medium term. Wang and Shi et al. optimized the frontier-based optimization model by combining environmentally extended input–output analysis (EEIOA) and DEA to calculate an environmental inefficiency score in the study of spatial heterogeneity and driving forces of environmental productivity growth in China (Wang et al., 2019). They found that from 2007 to 2012, all regions experienced environmental productivity progress. According to the driving factors of environmental productivity, seven regions can be divided into three modes (Wang et al., 2019).

There are three main findings from the above literature review. First, the research to date concerning green mining efficiency and sustainable development countermeasures based on the concept of green mining and the DEA approach, especially relating to China, is relatively rare. As for the green mining evaluation indicator system, the highly correlated literature is sparse. Second, there has been much less empirical research on mining industry efficiency performance using DEA than on electricity or other energy industries. In addition, the focus of most studies on environmental efficiency or energy utilization efficiency in China has been at the state, regional, or industry level, rather than at the enterprise level. Second, there is nearly no literature using a two-stage combined DEA model to assess integrated green mining efficiency, which incorporates mining efficiency in the first production stage and environmental governance efficiency in the second stage. Most of the existing literature has focused on only one aspect of the efficiency measurement, i.e., energy production or environmental efficiency (Fang et al., 2009). Therefore, in this paper, to reveal the features of real-life production circumstances and reflect the relationship between mining and environmental governance efficiency performance, we attempted to establish a two-stage combined DEA evaluation model. Moreover, to measure green mining efficiency, we aimed to simultaneously examine the mining and environmental governance performance of China's coal industry at the enterprise level by conducting undesirable outputs conversion and distinguishing uncontrollable input variables between the two stages. Our goal was to enrich the understanding of the synergetic green mining performance of mining enterprises and thereby help the authorities formulate more targeted improvement policies.

MATERIALS AND METHODS

Following the seminal work of Charnes et al., DEA as a non-parametric approach to efficiency measurement has been widely studied and applied (Charnes et al., 1978). The classical models and their extensions include the constant returns to scale model (CCR), variable returns to scale model (BCC), additive model, and slacks-based DEA models (Cook and Seiford, 2009). Compared to other measures of productivity and efficiency, the utility of DEA is a function of its ability to analyze efficiencies in systems featuring multiple inputs and outputs. DEA, as a useful tool for performance analysis, is used to evaluate the relative efficiencies of DMUs using some specific linear programming models (Tong and Ding, 2008). DEA has a number of advantages. First, it does not require any prior assumptions on the relationships between input and output data (it is therefore a non-parametric approach) (Seiford and Thrall, 1990; Zhou and Ang, 2008). Second, it only requires physical quantities of inputs and outputs for evaluating technical and scale efficiency indicators (i.e., only allocation efficiency needs fact or prices), and thus, the information required for DEA is less than that in the traditional case (Qiu-ying, 2019). Third, it is a more objective efficiency assessment because the weighting of each index is the optimal weighting determined by dimension less real data from the DMU (Tong and Ding, 2008). In addition, as Tong and Ding point out, the reason for DMU inefficiency can be found through a projection analysis of each DMU, and then, an improvement can be planned for the future. All of the above-mentioned advantages are sufficient for us to study the characteristics of the subject in this paper.

Basic Equations

In this section, we introduce a slacks-adjusted two-stage combined with input- and output-oriented BCC model. We considered applying the linear transformation function simultaneously to switch the undesirable outputs in the first stage and incorporating undesirable outputs as uncontrollable input variables to measure the second stage efficiency of coal mining enterprises located in central-west China in 2019. According to the production features of each evaluation unit, we primarily adopted the input- and output-oriented BCC equations as a reference foundation for building our two-stage slacks-adjusted combination model. Under the constraints of variable returns of scale (VRS), the production possibility set of BCC theory is defined as:

$$P^{VRS} = \left\{ (X, Y) | X \geq \sum\nolimits_{j=1}^{n} \lambda_j X_j, Y \leq \sum\nolimits_{j=1}^{n} \lambda_j X_j, \sum\nolimits_{j=1}^{n} \lambda_j = 1, \lambda_j \geq 0, j = 1, 2, \cdots, n \right\} \quad (1)$$

The input-oriented equations of BCC are:

min θ_0

$$\begin{aligned} s.t.\theta_0 x_{10} &\geq \sum_{j=1}^{n} \lambda_j x_{ij}, \quad i = 1, 2, \cdots, m \\ y_{r0} &\leq \sum_{j=1}^{n} \lambda_j y_{rj}, \quad r = 1, 2, \cdots, s \\ \sum_{j=1}^{n} \lambda_j &= 1 \\ \lambda_j &\geq 0, \quad j = 1, 2, \cdots, n \end{aligned} \quad (2)$$

The output-oriented equations of BCC are:

minφ_0

$$\begin{aligned} s.t. \sum_{j=1}^{n} \lambda_j x_{ij} &\geq x_{10}, \quad i = 1, 2, \cdots, m \\ \sum_{j=1}^{n} \lambda_j y_{rj} &\geq \varphi_0 y_{r0}, \quad r = 1, 2, \cdots, s \\ \sum_{j=1}^{n} \lambda_j &= 1 \\ \lambda_j &\geq 0, \quad j = 1, 2, \cdots, n \end{aligned} \quad (3)$$

Building a Two-Stage Green Mining System Model

Currently, according to the actual conditions of China's coal enterprise operating system, and the imperative for green mining, the coal enterprises should simultaneously conduct environmental governance and restoration through the promotion of resource recycling while exploiting the coal resource. The coal enterprise operating system can be divided into two subsystems, namely, coal mining subsystem and environmental governance subsystem, respectively. The mining subsystem refers to a sequential production assignment of exploiting, transportation, ventilation, drainage, equipment maintenance, power supply, water supply, and so on. Its main purpose is to produce coal and generate profits. Within the mining subsystem, the input cannot be entirely converted into desirable outputs such as marketable coal and valuable associated resources. The undesirable outputs of industrial pollutants inevitably appear in the production process due to the limitations of the existing mining technologies. Therefore, to fulfill the goal of environmental governance, a subsystem of environmental governance is necessary to transform the undesirable outputs and newly invested inputs into desirable outputs (Bian and Yang, 2010). The two synergetic subsystems constitute the entire green mining system and are connected by undesirable outputs in this two-stage production model (Toloo et al., 2017). The system framework model is shown in **Figure 1**.

To describe the two-stage system shown in **Figure 1**, we assume that there are $n \left(j = 1, \ldots, n\right)$ DMUs, and each DMU has two stages. For every $DMU_j (j = 1, \ldots, n)$, we put into m kinds of resources in the first stage $x_j^1 = (x_{1j}^1, x_{2j}^1, \ldots, x_{mj}^1)$ and the output of this stage is $y_j^1 = y_j^1 + z_j$; $y_j^1 = (y_{1j}^1, y_{2j}^1, \ldots, y_{sj}^1)$ represents main desirable outputs, and $z_j = (z_{1j}^1, z_{2j}^1, \ldots, z_{tj}^1)$ represents the pollutants generated during the mining process, t being the undesirable output.

In the second stage, we invest I kind of resource elements process the pollutants generated in the first stage $x_j^2 = (x_{1j}^2, x_{2j}^2, \ldots, x_{lj}^2)$; the final output of second stage is y_j^2, $y_j^2 = (y_{1j}^2, y_{2j}^2, \ldots, y_{hj}^2)$. Among the variables mentioned above, z_j is an intermediate variable of great significance, which represents both the undesirable output of the first stage and the partial input of the second stage (Wu et al., 2017). To evaluate the first stage efficiency, it is necessary to adopt an appropriate method to deal with the undesirable output of contaminants and convert them into desirable outputs to meet the requirement of the DEA method (Sueyoshi and Goto, 2012a). Contrary to the desirable outputs, the smaller the value of undesirable outputs, the better the model can operate. In reality, according to the DEA efficiency evaluation theory, there are several transformation methods for undesirable outputs, such as the directional distance function, curve measure evaluation method, and linear transformation function. In this study, we selected the linear transformation function to convert the undesirable outputs into normal desirable outputs (Zhou and Ang, 2008). We adopted the equation of $z_j^{'} = -z_j + z > 0 \left(j = 1, 2, \ldots, n\right)$ in which z represents a large enough vector large. After conversion, $z_j^{'}$ can be accepted as normal desirable outputs and adopted by the traditional DEA efficiency evaluation model.

Building a Two-Stage Combined DEA Model

According to the guidelines of the green mining concept, we decided to select the input-oriented radial BCC theory as the first stage modeling foundation (Sueyoshi and Goto, 2012c). In

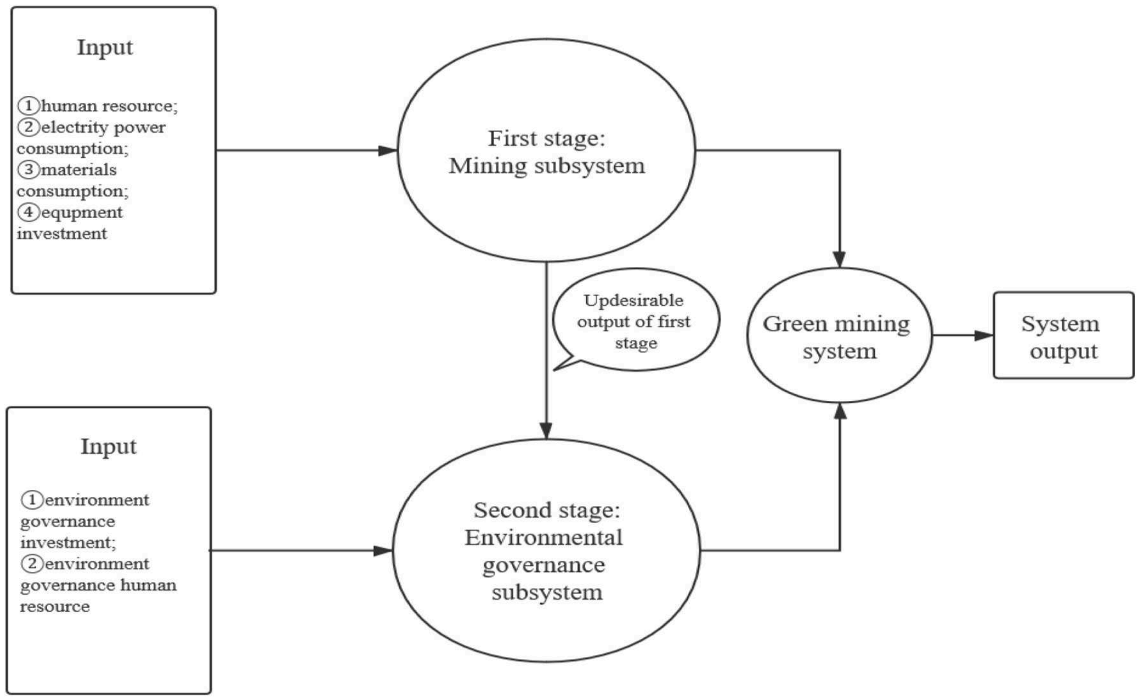

FIGURE 1 | Two-stage green mining system framework.

addition, to calculate the DMU efficiency of the first stage or of the mining subsystem, we introduced adjusted slack variables with constraint conditions and added the linear transformation function to refine the original BCC model and set up our own measurement method (Bi et al., 2014).

$$\begin{aligned}
& Min\theta_1 \\
& s.t. \sum_{j=1}^{n} \lambda_j x_{ij}^1 + s_i^- = \theta_1 x_{io}^1, \ \ i = 1, 2, \ldots, m \\
& \sum_{j=1}^{n} \lambda_j y_{rj}^1 - s_r^+ = y_{ro}^1, \ \ r = 1, 2, \ldots, s \\
& \sum_{j=1}^{n} \lambda_j z'_{pj} - s_p^+ = z'_{po}, \ p = 1, 2, \ldots, t, \\
& \sum_{j=1}^{n} \lambda_j = 1 \\
& \lambda_j, s_i^-, s_r^+, s_p^+ \geq 0
\end{aligned} \tag{4}$$

θ_1 represents the efficiency value of the first stage.

From the perspective of continuously pursuing improvements in environmental governance, we selected the output-oriented radial BCC theory as the second stage modeling foundation. Hence, we designed another DEA model to calculate the efficiency of the second stage DMU of the environment governance subsystem also through introducing adjusted slack variables only in the constraint conditions. In this stage, it is important to pay attention to the different input features. As discussed above, the undesirable output of contaminants from the first stage accounts for partial inputs for the second stage. These inputs are also uncontrollable, which should be processed by the uncontrollable input method (Yang and Pollitt, 2009). Meanwhile, the newly added input elements of the second stage should be processed by the adjustable input method.

$$\begin{aligned}
& Max\theta_2 \\
& s.t. \sum_{j=1}^{n} \lambda_j x_{kj}^2 + s_k^- = x_{ko}^2, \quad k = 1, 2, \ldots, l \\
& \sum_{j=1}^{n} \lambda_j z_{pj} = z_{po}, \quad p = 1, 2, \ldots, t \\
& \sum_{j=1}^{n} \lambda_j y_{qj}^2 - s_q^+ = \theta_2 y_{qo}^2, \quad q = 1, 2, \ldots, h \\
& \sum_{j=1}^{n} \lambda_j = 1 \\
& \lambda_j, s_k^-, s_q^+ \geq 0
\end{aligned} \tag{5}$$

θ_2 represents the efficiency value of the second stage.

Regarding the model construction, first, it is necessary to point out that we established the two-stage combined DEA model on the basis of the coal mining enterprise real production scenarios and green mining concept. Specifically, we divided the coal enterprise production system into two subsystems. One subsystem was defined as the coal mining process, while the other subsystem was defined as the comprehensive utilization of associated resources process, which can also be called the environmental governance process.

Second, we calculated the efficiency values of the different two stages through the constructed two-stage combined DEA model. Although the second stage of the DEA model seems relatively independent, we actually created the linkage between the two stages' model output by processing and transforming the undesirable contaminants generated from the first stage into desirable input elements for the second stage. According to the concept of green mining, a coal enterprise should strive toward recycling resources and environmental governance simultaneously. This two-stage combined model is able to not only reflect the real production scenarios but also measure the level of coordinated development of the two subsystems by providing efficiency values for the two stages.

Third, for each coal mining enterprise, this study combined two orientation DEA measures into one model to assess the efficiency value objectively in terms of economic development and environmental governance. We identified the first stage as the output-oriented production subsystem and the second stage as the input-oriented generation subsystem.

Establish the Two-Stage Evaluation Indicator System of Green Mining

First, according to the two-stage green mining system framework established in Literature Review, the first stage corresponds to the mining subsystem, through which the input elements can be transformed into coal output that can generate economic profits. We designed the input indicators of the mining subsystem based on the production costs and their sensitivity value sequence to coal output. Specifically, the input indicators are human resource costs, electricity and materials consumption costs (Huang et al., 2007), and fixed asset investment. The other production cost elements have been ignored because they represent only a small proportion of the total production costs. Meanwhile, the output indicators of the mining subsystem include total coal production, coal output value, and pollutants or associated resources during the mining process. The coal gangue is identified as representing solid waste (Ma et al., 2015). The liquid waste generated during the mining process is mainly mining water and industrial sewage. The coalbed methane is identified as representing waste gas. Thus, we selected the total coal production, coal gangue output, polluted mining water volume, and coalbed methane emission quantity as output indicators in the first stage. The undesirable outputs of pollutants or associated resources should be separated from the desirable outputs of coal in this stage. Obviously, the total coal output should be defined as desirable output elements and the coal gangue, polluted mining water, and coalbed methane should be defined as undesirable output elements.

The second stage corresponds to the environmental governance subsystem, through which the input elements can be converted into valuable output. It is critical to point out that the new input elements, such as environmental governance investment and relevant human resources, are indispensable inputs for the pollutant treatment and associated resource reutilization in this stage. As a result, the input indicators are composed of two parts in the second stage. These are, respectively, the pollutants or associated resources produced from the first stage, like coal gangue, polluted mining water, and coalbed methane, and the new inputs of environmental governance investment and the relevant human resources in the second stage. The output of the second stage refers to beneficial yields from pollution treatment and control. The comprehensive utilization of coal gangue has two aspects. One aspect is backfilling the mining subsidence area, and the other is the production of building materials. The abandoned mine water is treated and recycled back into production and domestic water. The coalbed methane produced during the mining process (mainly methane) is a safe and reliable clean energy source, which can be developed into multiple industrial feedstocks. Based on the strategic guidelines of the China Ministry of Environmental Protection and the Energy Bureau enacted in 2017, the utilization ratio of coalbed methane has been an important indicator of green mining. Therefore, we selected the comprehensive recycling utilization of coal gangue, polluted mine water, and coalbed methane as the output indicators for the second stage. The indicator system of green mining efficiency assessment is shown in **Table 2**.

Data and Sample

We selected 30 coal mining enterprises in the central and western regions of China that have received considerable attention from the National Energy Administration and the National Development and Reform Commission. They are defined as DMUs with three essential characteristics. The first is that the total coal production falls within the range of 3.6–7.8 million tons. The second is that they have similar resource endowment conditions, and the third is that they have all constructed some form of environmental governance structure. We obtained updated 2019 data through a questionnaire and field research. In addition, the enterprises are required to accept the relevant administrative authority's supervision and evaluation. Through long-term investigation and research into China's coal industry, we selected 30 coal enterprises that represent the real and universal situations of green mining in China. All the above factors describe the characteristics of the sample for this empirical study. To achieve a reasonable level of discrimination, one rule of thumb was to limit the number of input and output indicators. For example, the number of DMUs should be at least twice the total number of inputs and outputs (Chen, 2009). Here, we have 30 DMUs, 4 inputs and 4 outputs in the first stage, and 5 inputs and 3 outputs in the second stage. Thus, our results have a reasonable level of discrimination. The summary statistics of the original data (index form) are provided in **Table 3**.

EMPIRICAL STUDY

There are three main findings as shown in **Tables 4**, **5**, **Figures 2**, **3**. The efficiency values of the two-stage model are presented in **Table 4**. The θ_1 represents the efficiency value of the first stage,

TABLE 2 | The two-stage green mining efficiency evaluation indicator system.

Stage	Input/output	Indicator	Unit	Indicator description
The first stage (mining subsystem)	Input	Number of employees x_{1j}^1	Persons	Sum of actual labor resources
		Total electricity consumption x_{2j}^1	kwh	Actual amount of electricity consumed by production equipment
		Material consumption x_{3j}^1	RMB (Million)	Total amount of materials put into production
		Fixed asset investment x_{4j}^1		Purchase cost of fixed assets equipment for production
	Output	Coal production y_{1j}^1	Tons (Million)	Total coal production in first stage
		Associated coal gangue y_{2j}^1	Tons (10, 000)	Coal gangue associated with coal production process (representing the industrial solid waste)
		Contaminated mine water y_{3j}^1		Mine water contaminated during the coal production process (representing the industrial liquid waste)
		Associated gas volume y_{4j}^1	Cubic meters (100 million)	Quantity of gas emissions during the coal production process (representing the industrial gas waste)
The second stage (environmental governance subsystem)	Input	Environmental management investment x_{1j}^2	RMB (Million)	Amount of money invested in environmental governance
		Number of human resources for environmental governance x_{2j}^2	Persons	Amount of human resources invested in environmental governance
		Associated coal gangue x_{3j}^2	Tons (10, 000)	Coal gangue associated with coal production
		Contaminated mine water x_{4j}^2		Mine water contaminated during the coal production process
		Associated gas volume x_{5j}^2	Cubic meters (100 million)	Quantity of gas emissions during the coal production process
	Output	Comprehensive utilization of coal gangue y_{1j}^2	Tons (10, 000)	Comprehensive utilization capability of associated coal gangue (representing one of the environmental governance standards)
		Standard discharge of mine wastewater y_{2j}^2		Treatment and recycling capability of contaminated mine water (representing one of the environmental governance standards)
		Comprehensive utilization of mine gas y_{3j}^2	Cubic meters (100 million)	Comprehensive utilization capability of waste gas (representing one of the environmental governance standards)

TABLE 3 | Summary statistics of input and output indicators.

	X_1^1	X_2^1	X_3^1	X_4^1	Y_1^1	Y_2^1	Y_3^1	Y_4^1
Max	5,700.00	320.62	291.98	620.10	789.00	241.23	279.20	4092.00
Min	722.00	103.20	78.65	66.80	364.90	80.72	71.36	96.50
Mean	3,997.31	208.74	163.69	328.13	589.94	146.04	158.07	1,924.70
SD	1,058.15	49.53	43.56	139.96	117.45	39.82	44.25	921.80
	X_1^1	X_2^1	X_3^1	X_4^1	X_5^1	Y_1^1	Y_2^1	Y_3^1
Max	659.00	165.00	241.23	279.20	4,092.00	219.95	241.92	3,563.04
Min	215.00	48.00	80.72	71.36	96.50	36.92	50.24	46.35
Mean	437.53	96.87	146.04	158.07	1,924.70	78.03	92.75	756.93
SD	125.24	24.18	39.82	44.25	921.80	35.67	37.45	733.56

and the θ_2 represents the efficiency value of the second stage. To illustrate the real status of the two-stage efficiency level for each DMU, we drew the histogram in **Figure 2** according to the data given in **Table 4**. The fluctuation features and ranking differences of the two-stage efficiency level of each DMU can be observed clearly in **Figure 3**.

First, we recognized that the efficiency values for both stages fluctuated dramatically among the 30 DMUs, as portrayed in **Figures 2, 3**. They show that there was great potential for efficiency improvement in various coal enterprises, especially in the environmental governance stage. For the coal enterprises whose efficiency levels in the second stage were relatively low, it was apparent that efforts should be made to improve both mining and environmental governance efficiency and to maintain a balance between environmental and economic benefits.

Second, from the comparison of the efficiency value ranking scores, the 30 coal enterprises generally fell into three categories. In this article, we defined the categories largely on the ranking

TABLE 4 | The calculated efficiency values of the two-stage model for each DMU.

DMU	θ_1	θ_2	DMU	θ_1	θ_2
S01	0.63	0.61	S16	1.00	1.00
S02	0.84	0.67	S17	0.92	0.73
S03	0.71	0.54	S18	0.91	0.63
S04	0.82	0.73	S19	0.76	0.64
S05	1.00	1.00	S20	0.88	0.72
S06	1.00	1.00	S21	0.76	0.61
S07	0.86	1.00	S22	0.68	0.76
S08	0.67	0.55	S23	0.74	0.63
S09	0.86	0.87	S24	0.98	0.85
S10	0.81	0.78	S25	0.88	0.63
S11	0.68	0.57	S26	0.93	0.81
S12	0.78	0.64	S27	0.78	0.60
S13	0.71	0.71	S28	0.54	0.53
S14	1.00	1.00	S29	0.99	0.70
S15	0.99	0.78	S30	0.68	0.64

TABLE 5 | Detailed calculation results relating to material consumption.

DMU	Score	Benchmark (Lambda)	Proportionate movement	Slack movement	Projection
S18	0.91	S05(0.32); S14(0.38); S16(0.31)	−18.73	−68.53	125.14

scores of the two-stage efficiency level. The top 6 of the two-stage efficiency values ranking constituted the first category, while the last 6 of the two-stage efficiency values ranking constituted the third category, and the middle 7–24 of the two-stage efficiency values belonged to the second category. The enterprises whose two-stage efficiency values were simultaneously high among the sample enterprises, i.e., whose efficiency value ranked at a high position in both stages, with hardly any difference, such as S05, S06, S14, and S16, are clearly apparent in **Figures 2, 4** and were classified into the first category. It is important to highlight that the first category enterprises ranked highly in terms of both mining and environmental governance. Consequently, the synergetic development level in the two stages is the highest among the sample. Actually, these enterprises were continuously engaged in seeking synergetic performance growth in both the mining stage and environmental governance stage. The enterprises whose second stage efficiency values were lower than those of the first category at different degrees, and whose efficiency value ranking scores were also lower than those of the first category, i.e., S02, S04, S07, S08, S09, S10, S12, S13, S15, S17, S18, S19, S20, S21, S22, S23, S24, S25, S26, S27, S29, and S30, are clearly apparent in **Figures 2**, **4** and belong to the second category. It is also meaningful to note that deviations in ranking of the efficiency value of the second stage not only existed but also were larger than those of the first category. Logically, the synergetic development level of the second stage was lower than that of the first category. Obviously, in reality, these enterprises had tended to focus on mining efficiency while neglecting environmental governance to some degree. Consequently, they generally had poor environmental governance performance. The enterprises whose efficiency level ranked in the last six positions, such as S01, S03, S11, and S28 can be seen in **Figures 2, 4** and are classified as belonging in the third category. It is not difficult to surmise that it was the poor operation standards that lead to the lowest efficiency values ranking status of the third category enterprises. Undoubtedly, the third category enterprises had a poor synergetic development level of mining and environmental governance.

In addition, we determined the enterprise percentage of the three different categories as demonstrated in **Figure 5**. It can be seen that the second category enterprises accounted for the highest percentage among all the sample enterprises. The first category enterprises accounted for almost the same percentage among all the sample enterprises. This percentage distribution situation resembled a spindle structure. In reality, this kind of distribution structure also conforms with the real green mining development status of coal mining enterprises in China at the present stage.

Third, we were able to obtain the specific data and corresponding countermeasures to improve the efficiency levels. Detailed information about the efficiency value, benchmark (lambda), proportionate movement, slack movement, and projection value of each input and output can be achieved from the exported model calculation results. Owing to space limitations, we chose one input of material consumption from DMU18 in the first stage to be displayed in **Table 5**. We devised countermeasures to adjust its input value to optimize its efficiency value according to the corresponding parameters exported from the model calculation results. Based on the data information in the proportionate movement and slack movement columns, we adjusted the amount and direction of input elements to reach the projection value. Correspondingly, the efficiency value can be optimized eventually. For instance, to reach the projection value and optimize the efficiency value of DMU18 in the first stage, we can diminish the input value of material consumption in the first stage by 0.6853 million yuan on the basis of the data information found in the proportionate movement column. Meanwhile, we can decrease the value of the input element of material consumption by DMU18 in the first stage by 0.1873 million yuan according to the data information found in the slack movement column to reach the projection value of 1.2514 million yuan, thereby improving the efficiency value rationally. Actually, we can carry out such adjustments for all the input and output indicators of the two stages according to the parameters exported from the MAXDEA calculation results to realize green mining performance improvement across all 30 DMUs. Owing to space limitations, we displayed the full information in **Appendix**. By generating quantified evidence, all of these precise adjustments indicate that this empirical study is exactly what is needed by the coal authorities to improve green mining efficiency.

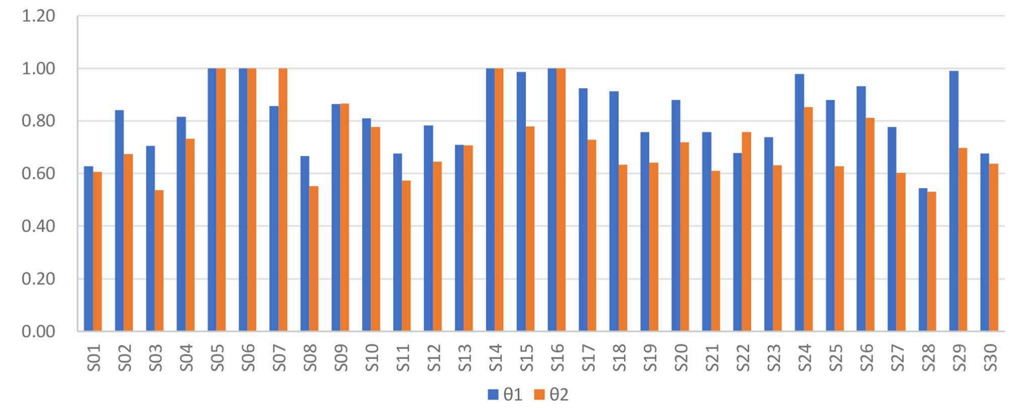

FIGURE 2 | The two-stage efficiency value of each decision-making unit (DMU).

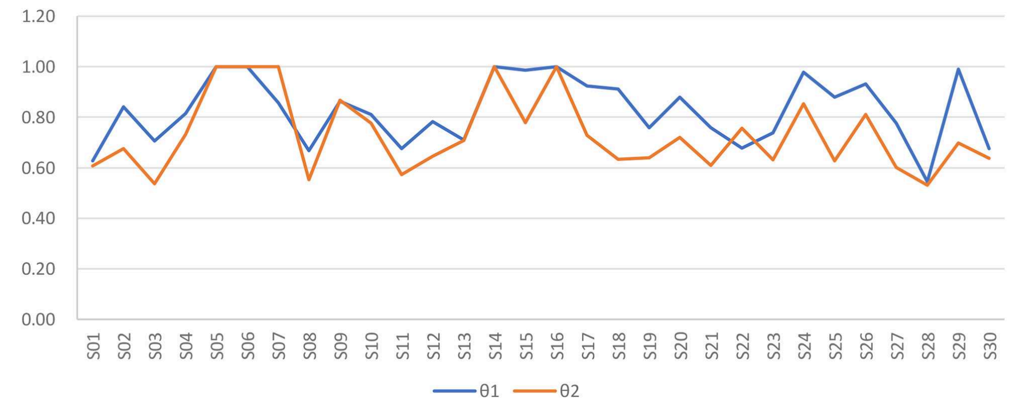

FIGURE 3 | The fluctuation curve of the two-stage efficiency level.

CONCLUSIONS

This study set up a two-stage green mining system structure and the correlated input–output indicator system to evaluate green mining efficiency. In addition, a two-stage combined DEA model was proposed to assess the mining subsystem and environmental governance subsystem efficiency of 30 sample coal enterprises situated in China's central-west region in 2019. This empirical study provides detailed information about the efficiency value, efficiency ranking level, benchmark of scale to return, value of slack movement, value of proportionate movement, and value of projection for the 30 DMU. Together, all of this information provides policy makers (especially at the enterprise level) with valuable insights into green mining and improvement countermeasures. DEA has been widely applied to evaluate the performance of the energy industry. However, few studies to date have attempted to deal with the case of mining enterprises by evaluating their mining and environmental governance performance simultaneously. The four key findings of this study were as follows.

First, the coal enterprises fell into three categories based on a comparison of their two-stage efficiency values and ranking status. The first category enterprises had high efficiency ranking (top 6) in terms of both mining and environmental governance and their synergetic development level in the two stages was the highest among the sample. Consequently, the enterprises in the first category were regarded as being green mining enterprises with a high level of efficiency. The enterprises in the second category had a lower efficiency ranking in both mining and environmental governance than those in the first category. Moreover, the larger deviations in the efficiency ranking in the second stage of the second category revealed that the synergetic development level in the two stages was lower than that of the first category. In reality, the second category enterprises could be generally regarded as green mining enterprises with middle-level efficiency. The third category enterprises had the lowest efficiency ranking (lowest 6) in the two stages. Accordingly, the operation capability and synergetic development level of mining and environmental governance were both poor. It was therefore unrealistic to discuss the green mining efficiency level of the third category enterprises.

Second, we determined the enterprise percentage of the three different categories. From **Figure 5**, it can be seen that the second category enterprises accounted for the highest percentage

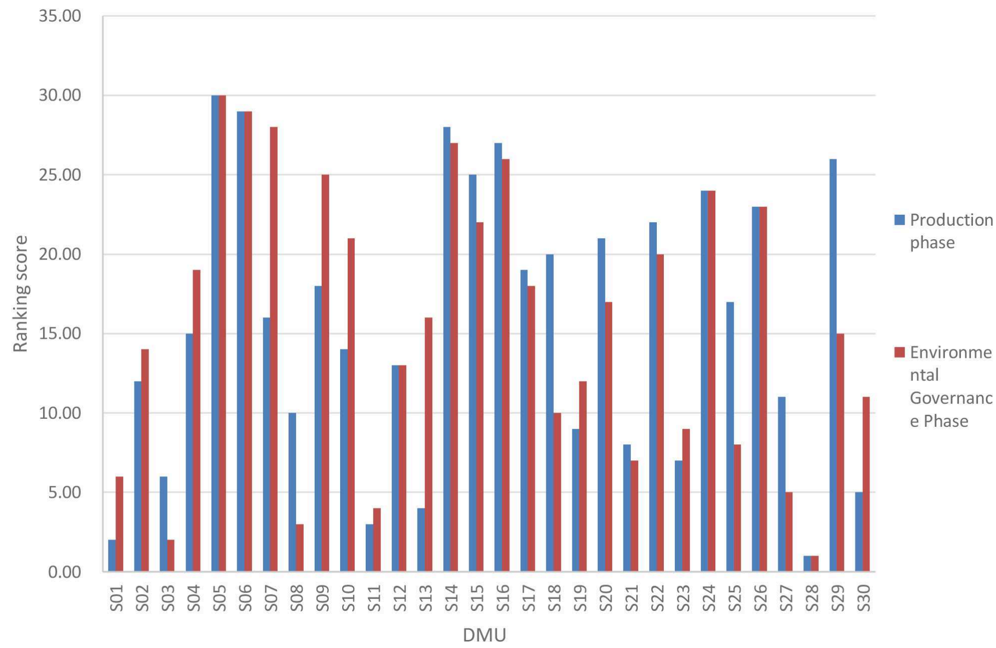

FIGURE 4 | The efficiency level ranking of the two stages for each DMU.

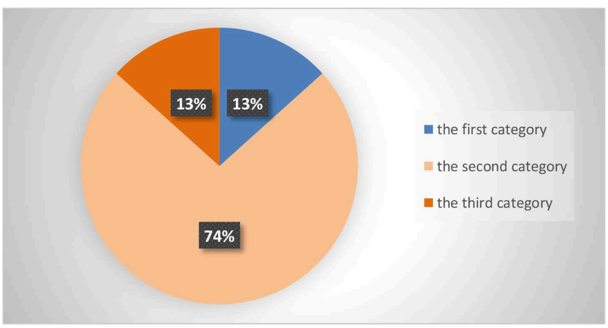

FIGURE 5 | The enterprise percentage distribution of the three different categories.

among all the sample enterprises. There was almost no difference in the ratio of the first and the third category enterprises. They both accounted for 13% of the sample enterprises. This percentage distribution situation embodied the features of a spindle structure. Actually, this kind of distribution situation also conforms with the real green mining development status of mining enterprises in China at the present stage. This finding is helpful for policy makers tasked with formulating rational countermeasures geared at optimizing the layout of the coal industry in the central and western area by adjusting the percentage distribution.

Third, the exported parameters information from the two-stage combined DEA model definitely provided a quantitative basis for efficiency level improvements. This is crucial for coal enterprise managers who are trying to pursue continuous progress in green mining implementation and operation capability.

Fourth, several specific policy implications and improvement countermeasures for mining enterprises come to light from the empirical study results. With respect to the grim environmental damage that has accompanied coal mining in China for decades, high priority should be given to the establishment of a green mining policy system to encourage mining enterprises to shoulder the responsibility for implementing green and low-carbon development.

From the perspective of optimizing coal mining industrial layout, the authorities should create a green mining efficiency evaluation system in coal mining enterprises based on the two-stage model and, in strict accordance with the efficiency ranking status of the two-stage model, formulate a set of rules needed to eliminate the enterprises that have poor operations. According to our empirical study, the third category enterprises had the lowest efficiency value rankings in the two-stage model. This means that based on the quantified evaluation results, such enterprises should be eliminated. Meanwhile, to boost the green mining efficiency of the mining sector, the authorities should also design incentive policies to stimulate the smart expansion and growth of the first category enterprises.

From the perspective of technology innovation, the authorities should reinforce the application and reformation of green mining technologies. Currently, green mining technologies primarily refer to mine filling, water preservation, simultaneous extraction of coal and gas, oxidizing utilization of ventilation air methane (VAM), and gangue discharge reduction. Specifically, the authorities should formulate regulations and establish standards to encourage the application of green mining technologies and simultaneously curb the use of old mining methodologies at the coal enterprise level. The government should also foster green mining technology innovations through cooperation mechanisms by forging efficient operation frameworks organized by government sectors, commercial corporations, and coal enterprises. It is essential to identify priority areas of technology application and innovation. Methane extraction and comprehensive utilization technologies are definitely of great significance in improving the environmental governance efficiency in the second stage. Therefore, it is imperative to propel the policy design with respect to the application and innovation of methane extraction and comprehensive utilization technologies in coal mining enterprises.

In terms of institutional innovation, to implement rigorous control over production behaviors that intentionally ignore environmental performance, the authorities should strengthen the relevant legislation and regulations. As for positive institutional design, feasible tax subsidies, and financial aid policies should be created to encourage enterprises to promote the comprehensive utilization of coalbed methane, coal gangue, and other associated resources. For instance, a value-added tax (VAT) exemption policy for imported equipment should be issued to motivate enterprises to invest in advanced equipment that facilitates clean production and green mining implementation. In addition, a green mining assistance fund could be established from the central government budget to finance the renovation of coal mine gas control technologies. Meanwhile, green mining system channels could be increased through the issuance of treasury bonds and creation of financial instruments (Zhu et al., 2019). As for public governance, the authorities should build and improve the stakeholder common governance institutions to achieve the goal of joint progress between enterprises and the society. Co-governance mechanisms could also serve as important factors for conducting transparent and strict supervision of information disclosure pertaining to the environmental governance performance of coal enterprises.

DATA AVAILABILITY STATEMENT

All datasets generated for this study are included in the article/supplementary material.

AUTHOR CONTRIBUTIONS

YW conceived the idea and developed the model. YL and SW collected the data and finished the programming. SW analyzed the results and wrote the paper.

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REFERENCES

Bajec, P., and Tuljak-Suban, D. (2019). An integrated analytic hierarchy processslack based measure-data envelopment analysis model for evaluating the efficiency of logistics service providers considering undesirable performance criteria. *Sustainability* 11, 1–18. doi: 10.3390/su11082330

Bi, G.-B., Song, W., Zhou, P., and Liang, L. (2014). Does environmental regulation affect energy efficiency in China's thermal power generation? Empirical evidence from a slacks-based DEA model. *Energy Policy* 66, 537–546. doi: 10.1016/j.enpol.2013.10.056

Bian, Y., and Yang, F. (2010). Resource and environment efficiency analysis of provinces in China: a DEA approach based on Shannon's entropy. *Energy Policy* 38, 1909–1917. doi: 10.1016/j.enpol.2009.11.071

Charnes, A., Cooper, W. W., and Rhodes, E. (1978). Measuring the efficiency of decision making units. *Eur. J. Oper. Res.* 2, 429–444. doi: 10.1016/0377-2217(78)90138-8

Chen, T.-H. (2009). Performance measurement of an enterprise and business units with an application to a Taiwanese hotel chain. *Int. J. Hospitality Manage.* 28, 415–422. doi: 10.1016/j.ijhm.2008.10.010

Cook, W. D., and Seiford, L. M. (2009). Data envelopment analysis (DEA) - thirty years on. *Eur. J. Oper. Res.* 192, 1–17. doi: 10.1016/j.ejor.2008.01.032

Fang, H., Wu, J., and Zeng, C. (2009). Comparative study on efficiency performance of listed coal mining companies in China and the US. *Energy Policy* 37, 5140–5148. doi: 10.1016/j.enpol.2009.07.027

Franks, D. M., Brereton, D., and Moran, C. J. (2010). Managing the cumulative impacts of coal mining on regional communities and environments in Australia. *Impact Assess. Proj. Appraisal* 28, 299–312. doi: 10.3152/146155110X12838715793129

Huang, J. J., Chen, Z. Y., Jiang, B. (2007). Research on investment estimation of environmental management engineering of abandoned dew mining mountain. *Geol. Hydrobiol. Eng.* 109–112.

Kirkey, J. (2014). *Eco Friendly Mining Trends for 2014.* Available online at: https://www.mining-technology.com/features/featureenvironment-friendly-mining-trends-for-2014-4168903/

Ma, J., Yu, Z. M., and Shu, S. H. (2015). Environmental hazards and measures of coal gangue to mining area. *Coal Eng.* 47, 70–73.

Mamurekli, D. (2010). Environmental impacts of coal mining and coal utilization in the UK. *Acta Montanistica Slovaca* 15, 134–144.

Nurmi, P. A. (2017). Green mining - a holistic concept for sustainable and acceptable mineral production. *Ann. Geophys.* 60, 1–7. doi: 10.4401/ag-7420

Qiu-ying, L. (2019). Input and output efficiency of urban agglomerations in China using DEA multi-stage model %. *J Ecol. Econ*. 15, 95–100.

Seiford, L. M., and Thrall, R. M. (1990). Recent developments in DEA: the mathematical programming approach to frontier analysis. *J. Econ.* 46, 7–38. doi: 10.1016/0304-4076(90)90045-U

Shao, Y., and Han, S. (2019). The synergy in the economic production system: an empirical study with Chinese Industry. *Sustainability* 11, 1–12. doi: 10.3390/su11040980

Shi, H. Q. (2012). Mine green mining. *2012 Int. Confer. Future Energy Environ. Mater*. 16(Pt A), 409–416. doi: 10.1016/j.egypro.2012.01.067

Shi, X., Rioux, B., and Galkin, P. (2018). Unintended consequences of China's coal capacity cut policy. *Energy Policy* 113, 478–486. doi: 10.1016/j.enpol.2017.11.034

Sueyoshi, T., and Goto, M. (2010). Should the US clean air act include CO2 emission control?: examination by data envelopment analysis. *Energy Policy* 38, 5902–5911. doi: 10.1016/j.enpol.2010.05.044

Sueyoshi, T., and Goto, M. (2012a). DEA radial measurement for environmental assessment and planning: desirable procedures to evaluate fossil fuel power plants. *Energy Policy* 41, 422–432. doi: 10.1016/j.enpol.2011.11.003

Sueyoshi, T., and Goto, M. (2012b). Efficiency-based rank assessment for electric power industry: a combined use of Data Envelopment Analysis (DEA) and DEA-discriminant analysis (DA). *Energy Economics* 34, 634–644. doi: 10.1016/j.eneco.2011.04.001

Sueyoshi, T., and Goto, M. (2012c). Environmental assessment by DEA radial measurement: U.S. coal-fired power plants in ISO (Independent System Operator) and RTO (Regional Transmission Organization). *Energy Econ.* 34, 663–676. doi: 10.1016/j.eneco.2011.08.016

Sueyoshi, T., and Yuan, Y. (2015). China's regional sustainability and diversified resource allocation: DEA environmental assessment on economic development and air pollution. *Energy Econ.* 49, 239–256. doi: 10.1016/j.eneco.2015.01.024

Sueyoshi, T., and Yuan, Y. (2018). Measuring energy usage and sustainability development in Asian nations by DEA intermediate approach. *J. Econ. Struct.* 7:6. doi: 10.1186/s40008-017-0100-0

Sueyoshi, T., Yuan, Y., Li, A., and Wang, D. (2017). Social sustainability of provinces in China: a Data Envelopment Analysis (DEA) window analysis under the concepts of natural and managerial disposability. *Sustainability* 9, 1–18. doi: 10.3390/su9112078

Tao, Y., and Zhang, S. (2013). Environmental efficiency of electric power industry in the Yangtze River Delta. *Math. Comput. Model.* 58, 927–935. doi: 10.1016/j.mcm.2012.10.025

Toloo, M., Emrouznejad, A., and Moreno, P. (2017). A linear relational DEA model to evaluate two-stage processes with shared inputs. *Comput. Appl. Math.* 36, 45–61. doi: 10.1007/s40314-014-0211-2

Tong, L., and Ding, R.-J. (2008). Efficiency assessment of coal mine safety input by data envelopment analysis. *J. China Univ. Mining Technol.* 18, 88–92. doi: 10.1016/S1006-1266(08)60019-X

Wang, J., Wang, K., Shi, X., and Wei, Y.-M. (2019). Spatial heterogeneity and driving forces of environmental productivity growth in China: would it help to switch pollutant discharge fees to environmental taxes? *J. Clean. Prod.* 223, 36–44. doi: 10.1016/j.jclepro.2019.03.045

Wang, Q., Su, B., Sun, J., Zhou, P., and Zhou, D. (2015). Measurement and decomposition of energy-saving and emissions reduction performance in Chinese cities. *Appl. Energy.* 151, 85–92. doi: 10.1016/j.apenergy.2015.04.034

Wang, Q., Zhao, Z., Zhou, P., and Zhou, D. (2013). Energy efficiency and production technology heterogeneity in China: a meta-frontier DEA approach. *Econ. Model.* 35, 283–289. doi: 10.1016/j.econmod.2013.07.017

Wu, J., Li, M., Zhu, Q., Zhou, Z., and Liang, L. (2019). Energy and environmental efficiency measurement of China's industrial sectors: a DEA model with non-homogeneous inputs and outputs. *Energy Econ.* 78, 468–480. doi: 10.1016/j.eneco.2018.11.036

Wu, J., Xiong, B., An, Q., Sun, J., and Wu, H. (2017). Total-factor energy efficiency evaluation of Chinese industry by using two-stage DEA model with shared inputs. *Ann. Operations Res.* 255, 257–276. doi: 10.1007/s10479-015-1938-x

Xian, Y., Wang, K., Shi, X., Zhang, C., Wei, Y.-M., and Huang, Z. (2018). Carbon emissions intensity reduction target for China's power industry: an efficiency and productivity perspective %. *J. Clean. Prod.* 197, 1022–1034. doi: 10.1016/j.jclepro.2018.06.272

Xie, B.-C., Fan, Y., and Qu, Q.-Q. (2012). Does generation form influence environmental efficiency performance? An analysis of China's power system. *Appl. Energy* 96, 261–271. doi: 10.1016/j.apenergy.2011.11.011

Xie, L., Chen, C., and Yu, Y. (2019). Dynamic assessment of environmental efficiency in chinese industry: a multiple dea model with a gini criterion approach. *Sustainability* 11, 1–12. doi: 10.3390/su11082294

Yang, H., and Pollitt, M. (2009). Incorporating both undesirable outputs and uncontrollable variables into DEA: the performance of Chinese coal-fired power plants. *Eur. J. Oper. Res.* 197, 1095–1105. doi: 10.1016/j.ejor.2007.12.052

Yang, Z., and Wei, X. (2019). The measurement and influences of China's urban total factor energy efficiency under environmental pollution: based on the game cross-efficiency DEA. *J. Clean. Prod.* 209, 439–450. doi: 10.1016/j.jclepro.2018.10.271

Zhang, R., Lu, C.-C., Lee, J.-H., Feng, Y., and Chiu, Y.-H. (2019). Dynamic environmental efficiency assessment of industrial water pollution. *Sustainability* 11, 1–22. doi: 10.3390/su11113053

Zhou, P., and Ang, B. W. (2008). Linear programming models for measuring economy-wide energy efficiency performance. *Energy Policy* 36, 2911–2916. doi: 10.1016/j.enpol.2008.03.041

Zhou, Y., Xing, X., Fang, K., Liang, D., and Xu, C. (2013). Environmental efficiency analysis of power industry in China based on an entropy SBM model. *Energy Policy* 57, 68–75. doi: 10.1016/j.enpol.2012.09.060

Zhu, N., Bu, Y., Jin, M., and Mbroh, N. (2019). Green financial behavior and green development strategy of Chinese power companies in the context of carbon tax. *J. Clean. Prod.* 245:118908. doi: 10.1016/j.jclepro.2019.118908

Conflict of Interest: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

APPENDIX

TABLE A1 | Detailed calculation results for all 30 enterprises.

DMU	Score	Benchmark (Lambda)	Proportionate movement (material consumption)	Slack movement (material consumption)	Projection (material consumption)
S01	0.63	S05(0.18); S06(0.37); S16(0.45)	−64.79	−3.06	106.15
S02	0.84	S05(0.04); S06(0.96)	−30.02	−60.23	97.54
S03	0.71	S05(0.34); S06(0.36); S16(0.29)	−65.06	−57.42	98.95
S04	0.82	S05(0.41); S06(0.10); S14(0.13); S16(0.35)	−28.41	−17.13	108.05
S05	1.00	S05(1.00)	0.00	0.00	78.65
S06	1.00	S06(1.00)	0.00	0.00	98.30
S07	0.86	S05(0.096); S06(0.50); S14(0.40)	−20.51	0.00	123.19
S08	0.67	S05(0.66); S14(0.24); S16(0.10)	−62.07	−20.45	103.78
S09	0.86	S05(0.26); S06(0.62); S14(0.12)	−16.01	0.00	101.13
S10	0.81	S05(0.59); S06(0.17); S14(0.24)	−36.41	−52.65	103.04
S11	0.68	S06(0.59); S14(0.12); S16(0.29)	−64.28	−20.46	113.56
S12	0.78	S05(0.45); S14(0.19); S16(0.36)	−43.15	−43.99	111.46
S13	0.71	S05(0.58); S16(0.42)	−57.84	−43.93	97.43
S14	1.00	S14(1.00)	0.00	0.00	165.30
S15	0.99	S05(0.10); S06(0.01); S14(0.38); S16(0.52)	−1.85	−5.29	135.06
S16	1.00	S16(1.00)	0.00	0.00	123.70
S17	0.92	S06(0.56); S14(0.44)	−13.02	−31.16	127.83
S18	0.91	S05(0.32); S14(0.38); S16(0.31)	−18.73	−68.53	125.14
S19	0.76	S06(0.88); S14(0.12)	−70.53	−115.20	106.25
S20	0.88	S05(1.00)	−10.80	0.00	78.65
S21	0.76	S05(0.91); S06(0.01); S16(0.08)	−40.12	−42.86	82.45
S22	0.91	S05(0.75); S14(0.25)	−15.39	−61.55	100.26
S23	0.74	S05(0.02); S06(0.98)	−49.54	−42.27	97.83
S24	0.98	S06(0.10); S14(0.10); S16(0.79)	−3.03	−14.27	125.48
S25	0.88	S06(0.90); S14(0.10)	−18.27	−27.63	105.09
S26	0.93	S05(0.35); S06(0.38); S16(0.27)	−7.22	0.00	98.38
S27	0.78	S05(0.39); S06(0.57); S14(0.03)	−26.65	0.00	92.75
S28	0.54	S05(0.58); S06(0.20); S14(0.03; S16(0.20)	−81.22	−3.22	93.95
S29	0.99	S05(0.08); S14(0.40); S16(0.52)	−1.45	−18.62	136.91
S30	0.68	S05(0.55); S06(0.02); S16(0.43)	−57.58	−22.04	98.36

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The Impacts of Reducing Renewable Energy Subsidies on China's Energy Transition by Using a Hybrid Dynamic Computable General Equilibrium Model

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This paper develops a hybrid computable general equilibrium model to explore the impacts of reducing renewable energy subsidies on China's energy transition in various scenarios. The results of the benchmark scenario indicate that China can realize its regulatory goals in energy consumption and structure and carbon emission intensity in 2030. This paper sets various policy scenarios to simulate the impacts of reducing renewable subsidies between 2021 and 2030. The analytical results of the scenarios indicate that the government's 2030 target for total energy and natural gas consumption and carbon emission intensity can be achieved. However, the target for non-fossil energy is hard to fulfill when the renewable energy subsidy is reduced. The empirical results also indicate that a moderate renewable energy subsidy associated with significant technical progress in renewable energy is a crucial way for China to fulfill government targets and energy transition in 2030.

Keywords: energy transition, hybrid dynamic computable general equilibrium model, renewable energy, reducing subsidies, policy scenarios

INTRODUCTION

In recent years, under the challenge of environmental degradation and climate change, the global renewable energy has made great progress with the strong support of government policies (Ji et al., 2019; Xu et al., 2019; Zhang and Ji, 2019). In order to effectively promote the development of renewable energy, such as wind power and solar power, China has also established a complete policy support system for renewable energy (Ji and Zhang, 2019). China has formulated a series of policies to promote renewable energy since 2006, especially the benchmark feed-in tariff (listed in **Tables 1**, **2**) and tax incentives. The added-value tax is levied by half, and the enterprise income tax is exempted from the first year to the third year and is halved from the fourth year to the sixth year when the projects of wind and solar power receive income. Those policies have effectively improved the economic benefits of wind and solar power enterprises and broaden renewable energy prospects in China.

TABLE 1 | Benchmark feed-in tariff of wind power.

Resource areas	Benchmark feed-in tariff (yuan /kWh)				
	2009	2014	2015	2018	New onshore wind power (2018)
Class I	0.51	0.49	0.47	0.44	0.40
Class II	0.54	0.52	0.50	0.47	0.45
Class III	0.58	0.56	0.54	0.51	0.49
Class IV	0.61	0.61	0.60	0.58	0.57

TABLE 2 | Benchmark feed-in tariff of solar power.

Resource areas	Benchmark feed-in tariff (yuan /kWh)			
	2013	2015	2017	2018
Class I	0.90	0.80	0.55	0.5
Class II	0.95	0.88	0.65	0.6
Class III	1.00	0.98	0.75	0.7

China has experienced rapid development in renewable energy and has been the biggest generator of wind and solar power in the world. By the end of 2018, the installed capacity of wind and solar power reached 360 GW. The generation of wind and solar power totaled 600 TWh, comprising nearly 9% of total electricity generation. Moreover, China has set an ambitious target for non-fossil fuel energy in the Energy Production and Consumption Revolution Strategy (2016–2030): the ratio of non-fossil fuel energy will be 20% and more than half the total energy consumption in 2030 and 2050, respectively. Recently, subsidies for renewable energy in China have declined with the expansion in the scale and technical progress in renewable energy. In particular, the government wants to achieve grid parity in wind and solar power in 2020. In 2019, the government stipulated that the price of new centralized onshore and offshore wind power projects permitted should be determined through market competition. Because the subsidy policy in China is crucial for promoting renewable energy development, it is important to assess the impacts of a reduction in subsidies on renewable energy and energy transition.

The computable general equilibrium (CGE) model incorporates all economy components and all economic links into a unified framework based on the general equilibrium theory of Walras. It describes sectoral interactions in the economy and can simulate the impacts and feedback from energy and environmental policy shocks on energy, the economy, and the environment. Therefore, it is widely used in energy and environmental policy evaluation (Pui and Othman, 2017; Li et al., 2018; Tran et al., 2019). As a top-down macro-model, CGE has the advantage of simulating the impact of policy on macroeconomic activities, but it has difficulty describing microcharacteristics in energy, emissions reduction technology, cost, and so on. The bottom-up microtechnology model can describe the technical and economic characteristics of energy and emission reduction technology. To achieve the advantages of both top-down and bottom-up models, a hybrid CGE model emerged that integrates the ideas of the two models (Xie et al., 2018).

The first kind of the hybrid CGE model combines a bottom-up energy partial equilibrium model that reflects energy information and a top-down CGE model. Tuladhar et al. (2009) analyzed the macroeconomic impacts of US climate change policies for three different emissions pathways using a top-down (multiregion national model, MRN) bottom-up (North American electricity and environment model, NEEM) integrated model. The MRN is a forward-looking, dynamic CTE model of the United States. The NEEM is a flexible, partial equilibrium model of the North American electricity market, taking into account demand growth, available generation, environmental technologies, and both current and future environmental regulations. Martinsen (2011) introduced energy technology learning in a national CGE model through soft links to a global technology rich energy systems model and a national energy systems model (Markal Norway) and analyzed the influence of global policy scenarios, particularly spillover of technology learning, on the energy demand of non-energy sectors of the economy. Arndt et al. (2016) developed a sequential approach to link a bottom-up energy sector model (South African TIMES Model, or SATIM) with a detailed dynamic general equilibrium model of South Africa, which is an intertemporal bottom-up partial equilibrium optimization model of South Africa's energy sector. The approach is designed to simultaneously address the shortcomings and maintain the benefits of detailed energy sector and general equilibrium models. Helgesen et al. (2018) linked a bottom-up energy system model[1] and a top-down CGE model to analyze both the energy system impacts and the economic impacts of reducing greenhouse gas emissions in transportation. Wu et al. (2019) adopted a hybrid of these approaches, which employed a soft link between the Asia-Pacific integrated model/CGE for Taiwan (top-down) and the Taiwan 2050 Calculator (bottom-up), to evaluate the effects of energy efficiency improvements in Taiwan. Related hybrid CGE models include Lanz and Rausch (2011) and Igos et al. (2015).

The second kind of the hybrid CGE model is a submodule of energy technology functions, which reflects the characteristics of energy technology and the economy, embedded in a top-down CGE model. Sue (2006, 2008) constructed an energy social accounting matrix, which embodied the subdivision of different power technology characteristics. Then, a hybrid CGE model was established, which included a bottom-up power technology functions module and a top-down CGE model. A dynamic CGE model for global carbon emission prediction and policy assessment (EPPA) was established by the MIT Joint Program on the Science and Policy of Global Change (Jacoby et al., 2004, 2014; Paltsev et al., 2005), which includes the submatrix and production function submodule reflecting the technical and economic characteristics of energy and power technology and the

[1]Norway Integrated Markal Efom System model, which gives a detailed description of the entire energy system, including all resources, energy production technologies, energy carriers, demand devices, and sectoral demand for energy services.

economy. Böhringer and Rutherford (2006, 2008) established a hybrid model combining an energy sector segmentation model with a CGE model based on an idea in the EPPA model and analyzed energy and environmental policies, such as gradually abolishing nuclear energy, a green quota, and a carbon tax. Using the method of subdividing the energy sector in the MIT EPPA model, Zhang et al. (2012, 2013) developed a CGE model with global coverage that disaggregated China's 30 provinces, including details on the energy system, and applied it to assess the impact of the current binding provincial carbon dioxide (CO_2) emission intensity targets. Wu et al. (2016, 2017) established a CGE model of China's multiregional energy–environment–economy with 30 regions and 17 sectors based on the MIT EPPA model. Meng et al. (2018) used a CGE model that integrates an electricity supply model, in which the electricity industry was disaggregated into eight sectors, to measure the effects of an emission trading scheme (ETS) on the energy sector and economy in Australia. Relevant hybrid CGE models also include Proença and Aubyn (2013), Cai and Arora (2015), Yun et al. (2016), Tabatabaei et al. (2017), and Lou (2017).

The most important difference between the two kinds of hybrid CGE models is the interconnection between the bottom-up model of energy information and the top-down macro-CGE model. The first kind of model, a microlocal equilibrium model and a macro-CGE model, is constructed under different economic assumptions. Researchers mainly integrate the results of the core variables in the two models and adjust the relevant exogenous parameters through external artificial operations, and the core variables in the two models achieve uniform convergence by a soft-link mechanism. Sometimes it is difficult to obtain the optimal solution.

The second kind of model connects the two models through specific functions. The information processing and interaction between the two models are automatically completed by programming, so the optimal solution to the two models can achieve uniform convergence. Many hybrid CGE models have been developed based on the second model.

This paper develops a hybrid CGE model of China's energy and environmental policy evaluation following the approach in this second model. The model disaggregates China's energy sectors into 11 subsectors to reflect the technical and economic characteristics of various energy sources with the biproportional scaling method and the method used in preparing China's input–output table for 2012 (Department of National Economic Accounting National Bureau of Statistics, 2014), and then construct the energy factors input functions module. Lastly, we develop a hybrid CGE model by embedding the energy factors input functions module into the production functions module. Using a hybrid CGE model, this paper determines the impacts of a policy to reduce subsidies for renewable energy and energy transformation in China in various scenarios.

The rest of this paper is as follows. The section *Methodology* proposes a hybrid CGE model, the section *Sectoral Setting and Data Sources* describes the sector setting and data sources, the section *Setting Policy Scenarios* describes different scenarios of the policy to reduce subsidies, the section *Empirical Results and Discussion* analyzes and discusses the results, and the section *Conclusions and Policy Implications* concludes this paper.

METHODOLOGY

The Proposed Hybrid CGE Model

We develop a hybrid CGE model of China's energy and environmental policy evaluation including five functional modules, production, trade, income and expenditure, carbon emissions and social welfare, and market clearing and model closure. **Figure 1** illustrates the structure of the proposed model, and the main functions of each module are explained in the **Supplemental Material**.

Production Module

About the structure of the input factors in terms of production functions, we first combine capital and energy input as capital–energy composition, then combine capital–energy input with labor input as labor–capital–energy composition. Lastly, a sector's final output is produced by labor–capital–energy composition input and intermediate input. This paper uses a Leontief function to combine labor–capital–energy composition with intermediate input and the constant elasticity of substitution (CES) function to combine other input factors.

This paper explores the impact of a reduction in subsidies on China's energy transition and renewable energy development. To embody the technological and economic characteristics of various types of energy and get robust simulation results, we disaggregate the energy sector in detail as shown in the production module of **Figure 1**. First, the coal sector comprises coal and coke, the petroleum sector includes crude oil and petroleum energy, the gas energy sector includes natural gas and gas, and clean energy comprises hydroelectricity, nuclear, wind power, solar power, and others. Second, according to the substitution relationship among energy sources, petroleum energy and gas energy are combined as petroleum and gas energy, then the fossil fuel-based energy is disaggregated into coal and composite petroleum and gas. At the same time, electrical power is further divided into thermal and clean power. Lastly, energy input consists of fossil fuel-based energy and electricity. Ultimately, the energy sector is disaggregated into 11 subsectors listed at the bottom of **Figure 1**.

Trade Module

In this module, the constant elasticity transformation (CET) function is employed to allocate the sectors' domestic products, and the producers determine the optimal allocation strategy among various markets in the given production technology constraints. The sectors' demand function for domestic production follows the "Armington hypothesis," and consumers minimize costs by optimizing the mix of domestic and imported products.

Income and Expenditure Module

This module encompasses income and expenditure of residents, enterprises, and government. The resident revenue is derived from labor factor income, capital factor income, government

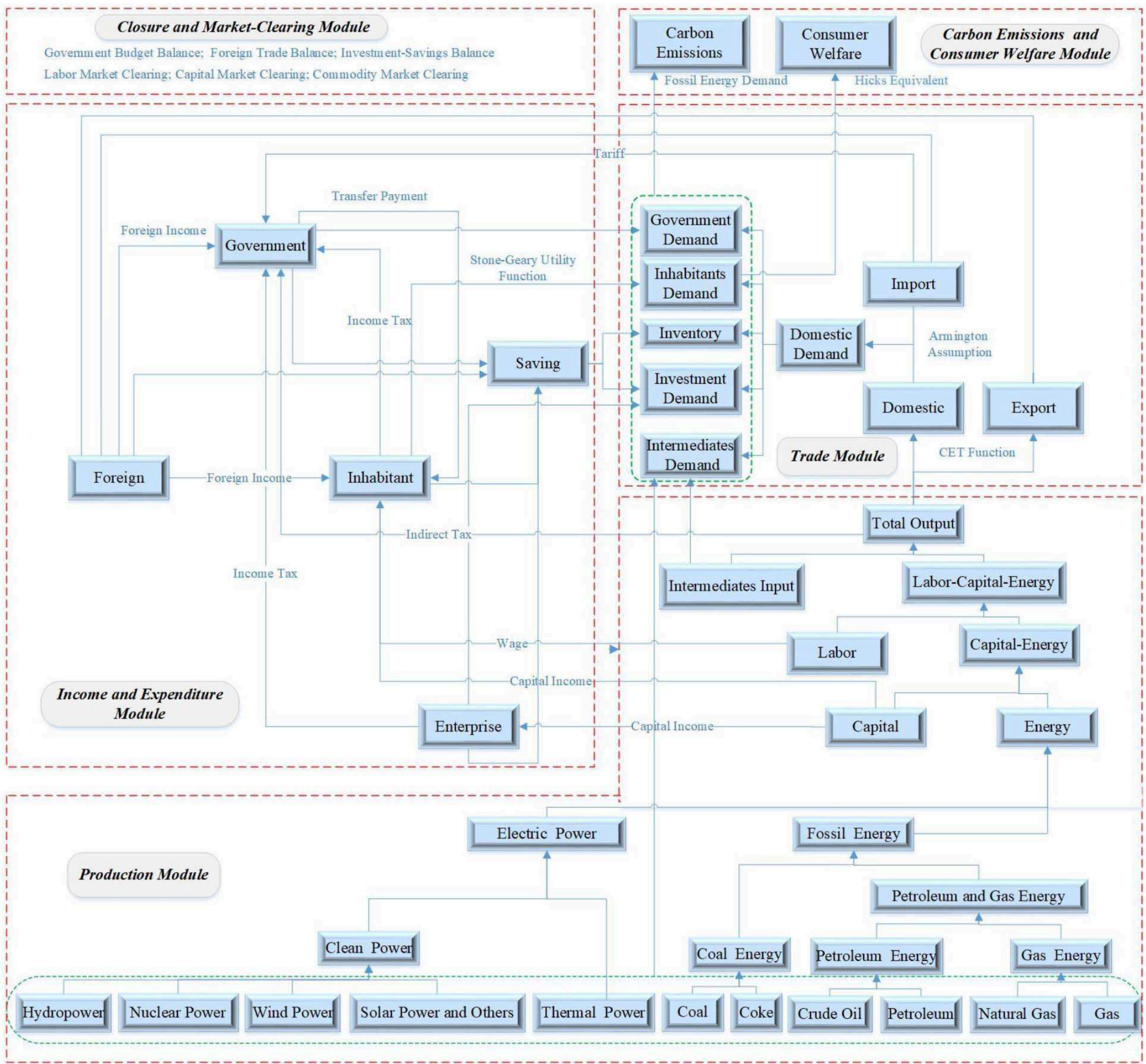

FIGURE 1 | Framework of the hybrid CGE model.

and enterprise transfer payment to residents, as well as overseas income. The resident expenditure includes consumption and savings, wherein the resident expenditure function is demonstrated by the Stone–Geary utility function. The enterprise income is mainly from the capital factor revenue, and its expenditure comprises the transfer payment to residents, savings, and stock. Government owes its income from taxes and foreign, and government expenditure is intended for government consumption and savings, transfer payments to residents, and assistance to foreign countries.

Carbon Emissions and Consumer Welfare Module

The carbon emissions in this paper refer to the ones from energy use. Hicks equivalent variation is applied to measure the impact of external policy change on the resident welfare. That is, we evaluate the changes in resident utility levels before and after the policy implementing on the basis of commodity price.

Closure and Market-Clearing Module

The market-clearing functions module involves equilibrium of labor market, capital market, and commodity market. This paper assumes that: (a) the wage level is an endogenous variable, and the labor market realizes full employment; (b) the capital return rate is an endogenous variable, and the capital can be fully utilized through the free flow of capital; and (c) the commodity price is an endogenous variable, and the balance between supply and demand of departmental commodities is capable of emerging.

TABLE 3 | Statistical number of model function and endogenous variables.

Functions module	Functions number	Endogenous variables number
Production functions module	$36n + nj$	$37n + nj + 2$
Trade functions module	$8n$	$8n + 1$
Income and expenditure module:		
Resident functions	$2n + 6$	$2n + 6$
Enterprise functions	$2n + 5$	$2n + 5$
Government functions	$3n + 7$	$3n + 7$
Carbon Emissions and Consumer Welfare Functions Module	3	3
Closure and Market-Clearing Functions Module	$3n + 9$	$2n + 6$
Total	$54n + nj + 30$	$54n + nj + 30$

The closure functions module includes saving–investment balance, government budget balance, and international payment balance. In this paper, the exchange rate is set endogenously while the foreign savings are set exogenously. The import and export are adjusted by the change of the exchange rate, ultimately to achieve the balance of payments.

Model Equations and Endogenous Variable

Table 3 shows the number of functions and endogenous variables of each module in this model and indicates that the number of equations equals the number of endogenous variables. Therefore, the model proposed in this paper is computable and has a solution.

Model Dynamic

The dynamic process of the model involves labor growth, technological progress (total factor productivity, TFP), and capital accumulation and allocation. In this paper, the labor growth and technological progress are given exogenously. The capital allocation among sectors is determined by the return rate of the sector capital, the average return, and the supply of the social capital based on a CET function.

$$
\begin{aligned}
L_{t+1} &= L_t \cdot \left(1 + lag_t\right) \\
TFP_{i,t+1} &= TFP_{i,t} \cdot \left(1 + tfpg_{i,t}\right) \\
K_{i,t} &= \alpha_i^{-\rho} \cdot \left(\frac{R_{i,t}}{AR_t}\right)^{\rho} \cdot KS_t \\
KS_t &= sum\left(i, \alpha_i \cdot K_{i,t}^{\frac{(1+\rho)}{\rho}}\right)^{\frac{\rho}{(1+\rho)}} \\
KS_{t+1} &= KS_t - \sum_i K_{i,t} \cdot depr_i + TINV_t
\end{aligned}
$$

where the subscript t is time. L_t denotes the labor supply. lag_t is the labor growth. $TFP_{i,t}$ is the total factor productivity, $tfpg_{i,t}$ is the growth of the total factor productivity, and $K_{i,t}$ is the capital demand of sector i. KS_t is the total supply of the social capital. $TINV_t$ is the total social investment. $R_{i,t}$ is the return on capital of sector i. AR_t is the average return on the social capital. $depr_i$ is the capital depreciation, and α_i is the capital demand share of sector i. ρ denotes the alternative elasticity correlation coefficient of capital demand between sectors.

SECTORAL SETTING AND DATA SOURCES

Sectoral Setting

In order to measure the impacts of policy change on clean energy and carbon emissions, the energy sector is disaggregated into 11 subsectors as shown in **Figure 1**. Consequently, 31 industries are compiled based on China's 2012 Input/Output table, as listed in **Table 4**.

This paper disaggregates the petroleum and natural gas extraction sector in China's 2012 IO tables into two subsectors, the petroleum extraction sector and the natural gas extraction sector, because the input structure of the production processes and the allocation of the outputs of petroleum extraction and natural gas extraction differ significantly using the biproportional scaling method. Similarly, in *the method of preparing China's 2012 IO table* (Department of National Economic Accounting National Bureau of Statistics, 2014), the production and supply of electricity are subdivided into the production and distribution of thermal power, the production and distribution of hydropower, the production and distribution of nuclear power, the production and distribution of wind power, the production and distribution of solar power, and others.

In the IO tables published in China, the "oil exploitation" and "natural gas exploitation" are statistically managed as two different sectors only in 1997, while they are termed as a single department of "oil and gas exploitation" in other years. So this paper splits the "oil and gas exploitation" into two subsectors of "oil exploitation" and "natural gas exploitation" in the 2012 IO table by the following steps: (1) We firstly merge the basic flow chart of the 1997 IO table into 26 sectors then adjust the 2012 IO table to 25 sectors, which are consistent with those in 1997 (excluding the "oil and gas exploitation" sector). (2) According to the comparison of "China energy balance table (standard quantity)" in *China Energy Statistics Yearbook 2013* and the 2012 IO table, this paper determines the sum of rows and columns of the intermediate input and demand of "oil exploitation" and "natural gas exploitation" in the 2012 IO table. (3) Taking the sum of rows and columns of intermediate input and demand in the 2012 IO table as the target control variables (26 sectors), we update the structure data of the intermediate input and demand in 1997 IO table through the biproportional scaling technique. (4) The intermediate input and demand data of the "oil and gas exploitation" sector in the 2012 IO table (25 sectors) are disaggregated based on the ratio coefficient of intermediate input and demand of "oil exploitation" and "natural gas exploitation" in the updated 1997 IO table. (5) The data of household consumption, government consumption, capital investment, stock import, export, and added value in the "oil exploitation" sector and the "natural gas exploitation" sector are determined according to the 2012 IO table and the "China energy balance table (standard quantity)" in *China Energy Statistics Yearbook 2013*.

TABLE 4 | Sectoral classification.

Code	Sectors	Code	Sectors
1	Agriculture, Forestry, Animals Husbandry, and Fishing	17	Finance and Insurance
2	Mining and Processing of Other Ores	18	Real Estate, Tenancy, and Business Services
3	Manufacture and Processing of Food and Tobacco	19	Other services
4	Manufacture and Processing of Textiles and Related Products	20	Processing of Nuclear Fuel
5	Processing Manufacture of Timber, Paper, Printing, and Articles for Culture, Education, and Sports Activity	21	Mining and Washing of Coal
6	Chemical Industry	22	Coking
7	Manufacture of Cement, Lime, and Gypsum	23	Extraction of Petroleum
8	Manufacture of Nonmetallic Mineral Products	24	Processing of Petroleum
9	Smelting and Pressing and Manufacture of Metals and Related Products	25	Extraction of Natural Gas
10	Manufacture of Machinery and Equipment	26	Production and Distribution of Gas
11	Manufacture of Communications Equipment, Measuring Instruments, and Other Manufacturing	27	Production and Distribution of Thermal Power
12	Production and Distribution of Water	28	Production and Distribution of Hydropower
13	Construction	29	Production and Distribution of Nuclear Power
14	Transport, Storage, and Post	30	Production and Distribution of Wind Power
15	Wholesale, Retail Trade, Hotel, and Restaurants	31	Production and Distribution of Solar Power and Other
16	Information Transfer, Computer Services, and Software		

The specific splitting procedure of the power generating and supply sector is depicted as follows: (1) According to the rules of *The Method of Preparing the China Input–Output Table 2012*, we format the share of intermediate input and added value of various power sectors based on the data such as cost statement and profit statement of various power generating, transmission, and supply enterprises in 2012. (2) Fossil energy is fully consumed by the thermal power sector, and nuclear fuel is used for generating nuclear power during the power generation process. (3) The input demand for power of thermal power, hydropower, nuclear power, wind power, solar power, and other power sectors comes from their own sectors. (4) The power generating and supply sector (input structure) is divided into the thermal power, hydropower, nuclear power, wind power, solar power, and other electric power according to the row sum of generation and average feed-in-tariff of all kinds of electric power in 2012 as the control variable. (5) The product allocation (output structure) between the intermediate input and the final demand of the power production and supply sectors is determined by the output value of each sector.

Data Sources

The basic data are from the 2012 IO table, *2012 Statistical Yearbook, 2013 China Power Yearbook, China Energy Statistics Yearbook 2013* of the National Bureau of Statistics of the People's Republic of China, and annual statistics from the China Electricity Council.

The elasticity coefficients of production and trade functions are calibrated and set in the model referring to the relevant researches including Xuan (2002), Wang (2003), Tan (2008), Guo et al. (2014, 2019), and Chi et al. (2014). **Table S2** is the elasticity of substitution coefficients.

The model necessitates the calculation of the carbon emission coefficient for fossil energy. The calculating process is demonstrated as follows: (1) The fossil energy is divided into six categories including raw coal, crude oil, oil processing products, coke, natural gas, and gas, which are obtained from the "energy balance table" in *China Energy Statistics Yearbook 2013*. (2) The carbon emissions from coking and gas producing are eliminated from the total emissions of raw coal and crude oil. (3) The carbon emissions of oil processing products comprise from gasoline, kerosene, diesel, fuel oil, liquefied petroleum gas, refinery dry gas, and other petroleum products. (4) The average low-heat value of diverse fossil energy refers to *China Energy Statistics Yearbook 2013*. (5) The carbon emission factors of fossil energy come from the *2006 IPCC Guidelines for National Greenhouse Gas Inventories*. (6) To obtain the carbon emission coefficients of fossil energies, the carbon emissions of six different fossil energies are calculated and divided by the corresponding energy value in the IO table. The coefficients of carbon emissions are in **Table S3**.

SETTING POLICY SCENARIOS

First, we forecast energy consumption, carbon emissions, and the structure during the period 2012−2030 in a benchmark scenario against which the other policy scenarios can be compared. Following Li (2010) and Chi et al. (2014), this benchmark scenario includes parameters such as the growth rate of the labor, the total factor productivity (TFP), the input and output structure of intermediate goods, the consumer savings rate, and the trade surplus. The benchmark scenario assumes that the labor growth rate decreases gradually in the primary industry, first increases and then decreases after 2020 in the secondary industry, and increases gradually in the tertiary industry. The TFP is assumed to be 2.00% in the primary industry, 1.80% in the secondary industry, and 2.00% in the tertiary industry. In addition, the TFP is 2.50% in wind power and 3.00% in solar power. We assume that the intermediate input rate will continue to increase in agriculture but will be slightly lower in energy and resources, and during the simulation period, labor-intensive sectors will decrease. The consumer savings rate and the trade surplus are assumed to gradually decrease with economic development and social progress.

Then we discuss China's energy transition with an assumption of a decline in subsidies for renewable energy. Subsidies for wind and solar power in China are based on the FIT, so smaller subsidies significantly decrease the rate of return on power generation enterprises producing them. Based on changes in the rate of return, we design three scenarios with a reduction in subsidies.

Policy Scenario 1: Compared with the benchmark scenario, the rate of return on wind and solar power production falls by 20% as a result of a reduction in subsidies beginning in 2021.

Policy Scenario 2: Compared with the benchmark scenario, the rate of return on wind and solar power production falls by 30% as a result of a reduction in subsidies beginning in 2021.

Policy Scenario 3: Compared with the benchmark scenario, in 2021, subsidies on wind and solar power are eliminated. Comparing the FIT of wind and solar power in 2012 and desulfurized coal power in 2017, the average FIT of wind and solar power declined by 36 and 65%, respectively. By calculating the IO structure of wind and solar power, the rate of return on wind and solar power generation decreases by 40 and 70%, respectively, which we hypothesize will remain the predominant tendency.

China has been the biggest generator of wind and solar power. Because of technical progress in wind and solar power, their costs will continuously decrease, which in turn will promote the development of wind and solar power. Therefore, to explore the energy transition in the future, we design various scenarios involving reductions in subsidies for renewable energy linked with technical progress.

Policy Scenario 4: Based on scenario 3, we assume that the TFP in the generation of wind and solar power is 3.0 and 3.5%, respectively, which is 0.5 percentage points higher than in the benchmark scenario.

Policy Scenario 5: Based on scenario 3, we assume that the TFP in the generation of wind power reaches 3.5% (1.00% higher than the benchmark) and in solar power reaches 5.25% (2.25% higher than the benchmark).

Policy Scenario 6: Based on scenario 2, we assume that the TFP in the generation of wind and solar power is 0.5% higher than the benchmark, reaching 3.00 and 3.50%, respectively.

Policy Scenario 7: Based on scenario 2, we assume that the TFP in the generation of wind and solar power reaches 3.30 and 3.85%, respectively.

EMPIRICAL RESULTS AND DISCUSSION

Table 5 shows the impacts of a reduction in renewable energy subsidies on electricity generation and its structure. **Table 6** shows the impacts on energy consumption, carbon emissions, and carbon intensity. **Table 7** shows the impacts on the structure of energy, and **Table 8** reports the feasibility of meeting government targets.

Discussion Based on the Benchmark Scenario

According to a document issued by the Chinese National Development and Reform Commission (NDRC), China's Intended Nationally Determined Contributions (INDC), China pledged to a target around 2030 or earlier of a peak in carbon emissions and a decline in carbon emission intensity by 60–65% compared with the level in 2005. In addition, non-fossil fuel energy is targeted to comprise about 20% of primary energy consumption in 2030. According to the Energy Production and Consumption Revolution Strategy (2016–2030) issued by the NDRC, the target for total energy consumption is about 5 billion tons of standard coal equivalent (tce) in 2020 and about 6 billion tce in 2030. Non-fossil fuel energy will comprise 15% of primary energy consumption in 2020 and about 20% in 2030. Natural gas will comprise about 15% of primary energy consumption in 2030. According to the thirteenth 5-Year Plan for Energy Development issued by the NDRC, total energy consumption will be about 5 billion tce of which coal is 4.1 billion tons; electricity consumption is expected to be 6,800–7,200 TWh in 2020. Non-fossil fuel energy consumption will increase to more than 15% of total energy consumption, natural gas consumption will comprise 10%, and coal will decrease to <58% in 2020.

In the benchmark scenario, China's total electricity generation will increase significantly and reach 8,286.63 TWh in 2030. Although thermal power generation will steadily increase, its proportion of total power generation will decrease. Hydroelectric power will increase slightly, and its proportion will remain stable. Nuclear, wind, solar, and other types of power will increase significantly with an increasing share of total power generation. The structure of power generation is further optimized with the share of thermal power generation dropping to 60.17%, while the share of wind and solar power will increase to 11.74 and 7.99% of total electricity generation, respectively.

Total energy consumption will continuously increase and reach 5.941 billion tce, less than the government target of 6 billion tce in 2030. The proportion of non-fossil fuel energy will increase to 20.40% in 2030 and so will natural gas. Although coal consumption will still increase, its share of total energy consumption will decrease significantly and fall to 47.84% in 2030. Oil consumption will increase slightly at a stable proportion of total energy consumption and reach 16.08% in 2030, which is higher than the government target of 15%. Carbon emissions will increase continuously up to 146.42 billion tons, but carbon emission intensity will decrease significantly and fall to 0.9593 ton/RMB 10,000 in 2030. That is, carbon emission intensity, total energy consumption, and the energy structure can meet the government targets. The results of the benchmark scenario provide a baseline for the policy scenarios.

The Results in the Energy Subsidy Reduction Scenario (Scenarios 1–3)

As shown in **Table 5** and **Figure 2**, after reductions in subsidies for renewable energy, wind and solar power generation will significantly decline compared with the benchmark scenario, while thermal and total power generation will increase. Meanwhile, as subsidies are reduced further, wind, solar, and

TABLE 5 | Power generation and its structure (in TWh).

Scenarios	Forecast/Proportion	Year	Power generation	Type of power generation				
				Thermal power	Hydropower	Nuclear power	Wind power	Solar power and others
Benchmark scenario	Forecast	2012	4,986.50	3,925.50	855.60	98.30	103.00	4.10
		2015	5,715.44	4,232.42	1,082.61	174.14	192.65	33.61
		2020	6,898.95	4,740.29	1,208.95	288.38	423.34	238.00
		2025	7,501.78	4,875.81	1,248.19	324.91	626.65	426.22
		2030	8,286.63	4,986.45	1,299.03	366.08	973.16	661.91
	Proportion (%)	2020		68.71	17.52	4.18	6.14	3.45
		2025		65.00	16.64	4.33	8.35	5.68
		2030		60.17	15.68	4.42	11.74	7.99
Scenario 1	Forecast	2025	7,373.49	4,918.60	1,259.49	328.04	521.07	346.29
		2030	8,066.88	5,039.72	1,313.05	370.40	807.57	536.15
	Proportion (%)	2025		66.71	17.08	4.45	7.07	4.70
		2030		62.47	16.28	4.59	10.01	6.65
Scenario 2	Forecast	2025	7,306.54	4,941.84	1,265.55	329.73	464.83	304.60
		2030	7,952.31	5,068.77	1,320.59	372.74	719.45	470.75
	Proportion (%)	2025		67.64	17.32	4.51	6.36	4.17
		2030		63.74	16.61	4.69	9.05	5.92
Scenario 3	Forecast	2025	7,175.42	4,986.31	1,276.95	332.92	407.65	171.59
		2030	7,729.70	5,124.35	1,334.80	377.17	630.47	262.91
	Proportion (%)	2025		69.49	17.80	4.64	5.68	2.39
		2030		66.29	17.27	4.88	8.16	3.40
Scenario 4	Forecast	2025	7,222.51	4,967.20	1,272.18	331.57	459.82	191.76
		2030	7,894.52	5,077.64	1,323.22	373.51	793.70	326.46
	Proportion (%)	2025		68.77	17.61	4.59	6.37	2.65
		2030		64.32	16.76	4.73	10.05	4.14
Scenario 5	Forecast	2025	7,321.61	4,933.18	1,263.68	329.17	515.61	279.97
		2030	8,305.23	4,987.16	1,300.71	366.40	980.84	670.12
	Proportion (%)	2025		67.38	17.26	4.50	7.04	3.82
		2030		60.05	15.66	4.41	11.81	8.07
Scenario 6	Forecast	2025	7,369.68	4,919.70	1,259.98	328.16	523.29	338.56
		2030	8,170.91	5,014.94	1,307.13	368.50	901.85	578.49
	Proportion (%)	2025		66.76	17.10	4.45	7.10	4.59
		2030		61.38	16.00	4.51	11.04	7.08
Scenario 7	Forecast	2025	7,405.17	4,908.40	1,257.13	327.35	547.93	364.36
		2030	8,302.21	4,986.53	1,300.01	366.25	982.93	666.50
	Proportion (%)	2025		66.28	16.98	4.42	7.40	4.92
		2030		60.06	15.66	4.41	11.84	8.03

total power generation will fall rapidly. When the subsidy is eliminated in 2030, total electricity generation will be 6.72% lower than the benchmark scenario. With respect to the structure of power generation, compared with the benchmark scenario, the proportion of wind and solar power generation will shrink after subsidies are further reduced. After elimination of the subsidy in 2030, the ratio of wind and solar power to total electricity generation will fall to 8.16 and 3.40%, which is 3.58 and 4.59% lower than the benchmark scenario, respectively. By comparison, thermal power, hydropower, and nuclear power generation will increase because of their substitution effects on wind and solar power generation.

As shown in **Table 6** and **Figures 3**, **4**, compared with the benchmark scenario, total energy consumption will decrease in 2021 because of reductions in the subsidies. The elimination of renewable energy subsidies in 2030 will reduce the total energy consumption to 5,770.04 billion tce, lower than both the benchmark and the government target. However, in 2030, total carbon emissions will rise to 14.86 billion tons, 1.53% higher than the benchmark scenario. In addition, carbon emission intensity of the gross domestic product will reach 0.9799 tons/RMB10, 000, which is 2.14% higher than the benchmark scenario. The INDC reveals that carbon emission intensity in 2014 fell by 33.80% compared with the level in 2005. Impressively, the results of this study show that carbon emission intensity

TABLE 6 | Energy Consumption and Carbon Emissions.

Scenarios	Forecast/Variation	Year	Total energy consumption (Million tce)	Total carbon emissions (Million tons)	Carbon emission intensity (tons/RMB 10,000)
Regulation target		2030	<6000	Peak in 2030 or earlier	60–65% decrease compared with 2005
Benchmark scenario	Forecast	2012	4,021.38	8,846.33	1.6480
		2015	4,337.88	9,487.54	1.4204
		2020	4,990.30	11194.45	1.2434
		2025	5,379.95	12,619.99	1.0815
		2030	5,941.10	14,641.94	0.9593
Scenario 1	Forecast	2025	5,342.90	12,685.66	1.0888
		2030	5,873.69	14,730.10	0.9670
	Variation (%)	2025	−0.69	0.52	0.67
		2030	−1.13	0.60	0.80
Scenario 2	Forecast	2025	5,323.67	12,720.82	1.0927
		2030	5,838.65	14,777.23	0.9712
	Variation (%)	2025	−1.05	0.80	1.03
		2030	−1.72	0.92	1.23
Scenario 3	Forecast	2025	5,285.59	12,787.02	1.1010
		2030	5,770.04	14,865.43	0.9799
	Variation (%)	2025	−1.75	1.32	1.80
		2030	−2.88	1.53	2.14
Scenario 4	Forecast	2025	5,298.76	12,759.38	1.0977
		2030	5,820.25	14,794.38	0.9731
	Variation (%)	2025	−1.51	1.10	1.50
		2030	−2.03	1.04	1.44
Scenario 5	Forecast	2025	5,327.70	12,710.12	1.0912
		2030	5,950.09	14,655.55	0.9578
	Variation (%)	2025	−0.97	0.71	0.89
		2030	0.15	0.09	−0.16
Scenario 6	Forecast	2025	5,341.97	12,688.50	1.0888
		2030	5,906.58	14,694.11	0.9630
	Variation (%)	2025	−0.71	0.54	0.67
		2030	−0.58	0.36	0.38
Scenario 7	Forecast	2025	5,352.48	12,671.97	1.0866
		2030	5,948.09	14,649.94	0.9583
	Variation (%)	2025	−0.51	0.41	0.47
		2030	0.12	0.05	−0.10

is 41.79% lower in 2030 than in 2012. Hence, the carbon emission intensity in policy scenarios 1–3 is lower than the government target.

As shown in **Table 7** and **Figure 5**, consumption of non-fossil fuel energy will decline gradually as a result of the substitution effect among energy sources, and the consumption of coal, oil, and natural gas will increase as this occurs. In particular, in the subsidy-free scenario (scenario 3), consumption of non-fossil fuel energy in 2030 will fall to 16.59%, lower than both the benchmark scenario and the government target of 20%. In addition, the proportion of coal in total energy consumption in 2030 will rise to as much as 50.32%, which is 2.48 percentage points higher than the benchmark scenario as well as higher than the government target of <48%.

As a whole, if the subsidies for renewable energy are eliminated, the government target for total energy consumption and carbon emission intensity would be achieved, but it will fail to achieve the target for non-fossil energy in 2030.

The Results of Renewable Energy Subsidy Elimination Associated With Technical Progress (Policy Scenarios 4–5)

In policy scenario 5, wind and solar power generation will increase significantly because of technical progress, whereas thermal power, hydropower, and nuclear power will slightly decrease. Consequently, total consumption of electrical power and total energy will slightly increase, while carbon emissions

TABLE 7 | Subsector primary energy consumption (in million tce).

Scenarios	Forecast/Proportion	Year	Coal	Oil	Natural gas	Non-fossil fuel energy
Regulatory target		2030			15%	20%
Benchmark scenario	Forecast	2012	2,754.65	683.63	193.03	390.07
		2015	2,752.99	788.18	251.37	545.34
		2020	2,839.54	853.55	503.80	793.41
		2025	2,840.96	897.20	677.07	964.72
		2030	2,842.38	931.88	955.08	1,211.76
	Proportion (%)	2012	68.50	17.00	4.80	9.70
		2015	63.46	18.17	5.79	12.57
		2020	56.90	17.10	10.10	15.90
		2025	52.81	16.68	12.59	17.93
		2030	47.84	15.69	16.08	20.40
Scenario 1	Forecast	2025	2,860.38	900.82	679.65	902.05
		2030	2,865.94	936.46	959.44	1,111.85
	Proportion (%)	2025	53.54	16.86	12.72	16.88
		2030	48.79	15.94	16.33	18.93
Scenario 2	Forecast	2025	2,871.00	902.70	680.97	869.00
		2030	2,878.86	938.85	961.67	1,059.26
	Proportion (%)	2025	53.93	16.96	12.79	16.32
		2030	49.31	16.08	16.47	18.14
Scenario 3	Forecast	2025	2,891.45	906.13	683.32	804.70
		2030	2,903.71	943.19	965.65	957.49
	Proportion (%)	2025	54.70	17.14	12.93	15.22
		2030	50.32	16.35	16.74	16.59
Scenario 4	Forecast	2025	2,882.56	904.78	682.44	828.99
		2030	2,882.44	939.88	962.82	1,035.04
	Proportion (%)	2025	54.40	17.08	12.88	15.64
		2030	49.53	16.15	16.54	17.78
Scenario 5	Forecast	2025	2,866.72	902.37	680.87	877.74
		2030	2,841.20	933.36	957.26	1,218.27
	Proportion (%)	2025	53.81	16.94	12.78	16.48
		2030	47.75	15.69	16.09	20.47
Scenario 6	Forecast	2025	2,860.71	901.10	679.91	900.26
		2030	2,854.39	934.91	958.27	1,159.02
	Proportion (%)	2025	53.55	16.87	12.73	16.85
		2030	48.33	15.83	16.22	19.62
Scenario 7	Forecast	2025	2855.45	900.27	679.37	917.39
		2030	2841.43	932.80	956.44	1217.43
	Proportion (%)	2025	53.35	16.82	12.69	17.14
		2030	47.77	15.68	16.08	20.47

will decrease slightly. Like policy scenarios 1–3, the government target for non-fossil fuel energy in 2030 is not attained.

To achieve the non-fossil fuel energy target in 2030, we raise the technical progress in wind and solar power in policy scenario 5, enabling them to significantly increase compared with scenario 4. Wind, solar, and other types of power will account for 19.88% of total power generation, and the proportion of non-fossil fuel energy in total energy consumption will be 20.47% in 2030, which means that the government target for non-fossil fuel energy can be achieved in policy scenario 5. Thermal power, hydropower, and nuclear power generation will slightly increase; consequently, total power generation slightly increases compared with scenario 4. Because of a decline in fossil fuel energy consumption and a significant increase in non-fossil fuel energy consumption in 2030, carbon emissions will decrease, but total energy consumption will increase.

Although the government target can be achieved in scenario 5, doing so requires a technological leap in wind and solar power generation because this level of technical progress is too high for China to achieve. Therefore, in the next section, we consider scenarios with a moderate subsidy and technical progress in renewable energy.

The Results of Renewable Energy Subsidy Reduction Associated With Technical Progress (Policy Scenarios 6–7)

In scenario 6, the only difference is the level of renewable energy subsidies, which is moderate rather than zero as in scenario 4. Compared with scenario 4, wind and solar power generation will increase significantly and account for 18.12% of total power generation, while the generation of other types of power will decrease slightly. Consequently, total power generation will increase to 8,170.91 TWh in 2030. Because of the decrease in fossil fuel energy such as coal, oil, and natural gas, carbon emissions will decrease to 14,694.11 million tons, though total energy consumption will increase to 5,906.58 million tec in 2030. In 2030, non-fossil fuel energy will comprise 19.62% of total energy consumption, which indicates that the government target for non-fossil fuel energy can be basically achieved in scenario 6. If a relatively high level of renewable energy technical progress is achieved in scenario 7, then non-water renewable power will increase significantly and account for 19.87% of total power generation. Moreover, in 2030, non-fossil fuel energy consumption will increase and comprise 20.47% of total energy consumption, which is slightly higher than the government target of 20%. In addition, the consumption fossil fuel energy and carbon emissions will decrease compared with those in scenario 4. Although total energy consumption will slightly increase to 5,948.09 million tec, it will be lower than the government target of 6,000 million tec.

As a whole, **Table 8** indicates that government targets except in non-fossil fuel energy can be achieved in every policy scenario, and the target for non-fossil fuel energy will fail to be achieved if the subsidies for renewable energy are withdrawn. In addition, in scenario 4 (no subsidy), the government target for non-fossil fuel energy will not be achieved even though technical progress is improved. High technical progress in renewable energy is required to achieve the government target for non-fossil fuel energy, but the level in scenario 5 is too high for China to attain. Therefore, a moderate subsidy associated with feasible technical progress in renewable energy (scenarios 6 and 7) is an effective way to meet government targets in 2030 and is helpful for energy transition in China.

TABLE 8 | The feasibility of government regulatory targets in 2030.

Scenario	Total energy consumption	Carbon emission intensity	Proportion of natural gas	Proportion of non-fossil fuel energy consumption
Benchmark	√	√	√	√
Scenario 1	√	√	√	×
Scenario 2	√	√	√	×
Scenario 3	√	√	√	×
Scenario 4	√	√	√	×
Scenario 5	√	√	√	√
Scenario 6	√	√	√	√
Scenario 7	√	√	√	√

√ Target is achievable. × Target is not achievable.

CONCLUSIONS AND POLICY IMPLICATIONS

This paper develops a hybrid CGE model of China's energy and environment policy evaluation, which disaggregates China's energy sectors into 11 subsectors in order to reflect the technical and economic characteristics of various energy sources by the biproportional scaling method and the

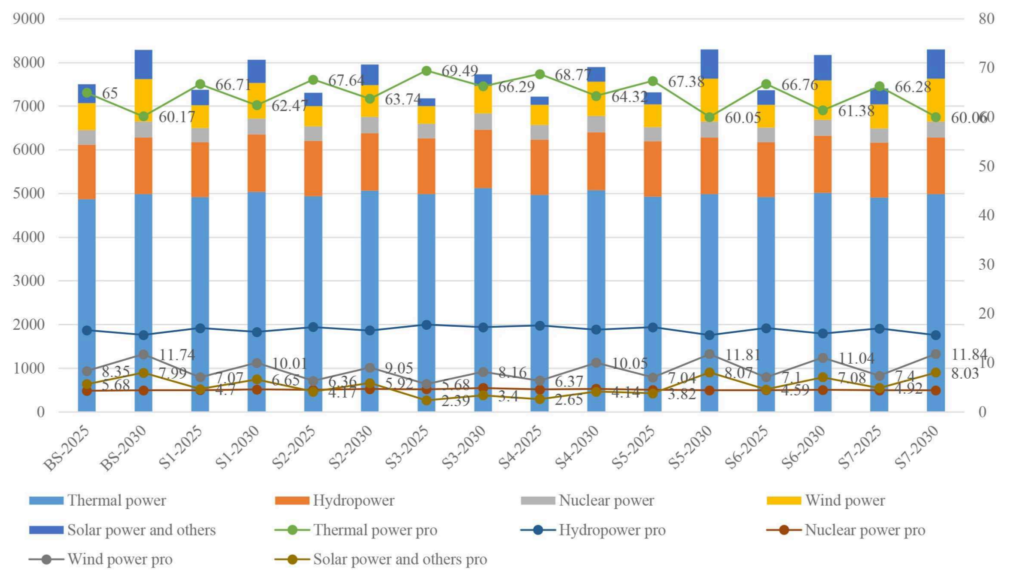

FIGURE 2 | Power generation and its structure in 2025 and 2030. Unit: TWh/%.

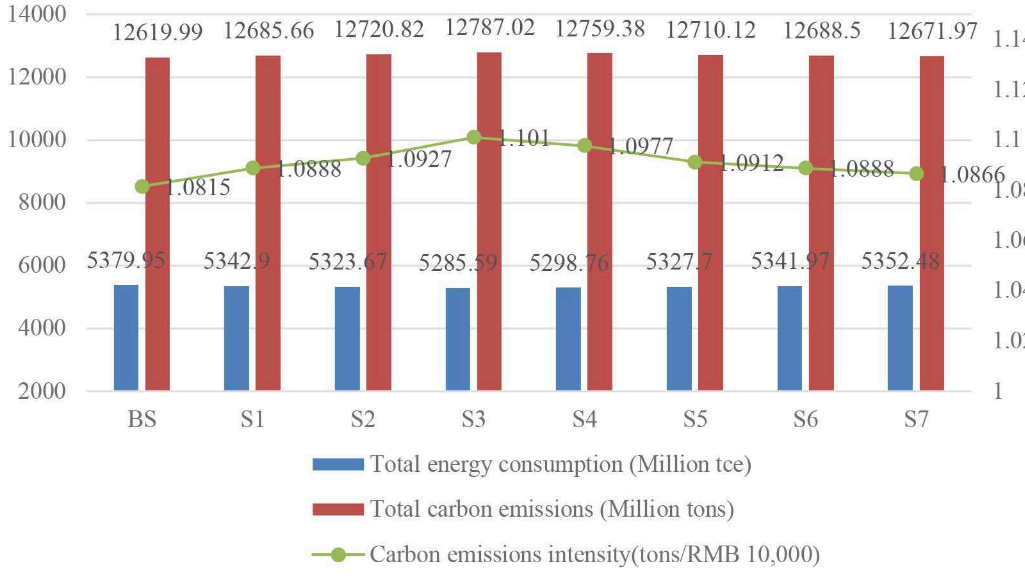

FIGURE 3 | Energy Consumption and Carbon Emissions in 2020.

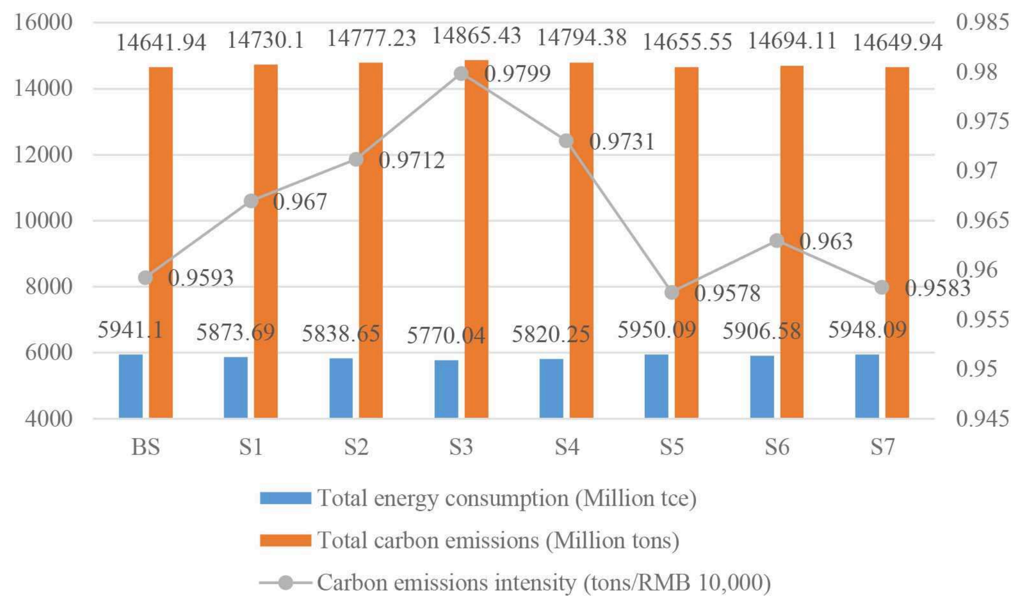

FIGURE 4 | Energy Consumption and Carbon Emissions in 2030.

Method of Preparing the China Input–Output Table 2012. Then we explore the impacts of reducing and eliminating subsidies on renewable energy development and energy transition in China using this hybrid dynamic CGE model. In the benchmark scenario, this paper estimates energy consumption and its structure, carbon emissions, and carbon intensity from 2012 to 2030. The forecast results are consistent with the Chinese government's target. Thus, the benchmark scenario provides a comparative baseline for policy simulations.

The elimination of subsidies for wind and solar power will result in a significant drop in the generation and proportion of wind and solar power in 2030. Particularly in the subsidy-free scenario, the consumption of non-fossil fuel energy falls, while the proportion of coal will rise significantly, exceeding the government's goal. Consequently, it is impossible to achieve the government's target.

In a renewable energy subsidy-free scenario, China could achieve its targets in energy transition and carbon emissions if the TFP of wind and solar power reaches 3.50 and 5.25%,

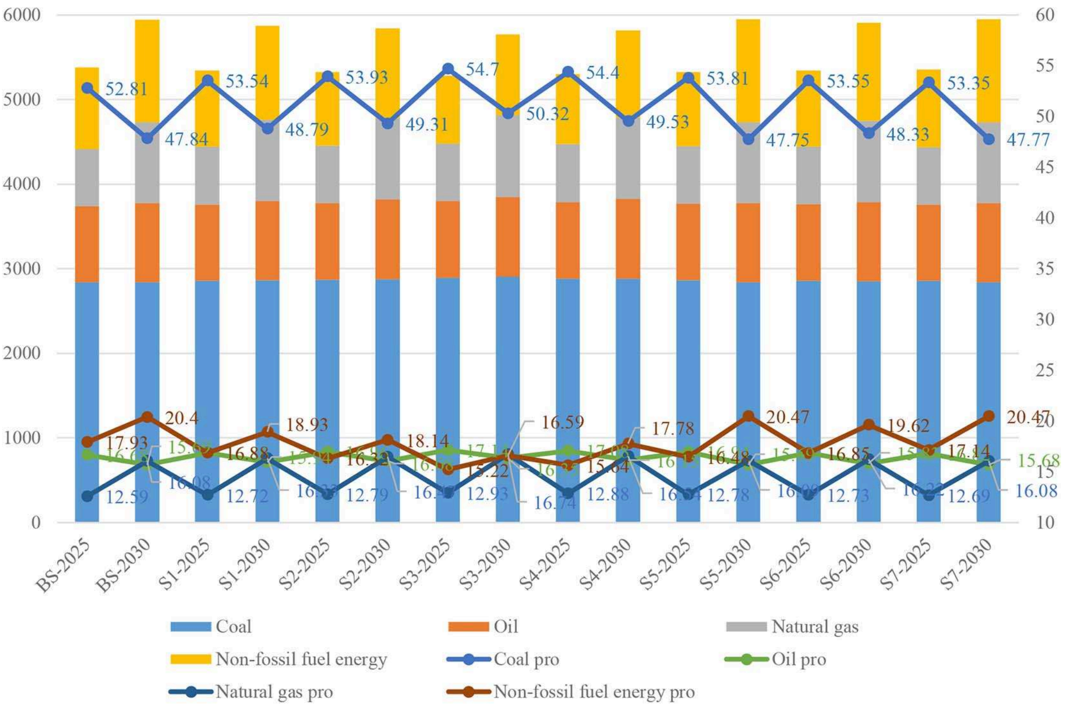

FIGURE 5 | Subsector primary energy consumption and structure in 2030 Unit: TWh/%.

respectively. However, doing so requires a leap in technological progress, especially in solar power, which is a huge challenge for China. In the scenario of a 30% reduction in the returns on wind and solar power based on the benchmark scenario, if China wants to achieve its targets in energy transition and carbon emissions, the TFP of wind and solar power must reach 3.30 and 3.85%, respectively, which are feasible goals for technical progress in wind and solar power in China.

In conclusion, the analytical results of the scenarios indicate that the government's 2030 target for total energy and natural gas consumption and carbon emission intensity can be achieved in each scenario. However, the government's target for non-fossil fuel energy is hard to achieve without subsidies for renewable energy. The empirical results also indicate that a moderate subsidy for renewable energy linked to significant technical progress in renewable energy is a crucial way for China to achieve its energy target and transition in 2030.

Technological progress is the crucial factor in reducing the generation cost and promoting the subsidies retreat of wind and solar power in China. Therefore, the government should actively encourage technological progress in wind and solar power generation and strengthen the policy support for this progress. The government should encourage relevant enterprises to strengthen technological innovation and its transformation and application and at the same time, according to the industry's technological progress, scientifically and reasonably gradually reduce wind and solar power subsidies.

DATA AVAILABILITY STATEMENT

The datasets generated for this study are available on request to the corresponding author.

AUTHOR CONTRIBUTIONS

ZG and XZ completed model design, simulation analysis, and discussion. HZ and SF completed English writing.

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SUPPLEMENTARY MATERIAL

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REFERENCES

Arndt, C., Davies, R., Gabriel, S., Makrelov, K., Merven, B., Hartley, F., et al. (2016). A sequential approach to integrated energy modeling in South Africa. *Appl. Energy* 161, 591–599. doi: 10.1016/j.apenergy.2015.06.053

Böhringer, C., and Rutherford, T. F. (2006). "Combining top-down and bottom-up in energy policy analysis: a decomposition approach," *ZEW Leibniz Centre for European Economic Research Discussion Paper, No. 06–007* (Mannheim).

Böhringer, C., and Rutherford, T. F. (2008). Combining bottom-up and top-down. *Energy Econ*. 30, 574–596. doi: 10.1016/j.eneco.2007.03.004

Cai, Y., and Arora, V. (2015). Disaggregating electricity generation technologies in CGE models: a revised technology bundle approach with an application to the U.S. *Clean Power Plan. Appl. Energy* 154, 543–555. doi: 10.1016/j.apenergy.2015.05.041

Chi, Y., Guo, Z., Zheng,Y., and Zhang, X. (2014). Scenarios analysis of the energies' consumption and carbon emissions in China based on a dynamic CGE model. *Sustainability* 6, 487–512. doi: 10.3390/su6020487

Department of National Economic Accounting and National Bureau of Statistics (2014). *The Method of Preparing the China Input-Output Table 2012*. Beijing: China Statistics Press.

Guo, Z., Zhang, X., Ding, Y., and Zhao, X. (2019). A forecasting analysis on China's energy use and carbon emissions based on a dynamic computable general equilibrium model. *Emerg. Markets Finance Trade*. doi: 10.1080/1540496X.2019.1597704. [Epub ahead of print].

Guo, Z., Zhang, X., Zheng, Y., and Rao, R. (2014). Exploring the impacts of a carbon tax on the Chinese economy using a CGE model with a detailed disaggregation of energy sectors. *Energy Econ*. 45, 455–462. doi: 10.1016/j.eneco.2014.08.016

Helgesen, P. I., Lind, A., Ivanova, O., and Tomasgard, A. (2018). Using a hybrid hard-linked model to analyze reduced climate gas emissions from transport. *Energy* 156, 196–212. doi: 10.1016/j.energy.2018.05.005

Igos, E., Rugani, B., Rege, S., Benetto, E., Drouet, L., and Zachary, D. S. (2015). Combination of equilibrium models and hybrid life cycle-input-output analysis to predict the environmental impacts of energy policy scenarios. *Appl. Energy* 145, 234–245. doi: 10.1016/j.apenergy.2015.02.007

Jacoby, H. D., Reilly, J. M., McFarland, J. R., and Paltsev, S. (2004). Technology and technical change in the MIT EPPA Model. *Energy Econ*. 28, 610–631. doi: 10.1016/j.eneco.2006.05.014

Jacoby, H. D., Reilly, J. M., McFarland, J. R., and Paltsev, S. (2014). *Technology and Technical Change in the MIT EPPA Model. MIT Joint Program on the Science and Policy of Global Change, Report No. 111*. MIT.

Ji, Q., Li, J., and Sun, X. (2019). New challenge and research development in global energy financialization. *Emerg. Markets Finance Trade* 55, 2669–2672. doi: 10.1080/1540496X.2019.1636588

Ji, Q., and Zhang, D. (2019). How much does financial development contribute to renewable energy growth and upgrading of energy structure in China? *Energy Policy* 128, 114–124. doi: 10.1016/j.enpol.2018.12.047

Lanz, B., and Rausch, S. (2011). General equilibrium, electricity generation technologies and the cost of carbon abatement: a structural sensitivity analysis. *Energy Econ*. 3, 1035–1047. doi: 10.1016/j.eneco.2011.06.003

Li, S. (2010). The Chinese economic growth prospect and outlook from 2011 to 2030. *Rev. Econ. Res*. 43, 2–27.

Li, W., Zhang, Y., and Lu, C. (2018). The impact on electric power industry under the implementation of national carbon trading market in China: a dynamic CGE analysis. *J. Clean. Prod*. 200, 511–523. doi: 10.1016/j.jclepro.2018.07.325

Lou, F. (2017). *The Dynamics Computable General Equilibrium Model of Science and Technology in China: Theory and Applications*. Beijing: China Social Sciences press.

Martinsen, T. (2011). Introducing technology learning for energy technologies in a national CGE model through soft links to global and national energy models. *Energy Policy* 39, 3327–3336. doi: 10.1016/j.enpol.2011.03.025

Meng, S., Siriwardana, M., Mcneill, J., and Nelson, T. (2018). The impact of an ETS on the Australian energy sector: an integrated CGE and electricity modelling approach. *Energy Econ*. 69, 213–224. doi: 10.1016/j.eneco.2017.11.017

Paltsev, S., Reilly, J. M., Jacoby, H. D., Eckaus, R. S., Mcfarland, J., Sarofim, M. C., et al. (2005). *The MIT Emissions Prediction and Policy Analysis (EPPA) Model: Version 4. MIT Joint Program on the Science and Policy of Global Change, Report No. 125*. MIT Center for Global Change Science, Cambridge, MA, USA.

Proença, S., and Aubyn, M. S. (2013). Hybrid modeling to support energy-climate policy: effects of feed-in tariffs to promote renewable energy in Portugal. *Energy Econ*. 38, 176–185. doi: 10.1016/j.eneco.2013.02.013

Pui, K. L., and Othman, J. (2017). Economics and environmental implications of fuel efficiency improvement in Malaysia: a computable general equilibrium approach. *J. Clean. Prod*. 156, 459–469. doi: 10.1016/j.jclepro.2017.04.067

Sue, W. I. (2006). The synthesis of bottom-up and top-down approaches to climate policy modeling: electric power technologies and the cost of limiting US CO_2 emissions. *Energy Policy* 34, 3847–3869. doi: 10.1016/j.enpol.2005.08.027

Sue, W. I. (2008). The synthesis of bottom-up and top-down approaches to climate policy modeling: electric power technology detail in a social accounting framework. *Energy Econ*. 30, 547–573. doi: 10.1016/j.eneco.2006.06.004

Tabatabaei, S. M., Hadian, E., Marzban, H., Marzban, H., and Zibaei, M. (2017). Economic, welfare and environmental impact of feed-in tariff policy: a case study in Iran. *Energy Policy* 102, 164–169. doi: 10.1016/j.enpol.2016.12.028

Tan, X. D. (2008). *Modeling and application of electric power computable general equilibrium model* (Ph.D. dissertation). North China Electric Power University, Beijing, China.

Tran, T. M., Siriwardana, M., Meng, S., and Nong, D. (2019). Impact of an emissions trading scheme on Australian households: a computable general equilibrium analysis. *J. Clean. Prod*. 221, 439–456. doi: 10.1016/j.jclepro.2019.02.273

Tuladhar, S. D., Yuan, M., Bernstein, P., Montgomery, W. D., and Smith, A. (2009). A top-down bottom-up modeling approach to climate change policy analysis. *Energy Econ*. 31(Suppl. 2), S223–S234. doi: 10.1016/j.eneco.2009.07.007

Wang, C. (2003). *Climate change policy simulation and uncertainty analysis: a dynamic CGE model of China* (Ph.D. dissertation), Tsinghua University, Beijing, China.

Wu, J., Albrecht, J., Fan, Y., and Xia, Y. (2016). The design of renewable support schemes and CO_2 emissions in China. *Energy Policy* 99, 4–11. doi: 10.1016/j.enpol.2016.09.045

Wu, J., Fan, Y., and Xia, Y. (2017). How can China achieve its nationally determined contribution targets combining emissions trading scheme and renewable energy policies? *Energies* 10:1166. doi: 10.3390/en10081166

Wu, Y., Liu, C., Hung, M., Liu, T., and Masui,. T. (2019). Sectoral energy efficiency improvements in Taiwan: evaluations using a hybrid of top-down and bottom-up models. *Energy Policy* 132, 1241–1255. doi: 10.1016/j.enpol.2019.06.043

Xie, W., Xiong, W., Pan, J., Ali, T., Cui, Q., Cui, D., et al. (2018). Decreases in global beer supply due to extreme drought and heat. *Nat. Plants* 4, 964–973. doi: 10.1038/s41477-018-0263-1

Xu, X., Wei, Z., Ji, Q., Wang, C., and Gao, G. (2019). Global renewable energy development: influencing factors, trend predictions and countermeasures. *Resour. Policy* 63:101470. doi: 10.1016/j.resourpol.2019.101470

Xuan, X. W. (2002). *Analysis the effect of sulfur-tax on the Chinese economy based on CGE model* (Ph.D. dissertation), Peking University, Beijing, China.

Yun, T., Cho, G. L., and Kim, J. (2016). Analyzing economic effects with energy mix changes: a hybrid CGE model approach. *Sustainability* 8:1048. doi: 10.3390/su8101048

Zhang, D., and Ji, Q. (2019). Energy finance: frontiers and future development. *Energy Econ*. 83, 290–292. doi: 10.1016/j.eneco.2019.07.003

Zhang, D., Rausch, S., Karplus, V. J., and Zhang, X. (2013). Quantifying regional economic impacts of CO_2 intensity targets in China. *Energy Econ*. 40, 687–701. doi: 10.1016/j.eneco.2013.08.018

Zhang, D., Rausch, S., Karplus,V. J., and Zhang, X. (2012). *Quantifying Regional Economic Impacts of CO_2 Intensity Targets in China. MIT Joint Program on the Science and Policy of Global Change, Report No. 230*. MIT Center for Global Change Science, Cambridge, MA, USA.

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The Heterogeneous Impact of Financial Development on Green Total Factor Productivity

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This study examines the heterogeneous impact of financial development on green total factor productivity for 40 countries over the period 1991 to 2014. Specifically, this paper describes financial development from the three aspects of banking, securities, and insurance. In developing countries, an inverted *U*-shaped relationship exists between financial development and green total factor productivity, whether it is in bank development, securities development, or insurance development. In developed countries, the development of bank and insurance tends to adversely affect green total factor productivity, while the development of securities has always had a positive impact on green total factor productivity. Securities development is more conducive to improving green total factor productivity than bank development.

Keywords: financial structure, financial development, green total factor productivity, heterogeneity, developed and developing countries

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INTRODUCTION

The needs to achieve sustainable development and reduce environmental pollution have prompted researchers to focus on the relationship between financial development and green total factor productivity (GTFP). Most relative research has extensively analyzed the impact of financial development on economic growth, concluding that financial development accelerates economic development (Wachtel, 2001; Caporale et al., 2015; Tripathy, 2019). However, with the increasing importance of environmental protection to economic development, we must not only focus on the total amount of economic growth but also consider the impact of economic development on the environment, that is, sustainable development (Longhofer and Jorgenson, 2017; Maes and Jacobs, 2017; Li Z. et al., 2020). The concept of sustainable development refers to transforming the extensive growth mode, which has high input dependence, to an intensive growth mode, which reduces input, increases output, and reduces pollution, so as to achieve an increase in total factor productivity (TFP), which is essentially improving green total factor productivity. Therefore, in the context of considering environmental factors, this paper explores the heterogeneous impact of financial development on GTFP.

As the main driving force for economic development, finance is gradually becoming the core of economic development. Greenwood and Jovanovic (1990) constructed a theoretical model and analyzed the mechanism of interaction between financial development and economic growth in the context of information asymmetry. They asserted that financial systems can effectively overcome the adverse selection and moral hazard caused by information asymmetry and allocate funds to investment projects with high profit prospects, which will, in turn, increase productivity. King Robert and Levine (1993) introduced the financial sector into the model of endogenous economic growth and pointed out that better financial systems improve productivity and thereby accelerate economic growth. Although most studies conclude that financial development promotes economic development, some studies have found that financial development is not good for economic development (De Gregorio and Guidotti, 1995; Aghion et al., 2004). Ruiz (2018) pointed out that the development of finance has a non-linear effect on economic growth. Asteriou and Spanos (2019) found that before and after the financial crisis, there were differences in the impact of financial development on economic growth.

TFP growth is an important source of long-term economic growth. Considering the undesirable output of energy input and pollution, GTFP is an important guarantee for the realization of sustainable economic growth. TFP is a comprehensive reflection of the role of technological progress in economic development and is often considered a source of analysis of economic growth (Solow, 1957; Baier et al., 2006). With the current rapid economic development and prominent environmental issues, we cannot ignore environmental factors when considering TFP (Li et al., 2019; Song et al., 2019; Xia et al., 2019). Although traditional TFP takes into account capital, labor inputs, and economic output, it does not take into account the input and undesirable output of energy. If the input of energy and undesired output are not considered in the measurement of TFP, the measurement results obtained will inevitably be biased. The aim when optimizing GTFP is to achieve the maximum output and the minimum environmental pollution under a given input (Song et al., 2020).

Financial development affects TFP mainly through technological progress and capital allocation (Li et al., 2018; Huang et al., 2019). Technological progress is essential to achieve sustainable economic growth (Li Y. et al., 2020). The research on financial development to promote TFP growth through technological progress started from the theory of endogenous growth proposed by Romer (1986). Because financially supported technological innovation has significant positive externalities, investment in research and development has promoted endogenous technological progress, thereby driving TFP growth. Buera et al. (2011) suggest that financial development can effectively reduce friction in the economic system and promote the growth of TFP through both efficiency improvement and technological progress. However, the impact of financial development on capital allocation is not always positive. Resource optimization can promote TFP growth, and resource mismatches can inhibit TFP growth. Buera and Shin (2013) found that in some emerging economies or developing countries with rapid economic growth, innovative high-tech SMEs have a short capital accumulation time and lack sufficient guarantee conditions, making it difficult to obtain financing, and resource mismatches caused by lagging financial development are not conducive to the growth of total factor productivity. Cole et al. (2016) state that inefficient capital allocation caused by capital mismatch in the financial system hinders the improvement of TFP in some countries.

At different stages of economic development, financial development has a heterogeneous effect on TFP, especially in different countries. Rioja and Valev (2004) pointed out that financial development and TFP may not be explained by a purely linear relationship. In different countries, the role of financial development in promoting TFP growth is significantly different, and an inverted U-shaped relationship exists between them. Seven and Coskun (2016) found that although financial development has a positive impact on economic growth, this promotion does not exist in some low-income countries. Financial markets with low levels of financial development are not able to form high-productivity trade sectors due to insufficient risk diversification functions, while low-productivity non-trade sectors are more likely to survive. A developed financial system can provide better risk diversification and risk hedging services, effectively reduce investors' risk concerns about technological innovation in enterprises, and then promote enterprises to carry out technological upgrades and innovation activities.

At present, related research mainly examines the relationship between financial development, TFP, and economic growth, but few studies have studied their relationship from the perspective of environmental pollution. Considering the problems of excessive consumption of natural resources and increasing environmental degradation, a purely gross domestic product (GDP)-oriented growth model has seriously undermined the sustainable development of the economy. Therefore, the first contribution of this paper is to consider the environmental factors and measure the GTFP of each country so as to identify the GTFP gap between different countries. Second, in the study of the impact of financial development on TFP, finance is often considered as a whole without distinguishing between different financial sectors. In fact, the role of different financial sectors varies significantly in the process of economic operations. Therefore, this paper examines the heterogeneous impact of financial development on GTFP for three different financial sectors: banking, securities, and insurance. This will help us explore the heterogeneous impact of different financial sector developments on GTFP. Finally, due to the differences between developing and developed countries, this paper conducts an empirical analysis of developing and developed countries, respectively. This will help us find the heterogeneous impact of financial development on GTFP in different countries.

The rest of the paper is organized as follows. Section Literature Review lays out a brief literature review of the impact of financial development on GTFP. Section Data and Methodology introduces the data and methodology for empirical research and the measured GTFP of each country. In section Results, we analyze the impact of financial development on GTFP and discuss it separately for developed and developing countries. Section Conclusion provides the main conclusions.

LITERATURE REVIEW

The impact of financial development on the environment is ambiguous. From the perspective of consumption, developed financial markets can make it easier for consumers to meet their own consumption needs, which have different impacts on the environment. The consumption of goods will increase energy consumption and pollution emissions (Nassani et al., 2017; Kwakwa et al., 2018). However, with financial support, consumers can purchase high-tech products that use clean energy or have low energy consumption, resulting in reduced energy consumption and reduced pollution emissions (Costantini et al., 2017; Gerarden et al., 2017). From a production perspective, financial development also has different impacts on the environment. The financing function of the financial system can meet the capital needs of the production sector, provide financial support for enterprises to expand reproduction, and effectively solve the adverse impact of financing constraints on the production expansion of enterprises. Enterprises have expanded production through financial support, and increased output has also led to increased emissions of pollutants (Shahzad et al., 2017; Pata, 2018). In addition, financial resources will flow to polluting enterprises with high returns, which will cause financial development to have a negative impact on the environment. On the other hand, financial development has reduced the risk of technological innovation, which is conducive to increasing investment in advanced production technologies, and has promoted technological progress (Kenney, 2011; Brown et al., 2013; Hsu et al., 2014). This has led to high energy consumption and highly pollution-producing technology being replaced by clean technology. In addition, financial development also reduces energy consumption and pollution emissions by allowing funds to flow to companies with high energy efficiency and efficient resource allocation.

Financial development will not always promote economic growth. When financial development reaches a certain level, financial development will not be conducive to economic growth (Arcand et al., 2015; Ntarmah et al., 2019). This implies that an inverted U-shape relationship between finance development and economic growth. Law et al. (2013) found that finance development promotes economic growth only within a certain range; the effect of finance development on economic growth is non-existent beyond this range. Law and Singh (2014) indicate that financial development promotes economic growth only when it is below a threshold, while financial development levels above that threshold will have a negative impact on economic growth. Fagiolo et al. (2019) find a robust inverted U-shaped relationship between finance depth and economic growth. Moderate financial development is conducive to economic growth, but excessive financialization can hamper economic growth.

DATA AND METHODOLOGY

Global Malmquist-Luenberger Productivity Index

The traditional TFP does not consider the impact of energy input and pollution emissions, cannot fully reflect sustainable development requirements, and may be biased (Zhang et al., 2011). Considering the undesirable output of energy input and pollution, the GTFP is an important guarantee for the transformation of the economic growth mode and the realization of sustainable economic growth. Solow's residual analysis is difficult to adapt to this requirement, so data envelopment analysis (DEA) is increasingly applied for the measurement of GTFP. Compared with Solow's residual analysis, DEA can avoid the bias caused by the form of the preset production function and the distribution characteristics of the error terms, and it has been widely used in the calculation of GTFP (Liao and Drakeford, 2019). In order to remedy the disadvantages of traditional TFP, which did not consider the undesired output, Chung et al. (1997) introduced pollution emissions into the DEA model as an undesired output. Färe et al. (2001) further used the Malmquist-Luenberger index method to measure the GTFP and decomposed it into a technology efficiency index and technology progress index. In order to overcome the slack variable problem of the directional distance function DEA model due to radial models, Tone (2001) introduced slacks-based measure DEA. In order to avoid the potential linear programming infeasibility problem in the Malmquist-Luenberger index, Oh (2010) proposed the Global Malmquist-Luenberger (GML) index to overcome the above shortcomings. Emrouznejad and Yang (2016) used the GML index to measure the productivity of manufacturing industries. Wang et al. (2019) used the GML index to investigate air pollution emission efficiency.

This paper uses the GML index to measure GTFP so as to avoid the overestimation of the productivity of the evaluation object by the DEA in the radial direction and the potential linear programming infeasibility problem in Malmquist-Luenberger index.

Each country is regarded as a decision-making unit. Suppose each country uses **N** inputs, $x = (x_1, x_2, \cdots, x_N) \in R_+^N$ to produce **M** desirable outputs, $y = \left(y_1, y_2, \cdots, y_M\right) \in R_+^M$, and **J** undesirable outputs, $\mathrm{b} = \left(b_1, b_2, \cdots, b_J\right) \in R_+^J$. The production possibility set is defined in Equation (1).

$$P^t(x^t) = \begin{cases} \left(y^t, b^t\right) \mid \sum_{k=1}^{K} z_k^t y_{km}^t \geq y_m^t, & m = 1, \cdots, M \\ \sum_{k=1}^{K} z_k^t b_{kj}^t \geq b_j^t, & j = 1, \cdots, J \\ \sum_{k=1}^{K} z_k^t x_{kn}^t \geq x_n^t, & j = 1, \cdots, N \\ z_k^t \geq 0, & k = 1, \cdots, K \end{cases} \tag{1}$$

where z_k^t denotes the weight of each observation. The aim with the production possibility set is to achieve the maximum output and the minimum environmental pollution under a given input.

This paper uses the directional distance function to overcome the undesired output problem. This function is defined in Equation (2).

$$\vec{D}_0(x, y, b; g) = max\left\{\beta : \left(y, b + \beta g\right) \in p(x)\right\} \tag{2}$$

where $g = (y, -b)$ is the direction vector of horizontal expansion of output, and β is the directional distance function value. Oh (2010) further improved this and proposed the concept of a global distance function, $p^G(x) = p^1\left(x^1\right) \cup p^2\left(x^2\right) \cup \cdots \cup p^T\left(x^T\right)$. This set is a combination of all current production possibility sets to avoid arbitrary selection problems. The GML can be calculated as in Equation (3).

$$GML_t^{t+1} = \frac{1 + \vec{D}_0^G(x^t, y^t, b^t; -x^t, -y^t, -b^t)}{1 + \vec{D}_0^G(x^{t+1}, y^{t+1}, b^{t+1}; -x^{t+1}, -y^{t+1}, -b^{t+1})} \quad (3)$$

GML indicates the growth rate of GTFP relative to the previous period. If $GML = 1$, this indicates that GTFP has not changed. If $GML > 1$, this indicates that GTFP increased compared to the previous period. If $GML < 1$, this indicates that GTFP decreased compared to the previous period. Therefore, the GTFP of each country can be calculated by Equation (4).

$$GTFP_i^t = GML_i^t \times GTFP_i^{t-1} \quad (4)$$

We should point out that the GTFP based on GML does not reflect the absolute value of productivity but, rather, the relative value.

To study the impact of financial development on GTFP, we first estimate panel regressions including financial development variables, the model for which is expressed by Equation (5). Then, we added the square of financial development to investigate whether there is an inverted U-shaped relationship between financial development and GTFP; that is, an initially increasing and subsequently decreasing influence of financial development. The model is expressed by Equation (6).

$$GTFP_{it} = \alpha_0 + \alpha_1 F_{it} + \alpha_2 \sum X_{it} + \varepsilon_{it} \quad (5)$$

$$GTFP_{it} = \alpha_0 + \alpha_1 F_{it} + \alpha_2 F_{it}^2 + \alpha_3 \sum X_{it} + \varepsilon_{it} \quad (6)$$

where GTFP represents the dependent variable, F represents the financial development, F^2represents the square of financial development, X is the control variable, $\alpha_0$is the intercept, while α_1, α_2, and α_3 are the coefficients of regression, and ε is white noise error disturbance.

Sample and Data

Due to the lack of relevant data in many countries and the fact that the existing relevant data only spans up to 2014, the data used in this study is limited to 40 countries and the period 1991–2014. There are big differences in the levels of financial development of developing countries and of developed countries. Developing countries concentrate on producing pollution-intensive products and primary products. In production, the developed countries specialize in producing clean products and service-intensive products, and the developing countries often face serious environmental pollution problems while they are developing their economies. Therefore, it is necessary to analyze developing and developed countries separately. There are 24 developed countries in the sample, namely Australia, Austria, Canada, Cyprus, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Israel, Japan, the Netherlands, New Zealand, Norway, Portugal, South Korea, Spain, Sweden, Switzerland, the Czech Republic, the United Kingdom, and the United States. There are 16 developed countries in the sample, namely Argentina, Brazil, China, Chile, Egypt, India, Indonesia, Iran, Mexico, Malaysia, the Philippines, Poland, Russia, South Africa, Thailand, and Turkey. All data used in this paper was obtained from the Penn World Table, WIPO statistics, and World Bank database.

The key to GTFP measurement using GML is to find input and output variables. With consideration given to the existing literature, the input variables in this paper comprise labor, capital, and energy consumption. The output variables in this paper comprise desirable and undesirable outputs (Zhang et al., 2011; Shi and Sun, 2017). The input and output variables employed in this paper are described as follows.

Capital: Capital input is measured by capital stock. We employ the perpetual inventory method to estimate the capital stock, which is measured in millions of constant 2010 dollars.

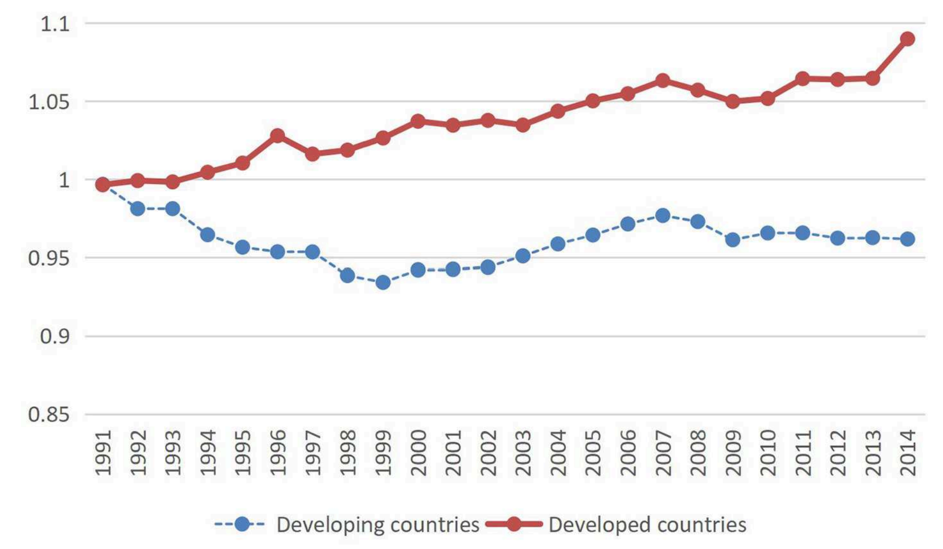

FIGURE 1 | GTFP in developed and developing countries.

Labor: Labor input is the number of people engaged in labor, and the unit is millions.

Energy consumption: Energy input is total energy consumption, measured as GDP divided by GDP per unit of energy consumption. The unit is 1,000 tons.

Desirable output: Desirable output is the real GDP, which is measured in millions of constant 2010 dollars.

Undesirable output: Undesirable output is carbon dioxide emission, which can be obtained from the World Bank database. The unit is millions of tons.

Based on these input and output variables, MaxDEA software was used to measure the GTFP. The resulting GTFP values for developed and developing countries are presented in **Figure 1**. We can find that the GTFP has maintained a continuous growth trend in developed countries, while the GTFP in developing countries showed a state of decline before rising and then remaining stable.

TABLE 1 | Descriptive statistics.

	Variable	Obs	Mean	Std. dev.	Min	Max
Whole	GTFP	960	1.0068	0.0986	0.6173	1.5350
	BANK	960	0.8225	0.4892	0.0565	2.6070
	STOCK	960	0.6018	0.4864	0.0565	2.6556
	INSU	960	0.0169	0.0079	0.0001	0.0499
	IP	960	5.2058	1.4741	0.9642	8.3294
	FDI	960	0.0333	0.0850	−0.4350	1.9810
	OPEN	960	0.6272	0.3427	0.1003	2.0528
	HC	960	2.8690	0.5583	1.4398	3.7343
	IS	960	0.3105	0.0678	0.1070	0.4850
	ES	960	0.1723	0.1516	0.0033	0.6138
	PGDP	960	9.6875	1.1467	6.2746	11.4254
Developed countries	GTFP	576	1.0373	0.0536	0.9192	1.4164
	BANK	576	1.0280	0.4407	0.2500	2.6070
	STOCK	576	0.6533	0.4522	0.0412	2.6375
	INSU	576	0.0214	0.0059	0.0001	0.0499
	IP	576	5.8892	1.3008	0.9642	8.3294
	FDI	576	0.0393	0.1081	−0.4350	1.9810
	OPEN	576	0.6805	0.3362	0.1633	2.0528
	HC	576	3.1874	0.3758	1.9661	3.7343
	IS	576	0.2808	0.0560	0.1070	0.4480
	ES	576	0.1476	0.1418	0.0033	0.6138
	PGDP	576	10.4915	0.4119	9.1323	11.4254
Developing countries	GTFP	384	0.9610	0.1285	0.6173	1.5350
	BANK	384	0.5141	0.3857	0.0565	1.6321
	STOCK	384	0.5246	0.5248	0.0001	2.6556
	INSU	384	0.0102	0.0054	0.0027	0.0277
	IP	384	4.1809	1.0701	1.3295	6.5226
	FDI	384	0.0242	0.0207	−0.0280	0.1170
	OPEN	384	0.5474	0.3373	0.1003	1.7472
	HC	384	2.3914	0.4326	1.4398	3.3572
	IS	384	0.3551	0.0589	0.2380	0.4850
	ES	384	0.2095	0.1583	0.0044	0.5783
	PGDP	384	8.4816	0.7794	6.2746	9.5943

Financial development should be considered from the perspectives of different financial sectors. However, most of the research on the relationship between financial development and economic growth has been conducted from the perspective of banks, ignoring the role of securities and insurance in economic operations. The development of securities and insurance is rooted in the development of the financial system and has become an indispensable factor in the current economic growth. Therefore, this paper describes financial development from the three aspects of banking, securities, and insurance. Bank development (BANK) is measured by the ratio of private credit from deposit money banks and other financial institutions to GDP. Securities development (STOCK) is measured by the ratio of stock market capitalization to GDP; that is, the market value of listed shares divided by GDP. Insurance development (INSU) is measured by ratio of insurance income to GDP, which is the depth of insurance.

In order to obtain robust results, we have added some control variables that may affect GTFP. Invention patents (IP) are a reflection of a country's innovation ability and can reflect the level of technological progress, which is measured by the logarithmic transformation of patent applications per million people. Foreign direct investment (FDI) has come to be seen as an engine of productivity growth and development; it also provides research and development funding for technology improvement, which is measured by the ratio of net inflows of FDI to GDP. The trade openness (OPEN) is measured by the proportions of total imports and exports in GDP. Human capital (HC) is measured by the human capital index. Industrial structure (IS) is calculated by the industrial added value as a percentage of GDP. Renewable energy is an important component of energy consumption and is conducive to sustainable economic development (Xu et al., 2019). Energy structure (ES) is measured by the share of renewable energy consumption in total final energy consumption. GDP per capita (PGDP) is the logarithmic transformation of GDP per capita, which is measured in millions of constant 2010 dollars.

Table 1 provides descriptive statistics for all variables in this empirical study. The whole sample shows that our primary

TABLE 2 | Panel unit root test.

Variables	LLC	Fisher-ADF
GTFP	−4.1197 (0.000)	206.11 (0.000)
BANK	−4.6351 (0.000)	137.48 (0.000)
STOCK	−6.6062 (0.000)	234.80 (0.000)
INSU	−2.7007 (0.0035)	212.49 (0.000)
IP	−2.6758 (0.0037)	252.33 (0.000)
FDI	−11.2567 (0.000)	488.39 (0.000)
OPEN	−4.5735 (0.000)	210.95 (0.000)
HC	−7.1705 (0.000)	425.63 (0.000)
IS	−3.2958 (0.0005)	275.84 (0.000)
ES	−4.2178 (0.000)	164.62 (0.000)
PGDP	−2.3481 (0.0094)	200.88 (0.000)

p statistics are shown in parentheses.

variable GTFP has a mean value of 1.0068. This means that, overall, green productivity has not improved. However, there is a significant difference between developed and developing countries. The GTFP in developed countries has a mean value of 1.0373, but GTFP in developing countries has a mean value of 0.9610. It can be seen that developed countries have better GTFP performance than developing countries. From the perspective of the development of the financial sector, BANK in the developed countries is 0.5139 higher than in the developing countries. STOCK in the developed countries is 0.1287 higher than in the developing countries. INSU in the developed countries is 0.0112 higher than in the developing countries. This shows that, from the overall level, whether in the development of banks, securities, or insurance, developed countries are significantly better than developing countries.

RESULTS

Before examining the impact of financial development on GTFP, we need to conduct a test for the stationarity of all variables. Levin-Lin-Chu (LLC) and the Fisher-Augmented Dickey-Fuller (Fisher-ADF) are commonly used methods to test data stationarity. **Table 2** shows the stationarity result of all variables. We can find that all the variables passed the stationary test, which indicates that the data we used in the empirical study are stationary.

We estimate a regression model of GTFP as a function of financial development. **Table 3** shows the regression result for the impact of bank development on GTFP. For the whole sample, BANK shows insignificant impact on GTFP. When we add the square of BANK to the regression model, we find that the estimated coefficient of BANK for GTFP is 0.0792, and the $BANK^2$ of the estimated coefficient for GTFP is −0.0454, both of which are statistically significant at 1%. This shows that an inverted U-shaped relationship exists between bank development and GTFP. Bank development will promote the improvement of GTFP, but this positive impact will decline with the development of banks. For the developing countries, we get similar conclusions. For developed countries, the BANK of the estimated coefficient for GTFP is −0.0101, statistically significant

TABLE 3 | Estimation of the impact of bank development on GTFP.

Dependent variable	Whole		Developed countries		Developing countries	
BANK	−0.0136 (−1.59)	0.0792*** (3.21)	−0.0101** (−2.23)	0.0156 (1.11)	−0.045 (−1.21)	0.3352*** (4.32)
$BANK^2$		−0.0454*** (−4.01)		−0.0126** (−1.93)		−0.2218*** (−5.52)
INN	0.0012** (1.97)	0.0028*** (3.94)	0.0012*** (4.15)	0.0016*** (4.49)	0.0001 (0.02)	0.0072 (1.24)
FDI	0.028 (1.22)	0.0451* (1.95)	0.0279** (2.49)	0.0326*** (2.84)	−0.0356 (−0.13)	−0.2272 (−0.82)
OPEN	0.0927*** (4.72)	0.082*** (4.17)	0.0446*** (3.28)	0.0381*** (2.73)	0.1347** (2.44)	0.0821 (1.52)
HC	−0.0222 (−1.11)	−0.0198 (−0.99)	−0.0161 (−0.84)	−0.0166 (−0.87)	−0.0192 (−0.49)	−0.0077 (−0.2)
IS	−0.3718*** (−4.92)	−0.3664*** (−4.89)	−0.0312 (−0.51)	−0.0468 (−0.77)	−0.6043*** (−4.14)	−0.4306** (−2.99)
ES	0.3669*** (5.48)	0.4075*** (6.07)	0.4207*** (8.08)	0.4397*** (8.32)	0.3369** (2.25)	0.2299 (1.59)
PGDP	0.0321* (1.71)	0.0299 (1.6)	0.1078*** (6.06)	0.1111*** (6.23)	0.016 (0.48)	−0.0121 (−0.37)
Intercept	0.762*** (5)	0.736*** (4.86)	−0.1196 (−0.79)	−0.1585 (−1.03)	0.9656*** (3.74)	1.0589*** (4.25)
N	960	960	576	576	384	384
R^2	0.1787	0.1929	0.5423	0.5454	0.0872	0.1587

*t statistics are shown in parentheses below the estimated coefficients. *, **, and *** denote statistical significance at the 0, 5, and 1% levels, respectively.*

TABLE 4 | Estimation of the impact of securities development on GTFP.

Dependent variable	Whole		Developed countries		Developing countries	
STOCK	0.0265*** (3.29)	0.0975*** (5.43)	0.0138*** (2.77)	0.0121 (0.94)	0.0356* (1.68)	0.1783*** (4.2)
$STOCK^2$		−0.0305*** (−4.41)		0.0008 (0.14)		−0.0541*** (−3.86)
INN	0.001* (1.76)	0.0011** (2.04)	0.0011*** (3.83)	0.0011*** (3.79)	0.0002 (0.03)	0.0013 (0.23)
FDI	0.0207 (0.91)	0.0221 (0.98)	0.025** (2.24)	0.025** (2.23)	−0.2118 (−0.72)	−0.3668 (−1.26)
OPEN	0.0899*** (4.59)	0.0875*** (4.51)	0.0484*** (3.6)	0.0483*** (3.57)	0.1383* (2.51)	0.118** (2.17)
HC	−0.0299 (−1.5)	−0.0369* (−1.87)	−0.0205 (−1.07)	−0.0199 (−1.02)	−0.035 (−0.89)	−0.0392 (−1.02)
IS	−0.3614*** (−4.85)	−0.3891*** (−5.25)	−0.0358 (−0.59)	−0.0339 (−0.55)	−0.5598*** (−3.91)	−0.5587*** (−3.98)
ES	0.3363*** (5.2)	0.3288*** (5.14)	0.4018*** (7.9)	0.4016*** (7.88)	0.2993** (2.01)	0.2874** (1.97)
PGDP	0.0152 (0.82)	−0.0011 (−0.06)	0.0871*** (4.87)	0.0876*** (4.78)	−0.0073 (−0.23)	−0.0362 (−1.12)
Intercept	0.9252*** (6.17)	1.0892*** (7.12)	0.0945 (0.61)	0.0872 (0.53)	1.1537*** (4.59)	1.379*** (5.44)
N	960	960	576	576	384	384
R^2	0.1860	0.2030	0.5445	0.5446	0.0906	0.1268

*t statistics are shown in parentheses below the estimated coefficients. *, **, and *** denote statistical significance at the 10, 5, and 1% levels, respectively.*

at 5%, which indicates that bank development has a significant negative impact on GTFP in developed countries. When we add the square of BANK in the regression model, we can get similar results to the whole sample and developing countries. This shows that, in the early stages of bank development, the increase in the level of bank development will improve GTFP. When bank development reaches a certain level, further bank development will become harmful to GTFP. This conclusion is consistent with the conclusion of Arcand et al. (2015). When the total credit to the private sector exceeds GDP, financial development begins to have a negative impact on economic growth.

Table 4 shows the regression result for the impact of securities development on GTFP. For the whole sample, the coefficient of STOCK is 0.0265, statistically significant at 1%, which indicates that securities development has a significant positive impact on GTFP. When we add the square of STOCK in the regression model, we can find that the coefficient of STOCK is 0.0975, and the coefficient of $STOCK^2$ is −0.0305, both of which are statistically significant at 1%. This shows that an inverted U-shaped relationship exists between securities development and GTFP. For the developing countries, we can get similar conclusions, unlike in the impact of bank development on GTFP. For developed countries, the coefficient of STOCK is 0.0138, statistically significant at 1%. When we add the square of STOCK in the regression model, neither STOCK nor $STOCK^2$ had a significant impact on GTFP. This shows that when securities development reaches a certain level, further securities development will always have a positive impact on GTFP. Securities development, to some extent, solves the problem of information asymmetry in indirect bank financing. Therefore, compared with indirect bank financing, securities development is more conducive to solving the problem of adverse selection and moral hazard and to reducing the transaction costs of social enterprises. Therefore, securities are more efficient than financial intermediaries such as banks.

In order to better explain the differences between the development of banks and the development of securities, we introduce a financing structure (FS) for empirical analysis. FS is measured by the market value of listed shares divided by money deposited in banks and other financial institutions. **Table 5** shows the regression result of the impact of the FS on GTFP. We can find that, whether in the full sample, developed or developing countries, FS always had a significant positive impact on GTFP. This shows that securities development is more conducive to improving GTFP than bank development.

In financial development, banks and securities are more often represented as economic functions that create value for society, while insurance is more often represented as a social security function. **Table 6** shows the regression result of the impact of insurance development on GTFP. For the whole sample, the coefficient of INSU is 1.2381, statistically significant at 5%, which indicates that securities development has a significant positive impact on GTFP. When we add the square of INSU

TABLE 5 | Estimation of the impact of financial structure on GTFP.

Dependent variable	Whole	Developed countries	Developing countries
FS	0.0181*** (4.03)	0.0055* (1.68)	0.0267*** (2.89)
INN	0.0009 (1.61)	0.001*** (3.59)	−0.0003 (−0.06)
FDI	0.0203 (0.89)	0.0251** (2.22)	−0.2553 (−0.89)
OPEN	0.0889*** (4.53)	0.0459*** (3.35)	0.1352** (2.47)
HC	−0.0341* (−1.7)	−0.0176 (−0.91)	−0.0459 (−1.17)
IS	−0.3882*** (−5.18)	−0.0341 (−0.55)	−0.5945*** (−4.18)
ES	0.3708*** (5.7)	0.4063*** (7.85)	0.3205** (2.18)
PGDP	0.0281 (1.54)	0.0983*** (5.6)	0.0077 (0.24)
Intercept	0.8165*** (5.56)	−0.0252 (−0.17)	1.0541*** (4.33)
N	960	576	384
R^2	0.1909	0.5408	0.1042

*t statistics are shown in parentheses below the estimated coefficients. *, **, and *** denote statistical significance at the 10, 5, and 1% levels, respectively.*

TABLE 6 | Estimation of the impact of insurance development on GTFP.

Dependent variable	Whole		Developed countries		Developing countries	
INSU	1.2381** (1.96)	8.8325*** (5.21)	−0.7617** (−2.09)	0.1216 (0.1)	7.0779*** (4)	33.454*** (6.64)
$INSU^2$		−168.19*** (−4.81)		−17.1428 (−0.72)		−909.54*** (−5.56)
INN	0.0009 (1.63)	0.001* (1.81)	0.0011*** (3.77)	0.0011*** (3.76)	0.0041 (0.7)	0.0169*** (2.81)
FDI	0.0279 (1.22)	0.0258 (1.14)	0.0247** (2.2)	0.0246** (2.19)	−0.0103 (−0.04)	−0.0762 (−0.28)
OPEN	0.0994*** (5.02)	0.1134*** (5.74)	0.0468*** (3.46)	0.0475*** (3.5)	0.1374** (2.54)	0.1191** (2.29)
HC	−0.0304 (−1.51)	−0.0295 (−1.49)	−0.0103 (−0.53)	−0.0095 (−0.48)	−0.0256 (−0.67)	0.0035 (0.09)
IS	−0.3709*** (−4.93)	−0.3538*** (−4.76)	0.0004 (0.01)	0.0068 (0.11)	−0.6207*** (−4.4)	−0.4402*** (−3.16)
ES	0.3312*** (5.09)	0.3078*** (4.77)	0.3932*** (7.7)	0.3921*** (7.68)	0.1816 (1.21)	0.0892 (0.62)
PGDP	0.0243 (1.33)	0.0129 (0.71)	0.0956*** (5.47)	0.0957*** (5.47)	−0.0203 (−0.65)	−0.0549* (−1.78)
Intercept	0.8305*** (5.64)	0.8589*** (5.9)	−0.0099 (−0.07)	−0.0263 (−0.18)	1.2259*** (5.01)	1.2551*** (5.34)
N	960	960	576	576	384	384
R^2	0.1798	0.2002	0.5418	0.5422	0.1224	0.1920

*t statistics are shown in parentheses below the estimated coefficients. *, **, and *** denote statistical significance at the 10, 5, and 1% levels, respectively.*

in the regression model, we can find the coefficient of INSU is 8.8325, and the coefficient of $INSU^2$ is -168.19; both of them are statistically significant at 1%. This shows that there an inverted *U*-shaped relationship exists between insurance development and GTFP. For the developing countries, we get similar conclusions. For developed countries, the coefficient of INSU is -0.7617, statistically significant at 1%. When we add the square of INSU in the regression model, neither INSU nor $INSU^2$ had a significant impact on GTFP. This shows that when insurance development reaches a certain level, it will always have a negative impact on GTFP. Insurance provides individuals, enterprises, and other microeconomic entities with a way to transfer uncertainty, reduces the risks and costs of microeconomic entities' losses, and is conducive to the continuous development of various economic activities. Therefore, insurance development has a positive impact on GTFP. However, as the scale of insurance development continues to increase, assets such as stocks, and funds in insurance investments are more susceptible to financial turmoil and market sentiment, and perfect social security may lead to a decline in workers' enthusiasm for work. Therefore, when insurance development reaches a certain level, it will have a negative impact on GTFP.

CONCLUSION

This paper shows that financial development has a heterogeneous impact on GTFP, whether in different financial sectors or in different countries. The GML index is used to measure the GTFP for 40 countries over the period from 1991 to 2014. In order to study the impact of the development of different financial sectors on GTFP, we conduct empirical testing from three perspectives of financial development: bank, securities, and insurance. We also compare the differences between developed and developing countries. The main conclusions are as follows.

An inverted *U*-shaped relationship exists between financial development and GTFP. Bank development, securities development, and insurance development can all promote the growth of GTFP, and this growth-promotion effect will decrease as their level of development increases.

The impact of financial development on GTFP is heterogeneous in developing and developed countries. In developing countries, an inverted *U*-shaped relationship exists between financial development and GTFP, whether it is bank development, securities development, or insurance development. In developed countries, the development of banks and insurance has a significant negative impact on GTFP, while the development of securities has a significant positive impact on GTFP.

The impact of bank, securities, and insurance development on GTFP is heterogeneous. In the early stages of bank development, the increase in the level of bank development will enhance its positive impact on GTFP. When bank development reaches a certain level, an increase in the level of bank development will reduce its positive impact on GTFP, and it will even have a negative impact on GTFP. The impact of insurance development on GTFP is similar to that of bank development. In contrast to the impact of bank and insurance development on GTFP, when securities development reaches a certain level, it will always have a positive impact on GTFP. Securities development is thus more conducive to improving GTFP than bank development.

DATA AVAILABILITY STATEMENT

The datasets generated for this study are available on request to the corresponding author.

AUTHOR CONTRIBUTIONS

TL conceived and designed the study. GL contributed by writing the manuscript.

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REFERENCES

Aghion, P., Bacchetta, P., and Banerjee, A. (2004). A corporate balance-sheet approach to currency crises. *J. Econ. Theory.* 119, 6–30. doi: 10.1016/j.jet.2003.06.004

Arcand, J. L., Berkes, E., and Panizza, U. (2015). Too much finance? *J. Econ. Growth* 20, 105–148. doi: 10.1007/s10887-015-9115-2

Asteriou, D., and Spanos, K. (2019). The relationship between financial development and economic growth during the recent crisis: evidence from the EU. *Finance Res. Lett.* 28, 238–245. doi: 10.1016/j.frl.2018.05.011

Baier, S. L., Dwyer, G. P Jr., and Tamura, R. (2006). How important are capital and total factor productivity for economic growth? *Econ. Inq.* 44, 23–49. doi: 10.1093/ei/cbj003

Brown, J. R., Martinsson, G., and Petersen, B. C. (2013). Law, stock markets, and innovation. *J. Finance* 68, 1517–1549. doi: 10.1111/jofi.12040

Buera, F. J., Kaboski, J. P., and Shin, Y. (2011). Finance and development: a tale of two sectors. *Am. Econ. Rev.* 101, 1964–2002. doi: 10.1257/aer.101.5.1964

Buera, F. J., and Shin, Y. (2013). Financial frictions and the persistence of history: a quantitative exploration. *J. Political Econ.* 121, 221–272. doi: 10.1086/670271

Caporale, G. M., Rault, C., Sova, A. D., and Sova, R. (2015). Financial development and economic growth: evidence from 10 new European Union members. *Int. J. Finance Econ.* 20, 48–60. doi: 10.1002/ijfe.1498

Chung, Y. H., Färe, R., and Grosskopf, S. (1997). Productivity and undesirable outputs: a directional distance function approach. *J. Environ. Manage.* 51, 229–240. doi: 10.1006/jema.1997.0146

Cole, H. L., Greenwood, J., and Sanchez, J. M. (2016). Why doesn't technology flow from rich to poor countries? *Econometricas* 84, 1477–1521. doi: 10.3982/ECTA11150

Costantini, V., Crespi, F., Marin, G., and Paglialunga, E. (2017). Eco-innovation, sustainable supply chains and environmental performance in European industries. *J. Clean. Prod.* 155, 141–154. doi: 10.1016/j.jclepro.2016.09.038

De Gregorio, J., and Guidotti, P. E. (1995). Financial development and economic growth. *World Dev.* 23, 433–448. doi: 10.1016/0305-750X(94)00132-I

Emrouznejad, A., and Yang, G. L. (2016). CO2 emissions reduction of Chinese light manufacturing industries: a novel RAM-based global Malmquist-Luenberger productivity index. *Energ. Policy* 96, 397–410. doi: 10.1016/j.enpol.2016.06.023

Fagiolo, G., Giachini, D., and Roventini, A. (2019). Innovation, finance, and economic growth: an agent-based approach. *J. Econ. Int. Coord.* 1–34. doi: 10.1007/s11403-019-00258-1

Färe, R., Grosskopf, S., and Pasurka, C. A. Jr. (2001). Accounting for air pollution emissions in measures of state manufacturing productivity growth. *J. Reg. Sci.* 41, 381–409. doi: 10.1111/0022-4146.00223

Gerarden, T. D., Newell, R. G., and Stavins, R. N. (2017). Assessing the energy-efficiency gap. *J. Econ. Lit.* 55, 1486–1525. doi: 10.1257/jel.20161360

Greenwood, J., and Jovanovic, B. (1990). Financial development, growth, and the distribution of income. *J. Political Econ. 98*, 1076–1107. doi: 10.1086/261720

Hsu, P. H., Tian, X., and Xu, Y. (2014). Financial development and innovation: cross-country evidence. *J. Financ. Econ.* 112, 116–135. doi: 10.1016/j.jfineco.2013.12.002

Huang, Z., Liao, G., and Li, Z. (2019). Loaning scale and government subsidy for promoting green innovation. *Technol. Forecast. Soc. Change.* 144, 148–156. doi: 10.1016/j.techfore.2019.04.023

Kenney, M. (2011). How venture capital became a component of the US national system of innovation. *Ind. Corp. Change* 20, 1677–1723. doi: 10.1093/icc/dtr061

King Robert, G., and Levine, R. (1993). Finance, entrepreneurship and growth. *J. Monet. Econ.* 32, 513–542. doi: 10.1016/0304-3932(93)90028-E

Kwakwa, P. A., Alhassan, H., and Aboagye, S. (2018). Environmental Kuznets curve hypothesis in a financial development and natural resource extraction context: evidence from Tunisia. *Quant. Finance Econ.* 2, 981–1000. doi: 10.3934/QFE.2018.4.981

Law, S. H., Azman-Saini, W. N. W., and Ibrahim, M. H. (2013). Institutional quality thresholds and the finance–growth nexus. *J. Bank. Finance* 37, 5373–5381. doi: 10.1016/j.jbankfin.2013.03.011

Law, S. H., and Singh, N. (2014). Does too much finance harm economic growth? *J. Bank. Finance* 41, 36–44. doi: 10.1016/j.jbankfin.2013.12.020

Li, J., Zhang, J., Zhang, D., and Ji, Q. (2019). Does gender inequality affect household green consumption behaviour in China? *Energy Policy.* 135:111071. doi: 10.1016/j.enpol.2019.111071

Li, Y., Ji, Q., and Zhang, D. (2020). Technological catching up and innovation policies in China: what is behind this largely successful story? *Technol. Forecast. Soc. Change* 153:119918. doi: 10.1016/j.techfore.2020.119918

Li, Z., Liao, G., and Albitar, K. (2020). Does corporate environmental responsibility engagement affect firm value? The mediating role of corporate innovation. *Bus. Strategy Environ.* 29, 1045–1055. doi: 10.1002/bse.2416

Li, Z., Liao, G., Wang, Z., and Huang, Z. (2018). Green loan and subsidy for promoting clean production innovation. *J. Clean. Prod.* 187, 421–431. doi: 10.1016/j.jclepro.2018.03.066

Liao, G., and Drakeford, B. (2019). An analysis of financial support, technological progress and energy efficiency: evidence from China. *Green Finance* 1, 174–187. doi: 10.3934/GF.2019.2.174

Longhofer, W., and Jorgenson, A. (2017). Decoupling reconsidered: does world society integration influence the relationship between the environment and economic development? *Soc. Sci. Res.* 65, 17–29. doi: 10.1016/j.ssresearch.2017.02.002

Maes, J., and Jacobs, S. (2017). Nature-based solutions for Europe's sustainable development. *Conserv. Lett.* 10, 121–124. doi: 10.1111/conl.12216

Nassani, A. A., Aldakhil, A. M., Abro, M. M. Q., and Zaman, K. (2017). Environmental Kuznets curve among BRICS countries: spot lightening finance, transport, energy and growth factors. *J. Clean. Prod.* 154, 474–487. doi: 10.1016/j.jclepro.2017.04.025

Ntarmah, A. H., Kong, Y., and Gyan, M. K. (2019). Banking system stability and economic sustainability: a panel data analysis of the effect of banking system stability on sustainability of some selected developing countries. *Quant. Finance Econ.* 3, 709–738. doi: 10.3934/QFE.2019.4.709

Oh, D. H. (2010). A global Malmquist-Luenberger productivity index. *J. Prod. Anal.* 34, 183–197. doi: 10.1007/s11123-010-0178-y

Pata, U. K. (2018). Renewable energy consumption, urbanization, financial development, income and CO_2 emissions in Turkey: testing EKC hypothesis with structural breaks. *J. Clean. Prod.* 187, 770–779. doi: 10.1016/j.jclepro.2018.03.236

Rioja, F., and Valev, N. (2004). Does one size fit all: a reexamination of the finance and growth relationship. *J. Dev. Econ.* 74, 429–447. doi: 10.1016/j.jdeveco.2003.06.006

Romer, P. M. (1986). Increasing returns and long-run growth. *J. Political Econ.* 94, 1002–1037. doi: 10.1086/261420

Ruiz, J. L. (2018). Financial development, institutional investors, and economic growth. *Int. Rev. Econ. Finance* 54, 218–224. doi: 10.1016/j.iref.2017.08.009

Seven, U., and Coskun, Y. (2016). Does financial development reduce income inequality and poverty? Evidence from emerging countries. *Emerg. Mark. Rev.* 26, 34–63. doi: 10.1016/j.ememar.2016.02.002

Shahzad, S. J. H., Kumar, R. R., Zakaria, M., and Hurr, M. (2017). Carbon emission, energy consumption, trade openness and financial development in Pakistan: a revisit. *Renew. Sust. Energ. Rev.* 70, 185–192. doi: 10.1016/j.rser.2016.11.042

Shi, X., and Sun, S. (2017). Energy price, regulatory price distortion and economic growth: a case study of China. *Energ. Econ.* 63, 261–271. doi: 10.1016/j.eneco.2017.02.006

Solow, R. M. (1957). Technical change and the aggregate production function. *Rev. Econ. Stat.* 39, 312–320. doi: 10.2307/1926047

Song, Y., Chen, S., and Zhang, M. (2020). Local government heterogeneity and regional environmental cooperation—evolutionary game analysis based on Chinese decentralization. *Chinese J. Manage. Sci.* 28, 201–211. doi: 10.16381/j.cnki.issn1003-207x.2020.01.017

Song, Y., Ji, Q., Du, Y. J., and Geng, J. B. (2019). The dynamic dependence of fossil energy, investor sentiment and renewable energy stock markets. *Energ. Econ.* 84:104564. doi: 10.1016/j.eneco.2019.104564

Tone, K. (2001). A slacks-based measure of efficiency in data envelopment analysis. *Eur. J. Oper. Res.* 130, 498–509. doi: 10.1016/S0377-2217(99)00407-5

Tripathy, N. (2019). Does measure of financial development matter for economic growth in India? *Quant. Finance Econ.* 3, 508–525. doi: 10.3934/QFE.2019.3.508

Wachtel, P. (2001). Growth and finance: what do we know and how do we know it? *Int. Finance* 4, 335–362. doi: 10.1111/1468-2362.00077

Wang, K. L., Miao, Z., Zhao, M. S., Miao, C. L., and Wang, Q. W. (2019). China's provincial total-factor air pollution emission efficiency evaluation, dynamic evolution and influencing factors. *Ecol. Indic.* 107:105578. doi: 10.1016/j.ecolind.2019.105578

Xia, Y., Kong, Y., Ji, Q., and Zhang, D. (2019). Impacts of China-US trade conflicts on the energy sector. *China Econ. Rev.* 58:101360. doi: 10.1016/j.chieco.2019.101360

Xu, X., Wei, Z., Ji, Q., Wang, C., and Gao, G. (2019). Global renewable energy development: influencing factors, trend predictions and countermeasures. *Res. Policy* 63:101470. doi: 10.1016/j.resourpol.2019.101470

Zhang, C., Liu, H., Bressers, H. T. A., and Buchanan, K. S. (2011). Productivity growth and environmental regulations-accounting for undesirable outputs: analysis of China's thirty provincial regions using the Malmquist-Luenberger index. *Ecol. Econ.* 70, 2369–2379. doi: 10.1016/j.ecolecon.2011.07.019

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Oil Price Pass-Through Into Consumer and Producer Prices With Monetary Policy in China: Are There Non-linear and Mediating Effects

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Balancing the oil pass-through to consumer and producer prices is crucial for policymakers. This study aimed to advance associated thinking by examining how consumer and producer prices in China related to changes in global oil prices from 2006 to 2018. First, we investigated the pass-through of oil spot prices to consumer prices as indicated by the consumer price index (CPI) and means of consumption price index (MCPI), and to producer prices as indicated by the producer price index (PPI) and means of production price index (MPPI), with a monetary policy in China. This study also explored the non-linear and mediating effects of financial markets and government debt on linkages between oil prices and consumer/producer prices based on non-linear framework and causal steps approach, respectively. Our findings indicated some key points; for example, the pass-through of oil prices with a monetary policy in China shed light on a benchmark role in global oil markets. Additionally, the non-linear effect of oil prices on consumer/producer prices varied across the Brent and West Texas Intermediate (WTI) crude oil markets. The mediating effect of government debt also reflected the effectiveness in balancing the relationship between oil prices and producer prices. Government debt explained the −0.091 transition between the Brent oil price and the PPI and could explain the −0.095 transition between the Brent oil price and the MPPI, whereas the transition due to financial markets were −0.064 and −0.080, respectively. These outcomes have important implications for stabilizing price levels in countries.

Keywords: consumer and producer prices, non-linear, mediating effect, crude oil markets, financial markets, debts markets

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INTRODUCTION

What is the extent of oil price pass-through in relation to consumer and producer prices within Chinese monetary policy? This question sheds light on the crucial role oil price plays in macroeconomic instability (Hamilton, 1983; Kim, 2012; Bloch et al., 2015; Ratti and Vespignani, 2016; Sodeyfi and Katircioglu, 2016; Kang et al., 2017; Shi and Sun, 2017; Ji et al., 2019c). Multiple studies exploring the positive relationships between oil prices and consumer/producer prices have not yielded consistent results (Alvarez et al., 2011; Gomez-Loscos et al., 2011; Guo et al., 2016; Choi et al., 2018; Gong and Lin, 2018). Recently, Humbatova et al. (2019) modeled the dependence of the CPI on oil price and concluded that the CPI significantly and positively depends on oil price. Additionally, He and Lin (2019) studied the transmission from oil price to the PPI and showed that oil price also has a positive ability to affect the operation of the PPI. However, consumer/producer prices could be asymmetrically related to the volatility in oil prices (Ajmi et al., 2015; Sek and Lim, 2016; Castro et al., 2017; Rangasamy, 2017; Gonzalez-Concepcion et al., 2018); for instance, Ajmi et al. (2015) documented an asymmetric relationship by disentangling the effects of positive shocks from negative ones. Additionally, Lim and Sek (2017) concluded that the impact of oil prices may vary across oil exporting and importing economies, because of oil dependency factors; otherwise, oil prices exert negative effects on the CPI in organization for economic co-operation and development (OECD) countries (Katircioglu et al., 2015). This occurs because studies ignore the crucial effect of monetary policy on consumer and producer prices. Changes in the workings of monetary policy could have a recessionary influence, causing devastating oil shocks (Wen et al., 2019a); therefore, the monetary authorities may react to oil price shocks by implementing diverse monetary policies to stabilize macroeconomic performance during certain periods (Gomez-Loscos et al., 2011; Lim and Sek, 2018; Sek, 2019). Furthermore, the pass-through of oil price could be strongly related to the heterogeneous oil-dependence of various crude oil markets. In this context, the first objective of this research was to test the pass-through of oil prices, especially the Brent and WTI oil prices, in relation to consumer/producer prices within Chinese monetary policy.

Pass-through effects are primarily a problem caused by a non-linear relationship between oil prices and consumer/producer prices. Extensive studies have employed data showing the non-linear responses of consumer and producer prices to oil price increases and decreases (Ozdemir and Akgul, 2015; Yalcin et al., 2015; Guo et al., 2016; Ahmed et al., 2017; Sek, 2017, 2019; Long and Liang, 2018; Tiwari et al., 2019). It is widely accepted that non-linear relationships provide crucial information about the stabilizing effect of energy policies and the response of prices to positive and negative shocks; for instance, Myers et al. (2018) conducted a permanent-transitory decomposition to examine long-term and short-term relationships between oil prices, producer prices, and consumer prices. They found that oil prices could be regarded as a permanent shock. Similarly, Sek (2017) employed a non-linear autoregressive distributed lag (ARDL) model to explore the asymmetric effect of oil price changes on producer/consumer prices. They indicated that there is a limited effect of oil prices on the CPI in the long run, but that oil prices exert an indirect effect through the transmission from import prices to production costs. Sek (2019) divided the study's sample into oil-importing and oil-exporting countries, providing evidence that changes in oil prices could cause increases in consumer prices in oil-importing countries. As mentioned above, large-scale studies have provided feasible evidence for the asymmetric relationships between oil prices and consumer/producer prices, but one issue that remains unsolved is the non-linear nature of these relationships. It is well-known that oil dependency factors, such as refined oil prices, production costs, and the demand for refined oil products, may create non-linear price transmissions (Ozdemir and Akgul, 2015; Long and Liang, 2018; Ji et al., 2019d; Song et al., 2019; Tiwari et al., 2019). In this vein, this study explored the question of whether oil prices exert non-linear effects on consumer and producer prices, with the aim of providing a richer framework for identifying how authorities should respond to oil price shocks.

The pass-through effect of the oil price occurs via two indirect channels: financial markets and government debt. First, the fluctuation of oil prices could affect future stock prices, thereby impacting consumer/producer prices, since financial markets can be an important determinant of domestic economies (Razmi et al., 2016; Ji et al., 2018; Wen et al., 2019c; Zheng and Du, 2019). The link between oil price movements and financial markets has important implications for portfolio management, so the financial market channel was considered in this study (Arouri, 2011; Cong and Shen, 2013; Ahmed et al., 2017; Ji et al., 2019a). Theoretically, the oil price's relationship to production costs and future cash flow could affect confidence in financial markets (Liu et al., 2019a). As a result, higher oil prices may decrease share prices, dampening profits and changing investment strategies, thus further stabilizing domestic prices (Razmi et al., 2016; Wen et al., 2019b). The second channel concerns the fiscal changes used to model expected consumer and producer prices. It is widely accepted that rising oil prices often reflect fiscal revenues, causing a subsequent increase of government debt (Katircioglu et al., 2015; Sek and Low, 2016). However, little attention has been paid to the analysis of the fiscal channel in the oil price–consumer/producer price mechanism. Specifically, when oil prices change and government debt increases, this increases investors' willingness to invest in enterprises and results in a consequent stabilization of consumer/producer prices (Akar, 2019); therefore, the primary aim of this study was to explore the role of financial market and government debt channels in transmitting oil price shocks to consumer/producer prices.

The contributions of this study are 3-fold. Considerable evidence exists regarding oil price–consumer/producer price connections, but one issue that remains unresolved is monetary policy's role in this linkage. Even though previous studies have focused on the relationships between oil price, the PPI, and the CPI, no study has analyzed the pass-through of oil price with Chinese monetary policy, or analyzed the oil price-inflation pass-through, taking into account not only the CPI/PPI, but also two other measures of core inflation: the MCPI and MPPI. Both the Brent and WTI oil prices have displayed a new pattern of volatility since 2011. To analyze these factors, this paper included monetary policy to explore the Brent and WTI oil prices' pass-through to both the CPI/MCPI and the PPI/MPPI. This extension is crucial for capturing the fundamental reasons for price spreads in different crude oil markets, based on their typical price movement differences.

A second contribution of the study is its examination of the non-linear relationship between oil prices, consumer prices, and producer prices. Some related studies have pointed out that the pass-through of oil prices to the CPI and PPI is asymmetrical (Sek, 2017). It is well-known that oil prices and the CPI/PPI may exhibit non-linear relationships, due to factors, such as policy uncertainty, oil dependence, energy crises, etc. Furthermore, diverse mechanisms in the Brent and WTI oil prices could provide a heterogeneous pass-through to consumer and producer prices, suggesting that the extent of the relationship between oil prices and domestic prices could vary across crude oil markets. This allowed us to create a non-linear framework for oil price pass-through and to identify a heterogeneous effect in different local representative oil markets.

Finally, this study provides a rich framework for identifying the indirect effect of oil prices on consumer/producer prices through stock market and government debt channels. Most of the previous literature has investigated the financial market channels' (e.g., share prices') effect on oil price–consumer/producer prices pass-through, or has calculated the transmission coefficients of government debt from global oil prices to domestic prices. Very little is known about the extent and manifestations of this indirect effect, which is increasingly important for policymakers regarding government debt and equally important for explaining how government debt plays an indirect role in domestic price shocks.

The remainder of the study is structured as follows. Section The Pass-Through of Oil Prices to Consumer and Producer Prices With a Monetary Policy in China examines the pass-through of oil prices to consumer and producer prices. Section The Non-linear Pass-Through of Oil Prices With a Monetary Policy provides evidence of the non-linear effects, while section Mediating Mechanism of Oil Price Pass-Through on Consumer and Producer Prices depicts the mediating effect of financial markets and government debt on oil price–consumer/producer price mechanisms. The conclusions are presented in section Conclusions.

THE PASS-THROUGH OF OIL PRICES TO CONSUMER AND PRODUCER PRICES WITH A MONETARY POLICY IN CHINA

Vector Autoregressive Model

This study adopted a vector autoregressive (VAR) model to explore the oil price pass-through. Since the seminal work by Kilian (2009), the existing literature has explored the effect of oil price shocks on macroeconomics or financial markets (Kilian, 2009; Moya-Martinez et al., 2014; Pinho and Madaleno, 2016; Coronado et al., 2018). The role of oil prices in the overall economy has been widely documented in energy economics literature (Song et al., 2019; Xia et al., 2019a). The identification of oil price pass-through is crucial, not just for exploring oil price movements, but also for investigating the response of domestic prices to oil prices (Ratti and Vespignani, 2016; Sodeyfi and Katircioglu, 2016). In other words, oil price movements could be regarded as endogenous events, as is commonly believed. In particular, China's consumer price level has been seen to begin to settle down, compared with the previously high levels since 2014 (Wei, 2019). These comparative changes indicate that there may be a close relationship between oil prices and China's general price level for both consumer and producer prices. To solve this, we estimated a *p*th-order VAR for each variable with oil price (*op*), consumer prices (*cp*), and producer prices (*pp*). Thus, the reduction in this paper of VAR(p) could be written as (1):

TABLE 1 | Description of all variables.

	Variables	Abbreviation	Description
op	Brent oil price	OP1	This represents the Northwest Europe sweet markets.
	WTI oil price	OP2	This represents the North American markets.
cp	Consumer price index	CPI	This determines China's consumer prices.
	Means of consumption price index	MCPI	Social products used to meet consumers' demands in daily life.
pp	Producer price index	PPI	This determines China's producer prices.
	Means of production price index	MPPI	This is the main determinant in the productive process.
mp	M2	MS	
	1 week SHIBOR	IR	

$$\boldsymbol{Y_t} = \boldsymbol{C_0} + \sum_{i=1}^{p} \boldsymbol{C_i} \boldsymbol{Y_{t-i}} + \boldsymbol{\varepsilon_t}. \tag{1}$$

where $\boldsymbol{Y_t}$ is a three-dimensional price vector made up of three prices over time t; that is, *op*, *cp*, and *pp*. $\{\boldsymbol{C_i}\}_{i=1}^{p}$ stands for (3 × 3) matrices relating to the coefficient. Additionally, $\boldsymbol{\varepsilon_t}$ is a vector of residuals.

Second, this study tested the oil price pass-through with Chinese monetary policy. Based on (1), the measurements of the monetary policy were added as control variables, so the reduced form of VAR(p) is shown as (2):

$$\boldsymbol{Y_t} = \boldsymbol{\beta_0} + \sum_{i=1}^{p} \boldsymbol{\beta_i} \boldsymbol{Y_{t-i}} + MS_t + IR_t + \boldsymbol{\varepsilon_t}. \tag{2}$$

where MS_t and IR_t represent the money supply and the interest rate at time t, respectively. Additionally, we present a brief description of all the variables in **Table 1**.

Oil prices are determined by global markets. Overall, the changes in oil supply and demand in different countries highlight the benchmark role of the Brent and WTI oil prices in global crude oil markets. The WTI oil prices have historically outweighed those of Brent by $1–3 per barrel every trading day, due to West Texas's better oil quality. Nevertheless, this trend has been broken in recent years, due to changes in the demand of emerging economies for Brent oil and the US government legally restricting crude oil exports. Specifically, Brent largely represents the Northwest European sweet market, while WTI draws its oil from the USA, Canada, and Mexico. Because of diverse price mechanisms, this study selected the Brent and WTI oil prices to measure *op*. Data for the Brent and WTI oil prices was collected from the U.S. Energy Information Administration.

Considering China's consumer/producer price levels, we selected the CPI, MCPI, PPI, and MPPI to capture the consumer and producer price levels. It is widely accepted that the CPI and PPI help to determine China's consumer and producer

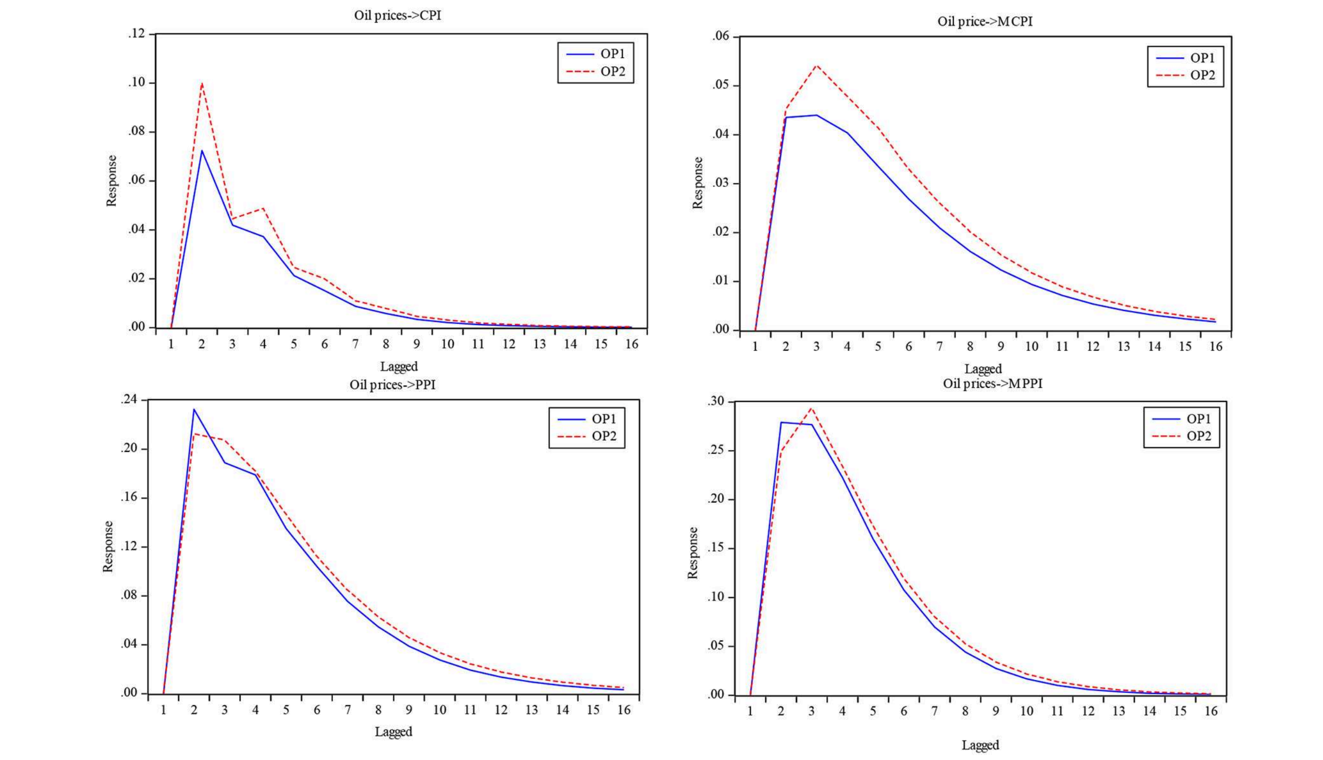

FIGURE 1 | The response of consumer/producer prices to oil prices without a monetary policy. OP1 and OP2 stand for Brent oil price and WTI oil price, respectively.

prices, respectively. Moreover, the MCPI could be regarded as a tool for measuring the social products that meet the demand of consumers in daily life. The MPPI is a direct measure of production and is the main determinant of the cost of production materials and labor. Therefore, this study also used the MCPI and MPPI to calculate consumer and producer prices. These price levels were collected from the National Bureau of Statistics of China.

To assess the Chinese monetary policy, this study employed two widely used metrics of monetary supply (MS) and 1-week SHIBOR (IR). We collected this data from the People's Bank of China. All the data was monthly data covering January 2006 to December 2018, transformed into log form because of the existence of heteroscedasticity. According to the results of a unit root test and lagged selection, we finally estimated VAR (3) to explore the oil price pass-through to the CPI, VAR (2) to investigate the oil price–MCPI/PPI mechanism, and VAR (1) for the mechanism of oil price–MPPI.

TABLE 2 | Statistical description of accumulated response without a monetary policy.

	Total periods	Max location	Average	Std.	Total
OP1->CPI	8	4	0.00014	0.00020	0.002674
OP2->CPI	8	4	0.00017	0.00026	0.003293
OP1->MCPI	9	3	0.00014	0.00016	0.002726
OP2->MCPI	10	3	0.00017	0.00018	0.003274
OP1->PPI	13	2	0.00058	0.00073	0.011014
OP2->PPI	8	4	0.00047	0.00083	0.009022
OP1->MPPI	9	2	0.00049	0.00085	0.009395
OP2->MPPI	9	2	0.00046	0.00079	0.008768

OP1 and OP2 stand for the Brent and WTI oil prices, respectively. Std. represents the standard deviation.

Oil Price Pass-Through Without a Monetary Policy in China

Exploring the impulse response is a standard process in the VAR model for depicting the lag pass-through of oil prices to consumer/producer prices. Additionally, the accumulated response could be an effective tool for capturing the total effect of oil prices on domestic price levels; therefore, **Figure 1** shows the changes in the pass-through of oil prices (Brent and WTI) to the domestic price levels used in this paper: the CPI, MCPI, PPI, and MPPI. The accumulated responses to oil prices are summarized in **Table 2**.

Consumer/producer prices showed positive relationships with oil prices, but not consistently. As shown in **Figure 1**, we observed that the oil prices were positively transmitted to consumer and producer prices, and this phenomenon was completed within the first 2–3 months. However, the results of the standardized response analysis showed a much greater change in producer prices than in consumer prices, which were

0.24–0.28 for producer prices and 0.05–0.10 for consumer prices. These results were not surprising, due to the dependence on oil. Crude oil is the lifeblood of our modern economic development. Movements in oil prices can change production costs, so higher oil prices may lead to an increase in production costs and a consequent decrease in production markets (He and Lin, 2019), which in turn may increase consumer/producer price levels. However, the inconsistent responses of the CPI/MCPI and the PPI/MPPI occurred because of the differences in dependence on oil between consumers and producers (Sakashita and Yoshizaki, 2016; Jongwanich et al., 2019). As a rule of thumb, we could conclude that producer prices were more sensitive than consumer prices to changes in oil prices.

There were differences in the pass-through of Brent and WTI oil prices to price levels of different types. Specifically, it was noteworthy that the pass-through of the WTI oil price to consumer price was higher than that of the Brent price over lagged periods, whereas the pass-through of the Brent oil price to producer prices was higher within the first 2 months. These differences suggest that both consumers and producers focused on WTI oil prices. This was due to the economic status of the United States, coupled with the trade agreement between China and the United States (Li et al., 2019b; Xu et al., 2019). Since the advent of the benchmark role played by Brent oil prices, producers have begun to reconcile global crude oil markets by using both the Brent and WTI oil prices in the short-term (Zhang and Zhang, 2015). This paper specifically explored the accumulated response of consumer and producer prices to oil prices.

First, the total pass-through of the oil price behaved quite heterogeneously with regard to consumer and producer prices. The accumulated response represented the effect of total oil price shocks on domestic price levels. Reflecting the dependence on oil, the pass-through of the Brent oil price to the PPI had, relatively, the highest performance (0.011), followed by the Brent oil price to the MPPI (0.009), with the Brent pass-through to the CPI ranking last (0.002).

It was particularly noteworthy that the durations of the periods of oil price pass-through, for both the Brent and WTI oil prices, were seemingly consistent. Generally, periods when oil price shocks converge to zero can reflect the general equilibrium between oil prices and China's consumer/producer prices. It is worth noting that the total period for the oil price–consumer/producer price mechanism could be 9 months, except for Brent–PPI and WTI–MCPI.

There were differences between the characteristics of oil price–domestic price transitions. In terms of average levels, we observed the difference between the two prices, with the pass-through of oil prices to producer prices being four times greater than that to consumer prices. This result was in line with the figures shown above. According to **Table 2**, the standard deviation of oil price–producer prices was generally larger than that of oil price–consumer prices. Moreover, we found that the Brent oil price appeared to be more stable than the WTI price, regardless of consumer prices (Gonzalez-Concepcion et al., 2018; Zivkov et al., 2019). In brief, the dependence on oil and the impact of oil price on producer prices, leaves countries macroeconomically vulnerable (Sakashita and Yoshizaki, 2016; Sek, 2017; Zhou et al., 2017).

Oil Price Pass-Through With a Monetary Policy in China

Having explored the relationship between oil prices and consumer/producer prices, this study further examined monetary policy factors, such as money supply and interest rate. As in section Oil Price Pass-Through Without a Monetary Policy in China, we first analyzed the accumulated response of consumer and producer prices. **Figure 2** depicts the response of consumer/producer prices to oil prices for both the Brent and WTI oil prices. In addition, **Table 3** summarizes the statistical descriptions of the accumulated responses.

Figure 2 shows several interesting results for the pass-through of oil prices with a monetary policy. On the one hand, the response of consumer/producer prices appeared similar to that without a monetary policy. It is worth noting that the positive response of consumer/producer prices to oil prices had the best performance within the first 2–3 months. This result matched the historical determining factors of market participants on relationships between oil prices and domestic price levels. On the other hand, the evaluation of oil price shocks with a Chinese monetary policy was similar to the results in section Oil Price Pass-Through Without a Monetary Policy in China; for example, the results suggested that the pass-through of the WTI oil price to the CPI was larger than for the Brent oil price. Taking into account the crucial role of monetary policy, we noticed the same picture for the oil price–CPI mechanism.

Nevertheless, there were differences between these two results. Specifically, the Brent oil price pass-through to the PPI was larger than that of the WTI oil price over the lagged periods. In view of the increasing role of Brent oil in global crude oil markets, and its pivotal role as a determinant of oil demand in emerging markets, the Brent oil market could be regarded as an important tool for measuring China's price levels.

The total pass-through of oil prices and the durational periods varied across consumer and producer price levels. As shown in **Table 3**, oil price movements generally had a larger impact on producer prices, as represented by the PPI and MPPI. The standard deviation of the oil price–producer prices mechanism was also larger than that of the response of consumer prices to oil prices. Since consumer prices are not oil-intensive, the CPI and MCPI may not heavily depend on oil price movements. In brief, this result implied that oil price is not a crucial contributor to consumer prices, thereby indicating that oil price movements are likely to have a greater impact on price levels that are more oil-dependent.

To see how reasonable this pass-through estimate was, we compared the accumulated responses obtained in sections Oil Price Pass-Through Without a Monetary Policy in China and Oil Price Pass-Through With a Monetary Policy in China. It was interesting to note that the comparison in **Figure 3** indicated that there were two differences, with and without a monetary policy. On the one hand, the accumulated response to the WTI oil prices showed an increasingly positive relationship between

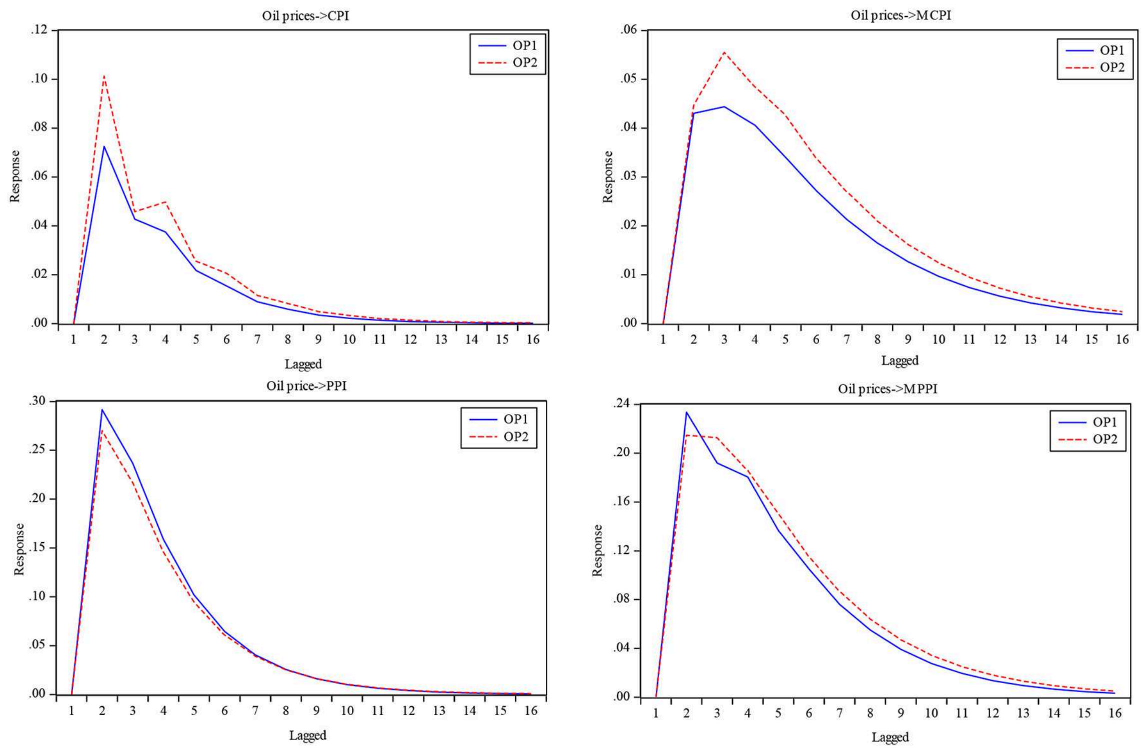

FIGURE 2 | The response of consumer/producer prices to oil prices with a monetary policy.

TABLE 3 | Statistical description of accumulated response according to monetary policy.

Impulse	Total periods	Max location	Average	Std.	Total
OP1->CPI	8	4	0.00014	0.00021	0.002727
OP2->CPI	10	4	0.00018	0.00026	0.003416
OP1->MCPI	9	3	0.00015	0.00016	0.002761
OP2->MCPI	10	3	0.00018	0.00019	0.003364
OP1->PPI	13	2	0.00059	0.00073	0.011114
OP2->PPI	8	4	0.00049	0.00085	0.009342
OP1->MPPI	9	2	0.00049	0.00085	0.009363
OP2->MPPI	9	2	0.00046	0.00079	0.008733

oil prices, consumer prices, and producer prices, except for the WTI–MPPI mechanism. On the other hand, the effects on producer prices were broadly similar in both models, except for the WTI–PPI mechanism. This difference was largely due to the forward-looking nature of money supply with regard to WTI oil prices and consumer prices. First, Brent oil prices are more stable than WTI prices because of the strong predictive power of economic policy uncertainty (Kang et al., 2017; Dong et al., 2019; Li and Zhong, in press). With monetary policies in China, the increasing role of WTI oil prices in affecting price levels, such as CPI, MCPI, and PPI, could highlight the oil price-consumer/producer prices mechanism. The primary aim of monetary policy is to stabilize consumer prices and further improve GDP growth; thus, the changing role of oil price with monetary policy in China could provide evidence for monitoring oil shocks at the macroeconomic level. In this vein, the evidence confirmed that monetary policy may be an accurate tool for capturing the pass-through of oil prices to consumer/producer prices (Razmi et al., 2016; Alvarez and Sanchez, 2019; Wen et al., 2019a). Overall, these results, combined with **Figure 2**, indicated that the pass-through of oil prices, coupled with a monetary policy, is indeed informative regarding consumer and producer prices.

THE NON-LINEAR PASS-THROUGH OF OIL PRICES WITH A MONETARY POLICY

Having found a significant pass-through of oil prices to consumer and producer prices, this paper further empirically investigated the non-linear pass-through. In this section, we first document the non-linear pass-through of oil prices to consumer prices with Chinese monetary policy, then we provide evidence of the oil price non-linear pass-through to producer prices.

Non-linear Framework

The results in section The Pass-Through of Oil Prices to Consumer and Producer Prices With a Monetary Policy in China indicated a linear relationship between oil price movements and changes in the corresponding price levels with a monetary policy

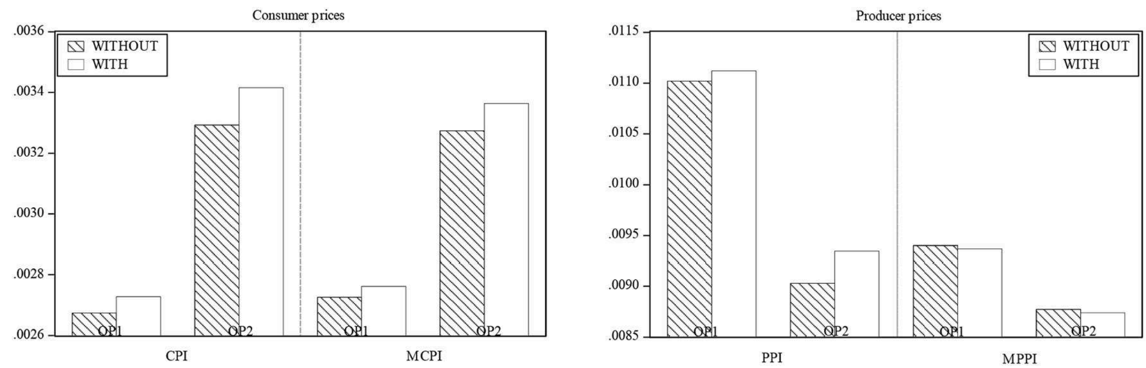

FIGURE 3 | The comparative pass-through of the oil price with and without a monetary policy.

TABLE 4 | The relationships between oil prices and consumer prices.

D.V.	**CPI**				**MCPI**			
op	**OP1**		**OP2**		**OP1**		**OP2**	
Model	**1**	**2**	**1**	**2**	**1**	**2**	**1**	**2**
α_1	0.357 (0.082)	1.004 (0.533)	0.437 (0.080)	1.787692 (0.470)	0.344 (0.085)	1.026 (0.555)	0.387 (0.085)	1.624 (0.502)
α_2		−0.652 (0.532)		−1.373 (0.471)		−0.688 (0.554)		−1.257 (0.503)
β_1	0.289 (0.078)	0.286 (0.079)	0.269 (0.074)	0.270 (0.072)	0.177 (0.082)	0.173 (0.082)	0.175 (0.078)	0.176 (0.077)
β_2	−0.216 (0.069)	−0.228 (0.069)	−0.142 (0.071)	−0.169 (0.070)	−0.296 (0.072)	−0.308 (0.073)	−0.240 (0.075)	−0.264 (0.075)
Ad_R^2	0.395	0.397	0.430	0.457	0.344	0.346	0.361	0.382

The standard errors are reported in parentheses. D.V. refers to dependent variable. OP1 refers to Brent oil prices, while OP2 refers to WTI oil prices. Ad_R^2 means the adjusted R^2 of the models.

in China. Therefore, this paper first assumed a linear framework to depict this relationship, specifically shown as (3):

$$pl_t = c_0 + \alpha_1 op_t + \beta_1 MS_t + \beta_2 IR_t + \varepsilon_t. \tag{3}$$

where pl_t stands for price levels in China, including four price indexes (the CPI, MCPI, PPI, and MPPI) at time t.

However, the pass-through of the oil price to price levels was expected to be non-linear. Due to the existence of diverse share prices, oil prices may exert an effect on consumer and producer prices that varies across oil price levels. In addition, it is widely accepted that excise duties play a crucial role in relationships between oil prices and consumer/producer prices (Alvarez et al., 2011). To provide an accurate assessment, we added a quadratic term into (3), which allowed us to capture the non-linear pass-through of oil prices. The corresponding equation could be defined as (4):

$$pl_t = c_0 + \alpha_1 op_t + \alpha_2 op_t^2 + \beta_1 MS_t + \beta_2 IR_t + \varepsilon_t. \tag{4}$$

Our interest lay mainly in α_2, which provided information on the non-linearly varying pass-through of oil prices to consumer and producer prices.

Data preprocessing was carried out for all the variables under standardization for oil prices, consumer prices, producer prices, and monetary policy, to insulate our regression results from spurious results. To do this, we employed Z-score normalization, so constant term c_0 could be omitted in (4). Lastly, we estimated the empirical specifications as shown in (5) and (6):

$$pl_t = \alpha_1 op_t + \beta_1 MS_t + \beta_2 IR_t + \varepsilon_t. \tag{5}$$
$$pl_t = \alpha_1 op_t + \alpha_2 op_t^2 + \beta_1 MS_t + \beta_2 IR_t + \varepsilon_t. \tag{6}$$

The Non-linear Pass-Through of Oil Prices to Consumer Prices With a Monetary Policy

Table 4 reports the results from regressing the pass-through of oil prices, for both the Brent and WTI oil prices, to the CPI and MCPI. Accordingly, Model 1 presented regressions drawn from Equation (5), and Model 2 reported regressions based on Equation (6).

The comparison in **Table 4** revealed that there was a non-linear pass-through of oil prices to consumer prices, which strongly related to the fundamentals of global oil markets. On the one hand, referring to the comparative results of Models 1 and 2, the positive relationships, with added quadratic terms

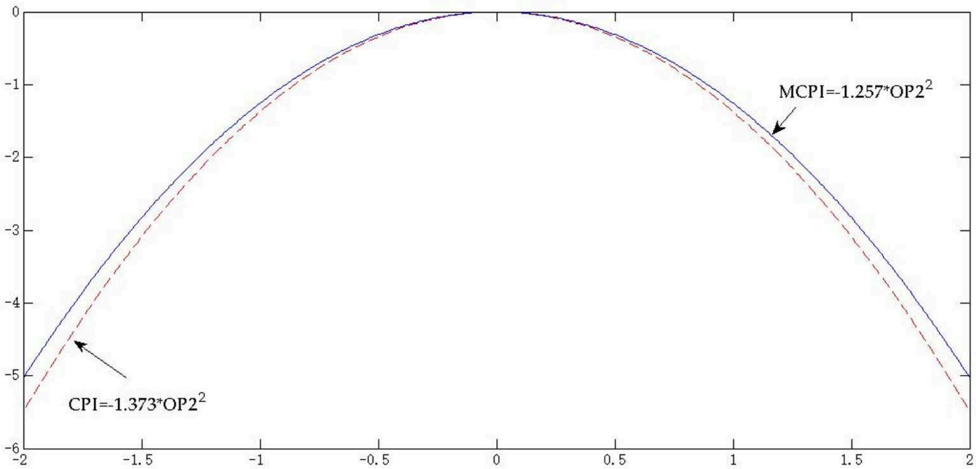

FIGURE 4 | Snapshot of the non-linear pass-through of the WTI oil price. For simplicity, we have omitted the other variables in Equation (6) and only report the non-linear term; thus, there is no effect of WTI oil price on consumer prices for both CPI and MCPI when they are located at the coordinates (0,0).

for both the CPI and MCPI, were stronger than those without non-linear terms. This result indicated that oil prices exert their effect on consumer prices in a non-linear way. On the other hand, the pass-through of oil prices to consumer prices behaved quite differently for crude oil markets. Since the Brent oil price was employed as an explanatory variable in Equation (6), it provided us with some empirical evidence concerning the fact that there was no significant non-linear effect on either the CPI or MCPI. By contrast, since the WTI oil price was employed as an explanatory variable, it was notable that the WTI oil price had a significantly inverted "U" pass-through to both the CPI and MCPI. In this manner, we were able to compare the pass-through of the Brent and WTI oil prices. These results heavily related to the spillover and fundamentals of different crude oil markets (Zhang et al., 2019a). On the spillover side, the evidence in section The Pass-Through of Oil Prices to Consumer and Producer Prices With a Monetary Policy in China indicated a greater response of consumer prices to WTI oil prices. This suggested that WTI plays a crucial role in changes in consumer prices. In terms of the different fundamentals between the Brent and WTI oil markets, higher market power and relative policy uncertainty increase economic uncertainty as a result of changes in consumer demand (Kang et al., 2017), which in turn affects the movement of consumer prices. To shed further light on the non-linear pass-through of WTI oil prices, in **Figure 4** we present the non-linear relationship between WTI oil prices and the CPI and MCPI.

The extent of the non-linear pass-through of WTI oil prices to different consumer prices differed significantly. It was clear that the inverted "U" relationship between the WTI oil price and the CPI was greater than that between the WTI oil price and the MCPI, at −1.373 and −1.257, respectively. On the one hand, this inverted "U" linkage could relate strongly to WTI's important role in the macroeconomic guidance of policy. From the perspective of the markets' role, it is widely accepted that oil price movements can immediately pass through to products that depend on oil prices, such as fuels and heating oils that are consumed by households. However, the inflationary effect of oil price movements is limited (Alvarez et al., 2011; Choi et al., 2018). With the increase of WTI oil prices, cleaner energies, such as electricity and natural gas, offer some alternative products for consumers. Additionally, the attitude of policy gives guidance to households, encouraging them to turn their attention to alternative products and, consequently, changing the relationships between WTI oil prices and both the CPI and MCPI (Hewitt et al., 2019). On the other hand, the diverse pass-through to the CPI and MCPI is heavily dependent on their characteristics; for instance, this result indicated the existence of diverse share prices. Accordingly, the share prices related to the CPI to WTI was higher than that of the MCPI. This result suggested a need to design a full range of CPI and further monitor the pass-through of the WTI oil price to consumer prices.

The Non-linear Pass-Through of Oil Prices to Consumer Prices With a Monetary Policy in China

This section discusses the non-linear pass-through of oil prices to producer prices. **Table 5** presents the regression results for the pass-through of oil prices, for both the Brent and WTI oil prices, to the PPI and MPPI. Specifically, Model 1 presents the regression results of Equation (5) and Model 2 reports the regression results of Equation (6).

The picture changed somewhat with regard to the pass-through of oil prices to producer prices. As expected, Brent oil prices exerted a "U" pass-through effect on producer prices, whereas the effect of the WTI oil prices on producer prices was linear. This interesting result could be related to the fact that the global oil benchmark has been transferred from the WTI to the Brent crude oil market. Section The Pass-Through of Oil Prices to Consumer and Producer Prices With a Monetary Policy in China provided evidence that the relationship between

TABLE 5 | The relationships between oil prices and producer prices.

D.V.	PPI				PPMI			
op	OP1		OP2		OP1		OP2	
Model	**1**	**2**	**1**	**2**	**1**	**2**	**1**	**2**
α_1	0.299 (0.102)	−0.795 (0.659)	0.394 (0.101)	0.142 (0.606)	0.286 (0.103)	−1.006 (0.663)	0.386 (0.102)	−0.048 (0.610)
α_2		1.104 (0.658)		0.256 (0.607)		1.305 (0.662)		0.442 (0.611)
β_1	−0.084 (0.098)	−0.077 (0.097)	−0.115 (0.093)	−0.115 (0.093)	−0.108 (0.098)	−0.100 (0.098)	−0.142 (0.093)	−0.143 (0.094)
β_2	−0.044 (0.086)	−0.024 (0.086)	0.031 (0.089)	0.036 (0.090)	−0.012 (0.087)	0.011 (0.087)	0.063 (0.090)	0.072 (0.091)
Ad_R^2	0.067	0.078	0.105	0.099	0.050	0.068	0.088	0.085

The standard errors are reported in parentheses. D.V. refers to dependent variable. OP1 refers to Brent oil prices, while OP2 refers to WTI oil prices. Ad_R^2 means the adjusted R^2 of the models.

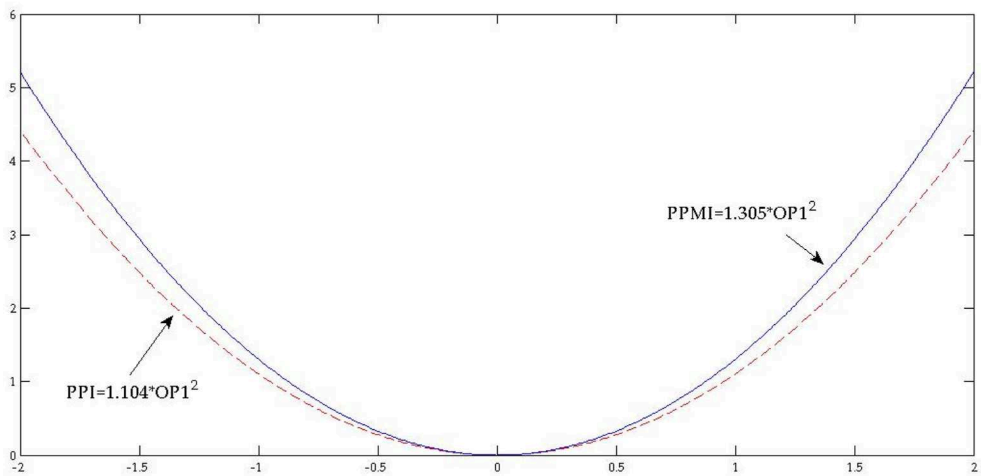

FIGURE 5 | Snapshot of the non-linear pass-through of the Brent oil price. For simplicity, we have omitted the other variables in Equation (6) and only report the non-linear term; thus, there is no effect of Brent oil price on consumer prices for both the PPI and MPPI when they are located at the coordinates (0,0).

the Brent oil price and producer prices, with the added effect of Chinese monetary policy, was stronger than that of the WTI oil price. This suggested a more crucial role for Brent oil prices in determining producer prices. Furthermore, because of the increasing demand in emerging markets and the restrictive policy of the US government, Brent oil overthrew WTI as the global oil benchmark and has, consequently, become directly linked to a larger market. In this manner, although most Brent oil has been destined for European markets, it is used as a price benchmark for other grades of oil. Overall, higher pass-through may take place for Brent oil price movements. To obtain more informative findings, in **Figure 5** we present the non-linear relationship between Brent oil prices and the PPI and MPPI.

Figure 5 gives a sense of the extent of the variation in the PPI and MPPI. Specifically, it is particularly interesting that the "U" relationship between the Brent oil price and the MPPI was greater than that between the Brent oil price and the PPI, at 1.305 and 1.104, respectively. Accordingly, the "U" pass-through of Brent oil prices to producer prices could heavily depend on the market power of Brent crude oil and the balance between oil supply and demand. As expected, higher oil prices could decrease producer price levels due to their specific impact on production costs. Nevertheless, non-linear pass-through may be impacted by financial policy and the balance of supply and demand in crude oil markets (Liao et al., 2019). Slumps in oil prices are reflected in an imbalance between supply and demand in crude oil markets, resulting in an increase in the demand for clean and renewable energy within countries. Consequently, the negative pass-through of Brent oil prices to producer prices gradually led to a decline in price regimes. With the increase of Brent oil prices, the positive pass-through to producer prices related to the increased dependence on refined oil products. Differences in energy policy in different economies may create heterogeneous mechanisms for international crude oil markets (Liu et al., 2019b).

TABLE 6 | The test results for the financial market channel.

	Step 2		Step 3				Step 4		
D.V.	SCI	SCI	CPI	MCPI	PPI	MPPI	CPI	MCPI	PPI
α_1^1	−0.201 (0.104)						0.448 (0.068)	0.424 (0.076)	0.318 (0.103)
α_1^2		−0.093 (0.106)							
γ_1			0.400 (0.059)	0.347 (0.063)	0.146 (0.079)	0.118 (0.081)	0.454 (0.052)	0.398 (0.058)	0.155 (0.079)
β_1	0.114 (0.099)	0.046 (0.097)	0.497 (0.058)	0.377 (0.063)	0.089 (0.079)	0.058 (0.080)	0.238 (0.064)	0.131 (0.072)	−0.126 (0.098)
β_2	0.073 (0.087)	0.102 (0.093)	−0.401 (0.058)	−0.468 (0.064)	−0.171 (0.080)	−0.131 (0.081)	−0.249 (0.056)	−0.325 (0.063)	−0.024 (0.086)
Ad_R^2	0.031	0.013	0.479	0.394	0.036	0.015	0.592	0.494	0.068

*The standard errors are reported in parentheses. D.V. refers to dependent variable. Ad_R^2 means the adjusted R^2 of the models. The results of Step 1 can be found in **Tables 4**, **5**.*

MEDIATING MECHANISM OF OIL PRICE PASS-THROUGH ON CONSUMER AND PRODUCER PRICES

Causal Steps Approach

In the previous section, we presented one mechanism for evaluating the pass-through of oil prices to consumer and producer prices: namely, its non-linear impact in relation to a monetary policy in China. This section now considers another mechanism for oil price pass-through to domestic prices. First, we provide evidence for the mediating effect of financial markets, then we document the effect of the government debt channel on the oil price–consumer/producer price mechanism.

Given the significant changes that have occurred in the financial and oil markets in last two decades, it was desirable to analyze the existence of a channel mechanism in the links between oil price movements and consumer/produce price levels (Alvarez et al., 2011; Razmi et al., 2016; Sek, 2019). To do this, this study used a causal steps approach to explore the mediating effect (Li et al., 2019c). Specifically, the causal steps were as follows:

Step 1. Estimate a regression for oil prices and consumer/producer prices as shown in (7)

$$pl_t = \alpha_1^j op_t^j + \beta_1 MS_t + \beta_2 IR_t + \varepsilon_t. \quad (7)$$

where op_t^j represents the oil price for market j at time t, $j = 1$ stands for the Brent oil price, and $j = 2$ for the WTI oil price. Step 1 proved to be satisfactory if α_1^j was significantly different from zero. If so, we then estimated according to step 2.

Step 2. Estimate a regression for oil price and the financial or government debt as shown in (8):

$$cha_t = \alpha_1^j op_t^j + \beta_1 MS_t + \beta_2 IR_t + \varepsilon_t. \quad (8)$$

where cha_t represents the channel variables, including the financial market and government debt. These variables were selected because they were commonly used background variables. Specifically, we selected the Shanghai (securities) composite index (SCI) to measure the financial markets and the government debt (GD) to depict debt. Step 2 proved to be satisfactory if α_1^j was significantly different from zero. If so, we next estimated step 3. If not, other variables were selected to depict the transition mechanism.

Step 3. Estimate a regression for financial markets or government debt and consumer/producer prices as shown in (9):

$$pl_t = \gamma_1 cha_t + \beta_1 MS_t + \beta_2 IR_t + \varepsilon_t. \quad (9)$$

Step 3 proved to be satisfactory if γ_1 was significantly different from zero. If so, we next estimated step 4. If not, other variables were selected to depict the transition mechanism.

Step 4. Estimate a regression for oil price, financial markets, or government debt, and consumer/producer prices as shown in (10):

$$pl_t = \alpha_1^j op_t^j + \gamma_1 cha_t + \beta_1 MS_t + \beta_2 IR_t + \varepsilon_t. \quad (10)$$

The coefficients in models (7)–(10) showed the different effects of oil prices on consumer/producer prices. Specifically, Equation (7) could capture the total effect of oil prices, while equation (10) reported the direct effect, and Equations (8) and (9) could be regarded as tools to measure the indirect pass-through of oil prices to consumer/producer prices.

Financial Market Channel's Role in Transmitting Oil Price Pass-Through to Consumer/Producer Prices

Following the causal steps approach, the mediation test was performed and the results reported in **Table 6**. Our interest lay in the significance of the coefficients in Equations (7)–(10).

Assessing the mediating effect of financial markets required some significance tests. As estimated in Equation (7), referring to Step 2 in **Table 6**, we noticed that the impact of the WTI oil price, measured by α_1^2, was not significantly different from zero. This result provided us with empirical evidence concerning the possibility that there may not be a significant mediating

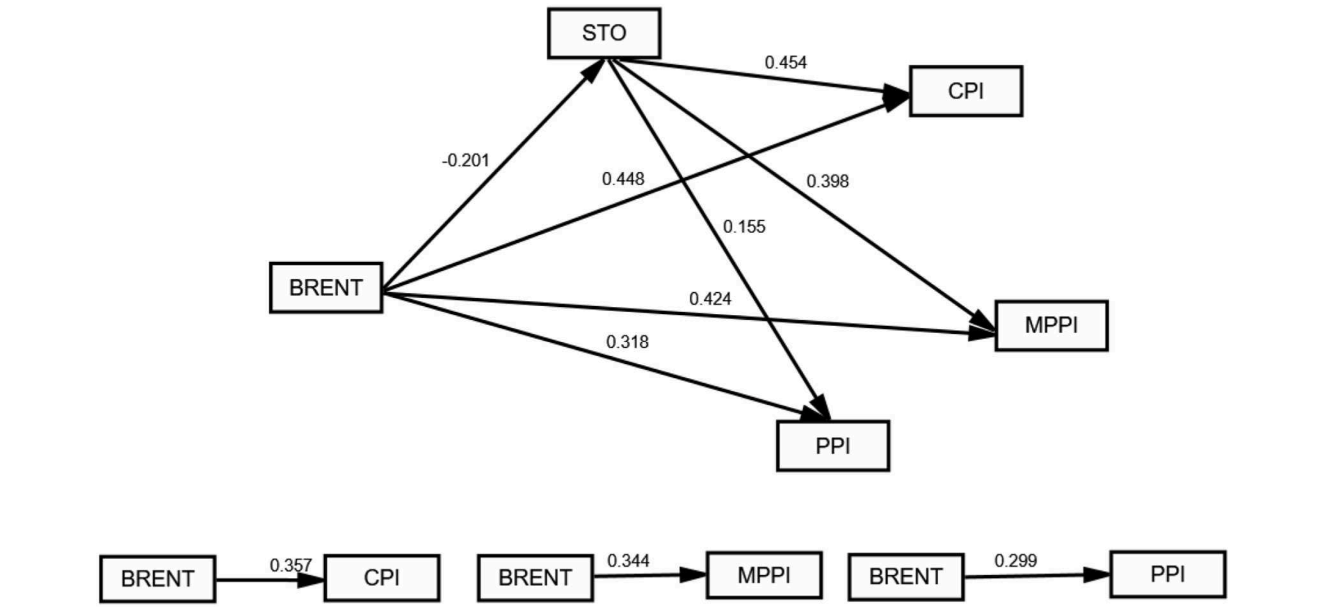

FIGURE 6 | The mediating effect of the financial market. The upper section of the figure reports the direct and indirect effects; the lower section of the figure shows the total effect.

effect of financial markets on the relationships between WTI oil prices and consumer/producer prices. Furthermore, we estimated Equations (9) and (10). According to Step 3 in **Table 6**, it was interesting to note that the financial market had no significant effect on the MPPI. Moreover, both the Brent oil prices and SCI played a significant role in the CPI, MCPI, and PPI. These results indicated the significant mediating effect of the financial market on the Brent oil price–consumer/producer prices pass-through. To shed further light on the mediating effect of the financial market, in **Figure 6** we present the results for a direct effect, indirect effect, and total effect.

The oil price–consumer/producer price mechanisms, combined with financial market channels, are summarized in **Figure 6**. Accordingly, Brent oil prices could indirectly transmit to the CPI through the financial market. Specifically, it was noteworthy that the direct effect of the Brent oil price on the CPI was 0.448, whereas the indirect effect was −0.091. These results showed that Brent oil price movements have an indirect negative effect on the CPI. This was no surprise, due to the market power of crude oil and the capital flow of households (Alvarez et al., 2011; Li et al., 2019a). On the one hand, because of the policy uncertainty, Brent oil markets could exert an effect on the expectations of participants in crude oil markets (Dong et al., 2019). Policy uncertainty, combined with the trade agreement between China and the USA, causes spillover between different financial markets, leading to vulnerability as a result of changes in investors' expectations (Li et al., 2018a; Xia et al., 2019b). Consequently, this result shed light on the increasing effect of the Brent oil markets on consumer prices. On the other hand, financial markets offer a channel for shared risk for households through changes in capital flow (Moya-Martinez et al., 2014). High oil prices affect investors' expectations by reducing the share price, which may, consequently, benefit consumer price levels. Therefore, these results suggested that the financial market could be regarded as a tool for stabilizing movements in the CPI.

Moreover, Brent oil prices could also indirectly affect producer prices, for both the PPI and MPPI, through the financial market. It is worth noting that the financial market explained the 0.064 transitions between the Brent oil price and the PPI and also explained the 0.080 transitions between the Brent oil price and the MPPI. This result related to the financialization of markets (Ji et al., 2019b). Considering the diverse aims of stakeholders, it is widely accepted that investors aim to maximize profits and reduce risks (Li et al., 2018b; Huang et al., 2019). Financial markets offer an opportunity for investors to share their risks and improve the investment environment in relation to the changes in production costs caused by oil price movements (Cong and Shen, 2013). Furthermore, investments in financial markets can provide extra profit for investors, decreasing the dependence of oil-related enterprises or economies (Zhang et al., 2019b). A higher indirect effect on the MPPI could be related to excise duties. The aggregate producer price level, measured by the PPI, could reduce the indirect effect, because of the possible hedge between the MPPI and other price indexes. These outcomes indicated a significantly negative mediating effect of financial markets.

The Government Debt Channel's Role in the Oil Price–Consumer/Producer Prices Mechanism

Table 7 reports the results of the causal steps approach for the government debt channel's role in the oil price–consumer/producer prices mechanism. Similarly, our interest lay in the significance of the coefficients in Equations (7)–(10).

Consistently with the results in section Financial Market Channel's Role in Transmitting Oil Price Pass-Through to Consumer/Producer Prices, to provide an accurate assessment of the mediating effect of government debt also required some significance tests. As estimated in equation (7), referring to Step 2 in **Table 7**, we noticed that the impact of both the Brent and WTI oil prices, measured by α_1^1 and α_1^2, were significantly different from zero. These results provided us with some empirical evidence concerning the fact that oil prices exert their effect in combination with government debt. We estimated equations (9)–(10). According to Step 3 in **Table 7**, it was interesting to note that government debt had no significant effect on consumer prices for either the CPI or MCPI. Moreover, both the Brent and WTI oil prices played a significant role in the PPI and MPPI. These results indicated the significant mediating

TABLE 7 | The test results for the government debt channel.

	Step 2		Step 3				Step 4			
D.V.	**GD**	**GD**	**CPI**	**MCPI**	**PPI**	**MPPI**	**PPI**	**MPPI**	**PPI**	**MPPI**
α_1^1	0.122 (0.04)						0.390 (0.10)	0.381 (0.10)		
α_1^2		0.102 (0.04)							0.470 (0.10)	0.465 (0.10)
γ_1			−0.124 (0.17)	−0.123 (0.17)	−0.577 (0.19)	−0.607 (0.19)	−0.749 (0.19)	−0.776 (0.19)	−0.746 (0.18)	−0.775 (0.19)
β_1	0.109 (0.04)	0.127 (0.04)	0.518 (0.07)	0.398 (0.08)	0.193 (0.09)	0.167 (0.09)	−0.002 (0.10)	−0.023 (0.10)	−0.020 (0.10)	−0.044 (0.10)
β_2	0.924 (0.04)	0.927 (0.04)	−0.234 (0.16)	−0.309 (0.16)	0.358 (0.19)	0.420 (0.19)	0.649 (0.19)	0.704 (0.20)	0.723 (0.19)	0.781 (0.19)
Ad_R^2	0.846	0.843	0.322	0.276	0.069	0.062	0.148	0.137	0.186	0.177

The standard errors are reported in parentheses. D.V. refers to dependent variable. Ad_R² means the adjusted R² of the models. The results of Step 1 can be found in ***Tables 4, 5****.*

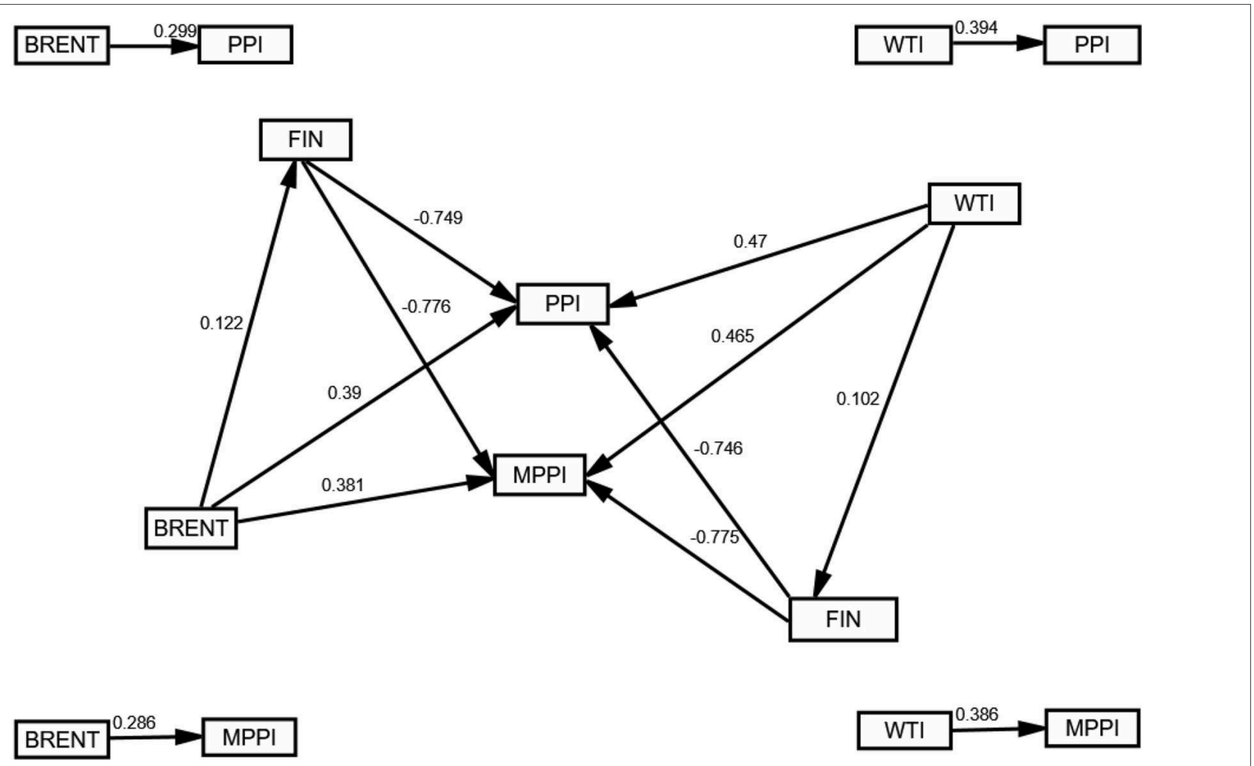

FIGURE 7 | The mediating effect of government debt. The center portion of the figure reports the direct and indirect effects. The areas around the figure show the total effect.

effect of government debt on the oil price–producer prices mechanism. To obtain more informative results, in **Figure 7** we examined the results for the direct effect, indirect effect, and total effect.

The comparison in **Figure 7** revealed that there was a negative mediating effect of government debt on the oil price–producer prices mechanism. On the one hand, there was a significant mediating effect of the government debt on the oil price–producer prices mechanism, which was not surprising, due to the relationship between government debt and both the PPI and MPPI. The primary aim of policymakers is to promote investment in enterprises and stabilize producer price levels (Sung, 2019); consequently, this is strongly related to the PPI and MPPI. In this manner, government debt could exert a mediating effect on the relationship between oil prices and producer prices for both the PPI and MPPI. These results suggested that government debt could be regarded as a tool for stabilizing the movements of producer prices. On the other hand, the negative effect of oil prices on government debt could capture the total effect of oil prices. Accordingly, it is worth noting that both the Brent and WTI oil prices had a greater mediating effect on government debt for the MPPI than for the PPI. Since the fiscal market was employed as a channel variable for the Brent oil price to producer prices mechanism, it provided us with evidence that there was a greater mediating effect of government debt on the Brent oil price–PPMI mechanism than on the Brent oil price–PI mechanism, at −0.095 and −0.091, respectively. Similarly, the mediating effect of government debt was greater on the WTI oil price–MPPI mechanism, at 0.079. By contrast, this effect on the WTI–PPI mechanism was 0.076. These diverse mediating effects captured the differences between refined oil-related enterprises and their relative producer prices (Xiao et al., 2013); therefore, due to the significant mediating effect of government debt on both the PPI and MPPI, we concluded that government debt plays a crucial role in changes in the mechanism of oil price pass-through to producer prices.

CONCLUSIONS

The pass-through of oil prices to consumer and producer prices could reflect the diverse dependence on oil across global oil markets. This paper aimed to advance this thinking by providing information on how price levels in China depend on movements in oil prices. Specifically, the VAR model was first employed to examine the response of consumer prices, as reflected by the CPI and MCPI, or producer prices as reflected by the PPI and MPPI, for both the Brent and WTI oil prices. Furthermore, we explored the non-linear pass-through of oil prices to both consumer and producer prices. Finally, this paper provided evidence of the mediating effect of financial markets, as well as government debt, on the oil price–consumer/producer price mechanisms.

The pass-through of oil prices to consumer and producer prices could be coupled with a monetary policy. On the one hand, the increasingly positive pass-through of WTI oil prices suggests an influential effect of monetary policy on the oil price–macroeconomic mechanism, due to the primary aim of monetary policy to stabilize price levels on both consumer and producer prices. On the other hand, a higher pass-through of the Brent oil price to producer prices provides evidence of the accuracy of monetary policy.

The non-linear effect of oil prices on consumer/producer prices varies across different crude oil markets. Specifically, the WTI oil price exerted a significantly inverted "U" pass-through to consumer prices for the CPI and the MCPI, and the inverted "U" relationship between WTI oil price and the CPI was stronger than that between the WTI oil price and the MCPI, at −1.373 and −1.257, respectively. Nevertheless, the pass-through of the Brent oil price to producer prices was significant and "U" shaped, and this "U" relationship between the Brent oil price and the MPPI was stronger than that between the Brent oil price and the PPI, at 1.305 and 1.104, respectively.

These mediating effects highlighted the indirect negative impact of oil price on consumer and producer prices, and these effects heavily depend on market power. Empirically, Brent oil prices could indirectly transmit to the CPI, PPI, and MPPI through the financial market. There were mediating effects of government debt on the linkages between both the Brent and WTI oil prices and producer prices, for the PPI and MPPI. Comparatively, the effect of government debt on the Brent oil price–producer prices mechanism, reflected by the PPI and MPPI (−0.091 and −0.095, respectively), was greater than that of financial markets (at −0.064 and −0.080, respectively).

Our outcomes should be valuable in helping to stabilize price levels. The effectiveness of policy depends heavily on the non-linear pass-through of oil prices; thus, policymakers should pay specific attention to stabilizing consumer or producer price levels. In other words, consumer prices relate to changes in the WTI oil market, whereas producer prices are linked to changes in Brent oil prices. In addition, the negative mediating effect of both financial markets and government debt offer an opportunity to prevent the spillover from the global crude oil market to the macroeconomic level; therefore, authorities should not only monitor the financialization of crude oil markets and enterprises, but also promote the effective role of government debt in the oil price–producer prices mechanism. Financial markets could thus be regarded as an accurate tool for stabilizing consumer price levels.

There are some possible limitations to this study; for example, this paper neglected the moderating mechanism of the oil price–price levels on both consumer and producer prices. Accordingly, economic policy uncertainty and institutional distance regarding different oil markets could exert a moderating effect. Additionally, the network structure of oil markets could be regarded as another moderating variable, providing a more accurate tool for policymakers and investors for regulations. Furthermore, the threshold of the mediating and moderating effects on oil price shocks would also be of great interest. In addition, the time-frequency dynamic spillovers between the global crude oil price and the general price levels, such as consumer or producer prices, could provide more evidence for investigating shocks in the external environment.

DATA AVAILABILITY STATEMENT

The datasets generated for this study are available on request to the corresponding author.

AUTHOR CONTRIBUTIONS

SC, SO, and HD: substantial contributions to the conception or design of the work and provide approval for publication of the content. SO and HD: the acquisition, analysis or interpretation of data for the work, drafting the work or revising it critically for important intellectual content.

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REFERENCES

Ahmed, R. R., Vveinhardt, J., Streimikiene, D., Ghauri, S. P., and Ahmad, N. (2017). Estimation of long-run relationship of inflation (CPI & WPI), and oil prices with KSE-100 index: evidence from johansen multivariate cointegration approach. *Technol. Econ. Dev. Econ.* 23, 567–588. doi: 10.3846/20294913.2017.1289422

Ajmi, A. N., Gupta, R., Babalos, V., and Hefer, R. (2015). Oil price and consumer price nexus in South Africa revisited: a novel asymmetric causality approach. *Energy Explor. Exploit.* 33, 63–73. doi: 10.1260/0144-5987.33.1.63

Akar, S. (2019). Testing the fiscal fatigue phenomenon in turkey using a long-run non-linear fiscal reaction function approach. *Q. Finance Econ.* 3, 645–660. doi: 10.3934/QFE.2019.4.645

Alvarez, L. J., Hurtado, S., Sanchez, I., and Thomas, C. (2011). The impact of oil price changes on Spanish and Euro area consumer price inflation. *Econ. Model.* 28, 422–431. doi: 10.1016/j.econmod.2010.08.006

Alvarez, L. J., and Sanchez, I. (2019). Inflation projections for monetary policy decision making. *J. Policy Model.* 41, 568–585. doi: 10.1016/j.jpolmod.2018.09.005

Arouri, M. E. (2011). Does crude oil move stock markets in Europe? A sector investigation. *Econ. Model.* 28, 1716–1725. doi: 10.1016/j.econmod.2011.02.039

Bloch, H., Rafiq, S., and Salim, R. (2015). Economic growth with coal, oil and renewable energy consumption in China: prospects for fuel substitution. *Econ. Model.* 44, 104–115. doi: 10.1016/j.econmod.2014.09.017

Castro, C., Jimenez-Rodriguez, R., Poncela, P., and Senra, E. (2017). A new look at oil price pass-through into inflation: evidence from disaggregated European data. *Econ. Polit.* 34, 55–82. doi: 10.1007/s40888-016-0048-9

Choi, S., Furceri, D., Loungani, P., Mishra, S., and Poplawski-Ribeiro, M. (2018). Oil prices and inflation dynamics: evidence from advanced and developing economies. *J. Int. Money Finance* 82, 71–96. doi: 10.1016/j.jimonfin.2017.12.004

Cong, R. G., and Shen, S. C. (2013). Relationships among energy price shocks, stock market, and the macroeconomy: evidence from China. *Sci. World J.* 9:171868. doi: 10.1155/2013/171868

Coronado, S., Jimenez-Rodriguez, R., and Rojas, O. (2018). An empirical analysis of the relationships between crude oil, gold and stock markets. *Energy J.* 39, 193–207. doi: 10.5547/01956574.39.SI1.scor

Dong, H., Liu, Y., and Chang, J. (2019). The heterogeneous linkage of economic policy uncertainty and oil return risks. *Green Finance* 1, 46–66. doi: 10.3934/GF.2019.1.46

Gomez-Loscos, A., Montanes, A., and Gadea, M. D. (2011). The impact of oil shocks on the Spanish economy. *Energy Econ.* 33, 1070–1081. doi: 10.1016/j.eneco.2011.05.016

Gong, X., and Lin, B. Q. (2018). Time-varying effects of oil supply and demand shocks on china's macro-economy. *Energy* 149, 424–437. doi: 10.1016/j.energy.2018.02.035

Gonzalez-Concepcion, C., Gil-Farina, M. C., and Pestano-Gabino, C. (2018). Wavelet power spectrum and cross-coherency of Spanish economic variables. *Empir. Econ.* 55, 855–882. doi: 10.1007/s00181-017-1295-5

Guo, J., Zheng, X. Y., and Chen, Z. M. (2016). How does coal price drive up inflation? Reexamining the relationship between coal price and general price level in China. *Energy Econ.* 57, 265–276. doi: 10.1016/j.eneco.2016.06.001

Hamilton, J. D. (1983). Oil and the macroeconomy since World-War-II. *J. Polit. Econ.* 91, 228–248. doi: 10.1086/261140

He, Y. D., and Lin, B. Q. (2019). Regime differences and industry heterogeneity of the volatility transmission from the energy price to the ppi. *Energy* 176, 900–916. doi: 10.1016/j.energy.2019.04.025

Hewitt, R. J., Bradley, N., Compagnucci, A. B., Barlagne, C., Ceglarz, A., Cremades, R., et al. (2019). Social innovation in community energy in Europe: a review of the evidence. *Front. Energy Res.* 7:31. doi: 10.3389/fenrg.2019.00031

Huang, Z., Liao, G., and Li, Z. (2019). Loaning scale and government subsidy for promoting green innovation. *Technol. Forecast. Soc. Change* 144, 148–156. doi: 10.1016/j.techfore.2019.04.023

Humbatova, S. I. Q., Garayev, A. I. O., Tanriverdiev, S. M. O., and Hajiyev, N. Q. O. (2019). Analysis of the oil, price and currency factor of economic growth in Azerbaijan. *Entrepreneur. Sustain. Iss.* 6, 1335–1353. doi: 10.9770/jesi.2019.6.3(20)

Ji, Q., Bouri, E., Roubaud, D., and Kristoufek, L. (2019a). Information interdependence among energy, cryptocurrency and major commodity markets. *Energy Econ.* 81, 1042–1055. doi: 10.1016/j.eneco.2019.06.005

Ji, Q., Bouri, E., Roubaud, D., and Shahzad, S. J. H. (2018). Risk spillover between energy and agricultural commodity markets: a dependence-switching covar-copula model. *Energy Econ.* 75, 14–27. doi: 10.1016/j.eneco.2018.08.015

Ji, Q., Li, J., and Sun, X. (2019b). New challenge and research development in global energy financialization. *Emerg. Markets Finance Trade* 55, 2669–2672. doi: 10.1080/1540496X.2019.1636588

Ji, Q., Liu, B.-Y., and Fan, Y. (2019c). Risk dependence of covar and structural change between oil prices and exchange rates: a time-varying copula model. *Energy Econ.* 77, 80–92. doi: 10.1016/j.eneco.2018.07.012

Ji, Q., Zhang, H.-Y., and Zhang, D. (2019d). The impact of opec on East Asian oil import security: a multidimensional analysis. *Energy Policy* 126, 99–107. doi: 10.1016/j.enpol.2018.11.019

Jongwanich, J., Park, D., and Wongcharoen, P. (2019). Determinants of producer price versus consumer price inflation in emerging Asia. *J. Asia Pac. Econ.* 24, 224–251. doi: 10.1080/13547860.2019.1574251

Kang, W., Ratti, R. A., and Vespignani, J. L. (2017). Oil price shocks and policy uncertainty: new evidence on the effects of us and non-us oil production. *Energy Econ.* 66, 536–546. doi: 10.1016/j.eneco.2017.01.027

Katircioglu, S. T., Sertoglu, K., Candemir, M., and Mercan, M. (2015). Oil price movements and macroeconomic performance: evidence from twenty-six oecd countries. *Renew. Sustain. Energy Rev.* 44, 257–270. doi: 10.1016/j.rser.2014.12.016

Kilian, L. (2009). Not all oil price shocks are alike: disentangling demand and supply shocks in the crude oil market. *Am. Econ. Rev.* 99, 1053–1069. doi: 10.1257/aer.99.3.1053

Kim, D. H. (2012). What is an oil shock? Panel data evidence. *Empir. Econ.* 43, 121–143. doi: 10.1007/s00181-011-0459-y

Li, J., Zhang, J., Zhang, D., and Ji, Q. (2019a). Does gender inequality affect household green consumption behaviour in China? *Energy Policy* 135:111071. doi: 10.1016/j.enpol.2019.111071

Li, Z., Dong, H., Huang, Z., and Failler, P. (2018a). Asymmetric effects on risks of virtual financial assets (VFAS) in different regimes: a case of Bitcoin. *Q. Finance Econ.* 2, 860–883. doi: 10.3934/QFE.2018.4.860

Li, Z., Huang, Z., and Dong, H. (2019b). The influential factors on outward foreign direct investment: evidence from the "The Belt and Road"? *Emerg. Markets Finance Trade* 55, 3211–3226. doi: 10.1080/1540496X.2019.1569512

Li, Z., Liao, G., and Albitar, K. (2019c). Does corporate environmental responsibility engagement affect firm value? The mediating role of corporate innovation. *Bus. Strategy Environ.* 29, 1045–1055. doi: 10.1002/bse.2416

Li, Z., Liao, G., Wang, Z., and Huang, Z. (2018b). Green loan and subsidy for promoting clean production innovation. *J. Clean. Prod.* 187, 421–431. doi: 10.1016/j.jclepro.2018.03.066

Li, Z., and Zhong, J. (in press). Impact of economic policy uncertainty shocks on China's financial conditions. *Finance Res. Lett.* doi: 10.1016/j.frl.2019.101303

Liao, G., Li, Z., Du, Z., and Liu, Y. (2019). The heterogeneous interconnections between supply or demand side and oil risks. *Energies* 12:2226. doi: 10.3390/en12112226

Lim, K. B., and Sek, S. K. (2017). "Examining the impacts of oil price changes on economic indicators: a panel approach," in *4th International Conference on Mathematical Sciences*, eds Z. H. Zamzuri, F. AbdulRazak, W. Z. W. Zin, and S. C. DzulKifli (Melville, NY: American Institute of Physics). doi: 10.1063/1.4981000

Lim, K. B., and Sek, S. K. (2018). "Investigating the impact of oil price changes on monetary policy: oil importing versus oil exporting countries," in *Proceeding of the 25th National Symposium on Mathematical Sciences*, eds D. Mohamad, A. B. Akbarally, H. Maidinsah, M. M. Jaffar, M. Mohamed, S. R. Sharif, and W. Rahman (Melville, NY: American Institute of Physics). doi: 10.1063/1.5041687

Liu, K., Luo, C., and Li, Z. (2019a). Investigating the risk spillover from crude oil market to brics stock markets based on copula-pot-covar models. *Q. Finance Econ.* 3, 754–771. doi: 10.3934/QFE.2019.4.754

Liu, Y., Dong, H., and Failler, P. (2019b). The oil market reactions to opec's announcements. *Energies* 12, 1–15. doi: 10.3390/en12173238

Long, S. B., and Liang, J. (2018). Asymmetric and nonlinear pass-through of global crude oil price to china's PPI and CPI inflation. *Econ. Res. Ekon. Istraz.* 31, 240–251. doi: 10.1080/1331677X.2018.1429292

Moya-Martinez, P., Ferrer-Lapena, R., and Escribano-Sotos, F. (2014). Oil price risk in the spanish stock market: an industry perspective. *Econ. Model.* 37, 280–290. doi: 10.1016/j.econmod.2013.11.014

Myers, R. J., Johnson, S. R., Helmar, M., and Baumes, H. (2018). Long-run and short-run relationships between oil prices, producer prices, and consumer prices: what can we learn from a permanent-transitory decomposition? *Q. Rev. Econ. Finance* 67, 175–190. doi: 10.1016/j.qref.2017.06.005

Ozdemir, S., and Akgul, I. (2015). Inflationary effects of oil prices and domestic gasoline prices: markov-switching-var analysis. *Pet. Sci.* 12, 355–365. doi: 10.1007/s12182-015-0028-7

Pinho, C., and Madaleno, M. (2016). Oil prices and stock returns: nonlinear links across sectors. *Portuguese Econ. J.* 15, 79–97. doi: 10.1007/s10258-016-0117-6

Rangasamy, L. (2017). The impact of petrol price movements on south african inflation. *J. Energy South. Afr.* 28, 120–132. doi: 10.17159/2413-3051/2017/v28i1a1597

Ratti, R. A., and Vespignani, J. L. (2016). Oil prices and global factor macroeconomic variables. *Energy Econ.* 59, 198–212. doi: 10.1016/j.eneco.2016.06.002

Razmi, F., Azali, M., Chin, L., and Habibullah, M. S. (2016). The role of monetary transmission channels in transmitting oil price shocks to prices in Asean-4 countries during pre- and post-global financial crisis. *Energy* 101, 581–591. doi: 10.1016/j.energy.2016.02.036

Sakashita, Y., and Yoshizaki, Y. (2016). The effects of oil price shocks on IIP and CPI in emerging countries. *Economies* 4:20. doi: 10.3390/economies4040020

Sek, S. K. (2017). Impact of oil price changes on domestic price inflation at disaggregated levels: evidence from linear and nonlinear ARDL modeling. *Energy* 130, 204–217. doi: 10.1016/j.energy.2017.03.152

Sek, S. K. (2019). Effect of oil price pass-through on domestic price inflation: evidence from nonlinear ARDL models. *Panoeconomicus* 66, 69–91. doi: 10.2298/PAN160511021S

Sek, S. K., and Lim, H. S. M. (2016). "An investigation on the impacts of oil price shocks on domestic inflation: A svar approach," in *Advances in Industrial and Applied Mathematics*, eds S. Salleh, N. Aris, A. Bahar, Z. M. Zainuddin, N. Maan, M. H. Lee, T. Ahmad, and Y. M. Yusof (Melville, NY: American Institute of Physics), 060002. doi: 10.1063/1.4954607

Sek, S. K., and Low, R. N. (2016). "Distinguishing the impacts of oil demand and oil supply on volatility of inflation: a comparative study on oil importing versus oil exporting," in *Advances in Industrial and Applied Mathematics*, eds S. Salleh, N. Aris, A. Bahar, Z. M. Zainuddin, N. Maan, M. H. Lee, T. Ahmad, and Y. M. Yusof (Melville, NY: American Institute of Physics), 060001. doi: 10.1063/1.4954606

Shi, X., and Sun, S. (2017). Energy price, regulatory price distortion and economic growth: a case study of China. *Energy Econ.* 63, 261–271. doi: 10.1016/j.eneco.2017.02.006

Sodeyfi, S., and Katircioglu, S. (2016). Interactions between business conditions, economic growth and crude oil prices. *Econ. Res.* 29, 980–990. doi: 10.1080/1331677X.2016.1235504

Song, Y., Ji, Q., Du, Y.-J., and Geng, J.-B. (2019). The dynamic dependence of fossil energy, investor sentiment and renewable energy stock markets. *Energy Econ.* 84:104564. doi: 10.1016/j.eneco.2019.104564

Sung, B. (2019). Do government subsidies promote firm-level innovation? Evidence from the korean renewable energy technology industry. *Energy Policy* 132, 1333–1344. doi: 10.1016/j.enpol.2019.03.009

Tiwari, A. K., Cunado, J., Hatemi-J, A., and Gupta, R. (2019). Oil price-inflation pass-through in the united states over 1871 to 2018: a wavelet coherency analysis. *Struct. Change Econ. Dyn.* 50, 51–55. doi: 10.1016/j.strueco.2019.05.002

Wei, Y. F. (2019). The relationship between oil and non-oil commodity prices and china's PPI and CPI: an empirical analysis. *Energy Sources B Econ. Plann. Policy* 14, 125–146. doi: 10.1080/15567249.2019.1630032

Wen, F., Min, F., Zhang, Y.-J., and Yang, C. (2019a). Crude oil price shocks, monetary policy, and China's economy. *Int. J. Finance Econ.* 24, 812–827. doi: 10.1002/ijfe.1692

Wen, F., Xiao, J., Xia, X., Chen, B., Xiao, Z., and Li, J. (2019b). Oil prices and chinese stock market: nonlinear causality and volatility persistence. *Emerg. Markets Finance Trade* 55, 1247–1263. doi: 10.1080/1540496X.2018.1496078

Wen, F., Zhao, Y., Zhang, M., and Hu, C. (2019c). Forecasting realized volatility of crude oil futures with equity market uncertainty. *Appl. Econ.* 51, 6411–6427. doi: 10.1080/00036846.2019.1619023

Xia, T., Ji, Q., Zhang, D., and Han, J. (2019a). Asymmetric and extreme influence of energy price changes on renewable energy stock performance. *J. Clean. Prod.* 241:118338. doi: 10.1016/j.jclepro.2019.118338

Xia, Y., Kong, Y., Ji, Q., and Zhang, D. (2019b). Impacts of china-us trade conflicts on the energy sector. *China Econ. Rev.* 58:101360. doi: 10.1016/j.chieco.2019.101360

Xiao, W. L., Zhang, W. G., Yao, Z., and Wang, X. H. (2013). The impact of issuing warrant and debt on behavior of the firm's stock. *Econ. Model.* 31, 635–641. doi: 10.1016/j.econmod.2013.01.007

Xu, X., Wei, Z., Ji, Q., Wang, C., and Gao, G. (2019). Global renewable energy development: influencing factors, trend predictions and countermeasures. *Res. Policy* 63:101470. doi: 10.1016/j.resourpol.2019.101470

Yalcin, Y., Arikan, C., and Emirmahmutoglu, F. (2015). Determining the asymmetric effects of oil price changes on macroeconomic variables: a case study of turkey. *Empirica* 42, 737–746. doi: 10.1007/s10663-014-9274-y

Zhang, D., Ji, Q., and Kutan, A. M. (2019a). Dynamic transmission mechanisms in global crude oil prices: estimation and implications. *Energy* 175, 1181–1193. doi: 10.1016/j.energy.2019.03.162

Zhang, D., Rong, Z., and Ji, Q. (2019b). Green innovation and firm performance: evidence from listed companies in China. *Resour. Conserv. Recycl.* 144, 48–55. doi: 10.1016/j.resconrec.2019.01.023

Zhang, Y.-J., and Zhang, L. (2015). Interpreting the crude oil price movements: evidence from the markov regime switching model. *Appl. Energy* 143, 96–109. doi: 10.1016/j.apenergy.2015.01.005

Zheng, Y., and Du, Z. (2019). A systematic review in crude oil markets: embarking on the oil price. *Green Finance* 1, 328–345. doi: 10.3934/GF.2019.3.328

Zhou, D. T., Yu, H. Y., and Li, Z. G. (2017). Effects of fluctuations in international oil prices on China's price level based on var model. *J. Discrete Math. Sci. Cryptogr.* 20, 125–135. doi: 10.1080/09720529.2016.1178909

Zivkov, D., Durskovic, J., and Manic, S. (2019). How do oil price changes affect inflation in central and Eastern European countries? A wavelet-based markov switching approach. *Baltic J. Econ.* 19, 84–104. doi: 10.1080/1406099X.2018.1562011

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Generation Expansion Planning Considering the Output and Flexibility Requirement of Renewable Energy: The Case of Jiangsu Province

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This study presents a generation expansion planning by incorporating the impacts of renewable energy on the generation mix. The wind–solar power output and its flexibility requirement are integrated into an optimization model to provide the realistic representation of wind and solar energy resources. The model is then used for the power system optimization planning of Jiangsu Province. A comparison of power demand, electricity price subsidies, and carbon emission intensity scenarios reveals the power planning scheme and optimization path for power system integrating increasing renewable energy. The results suggest that the installed capacity of renewable energy will increase from 21.6 to 133.2 GW in the baseline scenario during the planning period, with its share ranging from 17.9 to 53.7%. Solar photovoltaic power is expected to contribute 72% of renewable capacity and 39% of total capacity by 2050. The impact of electricity price subsidies on solar PV generation expansion is particularly significant. Additionally, the flexibility requirement of power systems can basically be satisfied with the available generation technologies; however, it would become severe if the flexibility requirement grows faster than the flexible generation.

Keywords: generation mix optimization, wind–solar power output, flexibility requirement, low-carbon power system, renewable energy

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INTRODUCTION

In the global Climate Change Action Plan for a 2°C reduction, the Chinese government promised to peak their CO_2 emission by 2030. As the main sector responsible for carbon emissions, power generation needs to undertake the primary mission of reducing CO_2 emission through a significant transformation from an energy structure where coal is a leading resource to a cleaner energy structure (Zhao et al., 2020). Jiangsu Province, the second highest electricity consumption area in the country, consumed around 6,128.3 TWh electricity in 2018. Its installed capacity was 126.6 GW, with thermal power accounting for 77% of the total (National Bureau of Statistics, 2019). In order to regulate its coal consumption and reduce CO_2 emissions, the Jiangsu Province proposed to increase generation capacity of non-fossil energy resources to more than 20% of the total capacity by 2020 (Jiangsu Provincial People's Government, 2017).

Wind and solar energy resources have great potential for utilization in Jiangsu Province. It is estimated that the resource potentials of wind and solar energy reach 2.1 and 15.8 GW, respectively

(Zhou et al., 2010; Zou and Yi, 2012), strongly favoring the realization of a renewable power system. However, the large-scale integration of variable renewables can render the power system more complex (Liu et al., 2019). Fluctuations in wind and solar energy power generation can lead to excessive or insufficient power supply in the short term. Moreover, balancing the power supply and demand is difficult owing to limited energy storage facilities. Thus, these uncertainties have to be compensated with high flexibility through real-time dispatch and response.

The traditional power system planning models focus on the optimal combination of power generation technologies to meet the power demand during the planning period. However, the impacts of renewable energy start to be considered into the planning models in recent studies. For example, several scholars have defined flexibility as the system's ability to rebalance the power demand and supply when large amounts of power generation from wind and solar energy are integrated (Deason, 2018). Among others, traditional dispatchable power plants provide generation supplement in times of low wind speed and solar irradiation; transmission grids provide spatial smoothing to match the power supply and demand in different regions; energy storage devices provide a temporal support to balance the fluctuation of VRE; and demand-side management provides flexible load resources to respond to unexpected power undulations (Deng and Lv, 2020).

To investigate the contribution of unit dispatch in long-term planning, some studies analyze the short-term variations in variable renewable energy (VRE) in long-term power systems planning using a combination method of the hourly unit commitment and capacity expansion planning models (Pereira et al., 2017). Gils et al. (2017) and Scholz et al. (2017) examined the correlation between VRE penetration, energy storage, and power transmission. They found that interregional transmission could play a significant role in wind-dominated scenarios, whereas energy storage technologies are adequately applied in solar-dominated scenarios. Zhang et al. (2017) developed an integrated source-grid-load planning model to find an optimal planning scheme for China. All the available resources of generation, transmission, and demand side have been considered to ensure a reasonable integration for renewable energy.

For power system planning at the provincial level, key factors for decision-making in terms of power generation expansion are system cost and decision risk (Fan et al., 2019). Furthermore, the power systems of Hebei and Fujian Provinces in China show great impacts on environmental tax and spatial distribution on the portfolio strategy of generation technologies (Sun et al., 2013; Wang et al., 2018). Especially, Zhang et al. (2015) evaluated the clean energy alternatives in Jiangsu Province and verified the priority of clean energy options such as solar photovoltaic (PV), wind, biomass, and nuclear energy. In order to absorb more wind resource, Zhao et al. (2009) and Hong et al. (2012) considered the use of more wind resources and investigated development strategies for wind integration, including flexible power plants, transmission grids, and energy storage. Nevertheless, a few system planning studies examining the regional power system consider the flexibility requirement brought by renewable energy generation.

This paper presents a planning model for the overall planning and deployment of the power system, integrated with increasing VRE resources, by incorporating the output and flexibility requirement resulting from wind and solar energy. It is significantly different from traditional capacity expansion planning model and is more suitable for the simulation of future renewable-dominated power system. The objective of the study is to provide possible integration options, such as installed and generation mixes, flexible power, and carbon emissions in long-term optimization paths. The results could provide evidence for constructing cleaner power systems by integrating highly variable renewable energy, utilizing available flexible power.

The remainder of this paper is organized as follows. The section Methodology describes the methodology of this study with detailed explanations of the wind–solar output model and the power system planning model. In the section Scenario Settings and Input Data, the input data and scenario setting are depicted. The section Results explains the main results of the wind–solar output and planning models. Finally, discussion and conclusion are presented in the section Discussion and Conclusion.

METHODOLOGY

This section establishes the mixed integer linear programming (MILP) model of power systems to study the power structure and the optimization path of the Jiangsu power sector, as shown in **Figure 1**. The model considers the massive input data of technology and economic restraints, flexibility factors, power demand, etc., in an attempt to minimize the system cost by addressing the main planning constraints.

In order to integrate more renewable energy resources, notably wind and solar energy, it is essential to take into consideration the power output of wind and solar energy as well as the flexibility requirement due to fluctuating power generation in the constraints. We examine the wind and solar generation capability of Jiangsu Province using large amounts of historical meteorological data, reflecting its real power generation capacity of wind and solar. As a result, the actual capacity factor is input into the MILP model to further optimize the development path of low-carbon generation technologies in sustainable scenarios.

Wind–Solar Power Output Models

Wind and solar power generation depends on the magnitude of wind speed and solar radiation characterized by strong randomness. Wind speed is modeled by the Weibull distribution; the probability distribution function is given in Appendix A1.

The expected output power is defined as follows:

$$E(P) = \int_0^{+\infty} P(v) f(v)\, dv = P_r F\left(v_f\right) - \frac{P_r}{v_r - v_c} \int_{v_c}^{v_r} F(v)\, dv \quad (1)$$

where v is the wind speed, $f(v)$ is the probability density function (PDF), $P(v)$ is the output power of a wind turbine, P_r is the rated power, v_c is the cut-in wind speed, v_r is the rated wind speed, and v_f is the cut-out wind speed.

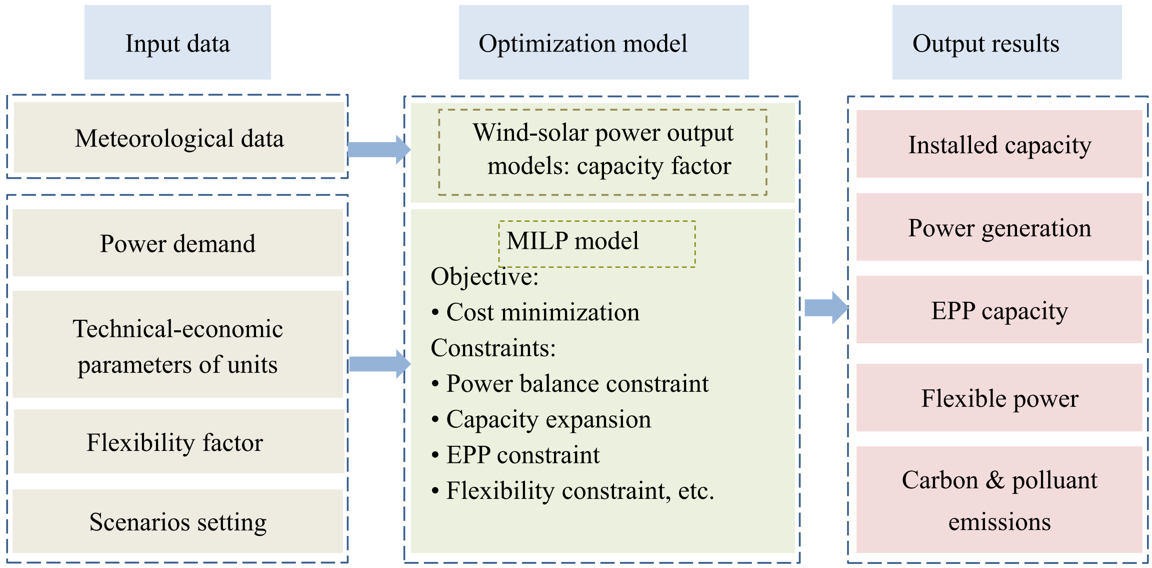

FIGURE 1 | Research method.

Solar PV power generation depends on the solar radiation intensity fitted by the Beta distribution (Wang, 2017). The PDF of the Beta distribution is given in Appendix A2. The solar to power conversion model is developed on account of the PV panel solar output (Wang et al., 2013), as shown below:

$$P\left(I_t\right) = \delta Y \left(\frac{I_t}{I_s}\right) \left[1 + \varphi \left(T_{cell} - T_s\right)\right] \tag{2}$$

where $P(I_t)$ is the output power of a PV panel, δ is the panel derating factor, Y is the PV array capacity, I_t is the radiation intensity, I_s is the standard radiation intensity, φ is the temperature power coefficient, T_{cell} is the PV array surface temperature, and T_s is the standard testing condition of PV cell temperature.

The actual capacity factor is approximated by the actual output power to maximum power production ratio. For a wind turbine or PV panel, the capacity factor is calculated as:

$$cf = \frac{P}{P_r} \tag{3}$$

where cf is the capacity factor, P is the output power per unit wind turbine or PV panel, and P_r is the nominal capacity per unit wind turbine or PV panel.

Optimization Model

In this section, the power system planning model is built to make decisions on the capacity expansion of power plants and the efficiency power plant (EPP), as well as flexible power, which determines the least-cost planning path of power systems. The mathematical formulas of the objective function and constraints are explained in the following.

Objective Function

The objective of the model is to minimize the system cost relating to the decision variables during the planning period, that is, from 2018 to 2050. This means that the objective function consists of capital cost, operation cost, and fuel cost of generator units, as well as the demand side investment cost, as shown in Equation (4). In addition, the subsidy of renewable generation is incorporated into the cost system to examine how the subsidy policy affects the power structure.

$$min \sum_{t=1}^{T} \frac{C_i^t + C_o^t + C_f^t + C_d^t - \epsilon^t C_s^t}{(1+r)^t} \tag{4}$$

where T is the length of the planning period, and C_i^t, C_o^t, C_f^t, C_d^t, and C_s^t give the generator units' capital cost, operation and maintenance cost, fuel cost, EPP investment cost, and the subsidy in year t, respectively. ϵ^t is a binary variable with value "0" for no subsidy and "1" otherwise, and r is the discount rate.

Capital cost of generator units

The capital cost is broken down by year for the lifetime of generator units.

$$C_i^t = \sum_{j=1}^{J} I_j^t \Delta R_j^t \frac{r\left(1+r\right)^{Y_j}}{\left(1+r\right)^{Y_j} - 1} \tag{5}$$

where j is the power plant type, such as coal, gas, hydropower, nuclear, wind, PV, and biomass; I_j^t is the investment cost per unit capacity of power plant type j in year t; R_j^t is the new installed capacity of power plant type j in year t; and Y_j is the expected lifetime of power plant type j.

Operation and maintenance cost

The operation and maintenance (O&M) cost of generator units in year t is calculated as follows:

$$C_o^t = \sum_{j=1}^{J} c_j^t R_j^t \varepsilon_j T_j^t \tag{6}$$

where c_j^t is the operation and maintenance cost per unit capacity of power plant type j in year t, R_j^t is the total installed capacity of power plant type j in year t, ε_j is the efficiency coefficient of power plant type j, and T_j^t is the annual operational hours of power plant type j in year t.

Fuel cost

Fuel cost is calculated from the fuel price and power generation in year t.

$$C_f^t = \sum_{j=1}^{J} f_j^t \varepsilon_j R_j^t T_j^t \tag{7}$$

where f_j^t is the fuel cost per unit capacity of power plant type j in year t.

Investment cost of EPP

The installation cost of EPP is converted into the annual equivalent cost as follows:

$$C_d^t = \sum_{d=1}^{D} \gamma_d^t c_d^t \Delta R_d^t \frac{r(1+r)^{Y_d}}{(1+r)^{Y_d} - 1} \tag{8}$$

where d is the EPP type, which includes the energy-saving motor, the energy-saving lamp, the ice thermal storage, and the energy-saving transformer; γ_d^t is a binary variable with value "1" if the EPP type d is applied in year t and "0" otherwise; c_d^t is the investment cost per unit capacity of EPP type d in year t; R_d is the new installed capacity of EPP type d in year t; and Y_d is the expected lifetime of EPP type d.

Electricity price subsidy

The electricity price subsidy for each generation technology is calculated as:

$$C_s^t = \sum_{j=1}^{J} c_{sj}^t E_j^t = \sum_{j=1}^{J} c_{sj}^t \varepsilon_j R_j^t \tag{9}$$

where c_{sj}^t is the electricity price subsidy per kilowatt-hour of power plant type j in year t.

Constraints

Power load constraint

The total power generation, net input power, and EPP load should meet the maximum yearly power load demand.

$$\sum_{j=1}^{J} \varepsilon_j R_j^t + \sum_{d=1}^{D} \delta_d^t R_d^t + P_o^t \geq P_d^t \tag{10}$$

where δ_d^t is the maximum load coincidence factor of EPP type d in year t; R_d^t is the total capacity of EPP type d in year t; P_o^t is the power transmitted from other regions in year t; and P_d^t is the maximum power load demand in year t.

Power supply and demand constraint

The annual power supply and demand must be balanced. The transmission of power and reduction in power demand should be taken into consideration.

$$\sum_{j=1}^{J} \varepsilon_j R_j^t T_j^t + \sum_{d=1}^{D} R_d^t T_d^t \delta_d^t l_d^t + E_o^t \geq E^t \tag{11}$$

where R_d^t is the total capacity of EPP type d in year t; T_d^t is the annual operational hours of EPP type d in year t; l_d^t is the efficiency coefficient of EPP type d in year t; E_o^t is the net input power in year t; and E^t is the total power demand in year t.

Installed capacity constraint

The total installed capacity is calculated as follows:

$$R_j^t = R_j^{t-1} + \Delta R_j^t \tag{12}$$

$$R_d^t = R_d^{t-1} + \gamma_d^t \Delta R_d^t \tag{13}$$

where R_j^{t-1} is the available capacity of power plant type j at the end of year t-1; and R_d^{t-1} is the available capacity of EPP type d at the end of year t-1.

The constraint of the total installed capacity is presented as:

$$R_j^t \leq R_{j,\lim}^t \tag{14}$$

where $R_{j,lim}^t$ is the installed ceiling of power plant type j in year t.

The expansion potential of generator units is limited by technical maturity and resource capacity. The annual new installed capacity of each power generation technology is limited as follows:

$$\Delta R_j^t \leq \Delta \overline{R}_j^t \tag{15}$$

where ΔR_j^t is the upper limit of the annual new installed capacity of power plant type j in year t.

Flexibility constraint

The flexibility requirement of the power system due to fluctuations in renewable energy generation needs to be met by adjusting the power structure (Sullivan et al., 2013). Besides, part of the power demand is satisfied by flexible generation technologies.

$$\sum_{j=1}^{J} f_j \varepsilon_j R_j^t T_j^t + E^t f_d \geq 0 \tag{16}$$

where f_j is the flexibility coefficient of power plant type j; and f_d is the flexibility coefficient of the demand load.

CO_2 emission constraint

The CO_2 emission constraint is set in accordance with the Chinese carbon emission peak policy. The upper limit is scheduled to decrease every year after 2030.

$$\sum_{j=1}^{J} \varepsilon_j R_j^t T_j^t e_{j,CO_2}^t \leq M_{CO_2}^t \tag{17}$$

$$\mathrm{M}_{\mathrm{CO_2}}^{\mathrm{t}} - \mathrm{M}_{\mathrm{CO_2}}^{\mathrm{t-1}} \begin{cases} \geq 0, & t \in [1, 12] \\ \leq 0, & t \in [13, 32] \end{cases} \tag{18}$$

where e_{j,CO_2}^t is the carbon emission factor per kilowatt-hour of type j of the power plant in year t; $M_{CO_2}^t$ is the upper limit of carbon emission in year t.

NO_x and SO_2 emission constraints

The pollutant constraints in the power sector are calculated as:

$$\sum_{j=1}^{J} \varepsilon_j R_j^t T_j^t e_{j,NO_x}^t \leq M_{NO_x}^t \tag{19}$$

$$\sum_{j=1}^{J} \varepsilon_j R_j^t T_j^t e_{j,SO_2}^t \leq M_{SO_2}^t \tag{20}$$

where e_{j,NO_x}^t is the NO_x emission factor for power plant type j in year t; $M_{NO_x}^t$ is the upper limit for NO_x emissions; e_{j,SO_2}^t is the SO_2 emission factor for power plant type j in year t; and $M_{SO_2}^t$ is the upper limit for SO_2 emissions.

SCENARIO SETTINGS AND INPUT DATA

There are six scenarios to examine the impacts of power demand, subsidies, and carbon emission reduction targets on the power technology development path in Jiangsu, as shown in **Table 1**. The electricity received from the outside is set as low, medium, and high. The electricity price subsidies and carbon price are assumed in Appendix B.

The upper limits of the new installed capacity of the various power generation modes during the planning period are assumed to be subjected to the resource reservation and exploitation limitation. According to Zhang et al. (2017), Ye (2013) and, Wang et al. (2014), the annual maximum installed capacity of each type of unit is calculated as follows. The ceiling for coal and gas power units is 9.36 and 5.2 GW, respectively, whereas the ceiling for wind and solar PV power is 3.64 GW. Once the "Second Nuclear Power Plant" proposed by the "13th Five-Year Plan of Jiangsu Province" commences generation, the construction ceiling of nuclear and hydropower will be 3.12 and 1.56 GW, respectively. The potential of biomass energy is about 0.52 GW.

The power supply planning for east China and the development plan for the state grid corporation expect the power from outside of Jiangsu to gradually increase from 36 GW in 2020 to 56 GW in 2050. The CO_2, SO_2, and NO_x emission factors are considered in accordance with the coal consumption per unit power generation as well as the Jiangsu government's regulation on the desulfurization and out-of-sale rate (Cheng et al., 2015). The fuel prices of coal, natural gas, uranium, and biomass are assumed on the basis of energy price predictions in the IMCTC (2019), CHDN (2019), Mao and Wang (2010), and Gao and Fan (2010). The techno-economic parameters of power generation technologies, such as life time, output factor, annual utilization hours, investment cost, and O&M cost, are listed in **Table 2** (Ye, 2013). The annual discount rate is 0.05.

The flexibility factor of each generation technology type represents its flexibility contribution to system operation; this ranges from −1 to 1 (Sullivan et al., 2013). As **Table 3** shows, wind and solar power requires great flexibility to smoothen their fluctuating generation; this can make their flexibility factor negative. Gas and hydropower, as well as biomass, could provide rapid responsiveness for fluctuating power; this can make their flexibility factor significant. As a base power source, coal power plants are not suitable for frequent starts and stops; this makes their flexibility factor slightly lower. Nuclear energy production is stable, but it is inconvenient to start and stop, providing flexible power output. Thus, its flexibility is 0. Besides, a part of the power demand needs to be met by flexible power.

RESULTS

The generation capability of wind and solar energy is calculated from the weather data and is substituted into the optimization model to represent the actual output of wind and solar energy. The planning results give the power structure predictions for Jiangsu Province from 2020 to 2050, exploring the transformation scenarios of the future power system, including the optimization path of the generation mixes, the emission path of air pollutants, and the development path of the EPP.

TABLE 1 | Characteristics of scenario setting.

Influencing factors	Scenarios	Code	Power demand	Outside power	Subsidy	Carbon emission reduction targets
Power demand	Low demand scenario	LD	Low	Low	×	General
	Regulatory demand scenario	REF	Medium	Medium	×	General
	High demand scenario	HD	High	High	×	General
Subsidies	Subsidy scenario	SP	Medium	Medium	√	General
Carbon emission reduction target	Low-carbon scenario	LC	High	High	×	Strong
	Enhanced low-carbon scenario	LCS	High	High	×	Very strong

TABLE 2 | Technical and economic parameters of power generation technology in the base year.

Power generation type	Lifetime (year)	Average output (%)	Annual utilization hours (h)	Investment cost (yuan/kW)	O&M cost (yuan/kWh)
Coal	30	0.65	8,760	4576.30	0.128
Gas	25	0.60	8,760	3460.80	0.131
Nuclear	40	0.90	8,760	10000.00	0.028
Wind	20	0.16	8,760	7493.34	0.014
Solar	25	0.26	8,760	6431.03	0.487
Hydropower	30	0.30	8,760	6975.00	0.007
Biomass	30	0.70	8,760	10090.00	0.300

TABLE 3 | Flexibility factors.

Technology	Coal	Gas	Nuclear	Wind	Solar PV	Hydropower	Biomass	Electricity consumption
Parameters	0.15	0.5	0	–0.08	–0.05	0.5	0.3	–0.1

The optimization algorithm is resolved in MATLAB.

TABLE 4 | The output factor of wind power.

Season	Mean (m/s)	Standard deviation (m/s)	c	k	E(P) (MW)	Output factor
Spring (3–5)	6.34	1.90	3.73	7.03	0.44	0.22
Summer (6–8)	5.38	2.06	2.75	6.06	0.31	0.155
Autumn (9–11)	5.00	2.03	2.58	5.63	0.26	0.13
Winter (12–2)	5.28	2.06	2.72	5.95	0.30	0.15

TABLE 5 | The output factor of solar power.

Season	Temperature (°C)	Illumination hours (h)	α	β	μ	$P(I_t)$ kW	Output factor
Spring (3–5)	16.2	13	1.88	4.52	0.29	1.40	0.28
Summer (6–8)	27.37	13.67	2.44	4.96	0.33	1.57	0.31
Autumn (9–11)	17.83	11	1.57	5.25	0.23	1.11	0.22
Winter (12–2)	10.4	10.33	1.91	5.97	0.24	1.17	0.23

The Power Output of Wind and Solar Energy

The output factor of wind power shown in **Table 4** is calculated taking the 2-MW Vestas V80 onshore wind turbine as an example. The output of wind energy in winter and spring is relatively high, whereas that in autumn is relatively low. The annual average output factor is about 0.1635, just below the output factor in spring. That is, seasonal fluctuations are obvious.

Referring to the Wuxi Suntech standard series of 5-kW polysilicon, the output factor of solar power calculated is shown in **Table 5**. The illumination time is relatively longer in spring and summer. The actual output of PV modules reaches 1.57 kW in summer with 31% output capability. However, the output of solar energy in autumn and winter is relatively low. The annual average output factor is 0.26, below the potential spring and summer output factor.

Planning Results

Power Generation Capacity Expansion

Figure 2 compares the installed capacity and power generation under three demand scenarios to generally show significant increases in both. The total installed capacity increases from 116 GW in 2018 to 248 GW in the REF and 275 GW in the HD scenarios by 2050. Similarly, power generation reaches 975.7–1,108.1 TWh in 2050 to meet the growing electricity demand.

From the perspective of power generation technologies, the generation mix changes from fossil-based energy to clean energy, as shown in **Figure 3**. The installed capacity of coal-fired technologies dominates initially, accounting for 67% of the total capacity in 2020, but then shows a significant decline in share after 2030, gradually substituted by the generation capacities of clean energy resources such as wind, solar PV, and hydropower technologies. Specially, the installed capacity of wind and solar energy resources increases significantly from 16 GW (14%) in 2020 to 117 GW (47%) in 2050. Correspondingly, the power generation from wind and solar PV reaches 264 TWh (24%) in the HD scenario in 2050, becoming the major power generation technology next to coal.

Resource constraints and policy restrictions have restrained the capacity growth of hydropower and nuclear energy, which increased only slightly, to have a relatively small share in the future capacity expansion. The application of biomass is confined by costly potential. Specially, the generation capacity of coal-fired power plants is higher in HD than in REF, probably due to the higher power demand that has to be satisfied on the premise of fixed total installed capacity.

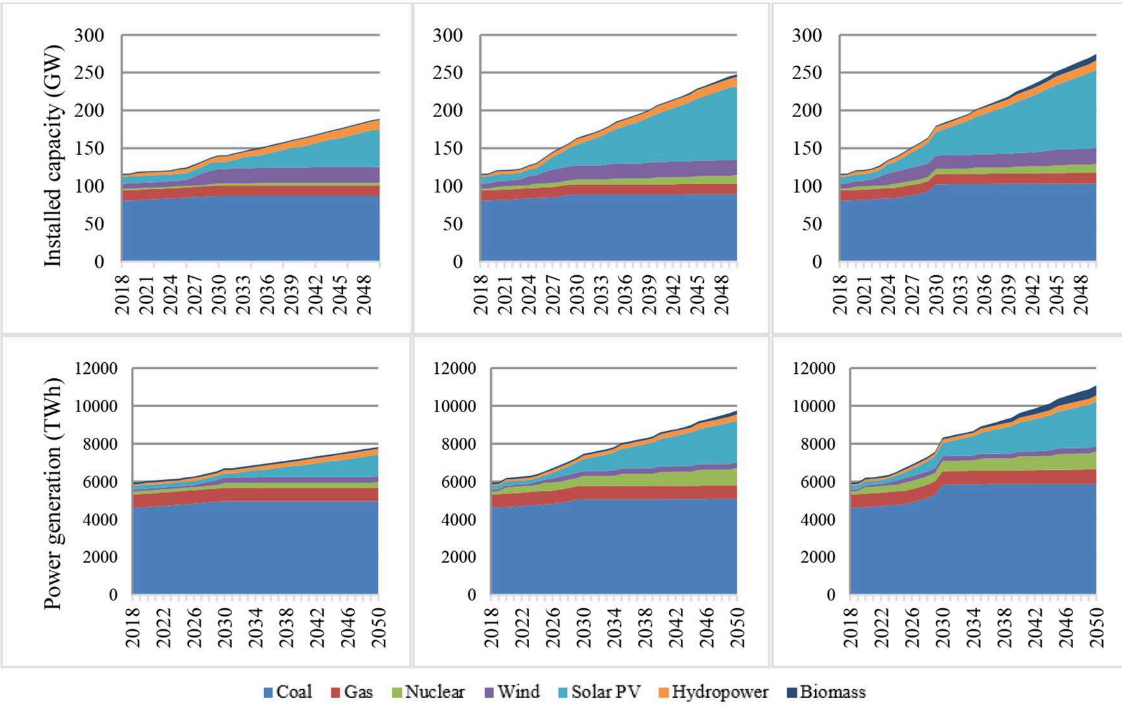

FIGURE 2 | Installed capacity and power generation in different demand scenarios (from left to right: LD, REF, and HD scenarios).

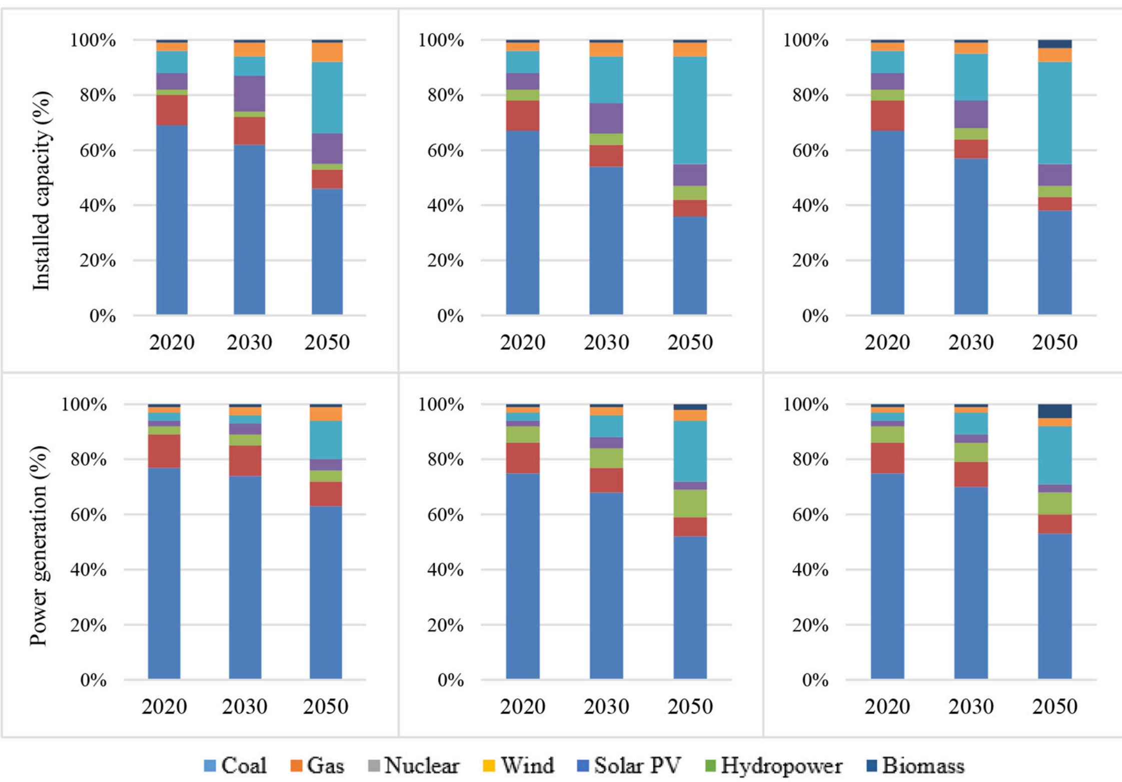

FIGURE 3 | Installed capacity and power generation (from left to right: LD, REF, and HD scenarios).

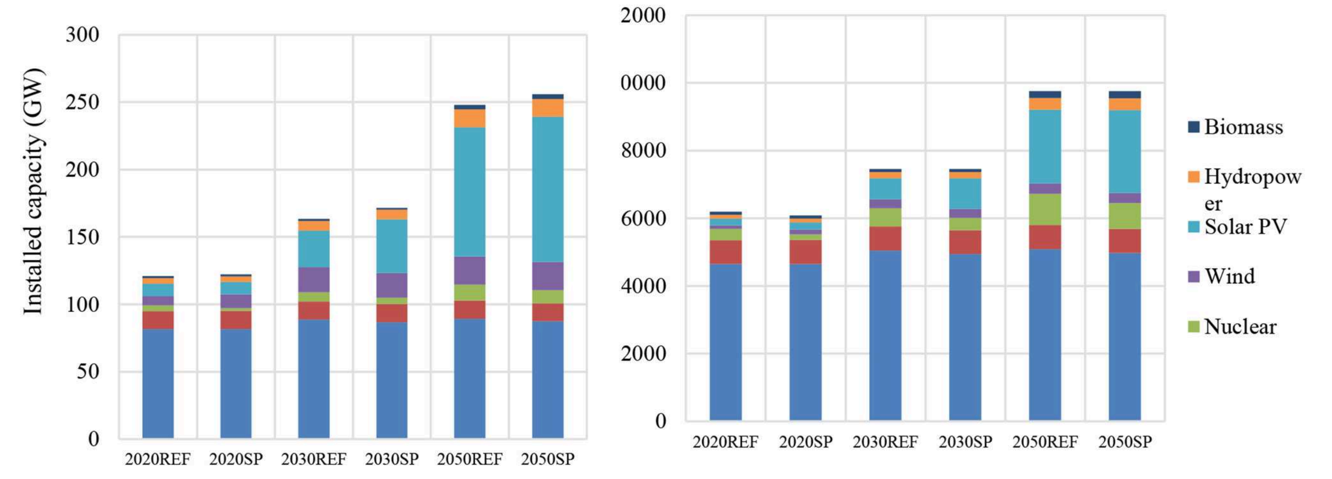

FIGURE 4 | Installed capacity and power generation in SP and REF scenarios.

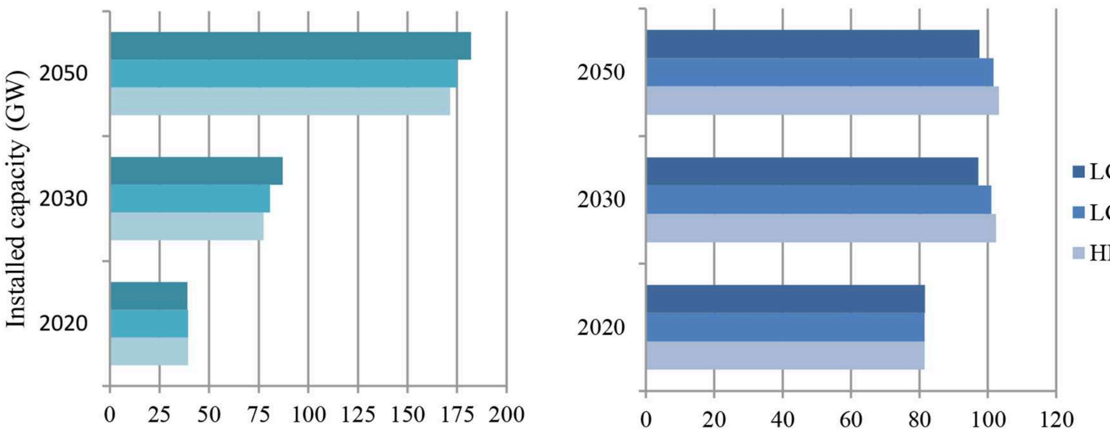

FIGURE 5 | The generation capacity of clean energy and coal in HD, LC, and LCS scenarios.

Figure 3 Installed capacity and power generation (from left to right: LD, REF, and HD scenarios)

Figure 4 compares the installed capacity and power generation between the REF and SP scenarios. Non-fossil fuel subsidies facilitate the construction and utilization of cleaner energy resources; this is more obvious after 2030 with 17% addition of nonfossil energy installation compared to that in REF. Take a special attention on solar PV; the generation capacity increases from 921 to 10,784 GW, representing explosive growth. However, wind power generation reaches 29.9 TWh by 2050, accounting for only 3% of the total generation due to the fact that the subsidies for wind power will be canceled in 2020. Similarly, in spite of considerable subsidies, gas and biomass show limited development because their high cost is responsible for weak competitiveness.

Carbon emission control policies led to a change in the power generation mix. Coal-fired units have been widely employed to meet the increasing power demand and peak load requirements; however, the need to reduce carbon emissions has led to their regulation. As shown in **Figure 5**, coal-fired generation shows an increase during 2020–2030 and then remains stable during 2030–2050. The generation capacity in the LCS scenario decreases by 6 GW in 2050 compared to that in HD. Conversely, clean energy, consisted of wind, PV, nuclear, and biomass, will be supported extensively under the emission mitigation policies. By 2050, coal-fired and clean energy generation will reach 555 and 553 TWh, respectively, that is, almost equal, thus replacing coal-fired generation.

EPP

EPP, characterized by environment-friendly energy conservation, is an ideal alternative electricity technology. The increasing demand loads would provide adjustable power demand to respond to the fluctuating power supply under demand-side management measures. **Figure 6** demonstrates the capacity of EPP in six scenarios. Taken as a whole, EPP would be

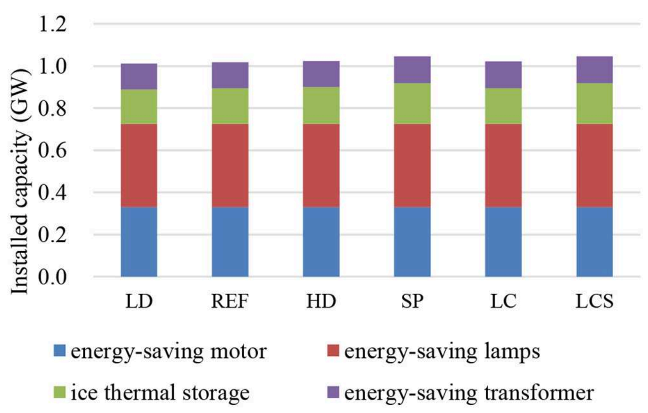

FIGURE 6 | The EPP capacity in 2050.

TABLE 6 | The emissions of CO_2, SO_2, and NO_x in six scenarios (in million tons).

Scenario	LD			REF			HD		
Time	CO_2	SO_2	NO_x	CO_2	SO_2	NO_x	CO_2	SO_2	NO_x
2020	300.91	0.08	0.37	300.91	0.08	0.37	300.93	0.08	0.37
2030	300.97	0.04	0.22	308.63	0.04	0.23	353.10	0.05	0.26
2050	292.60	0.02	0.07	306.66	0.02	0.07	352.85	0.02	0.08
Scenario	**SP**			**LC**			**LCS**		
Time	CO_2	SO_2	NO_x	CO_2	SO_2	NO_x	CO_2	SO_2	NO_x
2020	300.92	0.08	0.37	300.93	0.08	0.37	300.96	0.08	0.37
2030	303.47	0.04	0.22	348.81	0.05	0.26	337.37	0.04	0.25
2050	301.80	0.02	0.07	348.49	0.02	0.08	337.10	0.02	0.08

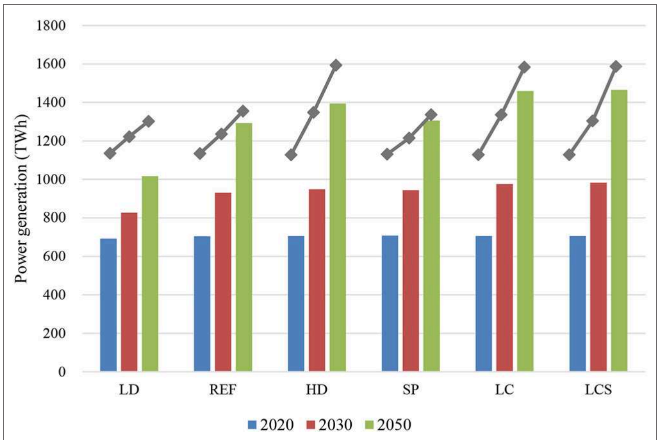

FIGURE 7 | The flexibility requirement and supply in six scenarios (histogram for flexibility requirement, line graph for flexibility supply).

incorporated in SP and LCS scenarios on a large scale. In particular, energy-saving lamps and energy-efficient motors will be applied widely, the total capacity of which will reach 0.7 GW in 2050. It is undeniable that load resources will play an important role in the future renewable-based power system with growing power generation from VRE.

System Flexibility

The flexibility requirement of a power system is calculated according to the power generation and flexibility factors. As **Figure 7** shows, the flexibility requirement gradually increases in the LD, REF, and HD scenarios to reach 1,017.6, 1,292.8, and 1,394.7 TWh, respectively, in 2050, with growth rates of 46.79, 83.57, and 97.62%, respectively, compared to 2020.

Compared to the REF scenario, the SP scenario shows faster growth in flexibility requirement, which reaches 1,306.3 TWh in 2050. This is mainly due to the government subsidies for renewable energy, which result in rapid development of wind power and photovoltaics and higher flexibility requirement. Furthermore, the flexibility requirements of the LC and LCS scenarios reach 1,489.7 and 1,465.1 TWh in 2050, with growth rates of 106.82 and 107.71% relative to 2020. The power sector would deploy more non-fossil energy, notably renewable energy, to meet the increasing power demand and high emission targets.

The flexibility supply in six scenarios collectively exceeds the flexibility requirement, with fill rates (supply/requirement) of 127.52, 104.52, 114.15, 102.35, 108.47, and 108.34%, respectively. This indicates that the actual available flexible power can basically meet the flexibility requirements, but might become relatively short in the REF, SP, LC, and LCS scenarios.

Carbon and Pollutant Emissions

Table 6 compares the emissions of SO_2, NO_x, and CO_2 in six scenarios from 2020 to 2050. The CO_2 emissions maintain a certain growth before 2030. In 2030, the total carbon emissions reach 300.9, 308.6, and 353.1 million tons in the LD, REF, and HD scenarios, respectively, indicating a certain increase. However, the carbon emission is slightly lower in the SP scenario because the subsidies for renewable energy will facilitate the replacement of coal-fired power generation with clean energy power generation. Besides, the CO_2 emission reductions in the LC and LCS scenarios are 15.75 and 4.36 million tons, respectively, compared with that in the HD scenario in the context of high power demand. It explains why the enhanced low-carbon policy has significant effect on emissions reduction.

Pollutant emissions gradually reduce during the planning period. SO_2 emissions will reduce from 0.08 to 0.01 million tons, while those of NO_x will reduce from 0.4 to 0.07 million tons in the REF scenario. There are higher emissions in the HD scenario, indicating a positive relationship between electricity demand and pollutant emissions. On the contrary, SO_2 and NO_x emissions are lower in the SP and LCS scenarios than in the REF and HD scenarios. This is because policy subsidies and enhanced low-carbon constraints have stimulative impacts on pollutant emissions. In the future, the impact of renewable energy instead of thermal power on gas emissions is not significant as the desulfurization and denitrification rate of thermal power units will reach 99% and 95%, respectively.

DISCUSSION AND CONCLUSION

This paper presents a planning method to find the cost-optimal planning path for the power system in Jiangsu Province taking into account the fluctuating power generation of wind and solar energy. Results show that the generation mix is subject to multiple factors, such as resource potential, subsidies, and carbon emission policies. A diversified power supply plan is provided for the whole planning horizon, where non-fossil energy is projected to contribute 58% of the installed capacity by 2050. However, the installed capacity of coal-fired units will reach 103 GW by 2050 under a high power demand scenario, well above the 87 GW in LD and 89 GW in REF. It is proved that the power demand is the major factor in motivating the expansion of coal power generation. Consequently, it is difficult to find a significant substitute for coal power with increasing power demand. Accordingly, carbon emission reduction continues to be a challenge even though carbon emissions will peak before 2030.

As stated above, subsidies facilitate the deployment of clean energy resource by converting coal-based power generation into renewable-based power generation. However, this effect will slow down in the subsequent planning period owing to the cancellation of subsidies for wind and solar power. The learning effect could be an alternative development path to further reduce the generation cost of wind and solar PV expansion. Furthermore, gas and biomass power show no much capacity expansion during the whole planning horizon because subsidies could not greatly offset their high generation costs. In order to boost the non-fossil energy generation, it is vitally important to put the focus on the subsidies for gas and biomass once wind and solar generation technologies become increasingly mature.

The flexibility requirement of wind and solar power as well as the demand side can be basically met by the existing flexible power generation technologies. Nevertheless, no much surplus flexible power will be available to respond to the increasing fluctuating renewable energy generation by 2050, especially in the REF and SP scenarios. That is, more flexibility resources need to be explored to largely integrate the penetration level of renewable energy, such as energy storage technologies and demand side response, as well as interregional transmission. These have not been considered in this paper owing to limited data availability and model computing power. However, flexible generation technologies may carry a greater expectation in scenarios of power demand, subsidies, and carbon emission control, which is attributed to the cost advantage and mature technology.

In the future, carbon capture and storage (CCS) technology will be widely applied in power systems to mitigate climate change, and hence should be included in the next power system planning. In addition, the planning on high temporal resolution should be focused in the future power systems with increasing VRE.

DATA AVAILABILITY STATEMENT

All datasets generated for this study are included in the article/**Supplementary Material**.

AUTHOR CONTRIBUTIONS

TL and XD designed the study and wrote the final paper. QY was responsible for the data collection. JX and JG built and calculated the model. All authors have made a significant contribution to this research and read and approved the final manuscript.

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SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fenrg.2020.00039/full#supplementary-material

REFERENCES

CHDN (2019). *2018 Natural Gas How Much a Cubic—2018 National Natural Gas Price List Introduction*. Available online at: https://www.xyj321.com/zx/67556.html

Cheng, R., Xu, Z., Liu, P., Wang, Z., Li, Z., and Jones, I. (2015). A multi-region optimization planning model for china's power sector. *Appl. Energy* 137, 413–426. doi: 10.1016/j.apenergy.2014.10.023

China energy medium and long term development strategy research group (2011). *China Energy Medium and Long-Term (2030, 2050) Development Strategy Research. Electric Power, Oil and Gas, Nuclear Energy, Environment Volume*. Beijing: Science Press.

Deason, W. (2018). Comparison of 100% renewable energy system scenarios with a focus on flexibility and cost. *Renew. Sustain. Energy Rev.* 82, 3168–3178. doi: 10.1016/j.rser.2017.10.026

Deng, X., and Lv, T. (2020). Power system planning with increasing variable renewable energy: a review of optimization models. *J. Clean. Prod.* 246, 1–15. doi: 10.1016/j.jclepro.2019.118962

Fan, J. L., Wang, J. X., Hu, J. W., Wang, Y., and Zhang, X. (2019). Optimization of China's provincial renewable energy installation plan for the 13th fve-year plan based on renewable portfolio standards. *Appl. Energy* 254, 1–16. doi: 10.1016/j.apenergy.2019.113757

Gao, H., and Fan, J. (2010). *Economy and Economic Aggregate of Renewable Energy Power Generation in China*. Beijing: China Environmental Science Press.

Gils, H. C., Scholz, Y., Pregger, T., Luca de Tena, D., and Heide, D. (2017). Integrated modelling of variable renewable energy-based power supply in Europe. *Energy* 123, 173–188. doi: 10.1016/j.energy.2017.01.115

Hong, L. X., Lund, H., and Möller, B. (2012). The importance of flexible power plant operation for Jiangsu's wind integration. *Energy* 41, 499–507. doi: 10.1016/j.energy.2012.02.038

IMCTC (2019). *China Thermal Coal Price Index*. Available online at: http://www.imcec.cn/zgdm.2019-02-19

Jiangsu Provincial People's Government (2017). *The 13th Five-Year Energy Development Plan of Jiangsu Province*. Available online at: http://dpc.wuxi.gov.cn/doc/2017/05/16/1323177.shtml

Li, D., Liu, J. Y., Liu, Y. B., and Gao, H. J. (2015). Joint secure & economic dispatch considering wind power, pumped storage and demand response. *Electr. Power Autom. Equip.* 35, 28–34. doi: 10.16081/j.issn.1006-6047.2015.02.005

Liu, J., Zhang, D., Cai, J., and Davenport, J. (2019). Legal systems, national governance and renewable energy investment: evidence from around the word. *Br. J. of Manage.* doi: 10.1111/1467-8551.12377. [Epub ahead of print].

Mao, Z., and Wang, C. (2010). Assessing the climate impact of renewable energy targets by bottom-up modeling. International Conference on Intelligent System Design & Engineering Application. *IEEE Comput. Soc.* 1, 394–399. doi: 10.1109/ISDEA.2010.112

National Bureau of Statistics (2019). *National Economic and Social Development Statistics Bulletin 2018*. Available online at: http://data.stats.gov.cn/easyquery.htm?cn=C01

Pereira, S., Ferreira, P., and Vaz, A. I. F. (2017). Generation expansion planning with high share of renewables of variable output. *Appl. Energy* 190, 1275–1288. doi: 10.1016/j.apenergy.2017.01.025

Scholz, Y., Gils, H. C., and Pietzcker, R. C. (2017). Application of a high-detail energy system model to derive power sector characteristics at high wind and solar shares. *Energy Econ.* 64, 568–582. doi: 10.1016/j.eneco.2016.06.021

Sullivan, P., Krey, V., and Riahi, K. (2013). Impacts of considering electric sector variability and reliability in the MESSAGE model. *Energy Strateg. Rev.* 1, 157–163. doi: 10.1016/j.esr.2013.01.001

Sun, Y. W., Wang, R., Liu, J., Xiao, L. S., Lin, Y. J., and Kao, W. (2013). Spatial planning framework for biomass resources for power production at regional level: a case study for Fujian Province, China. *Appl. Energy* 106, 391–406. doi: 10.1016/j.apenergy.2013.02.003

Wang, B., Liu, L., Huang, G. H., Li, W., and Xie, Y. L. (2018). Effects of carbon and environmental tax on power mix planning – A case study of Hebei Province, China. *Energy* 143, 645–657. doi: 10.1016/j.energy.2017.11.025

Wang, C., Ye, M., Cai, W., and Chen, J. (2014). The value of a clear, long-term climate policy agenda: a case study of china's power sector using a multi-region optimization model. *Appl. Energy* 125, 276–288. doi: 10.1016/j.apenergy.2014.03.079

Wang, C. S., Hong, B. W., and Guo, L. (2013). Dispatch strategies of PV-battery microgrid in different scenarios. *Power Syst. Technol.* 37, 1775–1782. doi: 10.1371/journal.pone.0088481

Wang, J. (2017). *Research on planning optimization of distributed photovoltaic power plants in connection with distribution network* (maeter's thesis). Southeast University, Nanjing, China.

Ye, M. (2013). *Regional optimization model and emission control policy simulation for China's power sector* (maeter's thesis). Tsinghua University, Beijing, China.

Zhang, L., Zhou, P., Newton, S., Fang, J. X., and Zhou, D. Q. (2015). Evaluating clean energy alternatives for Jiangsu, China: an improved multi-criteria decision making method. *Energy* 90, 653–964. doi: 10.1016/j.energy.2015.07.124

Zhang, N., Hu, Z., Shen, B., He, G., and Zheng, Y. (2017). An integrated source-grid-load planning model at the macro level: case study for China's power sector. *Energy* 126, 231–246. doi: 10.1016/j.energy.2017.03.026

Zhao, Y., Hao, L. S., and Wang, Y. P. (2009). Development strategies for wind power industry in Jiangsu Province, China: based on the evaluation of resource capacity. *Energy Policy* 37, 1736–1744. doi: 10.1016/j.enpol.2008.12.038

Zhao, Y. H., Cao, Y., Shu, X. P., Li, H., Shi, Q. L., and Zhang, Z. H. (2020). How China's electricity generation sector can achieve its carbon intensity reduction targets. *Sci. Total Environ.* 706, 1–13. doi: 10.1016/j.scitotenv.2019.135689

Zhou, Y., Wu, W. X., Hu, Y., Fang, X., and Liu, G. X. (2010). The assessment of available solar energy resources potential in Jiangsu Province. *Renew. Energy Resour.* 28, 10–13. doi: 10.13941/j.cnki.21-1469/tk.2010.06.042

Zou, Y. Q., and Yi, D. (2012). Brief discussion on the current situation of wind power development in Jiangsu. *J. Changzhou Institute Technol.* 25, 32–35. doi: 10.3969/j.issn.1671-0436.2012.03.009

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ORIGINAL RESEARCH
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The Asymmetric Effect of Oil Price Uncertainty on Corporate Investment in China: Evidence From Listed Renewable Energy Companies

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This study evaluates the asymmetric impact of international oil price uncertainty on firms' investment in China using a sample of listed renewable energy firms over the period 2000–2017 based on the fixed effect model. The empirical results show that the coefficient of oil price uncertainty on corporate investment is significantly negative, and it significantly affects corporate investment efficiency. Further, it reveals that from the total sample, no matter whether the oil price rises or falls, or the oil price is higher or lower, there is no asymmetry. However, after grouping companies according to the average investment opportunity, we found that for companies with better investment opportunities, the effect of oil price uncertainty on investment is asymmetric, since the coefficient of the interaction term between high oil prices and oil price uncertainty is significant positive. It also shows that increasing oil price uncertainty will reduce the investment efficiency of companies with poor investment opportunities, and the results of regression using inefficient investment as the explanatory variable also confirm this. Sale capital ratio, firm size, firm age, and administrative expense ratio are also vital factors in determining renewable energy firms' investment. This study has important policy implications for both government and enterprise.

Keywords: asymmetric effect, renewable energy, oil price uncertainty, investment, investment inefficiency

INTRODUCTION

In recent years, in order to solve its energy shortage problem and relieve the pressure of environmental pollution, the renewable energy sector in China was strongly encouraged by the government, and several supporting measures and regulatory guidelines have been introduced. In addition, the public's environmental demands have also prompted local governments to implement stricter environmental regulations, thereby encouraging companies to increase green investment (Liao and Shi, 2018). Correspondingly, China's investment in the renewable energy sector has increased significantly, from 3 billion USD in 2004 to more than 115.4 billion USD in 2015. However, the total amount of investment in this sector shrank by 32% to USD 78.3 billion in 2016, with the solar market in particular decelerating sharply[1]. From a global point of view, the growth of new investment in renewable energy went through a period of fast growth from 2004 until 2010,

[1] Bloomberg New Energy Finance, Global Trends in Renewable Energy Investment 2017.

and then it became volatile (as shown in **Figure 1**). At the same time, there is evidence that the development of China's renewable energy industry has encountered some problems. The study of Liu (2013) indicates that the recent sharp hike in China's wind power capacity may be attributed to overinvestment. Zhang et al. (2016) points out that the whole sector was exposed to high risks caused by rapid expansion, and confirms the existence of overinvestment in China's renewable energy sector. Zeng et al. (2017) reveals that the investment efficiency of Chinese new energy companies is relatively low. Therefore, determining which factors affect the investment of China's renewable energy companies, and thinking about how to increase firms' investment efficiency, has become a topic worthy of discussion.

There is no doubt that investment is related to the healthy development of companies. Studies have shown that external shocks, such as oil price shocks, have an increasingly important impact on corporate investment, including the investment behavior of energy companies (Bernanke, 1983; Pindyck, 1991; Elder and Serletis, 2010; Wang et al., 2017; Cao et al., 2019). Statistics show that during the period of the rapid development of China's renewable energy industry, international crude oil prices have experienced significant fluctuations. China is the world's largest oil importer with a dependence on oil imports of up to 70%, and the uncertainty of oil prices significantly affects the Chinese economy (Cheng et al., 2019). Even if the government adopts price control and other measures, it cannot eliminate the negative impact of oil price uncertainty on economic development (Shi and Sun, 2017). Taking the close relationship between renewable energy and fossil energy into consideration, oil price uncertainty, as one of the representative external shocks, may have a significant impact on the investment of Chinese renewable energy companies.

Compared to enterprises in other industries, the effect of oil price uncertainty on renewable energy enterprise's investment may be more complicated. In theory, the impact of oil price volatility on the investment of renewable energy companies is mainly in two aspects. One is that the uncertainty of oil prices means that the input cost of an enterprise is uncertain. Since oil can be used as one of the raw materials for renewable energy companies, uncertainty in oil prices can affect costs and benefits, which improves the company's business risks and default risks, and ultimately changes the investment behavior. Second, the uncertainty of oil prices can lead to uncertainty in demand for renewable energy products due to the partial substitution relationship between fossil energy and renewable electricity. And from this perspective, it may also bring some other changes for the companies, such as inefficient corporate investment behavior. If the uncertainty increases when oil prices are high, this means that risks and opportunities coexist for renewabke energy companies. In this case, different companies may have different attitudes toward investment, which may lead to changes in investment efficiency. Therefore, it requires more detailed research to discuss the response of renewable energy firms' investment to the changes of oil price uncertainty, especially considering the possible asymmetry. However, as far as we know, few articles have investigated this issue.

In this paper, we focus on the renewable energy industry in China and discuss the asymmetric influences of international oil price uncertainty on the investment of listed firms in this industry. We will mainly analyze the possible asymmetric impacts of oil price uncertainty on corporate investment. The article compares the impact of oil price uncertainty on investment when oil prices rise or fall, and when oil prices are high or low. It also investigates the different responses of companies with different investment opportunities to oil prices uncertainty. Finally, we analyzed the impact of oil price volatility on corporate inefficient investment. Our empirical results contributes to the growing body of literature by providing evidence that oil price uncertainty has an asymmetric impact on corporate investment of renewable energy firms and rise in oil price volatility will increase the possibility of over-investment.

The rest of the paper is structured as follows: in Section Literature Review, we give a review of relevant literature; Section Empirical Model Specification introduces the methods used in the empirical studies; in Section Data and Variables, we gives an introduction to sample selection, variable definition,

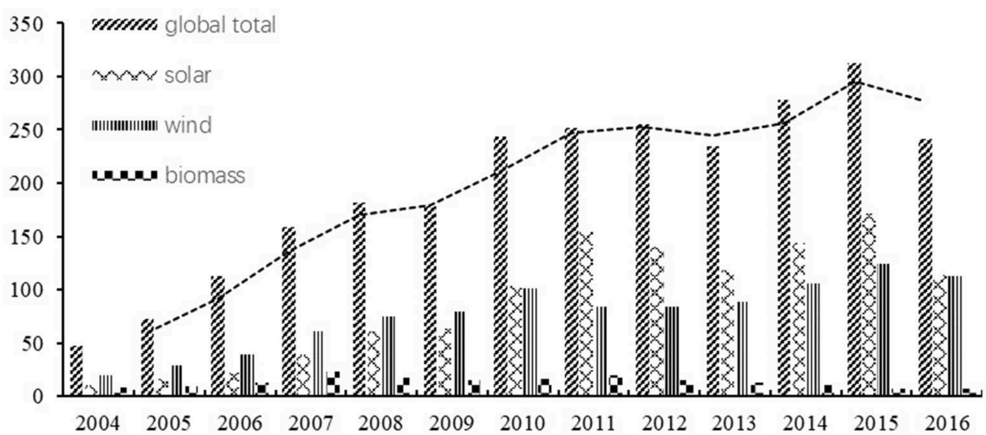

FIGURE 1 | Global statistics new energy investment by sector, 2004-2016, $BN (Source: UN Environment, Bloomberg New Energy Finance).

and statistical description.; Section Empirical Results reports the empirical regression results; and finally, Section Conclusion summarizes and concludes.

LITERATURE REVIEW

Investment Under Uncertainty

Many articles have analyzed the influence of uncertainty on corporate investment. Theoretically, there are several channels through which uncertainty may affect firms' investment. Based on the waiting value of real options, Dixit and Pindyck (1994) indicate that uncertainty will reduce the level of corporate investment if investment is irreversible. Appelbaum and Katz (1986) prove that under the uncertain circumstances, enterprises with high risk-aversion tend to reduce input and output, and points our that there is a negative correlation between corporate investment and uncertainty under the combined effects of investment irrevocability, financing constraints and risk aversion. But controversially, Abel (1983) emphasizes that risk may constitute an incentive to invest if the ability of firms to adapt after uncertainty is resolved, which implies a positive correlation between uncertainty and investment.

Empirically, numerous studies have examined whether investments respond to changes in uncertainty. Much attention has been given to macro uncertainty, such as volatility of stock market returns, interest rates and inflation. There are also many articles that study the correlation between capital investment and uncertainty using industry or firm-level data, but most of the research focus on the manufacturing industry, and there are lots of unresovled issues related to the uncertainty–investment relationship. Among these, Bloom et al. (2007) suggests that uncertainty can reduce firms' investment in response to shocks to sales, and argues that the company will become more cautious when the uncertainty of a company's stock returns is greater. Rashid (2011) report that high uncertainty significantly reduce firms' capital investment expenditures by testing the idiosyncratic and financial market uncertainty on the investment decisions of manufacturing firms. Baum et al. (2008) examine the uncertainty-investment relationship for U.S. firms, and concludes that investment responds negatively to firm-specific and CAPM-based uncertainty, whereas the uncertainty driven by S&P 500 index returns has a positive effect on firm-level investment. Beaudry et al. (2001) examine the impact of macroeconomic uncertainty on investment expenditure using the firm-level data from the UK, and maintain that inflation uncertainty has a negative and significant impact on investment. Baum et al. (2010) investigate the effect of uncertainty on corporate investment directly and the indirect effect via cash flow, it reveals that the impact of market uncertainty through cash flow on investment is negative. Gulen and Ion (2016) investigate the effect of economic policy uncertainty on corporate investment using the US data.

A few recent studies have begun to focus on the influence of uncertainty on the investment decision of Chinese companies. For instance, Xie (2009) examines how fluctuates in the volatility of daily stock returns affect corporate investment in China. The results indicate a negative effect, and it still holds even after controlling corporate investment opportunities and fund availability. Using data from listed companies in China, Xu et al. (2010) find a negative connection between total firm uncertainty and investment, Wang et al. (2014) shows that companies tend to reduce their investment expenditures when facing high economic policy uncertainty, Wang et al. (2014) indicate that the impact of policy and market uncertainty on corporate R&D expenditures is also negative. Taking external economic factors and managerial behavior into consideration, Wang et al. (2016a) studies the same issues and highlights the time-varying interaction between inflation uncertainty and managerial overconfidence, it concludes that overconfidence in management can exacerbate the reinforcing effect of low inflation uncertainty on overinvestment.

Investment Under Oil Price Uncertainty

With the increasing importance of natural resources in economic development, more and more scholars are paying attention to the impact of natural resources price volatility on coporate investment. Several empirical articles have studied the influence of oil price volatility on investment, and have reached a relatively consistent conclusion, that is, the former has a significant negative impact on investment. However, most of previous studies are limited to developed countries. Recently, focusing on the volatility of international oil prices, Elder and Serletis (2010) argue that this kind of uncertaity has had a statistically significant negative influence on several measures of investment, durables consumption and aggregate output in the United States. Henriques and Sadorsky (2011) investigate the effect of oil price uncertainty on firms' strategic investment in the USA and show that there exists a U shaped relationship between them. Using error correction techniques and data from US manufacturing companies, Yoon and Ratti (2011) find that higher energy price uncertainty reduces the positive effect of sales growth on investment. Kellogg (2014) estimate the impact of changes in uncertainty of future oil prices on investment, and discover that a surge in expected volatility of the future oil price reduce firms' drilling activity. Wang et al. (2017) investigate the influence of international oil price volatility on corporate investment expenditures in China. Lee et al. (2011) analyzes the effect of real oil price shocks on corporate investment from both direct and indirect impacts, and the results show that oil price shocks have a greater inhibitory effect on corporate investment for firms with high stock price volatility. Using firm-level data from 54 countries, the recent study of Phan et al. (2019) explores this effect again, and also reveals a negative impact of oil price uncertaity on investment.

The influence of international crude oil price uncertainty on the investment behavior of energy enterprises should be more special and complex, but few articles discuss this issue. It's worth noting that Mohn and Misund (2009) and Cao et al. (2019) have done some exploration in this area. The previous study used panel data from 15 oil and gas companies, and the latter study used data from Chinese renewable energy companies, both of which examined the impact of oil price uncertainty on investment. Unfortunately, the possible asymmetry in the relationship has not been addressed.

Investment Behavior of Renewable Energy Firms

Although few scholars have analyzed the effect of international oil price uncertainty on renewable energy companies' investment, there are many articles that have discussed the investment issues of renewable energy companies. For example, Wustenhagen and Menichetti (2012) propose a conceptual framework for renewable energy investment and reveales that risk, return, and policy all affect firms' current investment levels. Liu (2013) points out the overinvestment problem in wind power capacityand explores the factors that may affect companies' overinvestment Zhang et al. (2016) test the overinvestment hypothesis based on mainstream finance methodology and shows that renewable energy companies do have over-investment issues in China. Zeng et al. (2017) evaluates the investment efficiency of Chinese new energy companies using a four-stage semi-parametric DEA analysis framework, and finds that such companies have low investment efficiency. It states that the investment efficiency of Chinese new energy companies is affected by global and domestic macroeconomic conditions and characteristic variables of enterprises.

In summary, there are still some shortcomings in the research field of how does oil price uncertainty influence the investment of renewable energy enterprises. In particular, few scholars have conducted in-depth research on the possible asymmetry in the relationship. To make up for this gap, this is exactly what this article is trying to do.

EMPIRICAL MODEL SPECIFICATION

Benchmark Model

Given that a large amount of literature uses the Q investment model, we also use this model to test the effect of oil price volatility on corporate investment. Under standard neoclassical assumptions about firm behavior, the Q investment model can be represented as the following formula:

$$(I/K)_t = \alpha + \beta Q_t + \varepsilon_t \tag{1}$$

in which, I_t stands for firm's gross long-term investment, K_t represents the book value of the company's fixed capital stock, Q_t means the marginal q, and ε_t is a random error term. In empirical specifications, Equation (1) is usually augmented with other explanatory variables, and it has fixed effects for cross section and time. According to the studies of Baum et al. (2010), Henriques and Sadorsky (2011), Yoon and Ratti (2011) and Khan et al. (2017), the empirical model of this article is set as follows:

$$\begin{aligned}(I/K)_{i,t} = {} & \alpha + \gamma Voil_{t-1} + \beta_1\, TQ_{i,t-1} + \beta_2 (CF/K)_{i,t-1} \\ & + \beta_3 (S/K)_{i,t} + \delta Z_{i,\ t} + \mu_i + \theta_t + \varepsilon_{i,t}\end{aligned} \tag{2}$$

$(I/K)_{i,t}$ represents the investment-capital ratio, which is obtained by dividing the current investment by the fixed capital at the beginning of the period. *Voil* is the volatility of international oil prices. (CF/K) stands for cash flow scaled by the beginning-of-period capital stock, which indicates the possible role of liquidity. S/K means the firm's sale dividing by capital stock, and Z stands for the control variable vector. μ_i and θ_t stand for the firm-specific and time-specific fixed effects. In line with the research of other works (Chen et al., 2011; Jiang et al., 2011; McLean et al., 2012; Wang et al., 2016b), we add Tobin Q as a proxy variable for investment opportunities to the regression equation.

Asymmetry Analysis Model

Considering that there may be asymmetry in the impact of oil prices uncertainty, we further added an interaction term to the equation.

The first is to compare and analyze the different effects of oil price uncertainty when oil prices rise and fall. Therefore, we construct a dummy variable for oil price rise, $Doil_{pov}$, and the interaction term is Voil $\times$ $Doil_{pov}$. In addition to affecting investment spending, the uncertainty of oil prices may also affect corporate investment efficiency, we also include the interaction term Q and oil volatility $(TQ \times Voil)_{t-1}$, into the empirical model. Correspondingly, the extended models are set as:

$$\begin{aligned}(I/K)_{i,t} = {} & \alpha + \gamma Voil_{t-1} + \theta_1 \left(Voil \times Doil_{pov}\right)_{t-1} + \beta_1\, TQ_{i,t-1} \\ & + \beta_2 (CF/K)_{i,t-1} + \beta_3 (S/K)_{i,t} + \delta Z_{i,\ t} + \mu_i + \theta_t + \varepsilon_{i,t}\end{aligned} \tag{3}$$

The second is to introduce another dummy variable, $high_{oil}$, which measures whether the oil price is at a relatively high level, then the interaction term becomes to $TQ \times high_{oil}$. Based on the daily oil price data, we chose the median value of oil prices, \$75 per barrel, as the dividing line, and generate the dummy variable. Thus, $high_{oil}$ equals to 1 if Brent oil price is >75, otherwise it equals to 0. The empirical model is further extended as follows:

$$\begin{aligned}(I/K)_{i,t} = {} & \alpha + \gamma Voil_{t-1} + \rho_1\, (Voil \times TQ_i)_{t-1} \\ & + \rho_2 \left(Voil \times high_{oil}\right)_{t-1} + \rho_3 \lambda_2 \left(Voil \times TQ_i \times high_{oil}\right)_{t-1} \\ & + \beta_1\, TQ_{i,t-1} + \beta_2 (CF/K)_{i,t-1} + \beta_3 (S/K)_{i,t} + \delta Z_{i,t} \\ & + \mu_i + \theta_t + \varepsilon_{i,t}\end{aligned} \tag{4}$$

Finally, in order to further analyze the possible asymmetry in the impact of the uncertainty of oil prices, we divided the companies into two groups, that is, firms with good investment opportunities and firms with bad investment opportunities, and then conducted a comparative analysis of the two samples.

Inefficient Investment Analysis Model

In order to verify the effect of oil price uncertainty, we further analyze its impact on the inefficient investment of enterprises. The empirical model to identify its influence on inefficiency investment is set as:

$$\begin{aligned}\text{Ineff\_inv}_{i,t} = {} & \alpha + \gamma Voil_{t-1} + \alpha_1 (CF/K)_{i,t-1} + \alpha_2 ROA_{i,t} \\ & + \delta Z_{i,t} + \mu_i + \theta_t + \varepsilon_{i,t}\end{aligned} \tag{5}$$

$Ineff_{inv_{i,t}}$ stands for the inefficient investments, ROA is the return of total assets. The fixed effect model is implemented to estimate Equation (5).

Finally, we examine the impact of oil price uncertainty on corporate over-investment. The explanatory variables in the model are replaced by dummy variable, Over_Inv, which is equal to 1 if the enterprise is overinvested, otherwise it is equal to 0. Logit regression is used to estimate the following equation.

$$\begin{aligned}\text{Over\_Inv}_{it} &= \alpha + \gamma Voil_{t-1} + \rho(Voil \times high_{oil})_{t-1} \\ &+ \beta(CF/K)_{i,\,t-1} + \varepsilon_{i,t}\end{aligned} \tag{6}$$

DATA AND VARIABLES

Sample Selection

The information from Sina finance (http://finance.sina.com.cn/) are used to collect the renewable energy listed firms of China, similar to the methods of Broadstock et al. (2012), Zhang et al. (2016), and Cao et al. (2019). A total of 113 firms in solar, wind and biomass sectors that listed during the period from 1990 to 2017 are identified. The data used in the empirical analysis part is the unbalanced panel from 2000 to 2017. All the financial data used was collected from the RESSET financial research database (www.resset.cn).

Variable Definition

(1) Oil price uncertainty

The uncertainty of oil price is usually measured by two methods. One is the standard deviation of daily return of oil prices, and the other is the GARCH model. Following Sadorsky (2008) and Henriques and Sadorsky (2011), the annual oil price volatility ($Voil_t$) can be measured as:

$$Voil_t = \sqrt{\frac{1}{N-1}\sum_{t=1}^{N}(r_t - E(r_t))^2} \tag{7}$$

where r_t is the daily return of international oil price ($r_t = 100 \times \ln(P_t/P_{t-1})$, P_t is the daily oil price, N is the number of trading days in the year. Brent crude oil prices from the U.S Energy Information Agency are used in this paper.

Following Hamilton (2003), Sadorsky (2006), and Yoon and Ratti (2011), oil price uncertainty can be calculated using the GARCH (1, 1) model as shown blow:

$$r_t = \alpha + \sum_{i=1}^{m}\beta_i r_{t-i} + e_t \tag{8}$$

$$\sigma_t = \rho + \gamma e_{t-1}^2 + \delta\sigma_{t-1}^2 \tag{9}$$

According to the Akaike's Information Criterion (AIC), we begin with the fifth lag. the daily crude oil returns' volatilities in a particular year are estimated firstly, and then obtain their arithmetic mean, $Hoil_t$, as the indicator of international oil price annual uncertainty.

The daily Brent crude oil prices and daily crude oil return volatility are plotted in **Figure 2**. It shows that before 2005 and from 2008 to 2009, the volatility of oil prices was higher. While, during 2010–2014, oil prices were higher, but their volatility was relatively low. After entering the low oil price stage in 2015, the uncertainty of oil prices increased.

In the empirical analysis part, we mainly uses the volatility calculated by the first method as a measure of oil price

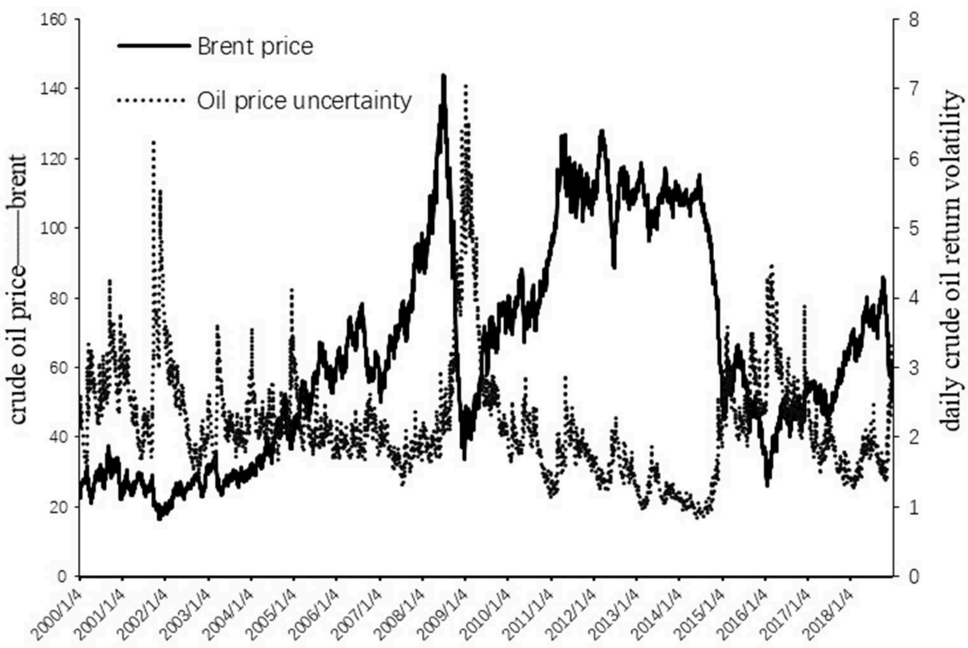

FIGURE 2 | The price and volatility of international crude oil.

uncertainty, and the volatility calculated by the GARCH model is used for robustness test.

(2) Dependent variable

The investment expenditures (I) used in this paper is measured as cash outflow for purchase of new fixed assets and other long-term assets minus any net cash recovered from the disposal of fixed assets as shown in the cash flow statement. Investment dividing by fixed assets at the beginning of the year, I/K, are used as the dependent variable.

We plot the annual average of the investment capital ratio (I/K) across sample firms in **Figure 3**. It shows that investment was booming during the period from 2000 to 2002, and it has shown obvious up and down fluctuations since 2003. Since 2014, the investment ratio has shown a clear upward trend. At the same time, international oil prices have begun to enter a low price and a small fluctuation range as shown in **Figure 1**.

In addition to the investment capital ratio (I/K), we also use inefficiency investment indicators as explanatory variables. In order to build this variable, we construct an expected investment model based on Biddle et al. (2009) and Gomariz and Ballesta (2014). The expected investment model is written as:

$$(I/K)_{it} = \rho_0 + \rho_1 sale\_growth_{it-1} + \epsilon_{it} \qquad (10)$$

where sales_growth$_{t-1}$ is the growth rate of sales in the previous year. This model is estimated for each year, and a positive (negative) residual indicates over- (under-) investment. We define the variable inefficiency investment (Ineff_inv) as the absolute value of the residual, which stands for the departure from the normal investment level. If the residual of the above regression is greater than zero, it can be considered that the enterprise has excessive investment in that year according to (Wang et al., 2016a). Therefore, we define the dummy variable of over-investment (Over_Inv) based on whether the residual is greater than zero or less than or equal to zero. Over_Inv is equal to 1 if ϵ_{it} is greater than zero, otherwise it equals to 0.

(3) Control variables

The control variables include cash flow capital ratio (CF/K), Tobin's Q (TQ), sale's capital ratio (S/K), leverage (lev.), firm size (size), administrative expense ratio (Adm., scaled by sales,), firm age (age), returns on total assets (ROA), State-owned shareholding ratio (stateshrp), and the shareholding ratio of the largest shareholder (owncon1).

Capital stock (K) is equal to the book value of fixed assets net of depreciation, Cash flow (CF) is calculated as the sum of the depreciation of fixed assets plus the operating profit before payments of tax, interest and preference dividends, which is consistent with Bond and Meghir (1994). Tobin's Q (TQ) is defined as the ratio of firms' total market value to total assets. The construction of these variables are similar to that of Chen et al. (2013) and Zhang et al. (2016).

The median value of Tobin's Q based on the average value of each enterprise in all years is used to distinguish whether a company has good investment opportunities or bad investment opportunities. That is, a company will be assigned to the group with good investment opportunities if the company's annual average for Tobin Q is greater than the median above, otherwise it is divided into the group with poor investment opportunities.

Descriptive Statistics

Thestatistics of main variables are summarized in **Table 1**. The continuous variables, I/K, CF/K, Sale/K, TQ, are winsorized at the 1st and 99th percentiles before they are used in the empirical analysis. It shows that the mean of firms' investment capital ratio is 0.5902, and the maximum and minimum values are 7.5618 and 0.0112 respectively. The average value of Tobin's Q is >1, which is 2.1367. The average value of the sales capital ratio is 7.0404, also very high. The average asset-liability ratio of the company is 48.81%. From the average value, management expenses account

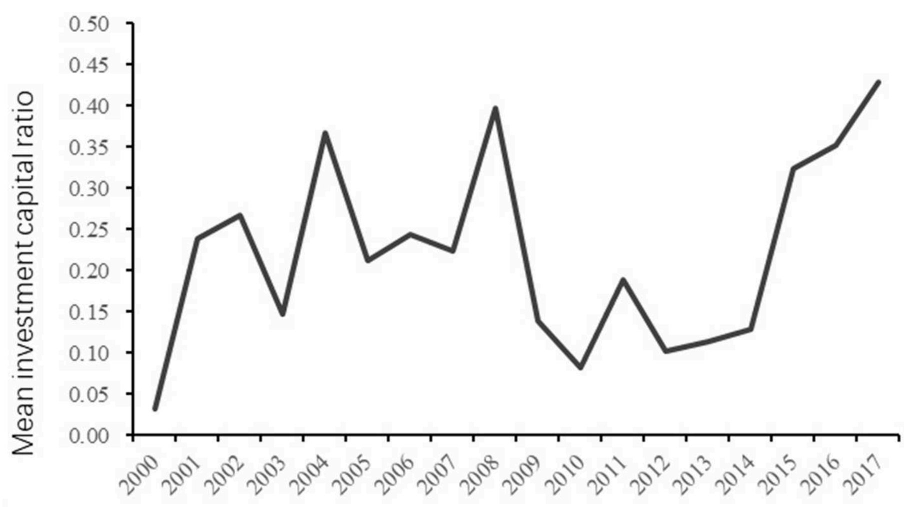

FIGURE 3 | Trend of corporate investment (annual average scaled by capital stock, I/K).

TABLE 1 | Descriptive statistics on the main variables.

Variable	Description	Obs.	Mean	SD.	Min	Max
I/K	Investment capital (fixed assets) ratio	1114	0.5902	0.9451	0.0112	7.5618
TQ	Tobin's Q, the ratio of the market value to replacement cost	974	2.1367	1.0808	0.8873	6.6339
CF/K	Cash flows scaled by fixed assets	1114	−0.9846	2.6252	−21.027	2.3284
Sale/K	Sales capital ratio	1115	4.5554	7.0404	0.1838	56.994
Sale_ growth	The growth rate of sales	1137	0.1722	0.3368	−1.9043	3.2188
Lev	Leverage rate, total debt to total assets ratio	1137	0.4881	0.2122	0.0395	2.8409
Size	Natural logarithm of total assets	1137	22.016	1.3423	18.9111	26.337
Adm.	The administrative expense ratio, administrative expenses as a percentage of sales	1135	0.0879	0.0800	0.0019	1.6678
ROA	Net profit divide the average value of total assets	1137	4.4237	7.8495	−56.048	87.736
Owncon1	Proportion of the first largest shareholder (%)	1110	0.3649	0.1766	0.0362	0.962
Stateshrp	Shareholding ratio of state-owned shares	1110	10.949	21.587	0.0000	97.873
Ineff_inv	Inefficiency investment: the absolute value of a deviation from normal investment level	920	0.4586	0.6709	0.0002	6.4001
Over_inv	Dummy variable, =1 if deviation from normal investment level is positive, otherwise = 0	920	0.2837	0.4510	0	1

TABLE 2 | The impact of oil price volatility on investment.

	(0)		(1)		(2)	
	OLS		Fixed effect		DPD (SYS-GMM)	
Variables	Coeff.	Sd.	Coeff.	Sd.	Coeff.	Sd.
$(I/K)_{t-1}$	-	-	-	-	0.3586***	(0.1068)
Voil $_{t-1}$	−0.3905*	(0.2298)	−0.4470*	(0.2719)	−0.5771**	(0.2479)
TQ_{it-1}	0.1297***	(0.0357)	0.1187***	(0.0430)	0.2105**	(0.1007)
$(CF/K)_{it-1}$	−0.0320**	(0.0160)	−0.0198	(0.0164)	0.0464	(0.0333)
(Sale/K) $_{it}$	0.0379**	(0.0151)	0.0457***	(0.0151)	0.0833***	(0.0262)
(Sale/K) $_{it-1}$	0.0037	(0.0117)	0.0026	(0.0105)	−0.0210	(0.0257)
$Ln(Brent)_{t-1}$	−0.2334	(0.9925)	−0.1868	(0.4179)	−0.4311	(0.3017)
Lev $_{it-1}$	−0.1617	(0.1079)	−0.4556***	(0.1614)	0.0618	(0.1872)
Age $_{it}$	−0.0169***	(0.0059)	−0.0371	(0.0703)	−0.0131**	(0.0065)
Size $_{it}$	0.0760**	(0.0373)	0.1239**	(0.0589)	0.1240***	(0.0461)
Adm $_{it}$	−0.1212	(0.2340)	0.6147**	(0.2588)	−0.1056	(0.2311)
$Owncon1_{it}$	−0.0119	(0.2159)	0.1575	(0.3252)	−0.2262	(0.2271)
$Stateshrp_{it}$	−0.0007	(0.0014)	0.0018	(0.0012)	−0.0001	−0.001
Year dummies	Yes		Yes		Yes	
Obs.	774		774		765	
NO. of firms	103		103		103	
R^2_adj.	0.213		0.222			
Sargan P					0.146	
AR1 P					0.0141	
AR2 P					0.125	

*The independent variable is I/K, Pool OLS, Fixed effect and system-GMM methods are used are used in model 0,1, and 2, respectively; Robust standard errors in parentheses, ***p < 0.01, **p < 0.05, *p < 0.1.*

for 8% of sales, the lowest is 0.19%. The mean of Ineff_inv is 0.4586. In samples with inefficient investment observations, about 28% of enterprises have over-investment.

EMPIRICAL RESULTS

Impact of Oil Uncertainty on Investment

The benchmark regression results are shown in **Table 2**. Models (0) to model (2) are the results of regression using three methods: pooled ordinary least squares method, fixed effect regression, and dynamic panel system-GMM. As shown in **Table 2**, no matter which model is used, the results obtained indicate that increasing oil price uncertainty will significantly reduce renewable firms' investment, and this result is consistent with previous studies. And the coefficients of investment opportunities (TQ), Sales ratio (Sale/K), firm size (Size) are all significantly positive in the three models. We also add the natural logarithm of Brent oil price variable, Lnbrent, into the regression equation and find that it has no significant effect on investment.

Asymmetric Effect of Oil Uncertainty on Investment

(1) Possible asymmetry tests when oil prices rise or fall

In order to verify whether there is a possible asymmetric effect, the dummy variable of whether the price of oil has risen, $Dpov_{oil}$ (= 1 when the oil price rises, otherwise it = 0), is introduced here. The empirical results are shown in **Table 3** below.

Based on the benchmark regression, in model (3), the interaction term between the dummy variable of whether oil price rise and oil price volatility, $(Voil{*}Dpov_{oil})_{t-1}$, is added. It can

TABLE 3 | The asymmetric effect of oil price uncertainty on investment (Oil price rise or fall).

	Total sample				Low TQ		High TQ	
Variables	**(3)**	**(4)**	**(5)**	**(6)**	**(3a)**	**(4a)**	**(3b)**	**(4b)**
Voil $_{t-1}$	−0.3038*	−0.3518	−0.3966*	−0.2995	−0.1269	0.1230	−0.9244**	−1.7570**
	(0.1670)	(0.2268)	(0.2118)	(0.2083)	(0.1553)	(0.2434)	(0.4236)	(0.7109)
$(Voil\ {*}Dpov_{oil})_{t-1}$	0.0358	−0.1304			0.0079	−0.0365	−0.0062	−0.6521*
	(0.0594)	(0.1154)			(0.0561)	(0.1398)	(0.1195)	(0.3538)
$(Voil\ {*}TQ)_{t-1}$		−0.0252		−0.0312		−0.1272**		0.0188
		(0.0378)		(0.0371)		(0.0526)		(0.0687)
$(Voil\ {*}TQ{*}\ Dpov_{oil})_{t-1}$		0.0546				0.0207		0.1200*
		(0.0343)				(0.0452)		(0.0671)
$(Voil\ {*}Dnetpov_{oil})_{t-1}$			0.0398	−0.0802				
			(0.0660)	(0.1325)				
$(Voil\ {*}TQ{*}Dnetpov_{oil})_{t-1}$				0.0372				
				(0.0325)				
TQ_{it-1}	0.1187***	0.1245	0.1187***	0.1670**	0.1477**	0.4094***	0.1164*	−0.0050
	(0.0430)	(0.0771)	(0.0430)	(0.0693)	(0.0715)	(0.1508)	(0.0663)	(0.1246)
$(CF/K)_{it-1}$	−0.0198	−0.0169	−0.0198	−0.0190	−0.0187	−0.0170	−0.0186	−0.0121
	(0.0164)	(0.0159)	(0.0164)	(0.0161)	(0.0116)	(0.0118)	(0.0212)	(0.0202)
$(Sale/K)_{it}$	0.0457***	0.0464***	0.0457***	0.0461***	0.0452*	0.0463*	0.0496**	0.0513**
	(0.0151)	(0.0152)	(0.0151)	(0.0151)	(0.0231)	(0.0238)	(0.0212)	(0.0214)
$(Sale/K)_{it-1}$	0.0026	0.0009	0.0026	0.0013	0.0140	0.0133	0.0004	−0.0003
	(0.0105)	(0.0112)	(0.0105)	(0.0109)	(0.0172)	(0.0162)	(0.0159)	(0.0173)
$Ln(Brent)_{t-1}$	−0.3491	−0.5408	−0.5118	−0.4613	−0.1541	−0.0563	−1.2723*	−2.6786**
	(0.2852)	(0.3503)	(0.3649)	(0.3560)	(0.2499)	(0.3479)	(0.7174)	(1.1062)
Lev_{it-1}	−0.4556***	−0.4544***	−0.4556***	−0.4618***	−0.5569**	−0.5572**	−0.3593	−0.3779*
	(0.1614)	(0.1591)	(0.1614)	(0.1640)	(0.2572)	(0.2418)	(0.2255)	(0.2176)
Age_{it}	0.0056	0.0071	0.0112	0.0062	−0.0010	−0.0102	0.0418	0.0808
	(0.0177)	(0.0185)	(0.0212)	(0.0201)	(0.0141)	(0.0158)	(0.0452)	(0.0522)
$Size_{it}$	0.1239**	0.1328**	0.1239**	0.1312**	0.1088	0.1143*	0.1978*	0.2227*
	(0.0589)	(0.0572)	(0.0589)	(0.0576)	(0.0652)	(0.0619)	(0.1136)	(0.1118)
Adm_{it}	0.6147**	0.6696**	0.6147**	0.6472**	0.6134*	0.6614**	0.8583	0.9506
	(0.2588)	(0.2827)	(0.2588)	(0.2752)	(0.3140)	(0.3124)	(0.7053)	(0.7210)
$Owncon1_{it}$	0.1575	0.0812	0.1575	0.1135	0.0450	0.0133	0.5626	0.2590
	(0.3252)	(0.3031)	(0.3252)	(0.3164)	(0.2546)	(0.2409)	(0.8498)	(0.7469)
$Stateshrp_{it}$	0.0018	0.0016	0.0018	0.0017	0.0003	0.0002	0.0052*	0.0055*
	(0.0012)	(0.0012)	(0.0012)	(0.0012)	(0.0013)	(0.0012)	(0.0031)	(0.0031)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.								
NO. of firms	103							
R^2_adj.	0.222	0.229	0.222	0.224	0.191	0.198	0.229	0.245

*The independent variable is I/K, fixed effect regression method is used; Robust standard errors in parentheses, ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. The net oil price increase are defined as* $NetP^{+}_{oil,t} = Max\ (0, P_{oil,t} - max(P_{oil,t-1}, P_{oil,t-2}, P_{oil,t-3}))$.

be found that the uncertainty of oil prices still has a significant negative impact on investment, but the coefficient of the interaction term $(Voil^{*}Dpov_{oil})_{t-1}$, is not significant, indicating that there is no significant asymmetry in this effect when oil prices rise or fall.

In model (4), we further add the interaction term of oil price volatility and Tobin Q, $(Voil^{*}TQ)_{t-1}$, and the interaction term of high oil price dummy variable, Tobin Q and oil price uncertainty $(Voil^{*}TQ^{*}Dpov_{oil})_{t-1}$, in the regression. Although the coefficients for $(Voil^{*}Dpov_{oil})_{t-1}$ and $(Voil^{*}TQ)_{t-1}$ are negative, they are not significant. The coefficients and statistical significance of other variables are all consistent with the results of model (1).

In models (5) and (6), we used a net oil price change indicator to measure the rise or fall in oil prices. That is, we compare the current oil price with the price of the past 3 years, if the current oil price is higher than the highest oil price in the past 3 years, it is defined as the net increase in oil price, corresponding net oil price increase dummy variable, $Dnetpov_{oil}$, is equal to 1, otherwise it equals to zero. The results of these two regressions are basically consistent with models (3) and (4), again indicating that in the entire sample, here is no asymmetry in the impact of oil price uncertainty on investment when prices rise or fall.

In the right four columns of **Table 3**, we further consider another possible asymmetry, that is, different companies may have different investment behaviors when they face uncertainties

TABLE 4 | The asymmetric effect of oil price uncertainty on investment (High or low oil prices).

	Total sample		Low TQ		High TQ	
Variables	**(7)**	**(8)**	**(7a)**	**(8a)**	**(7b)**	**(8b)**
$Voil_{t-1}$	−0.4082*	−0.4101*	−0.1499*	0.1183	−0.9063	−1.1729*
	(0.2243)	(0.2228)	(0.0865)	(0.1568)	(0.6796)	(0.6556)
$(Voil\ {}^{*}high_{oil})_{t-1}$	0.1931	−0.0262	0.1733	0.0629	0.7720*	0.0907
	(0.2706)	(0.2811)	(0.3254)	(0.2950)	(0.3899)	(0.6526)
$(Voil\ {}^{*}TQ)_{t-1}$		0.0143		−0.1307**		0.1131
		(0.0512)		(0.0562)		(0.0848)
$(Voil\ {}^{*}TQ^{*}\ high_{oil})_{t-1}$		0.0775		−0.0031		0.1805*
		(0.0492)		(0.0571)		(0.0905)
TQ_{it-1}	0.1187***	0.0387	0.1477**	0.4406***	0.1164*	−0.2564
	(0.0430)	(0.1265)	(0.0715)	(0.1398)	(0.0663)	(0.2186)
$(CF/K)_{it-1}$	−0.0198	−0.0159	−0.0187	−0.0178	−0.0186	−0.0075
	(0.0164)	(0.0154)	(0.0116)	(0.0119)	(0.0212)	(0.0194)
$(Sale/K)_{it}$	0.0457***	0.0468***	0.0452*	0.0462*	0.0496**	0.0496**
	(0.0151)	(0.0152)	(0.0231)	(0.0238)	(0.0212)	(0.0203)
$(Sale/K)_{it-1}$	0.0026	0.0008	0.0140	0.0144	0.0004	0.0015
	(0.0105)	(0.0112)	(0.0172)	(0.0168)	(0.0159)	(0.0165)
$Ln(Brent)_{t-1}$	0.0373	0.2684	−0.0690	0.1892	−1.3393	−0.4940
	(0.7360)	(0.7488)	(0.8321)	(0.8183)	(1.0880)	(1.6083)
Lev_{it-1}	−0.4556***	−0.4441***	−0.5569**	−0.5589**	−0.3593	−0.3778
	(0.1614)	(0.1659)	(0.2572)	(0.2456)	(0.2255)	(0.2383)
Age_{it}	−0.0101	−0.0213	−0.0045	−0.0184	0.0445	0.0088
	(0.0291)	(0.0288)	(0.0337)	(0.0327)	(0.0350)	(0.0532)
$Size_{it}$	0.1239**	0.1309**	0.1088	0.1122*	0.1978*	0.2030*
	(0.0589)	(0.0582)	(0.0652)	(0.0622)	(0.1136)	(0.1211)
Adm_{it}	0.6147**	0.6071**	0.6134*	0.6510**	0.8583	0.8631
	(0.2588)	(0.2625)	(0.3140)	(0.3082)	(0.7053)	(0.7153)
$Owncon1_{it}$	0.1575	0.1106	0.0450	0.0163	0.5626	0.2175
	(0.3252)	(0.3128)	(0.2546)	(0.2516)	(0.8498)	(0.7713)
$Stateshrp_{it}$	0.0018	0.0016	0.0003	0.0003	0.0052*	0.0059*
	(0.0012)	(0.0012)	(0.0013)	(0.0012)	(0.0031)	(0.0030)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	774	774	440	440	334	334
NO. of firms	103	103	47	47	56	56
R^2_adj.	0.222	0.230	0.191	0.197	0.229	0.256

*The independent variable is I/K, fixed effect regression method was used; Robust standard errors in parentheses, ***p < 0.01, **p < 0.05, *p < 0.1.*

in oil prices. Based on the average Tobin Q value of each company during the observation period, we divide the total sample into two sub-samples: companies with poor investment opportunities and companies with good investment opportunities. The division criterion is whether the average TQ of the enterprise is less than or greater than the median value of firms' average annual TQ. Based on these two subsamples, we performed the regression again, according to the design of Equation 3. The results of companies with poor investment opportunities are shown in models (3a) and (4a), and the results of companies with better investment opportunities are shown in models (3b) and (4b). The results show that among renewable energy companies with poor investment opportunities, the coefficient of the variable $(Voil^*TQ)_{t-1}$ is significantly negative, and other variables related to oil prices uncertainty are not significant, which indicates that increasing of oil prices uncertainty will not directly reduce the company's investment, but will indirectly reduce the company's investment by reducing the investment-investment opportunity sensitivity coefficient. However, this indirect impact does not exist in renewable energy companies with better investment opportunities.

The regression results of (3b) and (4b) further show that the coefficients of Voil $_{t-1}$ and $(Voil^*Dpov_{oil})_{t-1}$ are significantly negative, and the coefficient of the interaction terms $(Voil^*TQ^*Dpov_{oil})_{t-1}$, is significantly positive. It reveals that the oil price volatility has a significant inhibitory effect on the investment of renewable energy companies with better investment opportunities, and this effect is more obvious when the oil price rises, but if the oil price volatility increases when the oil price rises, it will also increase corporate investment-investment opportunities sensitivity coefficient, which means that it can promote enterprises to improve investment efficiency to a certain extent. In addition, the results of several control variables also differ in the two subsamples, for example, in the sub-sample with better investment opportunities, the oil price level variable, lnbrent, has a significant negative impact on investment, and the state-owned shareholding proportion coefficient is significantly positive, but in the other sub-sample, both coefficients are not significant. However, the debt ratio, lev_{t-1}, has a significant negative impact on the investment of companies with poor investment opportunities.

(2) Possible asymmetric tests when oil prices are higher or lower

The data description of the oil price and oil price volatility in **Figure 2** shows that when the oil prices are at a high level or a low level, the volatilities are different. We then analyze whether there is a third type of asymmetry, that is, whether the impact of oil price volatility on corporate investment when oil prices are higher is different from the effect when oil prices are lower. The results are given in **Table 4**.

In model (7), it shows the coefficient of oil price volatility is still significantly negative, however, the interaction term between the oil prices uncertainty and whether the price is higher $(Voil^*high_{oil})_{t-1}$, is not significant. Consistent with Model 4 in **Table 3**, two other interaction terms $(Voil^*TQ)_{t-1}$ and $(Voil^*TQ^*high_{oil})_{t-1}$ are added here, but they are also not significant, indicating that when the oil price is high or low in the entire sample, there is no asymmetry in the impact of oil price uncertainty on corporate investment.

Here, the entire sample is also divided into two groups of companies with poor investment opportunities and companies with better investment opportunities. We find that the oil price volatility has a significant negative impact on the investment of companies with poor investment opportunities in model (7a), with a coefficient of −0.1499, by comparison. The results of model (8a) show that an increase in oil price volatility will reduce the investment efficiency of such enterprises because the coefficient of $(Voil^*TQ)_{t-1}$ is significantly negative, Which is −0.1307.

In the enterprise with better investment opportunities, the coefficient of the variable $(Voil^*highoil)_{t-1}$ in the model (8a) is significantly positive, indicating that the enterprise will increase investment when the oil price is high. After adding the variables $(Voil^*TQ)_{t-1}$ and $(Voil^*TQ^*highoil)_{t-1}$ to the model (8b), the coefficient of variable $(Voil^*highoil)_{t-1}$ is no longer significant, but at this time the variable $(Voil^*TQ^*highoil)_{t-1}$ is significantly positive. The results indicate that there is asymmetry

TABLE 5 | The impact of oil price uncertainty on inefficiency investment.

Variables	(9)	(10)	(11)	(12)
Voil $_{t-1}$	0.1158**	−0.0281	0.0063	0.1143**
	(0.0552)	(0.0906)	(0.0347)	(0.0462)
$(Voil\ ^*Dpov_{oil})_{t-1}$		0.1321***		0.1534***
		(0.0488)		(0.0458)
$(Voil\ ^*high_{oil})_{t-1}$			0.1143***	0.2826***
			(0.0388)	(0.0827)
$(Voil\ ^*Dpovoil^*highoil)_{t-1}$				−0.2634***
				(0.0844)
$(CF/K)_{it-1}$	−0.0097	−0.0097	−0.0097	−0.0097
	(0.0122)	(0.0122)	(0.0122)	(0.0122)
$Ln(Brent)_{t-1}$	0.3229***	0.1370	-	-
	(0.1097)	(0.1598)	-	-
Lev $_{it-1}$	−0.1671	−0.1671	−0.1671	−0.1671
	(0.1244)	(0.1244)	(0.1244)	(0.1244)
ROA $_{it-1}$	0.0014	0.0014	0.0014	0.0014
	(0.0040)	(0.0040)	(0.0040)	(0.0040)
Size $_{it}$	−0.0032	−0.0032	−0.0032	−0.0032
	(0.0484)	(0.0484)	(0.0484)	(0.0484)
Age $_{it}$	−0.0337***	−0.0049	−0.0245*	0.0015
	(0.0123)	(0.0129)	(0.0133)	(0.0118)
$Owncon1_{it}$	−0.4739	−0.4739	−0.4739	−0.4739
	(0.3973)	(0.3973)	(0.3973)	(0.3973)
$Stateshrp_{it}$	−0.0008	−0.0008	−0.0008	−0.0008
	(0.0012)	(0.0012)	(0.0012)	(0.0012)
Year dummies	Yes	Yes	Yes	Yes
Obs.	896	896	896	896
No. of firms	110	110	110	110
R^2_adj.	0.107	0.107	0.107	0.107

*The independent variable is Ineff_Inv, fixed effect regression method was used; Robust standard errors in parentheses, ***p < 0.01, **p < 0.05, *p < 0.1.*

in the impact of oil price uncertainty in companies with better investment opportunities, and the main reason is that if oil price volatility increases when oil prices are high, such companies will increase investment efficiency.

Impact of Oil Price Uncertainty on Inefficiency Investment

The above empirical results show that When oil prices rise, and when oil prices are at a high level, oil price uncertainty can improve corporate investment efficiency, but it mainly exists in enterprises with better investment opportunities; oil price volatility will reduce the investment efficiency of enterprises with poor investment opportunities. In order to verify these results, we replace the explanatory variables with inefficiency investments (Ineff_Inv), and further analyze the impact of oil price uncertainty on corporate investment. **Table 5** reports the results obtained from the fixed-effect regression model.

It shows that oil price uncertainty has significant positive impact on firms' inefficiency investment in model (9), however, after considering the possible asymmetry in model (10), we find that coefficient of the interaction term between the dummy variable of positive oil price growth and oil price volatility $(\text{Voil}^*\text{Dpov}_{\text{oil}})_{t-1}$, is significantly positive, indicating the increase in oil price uncertainty will increase the company's inefficient investment level when oil prices are rising. The interaction term in model (11) is replaced by $(\text{Voil}^*\text{highoil})_{t-1}$, and its coefficient is also significantly positive, which is 0.1143. The results of these two regressions show that the uncertainty of oil prices has an asymmetric effect on the inefficient investment behavior of renewable energy companies. In model (12), we simultaneously add the two interaction terms of oil price uncertainty and rising oil price, oil price uncertainty and higher oil price to the regression equation, the result remains essentially the same.

In **Table 6**, we further adjust the explanatory variable to a dummy variable, Over_Inv, that is, whether the company has overinvestment, and the panel logit regression method is used. The explanatory variables in models (13)–(15) in **Table 6** are completely consistent with the variables in models (10)–(12) in **Table 5**. The empirical results here show that, compared with the decline in oil prices, the increase in the uncertainty of crude oil prices when the oil price rises will significantly reduce the possibility of increasing overinvestment, but it also means that the probability of underinvestment will increase. Similarly, the increase in crude oil price uncertainty when oil prices are higher than when oil prices are lower will also significantly reduce the likelihood of companies overinvesting.

TABLE 6 | The impact of oil price uncertainty on over-investment.

	Total sample			Low TQ			High TQ		
Variables	**(13)**	**(14)**	**(15)**	**(13a)**	**(14a)**	**(15a)**	**(13b)**	**(14b)**	**(15b)**
Voil_{t-1}	−1.0155	0.4003	−1.0155	−1.5799	0.1788	−1.5799	0.1656	0.9442	0.1656
	(0.9937)	(0.6909)	(0.9937)	(1.1982)	(0.8345)	(1.1982)	(1.9869)	(1.2539)	(1.9869)
$(\text{Voil}^*\text{Dpov}_{\text{oil}})_{t-1}$	−0.9657**		−0.9657**	−1.2609**		−1.2609**	−0.4374		−0.4374
	(0.4409)		(0.4409)	(0.5352)		(0.5352)	(0.8534)		(0.8534)
$(\text{Voil}^*\text{high}_{\text{oil}})_{t-1}$		-7.3087**	−18.4918***		−8.2258**	−22.4064***		−3.3904	−8.8633
		(3.5476)	(6.2474)		(4.1016)	(7.4329)		(7.4777)	(12.8566)
$(\text{Voil}^*\text{Dpov}^*_{\text{oil}}\text{highoil})_{t-1}$			4.4851***			5.3733***			2.5233
			(1.5029)			(1.8154)			(3.0724)
$(\text{CF/K})_{it-1}$	−0.0983**	−0.0944**	−0.0983**	−0.2888***	−0.2555**	−0.2888***	−0.0505	−0.0504	−0.0505
	(0.0394)	(0.0390)	(0.0394)	(0.1105)	(0.1031)	(0.1105)	(0.0444)	(0.0444)	(0.0444)
Ln(Brent)_{t-1}	12.3062***	5.1223	12.3062***	15.1671***	5.9099	15.1671***	4.7155	1.3125	4.7155
	(4.7224)	(3.2076)	(4.7224)	(5.6950)	(3.6979)	(5.6950)	(9.3554)	(6.6742)	(9.3554)
Lev_{it-1}	−1.9549**	−1.8362**	−1.9549**	−1.1165	−0.8967	−1.1165	−2.0713*	−2.0567*	−2.0713*
	(0.8246)	(0.8154)	(0.8246)	(1.2328)	(1.2058)	(1.2328)	(1.2064)	(1.2028)	(1.2064)
ROA_{it-1}	0.0215	0.0200	0.0215	0.0112	0.0102	0.0112	0.0122	0.0116	0.0122
	(0.0150)	(0.0150)	(0.0150)	(0.0295)	(0.0299)	(0.0295)	(0.0187)	(0.0186)	(0.0187)
Size_{it}	0.3020	0.3714*	0.3020	0.0772	0.2345	0.0772	0.7698*	0.7775**	0.7698*
	(0.2277)	(0.2252)	(0.2277)	(0.3225)	(0.3139)	(0.3225)	(0.3960)	(0.3962)	(0.3960)
Owncon1_{it}	−1.7177	−1.8468	−1.7177	−1.1370	−1.4991	−1.1370	−3.1756	−3.2009	−3.1756
	(1.4359)	(1.4243)	(1.4359)	(1.7911)	(1.7584)	(1.7911)	(2.8300)	(2.8248)	(2.8300)
Stateshrp_{it}	0.0143**	0.0141**	0.0143**	0.0082	0.0084	0.0082	0.0278**	0.0276**	0.0278**
	(0.0070)	(0.0069)	(0.0070)	(0.0089)	(0.0088)	(0.0089)	(0.0122)	(0.0122)	(0.0122)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	776	776	776	441	441	441	335	335	335
No. of firms	86	86	86	41	41	41	45	45	45

*The independent variable is Over_Inv, Logit regression method with fixed effect was used; Robust standard errors in parentheses, ***p < 0.01, **p < 0.05, *p < 0.1.*

Once again we divide the sample into two sub-samples. Models (13a) to (15a) are the results of companies with poor investment opportunities, and models (13b) to (15b) are the results of companies with good investment opportunities. The results of the sub-samples reveal that the above-mentioned effects of oil price uncertainty on corporate over-investment mainly occur in renewable energy companies with lower investment opportunities. Since in our sample, the sum of over-investment and under-investment dummy variables is equal to 1, this result also means that an increase in oil price volatility may increase the probability of underinvestment in companies with lower investment opportunities. This is also consistent with the significant impact of variable $(\text{Voil}^*\text{TQ})_{t-1}$ found in model (4a) and (8a) on the investment of low investment opportunity firms.

Robustness Tests

To ensure the robustness of the results, we use the alternative measure of oil price uncertainty, $Hoil_t$. We also adjusted the leverage ratio (Lev) in the control variable to the debt-to-capital ratio (D/K), which is defined as the sum of short-term loan, long-term loans and bonds payable on the balance sheet deflated by fixed assets at the beginning of the year. The results are highly consistent with the empirical results in **Tables 2–6** above.

CONCLUSION

China's central government has issued a number of policies since 2005, correspondingly, investment in the renewable energy sector has increased rapidly. However, such an investment is risky. One of the factors that cannot be ignored is the volatility of oil prices and the resultant uncertainties in macroeconomic and monetary policy.

In this paper, we examine the response of corporate investment to the uncertainty of oil prices, especially considering the possible asymmetric effects. The most obvious finding to emerge from this study is that the increasing in oil prices uncertainty have a significant negative impact on investment in China's renewable energy companies, and it significantly affects corporate investment efficiency. Asymmetry test results show that, from the total sample, no matter whether the oil price rises or falls, or the oil price is higher or lower, these factors do not have a significant impact on how the uncertainty of oil prices affects corporate investment, that is, there is no asymmetry. However, after grouping companies according to the average investment opportunity, we found that for companies with better investment opportunities, when oil prices are at a higher level, that is, greater than 75 US dollars per barrel, the variable of oil price uncertainty has a significant positive impact on corporate investment, because at this time such companies tend to improve investment efficiency. This study also revealed that oil price uncertainty reduces the investment efficiency of companies with poor investment opportunities, and the analysis of non-efficiency investment also verifies it, that is, this kind of uncertainty increases the inefficiency investment level of enterprises with poor investment opportunities and improves the probability of under-investment in such companies. The results related to firm characteristics has shown that sale capital ratio, firm size, firm age and administrative expense ratio are also crucial in the determination of renewable energy firms' investment.

Overall, the empirical evidence from this paper support the idea that the impact of oil price uncertainty on the investment of renewable energy companies in China is multi-faceted. For renewable energy entities, oil price volatility implies both risk and opportunities. The impact of oil price uncertainty on the investment of renewable energy enterprises in China is affected by whether the oil price is high or low, and whether the investment opportunities of enterprises are good or bad, etc. Therefore, the enterprise managers need to distinguish between different situations to cope with the influence of international oil price uncertainty on investment, to better grasp the investment opportunities and to improve firms' investment efficiency. And, for energy policy makers, the investment response of renewable energy companies in the face of changes in oil prices uncertainty should be considered when formulating oil and other energy policies.

DATA AVAILABILITY STATEMENT

The datasets generated for this study are available on request to the corresponding author.

AUTHOR CONTRIBUTIONS

HC finished the research and writing. PS responsible for data collection. LG works with the other authors for the discussion part.

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REFERENCES

Abel, A. B. (1983). Optimal investment under uncertainty. *Am. Econ. Rev.* 73, 228–233.

Appelbaum, E., and Katz, E. (1986). Measures of risk aversion and comparative statics of industry equilibrium. *Am. Econ. Rev.* 76, 524–529.

Baum, C. F., Caglayan, M., and Talavera, O. (2008). Uncertainty determinants of firm investment. *Econ. Lett.* 98, 282–287. doi: 10.1016/j.econlet.2007.05.004

Baum, C. F., Caglayan, M., and Talavera, O. (2010). On the sensitivity of firms' investment to cash flow and uncertainty. *Oxf. Econ. Pap.* 62, 86–306. doi: 10.1093/oep/gpp015

Beaudry, P., Caglayan, M., and Schiantarelli, F. (2001). Monetary instability, predictability of prices and the allocation of investment: an empirical investigation using UK panel data. *Am. Econ. Rev.* 91, 648–662. doi: 10.1257/aer.91.3.648

Bernanke, B. S. (1983). Irreversibility, uncertainty and cyclical investment. *Q. J. Econ.* 98, 85–106. doi: 10.2307/1885568

Biddle, G. C., Hilary, G., and Verdi, R. S. (2009). How does financial reporting quality relate to investment efficiency? *J. Account. Econ*. 48, 112–131. doi: 10.2139/ssrn.1146536

Bloom, N., Bond, S., and Van Reenen, J. (2007). Uncertainty and investment dynamics. *Rev. Econ. Stud.* 74, 391–415. doi: 10.1111/j.1467-937X.2007.00426.x

Bond, S., and Meghir, C. (1994). Dynamic investment models and the firm's financial policy. *Rev. Econ. Stud*. 61, 197–222. doi: 10.2307/2297978

Broadstock, D. C., Cao, H., and Zhang, D. (2012). Oil shocks and their impact on energy related stocks in China. *Energy Econ.* 34, 1888–1895. doi: 10.1016/j.eneco.2012.08.008

Cao, H., Guo, L., and Zhang, L. (2019). Does oil price uncertainty affect renewable energy firms' investment? Evidence from listed firms in China. *Finance Res. Lett.* doi: 10.1016/j.frl.2019.06.003. [Epub ahead of print].

Chen, A. A., Cao, H., Zhang, D., and Dickinson, D. G. (2013). The impact of shareholding structure on firm investment: evidence from Chinese listed companies. *Pac. Basin Finance J.* 25, 85–100. doi: 10.1016/j.pacfin.2013.08.002

Chen, S., Sun, Z., Tang, S., and Wu, D. (2011). Government intervention and investment efficiency: evidence from China. *J. Corp. Finance* 17, 259–271. doi: 10.1016/j.jcorpfin.2010.08.004

Cheng, D., Shi, X. P., Yu, J., and Zhang, D. Y. (2019). How does the Chinese economy react to uncertainty in international crude oil prices? *Int. Rev. Econ. Finance* 64, 147–164. doi: 10.1016/j.iref.2019.05.008

Dixit, A. K., and Pindyck, R. S. (1994). *Investment Under Uncertainty*. Princeton, NJ: Princeton University Press. doi: 10.1515/9781400830176

Elder, J., and Serletis, A. (2010). Oil price uncertainty. *J. Money Credit Bank.* 42, 1137–1159. doi: 10.1111/j.1538-4616.2010.00323.x

Gomariz, M. F. C., and Ballesta, J. P. S. (2014). Financial reporting quality, debt maturity and investment efficiency. *J. Bank. Finan*. 40, 494–506. doi: 10.1016/j.jbankfin.2013.07.013

Gulen, H., and Ion, M. (2016). Policy uncertainty and corporate investment. *Rev. Financ. Stud.* 29, 523–564. doi: 10.1093/rfs/hhv050

Hamilton, J. D. (2003). What is an oil shock? *J. Econom.* 113, 363–398. doi: 10.1016/S0304-4076(02)00207-5

Henriques, I., and Sadorsky, P. (2011). The effect of oil price volatility on strategic investment. *Energy Econ.* 33, 79–87. doi: 10.1016/j.eneco.2010.09.001

Jiang, L., Kim, J-B., and Pang, L. (2011). Control-ownership wedge and investment sensitivity to stock price. *J. Bank. Finance* 35, 2856–2867. doi: 10.1016/j.jbankfin.2011.03.017

Kellogg, R. (2014). The Effect of uncertainty on investment: evidence from texas oil drilling. *Am. Econ. Rev.* 104, 1698–1734. doi: 10.1257/aer.104.6.1698

Khan, M. K., He, Y., and Akram, U., and Sarwar, S. (2017). Financing and monitoring in an emerging economy: can investment efficiency be increased. *China Econ. Rev.* 45, 62–77. doi: 10.1016/j.chieco.2017.05.012

Lee, K., Kang, W. S., and Ratti, R. A. (2011). Oil price shocks, firm uncertainty, and investment. *Macroecon. Dyn.* 15, 416–436. doi: 10.1017/S1365100511000496

Liao, X. C., and Shi, X. P. (2018). Public appeal, environmental regulation and green investment: evidence from China. *Energy Policy* 119, 554–562. doi: 10.1016/j.enpol.2018.05.020

Liu, X. M. (2013). The value of holding scarce wind resource—a cause of overinvestment in wind power capacity in China. *Energy Policy* 63, 97–100. doi: 10.1016/j.enpol.2013.08.044

McLean, R. D., Zhang, T., and Zhao, M. (2012). Why does the law matter? investor protection and its effects on investment, finance, and growth. *J. Finance* 67, 313–350. doi: 10.1111/j.1540-6261.2011.01713.x

Mohn, K., and Misund, B. (2009). Investment and uncertainty in the international oil and gas industry. *Energy Econ.* 31, 240–248. doi: 10.1016/j.eneco.2008.10.001

Phan, D. H. B., Tran, V. T., and Nguyen, D. T. (2019). Crude oil price uncertainty and corporate investment: new global evidence. *Energy Econ.* 77, 54–65. doi: 10.1016/j.eneco.2018.08.016

Pindyck, R. (1991). Irreversibility, uncertainty and investment. *J. Econ. Lit.* 29, 1110–1148. doi: 10.3386/w3307

Rashid, A. (2011). How does private firms' investment respond to uncertainty? Some evidence from the United Kingdom. *J. Risk Finance* 12, 339–347. doi: 10.1108/15265941111158514

Sadorsky, P. (2006). Modeling and forecasting petroleum futures volatility. *Energy Econ.* 28, 467–488. doi: 10.1016/j.eneco.2006.04.005

Sadorsky, P. (2008). The oil price exposure of global oil companies. *Appl. Finan. Econ. Lett.* 4, 93–96. doi: 10.1080/17446540701537764

Shi, X. P., and Sun, S. Z. (2017). Energy price, regulatory price distortion and economic growth: a case study of China. *Energy Econ.* 63, 261–271. doi: 10.1016/j.eneco.2017.02.006

Wang, Y., Xiang, E., Cheung, A., Ruan, W. J., and Hu, W. (2017). International oil price uncertainty and corporate investment: evidence from China's emerging and transition economy. *Energy Econ.* 61, 330–339. doi: 10.1016/j.eneco.2016.11.024

Wang, Y. Z., Chen, C. R., Chen, L. F., and Huang, Y. S. (2016a). Overinvestment, inflation uncertainty, and managerial overconfidence: firm level analysis of Chinese corporations. *North Am. J. Econ. Finance* 38, 54–69. doi: 10.1016/j.najef.2016.07.001

Wang, Y. Z., Chen, C. R., and Huang, Y. S. (2014). Economic policy uncertainty and corporate investment: evidence from China. *Pac. Basin Finance J.* 26, 227–243. doi: 10.1016/j.pacfin.2013.12.008

Wang, Y. Z., Wei, Y. L., and Song, F. M. (2016b). Uncertainty and corporate R&D investment: evidence from Chinese listed firms. *Int. Rev. Econ. Finance* 47, 176–200. doi: 10.1016/j.iref.2016.10.004

Wustenhagen, R., and Menichetti, E. (2012). Strategic choices for renewable energy investment: conceptual framework and opportunities for further research. *Energy Policy* 40, 1–10. doi: 10.1016/j.enpol.2011.06.050

Xie, F. X. (2009). Managerial flexibility, uncertainty, and corporate investment: the real options effect. *Int. Rev. Econ. Finance* 18, 643–655. doi: 10.1016/j.iref.2008.11.001

Xu, L. P., Wang, J. W., and Xin, Y. (2010). Government control, uncertainty, and investment decisions in China's listed companies. *China J. Account. Res.* 3, 131–157. doi: 10.1016/S1755-3091(13)60022-2

Yoon, K. H., and Ratti, R. A. (2011). Energy price uncertainty, energy intensity and firm investment. *Energy Econ.* 33, 67–78. doi: 10.1016/j.eneco.2010.04.011

Zeng, S. H., Jiang, C. X., Ma, C., and Su, B. (2017). Investment efficiency of the new energy industry in China. *Energy Econ.* 70, 536–544. doi: 10.1016/j.eneco.2017.12.023

Zhang, D., Cao, H., and Zou, P. (2016). Exuberance in China's renewable energy investment: rationality, capital structure and implications with firm level evidence. *Energy Policy* 95, 468–478. doi: 10.1016/j.enpol.2015.12.005

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Dynamic Spillovers Between International Crude Oil Market and China's Commodity Sectors: Evidence From Time-Frequency Perspective of Stochastic Volatility

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We study the time-frequency dynamics of stochastic volatility spillovers between international crude oil markets and China's commodity sectors in the spectral representation framework of generalized forecast error variance decomposition (GFEVD). We find evidence that international crude oil markets has significant volatility spillover effects on China's bulk commodity markets, and the volatility spillovers are sensitive to extreme geopolitical or financial events. The net spillovers of international oil markets are almost positive and driven mainly by short-term components (within a week). However, uncertain financial factors from China such as the market-oriented reform in 2013 and the stock disaster in 2015 adversely affect the net oil-commodity volatility spillovers through the medium-term components (week to a month) and long-term components (month to a year). Moreover, the volatility spillover effects of crude oil prices on different commodity sectors in China are heterogeneous. Metal, coal coke, and steel ore and energy commodity sectors are more affected by crude oil prices, whereas nonmetal building materials and agricultural commodities are less affected. These outcomes implement necessary implications for investors and policymakers.

Keywords: crude oil prices, bulk commodity markets, stochastic volatility, volatility spillover effects, frequency decomposition

INTRODUCTION

In recent years, the linkages between oil and other commodity prices (including metals, industries, and agriculture) have increased (Ji and Fan, 2012; Wang et al., 2014; Luo and Ji, 2018) owing to the "financialization of commodities" (Vivian and Wohar, 2012; Creti et al., 2013; Fattouh et al., 2013; Adams and Glück, 2015; Basak and Pavlov, 2016; Liu K. et al., 2019; Liu Y. et al., 2019). In addition, the continuous replacement of fossil fuels by biofuels and the large-scale hedging strategies proposed for inflation caused by high oil prices have also enhanced the correlation of oil commodities (Ji and Fan, 2012). Affected by global economic fluctuations and geopolitical events, crude oil prices are prone to severe turbulence. For example, during the 2008 financial crisis, West Texas intermediate (WTI) crude oil prices fell by 75%, and then in the second half of 2014, international oil prices plummeted again, with a total drop of 50%. In China, the world's largest oil consumption economy, crude oil consumption has been increasing significantly. In 2018, it consumed 651 million tons of crude oil. Moreover, since 1993, China has changed from a net oil exporter to a net importer, and its import volume has increased year by year. In 2018, China's annual oil import volume reached 462 million tons, whereas domestic oil production is only 189 million tons. As early as 2013, the United States Energy Information Administration (EIA) has announced that China is the largest net importer of crude oil in the world economy. At the same time, China has maintained high economic growth rates in the past 40 years since reform and opening-up. The considerable energy demand brought about by the rapid growth of China's economy has affected the world's energy and financial markets, attracting widespread attention from international investors. Therefore, research on the volatility spillovers between international crude oil and China's commodity markets is of paramount importance for both policymakers and financial market participants.

Considerable research has focused on the relationship between crude oil prices and the economies of developed countries (Du and He, 2015; Zhang et al., 2017; Apergis et al., 2018), whereas relatively few studies are on developing countries. Fluctuations in crude oil prices can affect both developed and developing countries. More importantly, owing to relatively immature financial policies and investors, the uncertainty of oil prices may even have a more significant impact on developing countries (You et al., 2017). Besides, countries that rely on crude oil imports are more sensitive to changes in oil prices. However, the research on developing countries especially China is inadequate, despite their increasingly economic importance (Caporale et al., 2015; Shi and Sun, 2017; You et al., 2017; Cheng et al., 2019; Wang and Wang, 2019). In this study, we take the Chinese commodity sector as an example to study the dynamic impact of crude oil price fluctuations on the economies of developing countries.

The main objective of the current study is to explore the time-frequency patterns in the relationship between international crude oil volatility and different types of China's commodity price, as well as to quantify the dynamic volatility spillovers. The relationship between crude oil price and commodity markets may change with frequency because of the heterogeneous economic agents that interact in different markets. Specifically, market participants operate at different time frequencies, mainly owing to differences in their beliefs, goals, preferences, and risk tolerance. Long-term, medium-term, and short-term investors take different investment strategies. With the promotion of different types of investors, financial asset price volatility is heterogeneous at different frequencies (Baruník and Krehlík, 2018; Balli et al., 2019; Reboredo et al., 2020). Therefore, it is reasonable to assume that there are persistent relationships at various levels and that the sources of the cross-frequency connection between oil and the Chinese commodity market are different.

Unlike traditional financial assets, such as stocks and bonds, the price behavior of commodities has its characteristics (Balli et al., 2019). Because both the supply side and the demand side of diverse commodities are affected by different processes, their market prices have various movements (Diebold et al., 2017). However, the financialization of commodities has increased the dependence between different commodity markets, such as energy, coal mines, materials, metals, and agricultural products. After controlling for macroeconomic and other factors, even the unrelated commodity prices tend to change together (de Nicola et al., 2016). Crude oil prices are effective in transmitting shocks to other commodity markets (Choi and Hammoudeh, 2010; Nazlioglu et al., 2013; Ahmadi et al., 2016; Luo and Ji, 2018; Lovcha and Perez-Laborda, 2020). However, although literature has focused on the association between crude oil prices and a particular class of commodity (mostly energy or agricultural commodities), the findings are mixed and ambiguous in general, which may due to different modeling techniques and timescales (Tiwari et al., 2020). Moreover, the existing literature pays little attention to the connectedness between crude oil prices and various essential commodities. This lack of research justifies further study.

The idea of volatility connectedness is essential for financial risk management (Liu, 2016; Frahm, 2018; Li et al., 2018) and it appears especially crucial for exploring the investment potential and risk reduction across different commodity categories. Nazlioglu et al. (2013) examine interrelationships between energy and agricultural markets by the Granger causality test on variance and find that the dynamics of volatility transmission change significantly following the food price crisis. Beckmann and Czudaj (2014) use the generalized autoregressive (AR) conditional heteroskedasticity (GARCH) in mean vector AR (VAR) models to investigate the volatility spillover between various agricultural futures markets. Their results provide evidence for the short-term volatility transmission process in agricultural futures markets. Mensi et al. (2014) use both VAR–[Baba–Engle–Kraft–Kroner (BEKK)]–GARCH and VAR–dynamic conditional correlation (DCC)–GARCH models and provide evidence of significant return and volatility spillovers between international energy and cereal commodity markets. Diebold and Yilmaz (2009, 2012) propose the generalized forecast error variance decomposition (GFEVD) framework to construct the volatility spillover index (DY, henceforth). The DY framework provides quantitative measures of the magnitude and direction of the dynamic spillovers and is particularly suitable for studying the evolution of volatility spillovers over time. Then Baruník and Krehlík (2018) extend the DY framework to the time-frequency domain, providing measurements to decompose the volatility spillover index into different frequency components (BK, henceforth). The time-frequency decomposition of volatility spillovers is critical to understanding the propagation mechanism of volatility.

Using the time-series framework, we adopt the methodological approach that comprises the stochastic volatility (SV) estimation proposed by Kastner and Frühwirth-Schnatter (2014) and the time-frequency volatility connectedness estimation proposed by Baruník and Krehlík (2018) in a multivariate framework. Although previous literature mostly used the implied volatility model (Vivian and Wohar, 2012; Efimova and Serletis, 2014; Youssef et al., 2015; Jiang et al., 2019), this study focuses on the SV model, because the volatility of commodity market price is a stochastic process, and the SV model can perform better than the implied volatility or historical volatility measurements (Yang and Hamori, 2018; Balli et al., 2019). The motivation for this study is that it is crucial to measure the dynamic connectedness among the commodity or futures markets and the determinants of volatility spillover effect through novel methodologies. This analysis would be essential for policymakers to formulate relevant policies and would also provide investors more enormous diversification benefits in the commodity market.

Therefore, this study makes several contributions to the literature. First, as far as we know, this study is the first to explore the dynamic volatility spillovers between crude oil price and various China's commodity sectors including precious metals, nonferrous metals, coal coke, and steel ore; nonmetal building materials; energy products; chemical products; grains; oils and fats; and soft commodities. Some empirical studies have investigated the volatility connectedness between crude oil price and commodities of a particular class or group, such as the agricultural commodities (Nazlioglu et al., 2013; Mensi et al., 2014; Wang et al., 2014; Luo and Ji, 2018), the energy commodities (Ng and Donker, 2013; Lovcha and Perez-Laborda, 2020), the precious metals commodities (Ewing and Malik, 2013; Bildirici and Turkmen, 2015), and the industries commodities (Choi and Hammoudeh, 2010). However, the results of the current literature examining the relationship between energy prices and other commodity prices are mixed and generally ambiguous, which may be due to the use of different models based on various assumptions and analysis of different timescales (Tiwari et al., 2020). Because different processes influence both the demand side and the supply side of commodities, various price movements are be observed in different commodity sectors (Balli et al., 2019; Ji et al., 2019). The central position of crude oil in commodity markets and the economy as a whole is crucial. After considering the interactions between widely traded commodities including agriculture, metals, industries, and crude oil, no significant contribution was made in measuring the volatility spillover effects. Given that risk management and the international portfolio diversification strategies are implemented at the sector levels, it is important to study the heterogeneous impact of crude oil prices on different commodity sectors. Therefore, we are trying to fill the research gap by investigating the volatility transmission mechanism between crude oil prices and China's commodity market at the disaggregated sectors level instead of the aggregate market level.

Second, we combine the SV model and the GFEVD framework of the DY (2012) (DY12) to explore the dynamic spillovers between crude oil markets and China's bulk commodity. Previous studies (Vivian and Wohar, 2012; Efimova and Serletis, 2014; Youssef et al., 2015; Jiang et al., 2019; Yang and Hamori, 2018) adopt models that use historical or implied volatility measures. We highlight that the volatility of crude oil and other commodity price is a naturally stochastic process and that the SV model is superior in modeling commodity volatilities due to limited assumptions. Moreover, the GFEVD framework is a simple and intuitive measure of interdependence of volatilities, and the economic interpretation of spillover indicators in the GFEVD framework is closely related to recently developed risk measurements. Thus, our combination of the SV model and the GFEVD framework provides strong evidence for risk management of commodity markets and international portfolio strategies.

Third, we investigate the volatility transmission mechanism between crude oil and commodities, with an emphasis on the volatility spillover effects generated by shocks with heterogeneous frequency response. By adopting the GFEVD framework of the DY12 and the extended time-frequency connectedness measures of the BK (2018) (BK18), we track the long-, medium-, and short-term volatility spillovers from pairwise to systemwide, in a coherent way. It is reasonable and necessary to investigate the oil-commodity volatility spillovers at different time frequencies because multiple economic agents generally operate on diverse investment horizons owing to their differences in beliefs, preferences, levels of information assimilation, or risk tolerance.

Finally, China is a favorable setting to gain insight into volatility spillover effects between international crude oil prices and commodities. With the rapid rise and the increasing importance of developing countries, the impact of crude oil prices on financial markets in developing countries has become an important issue. However, developing countries, in particular China, have not received adequate research attention. To the best of our knowledge, no study is available regarding the dynamic time-frequency spillovers between crude oil markets and China's bulk commodity sectors, and we are trying to fill this research gap.

The remainder of the study is structured as follows. Section 2 introduces the empirical methodology. Section 3 describes the data, whereas Section 4 depicts the empirical results and findings. The conclusions are shown in Section 5.

EMPIRICAL METHODOLOGY

Stochastic Volatility Models

Previous empirical studies rely mostly on time-series models such as the ARCH and GARCH models (Engle, 1982; Engle and Bollerslev, 1986) to capture volatility structure of commodity prices (Vivian and Wohar, 2012; Efimova and Serletis, 2014; Youssef et al., 2015; Jiang et al., 2019). However, these time-series models do not provide a clear unified methodology to reveal volatility dynamics operating between the involved variables and to identify structural changes (Jebabli et al., 2014). The ARCH or GARCH models aim to model the volatility in a deterministic specification, which may lead the models to be trapped into model misspecification. Even with standard Student *t* innovations, the performance of ARCH or GARCH models in capturing tail behavior of commodity prices is still limited. Some important attributes are shown in financial time series (e.g. the commodity prices), which may play an essential role in determining the results of estimates and hypothesis tests, including unit roots, cointegration, causality, and structural breaks (Bekiros and Georgoutsos, 2008; Maslyuk and Smyth, 2009; Chen et al., 2014; Liu, 2016). Besides, the ARCH or GARCH models are affected by the shocks to the second moments, which are dependent on the first moments. In many cases, it is difficult for the ARCH or GARCH models to obtain convergence of the optimization algorithms used to estimate the parameters.

Considering the above aspects, we adopt the SV model to characterize crude oil prices and commodity market price volatility. The SV model captures the volatility process probabilistically (Kastner and Frühwirth-Schnatter, 2014) and thus is superior in modeling leverage effect and considering excess skewness and kurtosis of financial time series (Shephard and Andersen, 2009; Yang and Hamori, 2018). Besides, the SV model has significant flexibility in capturing empirical volatility owing to its limited assumptions and ability to capture contemporaneous fluctuations (Hafner and Preminger, 2010). The SV model describes the volatility process as an unobserved component that follows a specific latent stochastic process, such as the AR process of order 1. Let, $t = 1, ..., T$ be the natural log return for commodities at time t. Then the SV model is specified as follows:

$$r_t = r^{h_t/2}\varepsilon_t \tag{1}$$

$$h_t = \partial + \varphi(h_t - \partial) + \sigma\eta_t \tag{2}$$

where ε_t and η_t are independent standard normal innovations for all t belonging in $\{1, ..., T\}$. The unobservable process $h = (h_0, h_1, ..., h_T)$ appearing in state equation (2) is usually interpreted as the latent time-varying volatility having the initial state distribution $h_o\, |r, \phi, \sigma\ \tilde{}N(r, \sigma^2/(1-\phi^2)\ )$. The latent sequence controls the value or distribution of the observed data, especially the variance of the observed data. Equations (1, 2) are the SV model in its centered parameterization. Kastner and Frühwirth-Schnatter (2014) propose the centered parameterization of the above model:

$$r_t \sim\ N(0, r^{\partial+\sigma\hat{h}_t}) \tag{3}$$

$$\hat{h}_{ht} = \varphi\hat{h}_{ht-1} + \eta_t, \eta_t \sim\ N(0, 1) \tag{4}$$

Whether the first or second parameterization in the above model is preferred for estimation depends on "true" parameters (Kastner and Frühwirth-Schnatter, 2014). But the Markov chain Monte Carlo (MCMC) sampling techniques are necessary for Bayesian estimation because both of the parameters have intractable likelihoods. The authors also propose the ancillarity-sufficiency interweaving strategy (ASIS) to overcome the efficiency loss problem in the parameter estimation process. Kastner (2019) provides the R package stochvol to implement this method.

Volatility Spillover Measures

Since the global financial crisis (GFC), a growing number of studies are conducted to explore the connectedness between crude oil and commodity markets, and their methods can be broadly classified into several categories: VAR or structural VAR (SVAR) (Wang et al., 2014; de Nicola et al., 2016); GARCH models (Ji and Fan, 2012; Ewing and Malik, 2013; Jiang et al., 2019); Copula models (Koirala et al., 2015); nonparametric causality analysis (Nazlioglu et al., 2013); vector error correction model (VECM); Markov regime switching (MRS) models (Uddin et al., 2018); and forecast error variance decomposition (FEVD) (Diebold et al., 2017; Lovcha and Perez-Laborda, 2020). However, the previous literature generally underestimates connectedness among commodity markets of a particular class or group, while there are few studies focusing on the oil-commodity nexus at the industry level. Our research is different because we take into account commodities in various sectors and decompose the total volatility spillovers into different frequencies. The GFEVD framework, developed in a series of studies including Diebold and Yilmaz (2009, 2012, 2014), provides a simple and intuitive measure of interdependence of different asset returns or volatilities. This new methodology is adopted here because it can measure both the total and directional volatility spillovers between crude oil market and China's commodity sectors and can also reveal the levels of volatility spillovers within different markets. Moreover, the economic interpretation of the volatility spillover indices in the GFEVD framework is closely related to recently developed risk measurements (Diebold and Yilmaz, 2014), like the CoVaR (Adrian and Brunnermeier, 2011) or the marginal expected shortfall (Acharya et al., 2017). This is highly consistent with the goal of commodity market risk management in this article. On the other hand, the time-frequency version of the GFEVD framework developed by Baruník and Krehlík (2018) allows one to simultaneously capture the magnitude and direction of volatility spillovers over time and across frequencies. From an econometric point of view, this novel methodology not only captures time-varying information of volatility spillovers but also provides different frequency domains from aggregated correlations, which can identify specific frequencies that contribute the most to system connectedness.

Thus, we apply the GFEVD framework of DY12 to measure the volatility spillovers between crude oil prices and China's bulk commodity markets. Consider an N-variable VAR(P) system:

$$Y_t = \Phi_1 Y_{t-1} + \Phi_2 Y_{t-2} + ... + \Phi_p Y_{t-p} + \varepsilon_t,\ \ \varepsilon_t \sim\ N(0, \Sigma) \tag{5}$$

where Y_t denotes the $N \times 1$ vector at time t;ε_t is white noise; and $\omega_1, \omega_2, \ldots, \omega_p$ are coefficient matrices. With the $N \times N$ matrix lag-polynomial, $\Phi(L) = [\Phi_0 - \Phi_1 L - \cdots - \Phi_p L^p]$, where Φ_0 is the identity matrix and $\Phi_1, ..., \Phi_p$ are the $N \times N$ coefficient matrices, we can rewrite model (5) as follows:

$$\Phi(L)Y_t = \varepsilon_t \tag{6}$$

Next, we rewrite model (6) as the moving average process to get the dynamic structure in our system:

$$Y_t = \Psi(L)\varepsilon_t \tag{7}$$

where $\Psi(L) = [\Phi(L)]^{-1}$. We employ the GFEVD of H-step forecast to examine how much each volatility variable contributes to explaining other volatility variables:

$$(\Theta_H)_{k,j} = \frac{\sum_{j,j}^{-1}\sum_{h=0}^{H}((\Psi_h\Sigma)_{k,j})^2}{\sum_{h=0}^{H}(\Psi_h\Sigma\Psi_h^{'})_{k,k}} \tag{8}$$

where H is the forecast horizon and Ψ_h is a $N \times N$ matrix of moving average coefficients at lag h defined above. Following

Diebold and Yilmaz (2012), the volatility spillover is then defined by the shares of variance in the forecast contributed by other than own errors or equally as the ratio of the sum of the off-diagonal elements to the sum of the whole matrix:

$$S^H = \frac{\sum_{k=1,k\neq j}^{n} (\tilde{\Theta}_H)_{k,j}}{\sum_{k,j} (\tilde{\Theta}_H)_{k,j}} = 1 - \frac{\sum_{k=1}^{n} (\tilde{\Theta}_H)_{k,k}}{\sum_{k,j} (\tilde{\Theta}_H)_{k,j}} \tag{9}$$

where $(\tilde{\Theta}_H)_{k,j}$ is the standardized effects denoted as

$$(\tilde{\Theta}_H)_{k,j}=\frac{(\Theta_H)_{k,j}}{\sum_{j=1}^{n} (\Theta_H)_{k,j}} \tag{10}$$

Because the generalized impulse responses and variance decompositions are invariant to the ordering of variables, the directional spillovers of the DY12 can be calculated by the normalized generalized variance decomposition matrix. So it is clear that $(\tilde{\Theta}_H)_{k,j}$ can measure the SV spillover from the commodity market j to k, and S^H can measure the total SV spillover in our system. To get the net spillover of international crude oil prices to China's bulk commodity markets, we further calculate the net SV spillover index:

$$S_{k,j}^H = (\tilde{\Theta}_H)_{j,k} - (\tilde{\Theta}_H)_{k,j} \tag{11}$$

Of course, $S_{k,j}^H$ can also be used to examine net spillovers between different commodity markets in China.

Time-Frequency Decomposition of Volatility Spillover Measures

However, the volatility spillovers among commodity markets are not the same at different time frequencies, because agents with different preferences operate on different investment horizons. Following the BK18, we consider the time-frequency dynamics of the SV spillovers. We use the spectral representation framework of the GFEVD to implement frequency decomposition. We define the generalized causation spectrum over frequency $\omega \in (-\pi, \pi)$ as follows:

$$(f(\omega))_{k,j} = \frac{\Sigma_{j,j}^{-1} \left|(\Psi(e^{-i\omega})\Sigma)_{k,j}\right|^2}{(\Psi(e^{-i\omega})\Sigma\Psi'(e^{+i\omega}))_{k,k}} \tag{12}$$

where $\Psi(e^{-i\omega})= \sum_h e^{-i\omega h}\Psi_h \; h = 1, ..., H$, which is the Fourier transform of Ψ, with $i = \sqrt{-1}$. As noted by Baruník and Krehlík (2018), the forecast horizon H is not important as the GFEVD implemented here is unconditional. To obtain the generalized variance decompositions on frequency band d, $d = (a, b)$, a,b $\in$ $(-\pi,\pi)$, we weight $(f(\omega))_{k,j}$ by the frequency shares of the variance of the j-th volatility. Thus, the weighting function can be defined as follows:

$$\Gamma_k(\omega) = \frac{\Psi(e^{-i\omega})\Sigma\Psi'(e^{+i\omega})_{k,k}}{\frac{1}{2}\int_{-\pi}^{\pi} (\Psi(e^{-i\lambda})\Sigma\Psi'(e^{+i\lambda}))_{k.k} d\lambda} \tag{13}$$

The generalized variance decompositions on frequency band d are denoted as follows:

$$(\Theta_d)_{k,j} = \frac{1}{2}\int_d^{\infty} \Gamma_k(\omega)(f(\omega))_{k,j} d\omega \tag{14}$$

With the spectral representation of the generalized variance decompositions, we can easily calculate the scaled generalized variance decompositions:

$$(\tilde{\Theta}_d)_{k,j}=\frac{(\Theta_d)_{k,j}}{\sum_j (\Theta_\infty)_{k,j}} \tag{15}$$

where $(\Theta_\infty)_{k,j}=\frac{1}{2}\int_{-\pi}^{\pi} \Gamma_k(\omega)(f(\omega))_{k,j} d\omega$. Furthermore, we can calculate the total volatility spillover measures under the frequency band d as follows:

$$C_d^W = 100 \cdot (1 - \frac{Tr\{\tilde{\Theta}_d\}}{\sum \tilde{\Theta}_d}) \tag{16}$$

And the aggregate measure under frequency band d is

$$C_d^F = 100 \cdot (\frac{\sum \tilde{\Theta}_d}{\sum \tilde{\Theta}_\infty} - \frac{Tr\{\tilde{\Theta}_d\}}{\sum \tilde{\Theta}_d})=C_d^W \frac{\sum \tilde{\Theta}_d}{\sum \tilde{\Theta}_\infty} \tag{17}$$

Thus, C_d^F is defined as the frequency SV spillovers in our system. It is relatively easy to find the relationship between the frequency spillovers of the BK18 and the original total spillovers of the DY12:

$$\sum_{d_s} C_d^F = C \tag{18}$$

where C is the total spillovers of the DY12.

Therefore, this study combines the SV model with the GFEVD framework and its time-frequency version to study the dynamic spillovers between the crude oil market and China's bulk commodity sectors. Our research framework provides a better understanding of volatility in the commodity price, as previous studies gauge crude oil and commodity prices by only using the historical or implied volatility measures. Based on the SV models, we further adopt the GFEVD framework and its frequency decomposition to evaluate the magnitude and direction of SV spillovers between oil prices and the different commodity sectors over time and across time frequency.

DATA AND DESCRIPTIVE STATISTICS

In this paper, we mainly focus on the time-frequency dynamic spillovers among crude oil prices and China's bulk commodity sectors. Our underlying data are the daily spot closing prices of crude oil and commodity index in China. We adopt the WTI futures of the New York Mercantile Exchange from the EIA as the proxy for the benchmark of the international crude oil markets. We select a group of nine commodity sectors, including precious metals (NMFI), nonferrous metals (NFFI), coal coke and steel ore (JJRI), nonmetal building materials (NMBM), energy (ENFI), petrochemicals (CIFI), grains (CRFI), oils and fats (OOFI), and soft commodities (SOFI). Compared with the sectors in the existing literature (Chen, 2015; Jiang et al., 2019), these nine commodity sectors are comprehensive selections for the analysis of China's commodity markets. They can not only capture the price fluctuations of the entire commodity markets

TABLE 1 | China's commodity sectors and the detailed components.

Abbreviation	Sectors	Components
NMFI	Precious metals	Gold, silver
NFFI	Nonferrous metals	Aluminum, copper, lead, nickel, tin, zinc
JJRI	Coal coke and steel ore	Coking coal, coke, iron ore, rebar, hot coil, wire rod, ferrosilicon, ferromanganese
NMBM	Nonmetal building materials	Fiberboard, plywood, glass, PVC
ENFI	Energy	Coal, fuel oil
CIFI	Petrochemicals	Methanol, plastics, polypropylene, asphalt, rubber
CRFI	Grains	Corn, cornstarch, rice, soybeans, wheat
OOFI	Oils and fats	Palm oil, rapeseed meal, rapeseed oil, soybean meal, soybean oil
SOFI	Softs	Sugar, cotton

The detailed compilation method of China's commodity sector price indices in this article can be found from the Wind official database (http://www.wind.com.cn/). PVC

in China but also reflect the supply and demand relationship of different commodity sectors. According to data availability, the daily dataset of commodity sector price indices spans from 1 June 2009 to 31 May 2019, which yields a total of 2,434 observations from the Wind official database (http://www.wind.com.cn/). The Wind commodity sector indices, jointly compiled by Wind Corp., are based on a weighted average of the components selected for each sector. We exclude the Wind agricultural sideline products Index as the index starts at 01 September 2015. If we consider the agricultural sideline products sector, this will lead to a reduction in sample time by half. The selected commodity sectors and the particular components are reported in **Table 1**.

In order to easily observe all price series, we plot the daily WTI oil price and China's commodity sector price indices in **Figure 1**. From **Figures 1A,B**, we can find that these indices produced significant fluctuations during the entire sample period. First, after the financial crisis in 2008, the price indices showed an upward trend. Subsequently, during the period 2010–2011, affected by the European sovereign debt crisis, these price indexes experienced the most dramatic fluctuations. The most striking feature is that in the second half of 2014: owing to the impact of imbalance between supply and demand, WTI crude oil prices experienced the largest plunge in the entire sample period, but the decline in China's commodity sector price indexes was relatively flat. Besides, owing to the impact of the Chinese stock market crisis in 2015, China's commodity sector price indexes dropped a lot and then slowly rose back to previous levels.

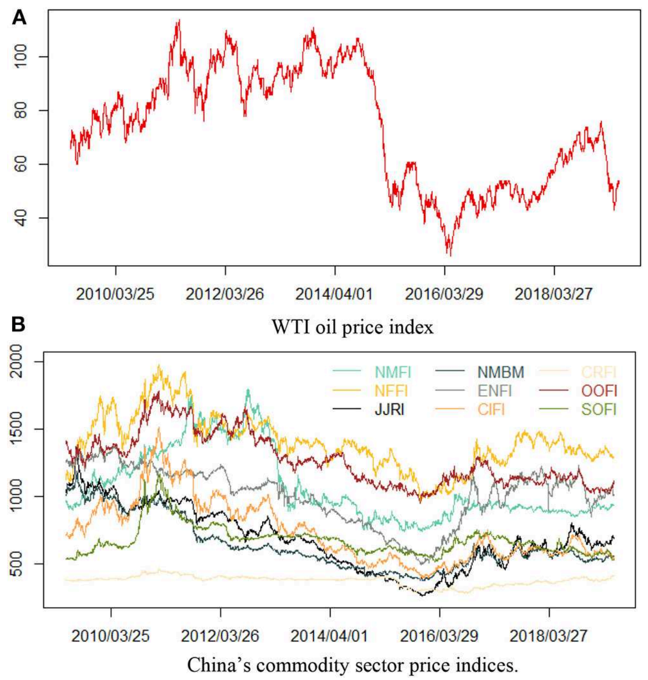

FIGURE 1 | The plot of price indexes. WTI, West Texas intermediate.

Then we calculated their logarithmic returns, that is, $r_t = \ln(p_t/p_{t-1})$. We provide descriptive statistics for the log returns in **Table 2**. The mean values of the indexes are nearly zero, and the standard deviation for the crude oil is more significant than that of the nine commodity sector price indices. This shows that the international crude oil market is more unstable. From the skewness and kurtosis values, we can find that China's commodity sector price indices have various dynamic statistical characteristics. Except for JJRI, the skewness of the other variables is <0, which indicates that they have a left-biased distribution. The kurtosis in six commodity markets (NMFI, JJRI, NMBM, ENFI, CRFI, and SOFI) exceeds 3, indicating a leptokurtic distribution. And the kurtosis of the remaining commodity markets is <3, showing a platykurtic distribution. According to the results of the Jarque–Bera (J-B) test, all return series reject the null hypothesis of normal distribution at a significance level of 1%. The augmented Dickey–Fuller (ADF) test results show that all series are stable at a significance level of 1%. At last, according to the Ljung–Box Q(20) statistics, there are high-order autocorrelations in the return series of the six commodity markets (NMFI, NFFI, JJRI, ENFI, CRFI, and SOFI), whereas the remaining sectors do not.

TABLE 2 | Descriptive statistics of variables.

	Min.	Max.	Mean	Std.	Skew.	Kurt.	J-B	ADF	Q(20)
WTI	−4.688	5.047	−0.005	0.899	−0.010	2.728	757.300***	−35.101***	22.969
NMFI	−4.040	2.849	0.000	0.518	−0.273	5.451	3,050.1***	−34.256***	34.519**
NFFI	−2.721	2.442	0.002	0.540	−0.179	2.855	842.1***	−35.280***	35.497**
JJRI	−3.297	2.862	−0.007	0.622	0.022	3.299	1,107***	−33.647***	36.468**
NMBM	−4.737	2.439	−0.011	0.469	−0.366	6.734	4,662.8***	−34.859***	12.306
ENFI	−7.727	4.899	−0.005	0.566	−0.925	22.500	51,770***	−37.438***	74.326***
CIFI	−2.575	2.657	−0.005	0.646	−0.165	1.310	185.8***	−33.993***	26.655
CRFI	−4.301	1.443	0.001	0.286	−1.318	24.319	60,850***	−37.601***	49.52***
OOFI	−2.014	2.024	−0.004	0.418	−0.162	1.596	270.04***	−35.368***	24.891
SOFI	−2.652	2.202	0.000	0.424	−0.189	4.693	2,253.7***	−34.144***	33.851**

*J-B, ADF, and Q(20) indicate the Jarque–Bera test, the augmented Dickey–Fuller test, and the Ljung–Box serial correlation test, respectively. "**" and "***" denote statistical significance at the 5 and 1% levels, respectively.*

TABLE 3 | Volatility spillover results of the DY(2012).

	WTI	NMFI	NFFI	JJRI	NMBM	ENFI	CIFI	CRFI	OOFI	SOFI	FROM
WTI	99.25	0.50	0.60	0.40	0.60	1.10	0.6	0.6	0.4	0.2	0.70
NMFI	2.00	99.17	1.40	0.20	1.00	1.60	0.20	0.10	0.30	1.50	0.76
NFFI	3.20	1.40	98.97	1.90	0.40	0.20	0.40	0.40	1.90	0.30	0.92
JJRI	2.80	1.60	1.60	98.86	1.10	0.20	0.20	2.20	1.40	0.30	1.04
NMBM	1.10	0.80	0.00	0.50	98.97	0.20	0.70	5.00	1.90	0.10	0.94
ENFI	2.70	0.00	3.00	3.10	1.80	98.51	1.00	0.60	2.40	0.30	1.36
CIFI	1.40	0.30	0.50	0.30	2.30	0.90	99.27	1.40	0.00	0.10	0.66
CRFI	0.90	0.80	0.10	2.40	5.90	1.40	0.80	98.47	3.00	0.00	1.40
OOFI	1.00	0.80	3.80	1.70	2.60	1.60	0.40	0.90	98.65	0.80	1.24
SOFI	0.30	1.80	0.70	0.50	1.40	0.70	0.80	0.70	0.40	99.27	0.67
TO	1.41	0.73	1.07	1.01	1.56	0.72	0.47	1.09	1.07	0.33	10.5
Net	0.71	−0.03	0.15	−0.03	0.62	−0.64	−0.19	−0.31	−0.17	−0.34	

EMPIRICAL RESULTS AND FINDINGS

The Stochastic Volatility Measures

Before starting MCMC for Bayesian estimation, we should specify the configuration and parameters. Following the Kastner and Frühwirth-Schnatter (2014), we choose the prior between 0 and 100 because it usually carries enough information. The prior variance of the logarithmic hyperparameter is set to 1. The burn-in size of MCMC aging size is set to 1,000, and the number of iterations after burn-in is set to 10,000. Last, to neutralize their possible effects, three thinning parameters are set as 1. **Figure 2** is the plot of posterior quantiles of the latent volatilities in percentages.

Figure 2 summarizes the time-series plots of posterior quantiles of the latent volatilities in percentages.

The posterior 5, 50, and 95% quantiles are plotted. Further study of SV spillovers is based on the 50% quantile level of the latent volatilities, that is, SV. For the sake of brevity, plots of posterior and prior densities are retained. The results show excellent convergence during the estimation process. Additional graphic information is available upon request from the author.

Figure 2 presents that the volatility of WTI oil price and China's commodity sector price indices varies significantly in the time, which reinforces the use of the GFEVD framework with SV to avoid biased estimation because posterior estimates of stochastic volatilities are significant. We observe that SV of most of China's commodity sector price indices has some sub-periods with similar evolutions as WTI oil. In fact, often when high volatilities are observed for WTI oil prices, volatilities in China's commodity sector prices are observed, but with different magnitudes. This observation suggests that there is volatility transmission from international crude oil markets to China's commodity sectors. The GFEVD framework allows us to test for that. **Figure 2** also illustrates that during the European sovereign debt crisis in 2011 and the Chinese stock market crisis in 2015, the SV of the variables is higher. This observation reveals the phenomenon of commodity market financialization. Moreover, **Figure 2** also shows that the SV of different China's commodity sector prices is significantly heterogeneous. For example, compared with that of other sectors, the SV of precious metals (NMFI) commodities (**Figure 2B**) is less susceptible to

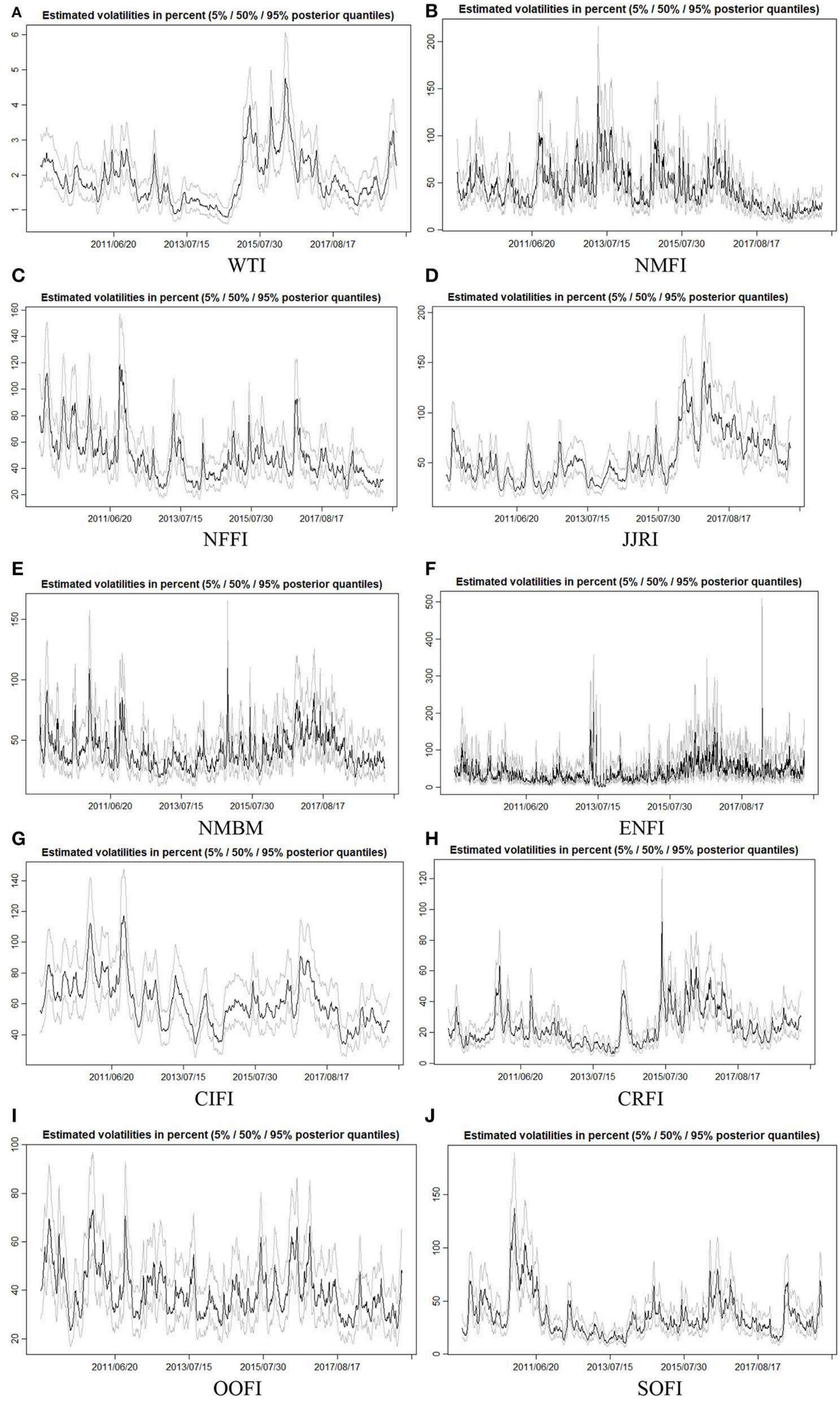

FIGURE 2 | The plots of estimated posterior stochastic volatility levels. **(A)** WTI, **(B)** NMFI, **(C)** NFFI, **(D)** JJRI, **(E)** NMBM, **(F)** ENFI, **(G)** CIFI, **(H)** CRFI, **(I)** OOFI, and **(J)** SOFI.

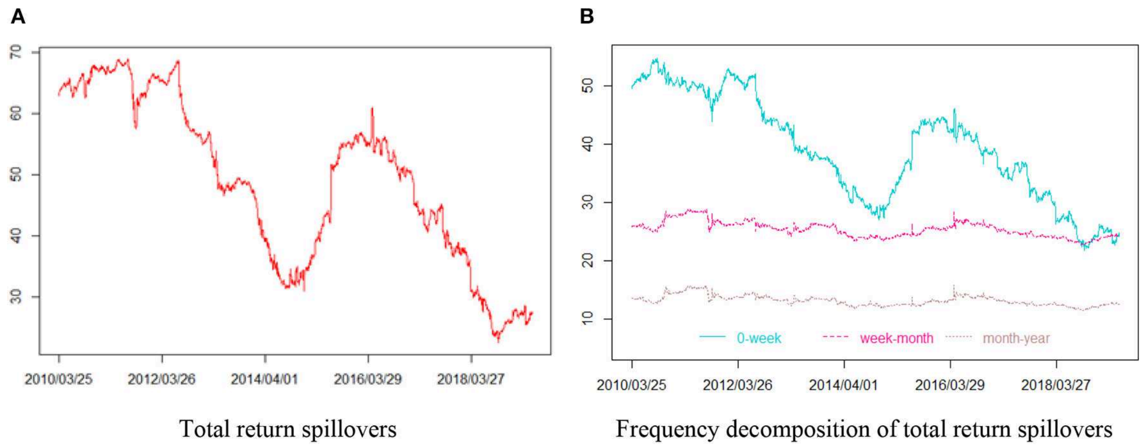

FIGURE 3 | Total return spillovers of West Texas intermediate (WTI) futures and China's bulk commodity sectors. **(A)** The total return spillovers measured by Diebold and Yilmaz (2012), lag = 2, window size = 200. **(B)** The frequency decomposition measured by Baruník and Krehlík (2018), lag = 2, window size = 200. Short term: frequencies from 1 to 5 days' period (0 week, dark turquoise). Medium term: frequencies from 5 to 20 days' period (week–month, deep pink). Long-term: frequencies from 20 to 200 days' period (month–year, rosy brown).

crisis events. This indicates that precious metals can be used to hedge uncertainty and that it is an alternative investment tool. This feature of **Figure 2** provides evidence for our subsequent study of the heterogeneous spillover effects of oil prices on different China's commodities sectors.

Dynamic Spillovers Between Crude Oil Prices and China's Bulk Commodity Sectors

We use the framework of GFEVD (DY12) to recover the dynamic spillovers between crude oil prices and China's bulk commodity sectors, and then we use the spectral representation of GFEVD (BK18) to investigate the time-frequency dynamic spillovers. According to Baruník and Krehlík (2018), if the forecasting horizon $H < 100$, the model is invalid. Consequently, we use a 100-day ahead forecasting horizon for variance decomposition, that is, $H = 100$. In fact, the forecast horizon H is not as important as the GFEVD implemented here, which is unconditional. Because the static results of the GFEVD framework over the entire sampling period may smooth out the results when the relationship between the variables changes over time (Lovcha and Perez-Laborda, 2020), this paper considers both the static and dynamic spillover effects to obtain more comprehensive estimations. For the dynamics of spillover effects, we employ the moving-window method to analyze the DY12 and BK18. Similar to the existing literature (Toyoshima and Hamori, 2018; Balli et al., 2019; Wang and Wang, 2019) we set the length of the window at 250 trading days, 370 trading days, and 500 trading days. We find that the plots of these trading days have almost the same trends. For the sake of simplicity, we only present the results of a rolling window of 500 trading days. The plots of other window lengths are available upon request from the authors. In addition, we choose the optimal lag order of the VAR according to the Akaike information criterion (AIC). In frequency domain, following Baruník and Krehlík (2018), we use Fourier transform to decompose the spillover measures of the DY12 into three different frequency bands. The frequency bands are up to 1 week, 1 week to 1 month, and 1 month to a year calculated as $C^F_{d_s}$ on the corresponding bands of $d_1 \in [1,5]$, $d_2 \in [5,20]$, $d_3 \in [20,200]$ trading days. We refer to frequency bands accordingly as short-term, medium-term, and long-term frequencies.

First, we measure the total spillovers of the log returns in our system. **Figure 3** shows total return spillovers of WTI futures and China's bulk commodity sectors. The left plot (**Figure 3A**) is measured by the DY(2012), and the right part (**Figure 3B**) is measured by the BK(2018). As shown in **Figure 3A**, the overall return spillover is informative and time varying. In the beginning, the total return spillover of the entire system is relatively high, which may be associated with the European sovereign debt crisis of 2010–2011, when financial institutions in some European countries were over-indebted and government debt could not be refinanced. At the same time, the political unrest in the Middle East and North Africa, particularly in countries such as Libya and Egypt, may contribute to the high level of the overall return spillovers. After the commodity markets started to recover from this crisis, the return spillovers slowly dropped back, reaching the lowest point around mid-2014. From the second half of 2014, the overall return spillovers began to increase dramatically, which may be influenced by the 2014 international crude oil crisis. Note that the overall return spillovers are at its second peak during 2015–2016, second only to the European debt crisis period, which may be related to the Chinese stock market disaster. In June 2015, the Chinese stock market experienced massive fluctuations with the Shanghai Composite Index fell from 5,174 points to 3,373 points. The disruption of the Chinese stock market increased the uncertainty of the oil market and commodity sectors, leading to a significant increase in the total return spillovers. The findings complement the finding of Balli et al. (2019) and Wang and Wang (2019), who reported that

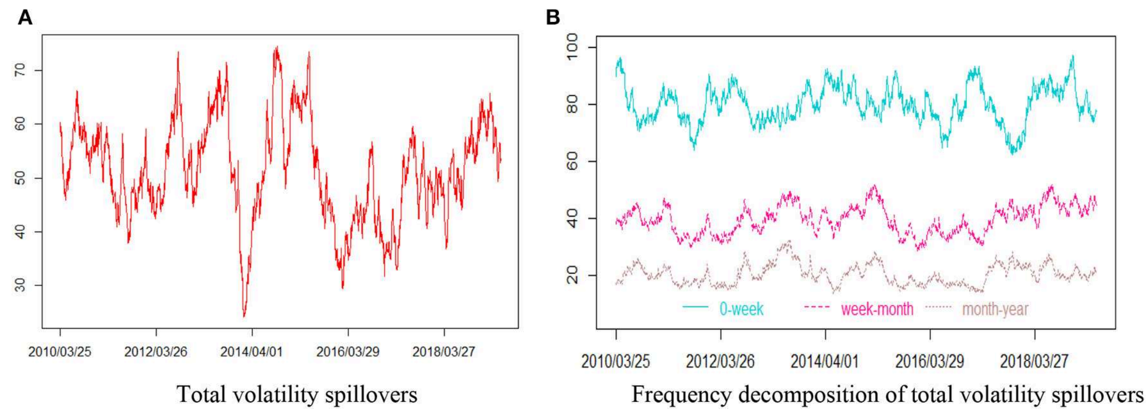

FIGURE 4 | Total volatility spillovers of West Texas intermediate (WTI) futures and China's bulk commodity sectors. **(A)** The total volatility spillovers measured by Diebold and Yilmaz (2012), lag = 2, window size = 200. **(B)** The frequency decomposition measured by Baruník and Krehlík (2018), lag = 2, window size = 200. Short-term: frequencies from 1 to 5 days period (0-week, dark turquoise). Medium-term: frequencies from 5 to 20 days period (week-month, deep pink). Long-term: frequencies from 20 days to 200 days period (month-year, rosy brown).

commodity markets displayed closer interconnectedness during financial crisis periods such as the GFC and China's 2015 financial crisis. After hitting the highest points, the total return spillovers slowly dropped again. **Figure 3B** displays the time-frequency dynamics of return spillovers. As seen in **Figure 3B**, the return spillovers of short-term frequency (in dark turquoise) display a similar trend with the total return spillovers in **Figure 3A**, whereas the return spillovers of medium-term (in deep pink) and long-term (in rosy brown) frequencies are both relatively smooth. Moreover, the return spillovers of the short-term frequency component are almost always more significant than those of the medium-term and long-term frequency components. Thus, it is evident that the return spillover in our system is driven mostly by the high-frequency information within a week. The frequency components of total volatility spillovers indicate that total return spillovers among crude oil and China's commodity sectors are mostly driven by the transmission of shocks in the short term.

We turn next to the overall volatility spillover in our system with the framework of the DY12 and the BK18 on the SV series. As shown in **Figure 4**, the total volatility spillovers display a "zig" pattern at first glance. Comparing **Figure 4** with **Figure 3**, we see that the total volatility spillovers are more volatile than the total return spillovers and that the total volatility spillovers react more violently to extreme events than returns. In **Figure 4A**, during the 2010–2011 European sovereign debt crisis and 2015 China stock market disaster, the total volatility spillovers of the entire system are large. And the total volatility spillovers increased most sharply in 2014, which may be caused by the international oil crisis. In addition, we can also identify the impact of other important economic or geopolitical events from **Figure 4A**, such as Iran's geopolitical tensions in 2012, China's market-oriented reform on July 20, 2013 and Organization of Petroleum Exporting Countries's (OPEC's) production cut agreement at the end of 2017 and so on. Our findings are consistent with the view that these events represent important geopolitical and economic factors affecting risk spillovers or the shocks of oil supply and demand (Krehlík and Baruník, 2017; Wang and Wang, 2019). As displayed in **Figure 4B**, it is clear that the total volatility spillover in our system is also mainly driven by high-frequency information (in dark turquoise), although the contribution of the medium-frequency and low-frequency components is significant. In other words, the total risk spillover between crude oil and China's bulk commodity sectors is primarily driven by the transmission of shocks in the short term (within a week). This means that the commodity markets process information quickly, so the shocks on any commodity market are usually passed quickly to others within a week. Importantly, this result can help us better understand how financial shocks and geopolitical events affect frequency volatility spillovers among various commodity markets.

Then, our empirical analysis focuses on the directional spillovers from crude oil prices to China's commodity sectors and their frequency components. As illustrated in **Figure 5**, the volatility spillovers from crude oil prices to China's commodity sectors also display a "zig" pattern, which implies the volatility spillovers from crude oil prices to China's commodity sectors are highly susceptible to economic and political global shocks. Some local increases or decreases in **Figure 5** can be associated with the economic or geopolitical events that are affecting oil-commodity volatility spillovers. For example, volatility spillovers from the crude oil market to China's commodities sector, especially within the frequency band of up to 1 week, increased significantly in 2012, 2014, and 2018, which may be associated with Iran's geopolitical tensions in 2012, the international oil crisis in 2014, and U.S. economic sanctions on Iran in 2018. It is also noteworthy that the results of frequency decomposition in **Figure 5B** reconfirm that any information shocks from the crude oil market can get transmitted to China's commodity sectors very quickly.

To provide further insights into the volatility spillovers, **Figure 6** offers net volatility spillovers from the oil market to

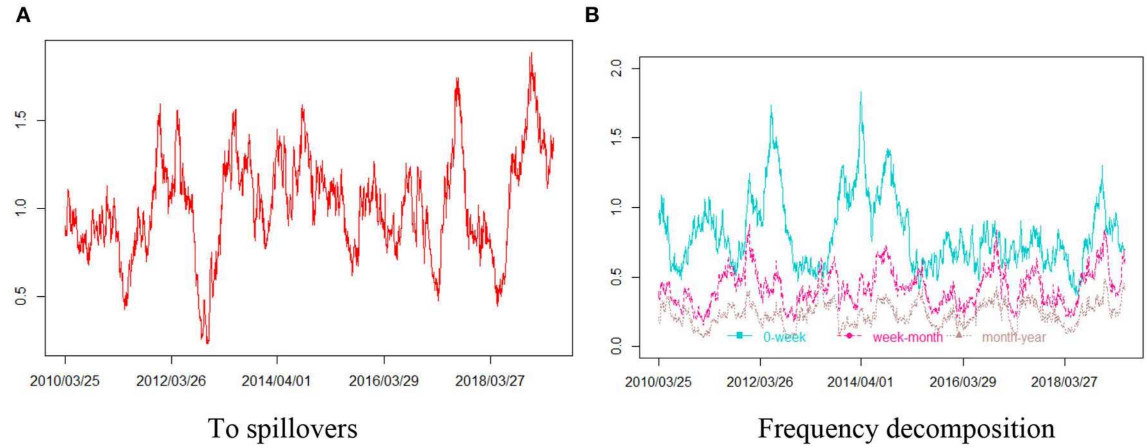

FIGURE 5 | Volatility spillovers from West Texas intermediate (WTI) to China's bulk commodity sectors. **(A)** The total volatility spillovers from WTI to China's bulk commodity sectors measured by Diebold and Yilmaz (2012), lag = 2, window size = 200. **(B)** The frequency decomposition measured by Baruník and Krehlík (2018), lag = 2, window size = 200. Short-term: frequencies from 1 to 5 days period (0-week, dark turquoise). Medium-term: frequencies from 5 to 20 days period (week-month, deep pink). Long-term: frequencies from 20 days to 200 days period (month-year, rosy brown).

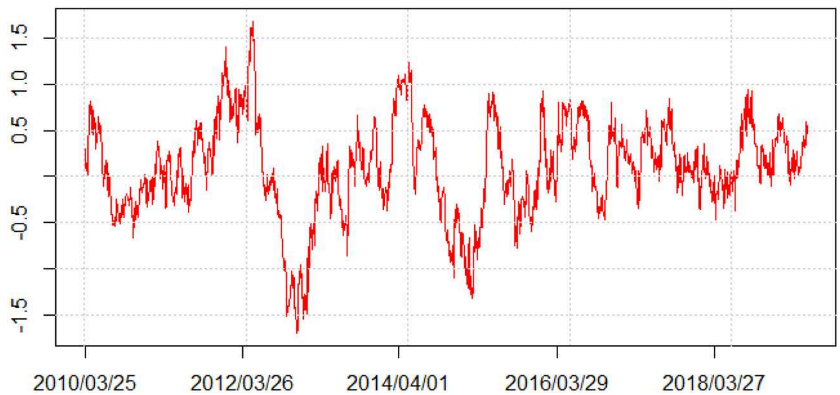

FIGURE 6 | Net volatility spillovers from West Texas intermediate (WTI) to China's bulk commodity sectors.

China's commodity sectors. When the value of the net volatility spillovers is positive, it represents that the international crude oil market is a spillover contributor; that is, it transmits net volatility spillovers to China's commodity sectors, and therefore, it is called a "spillover transmitter." On the other hand, if the net spillover value is negative, it implies that the international crude oil market is a net receiver; that is, it receives the spillovers from China's commodity sectors, and therefore, it is called a "spillover receiver." As illustrated in **Figure 6**, the net spillovers from crude oil prices to China's commodity sectors are mostly positive. This means that the fluctuations of international crude oil prices have a significant spillover effect on China's commodity sectors, suggesting that the crude oil market is a spillover transmitter of our system. However, in a few periods, the net spillovers are negative, such as during China's market-oriented reform in 2013 and the Chinese stock market disaster in 2015. This indicates that individual severe shocks from China's bulk commodity markets are likely to increase the uncertainty of international crude oil markets. Our conclusion is consistent with the research on the relationship of crude oil markets and the Chinese stock market (Bai and Koong, 2018; Wang and Wang, 2019). There is no doubt that with the opening and development of China's financial market, its influence on the international financial market is increasing. The local increase or decrease of **Figure 6** can even more easily identify some important economic or geopolitical events that affect oil-commodity volatility spillovers than **Figure 5**. For instance, Iran's geopolitical tensions in 2012 and the international oil crisis in 2014 possibly increase the net spillovers from WTI to China's bulk commodity sectors.

Accurately, the time-frequency components of the net volatility spillovers are reported in **Figure 7**. As seen in **Figure 7**, over most of the sample periods, the signs of different time-frequency net volatility spillovers are consistent, and the short-term net volatility spillovers are larger than the medium-term and long-term components, which reconfirms the importance

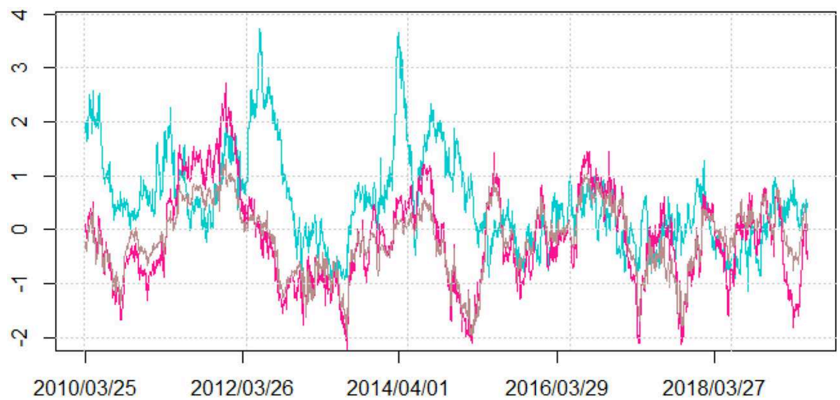

FIGURE 7 | Frequency decomposition of net volatility spillovers from West Texas intermediate (WTI) to China's bulk commodity sectors. The explanation of frequency decomposition is consistent with **Figure 1**.

TABLE 4 | Net volatility spillover results from oil market to China's commodity sectors.

Net spillovers	WTI-NMFI	WTI-NFFI	WTI-JJRI	WTI-NMBM	WTI-ENFI	WTI-CIFI	WTI-CRFI	WTI-OOFI	WTI-SOFI
DY(2012)	1.5	2.6	2.4	0.5	1.6	0.8	0.3	0.6	0.1
BK(2018) with short-term frequency	0.9	1.6	1.5	0.3	1.0	0.6	0.2	0.4	0.1
BK(2018) with medium-term frequency	0.4	0.7	0.5	0.2	0.3	0.2	0.1	0.2	0.0
BK(2018) with long-term frequency	0.1	0.2	0.2	−0.1	0.1	0.1	0.0	0.0	−0.1

WTI, West Texas intermediate; DY(2012), Diebold and Yilmaz (2012); BK(2018), Baruník and Krehlík (2018).

of short-term factors. This result is also consistent with the conclusion of total return and volatility spillovers (**Figures 3**, **4**), confirming that the net spillovers from the crude oil market to China's commodity sectors are dominated by short-term information (within a week). Meanwhile, the net volatility spillovers of the medium-term and long-term components cannot be underestimated, especially during 2011, 2013, and 2015, which may be associated with the European sovereign debt crisis of 2010–2011, China's market-oriented reform in 2013, and the Chinese stock market disaster in 2015. There are significant differences in the signs of different net volatility spillover components. Even though the short-term net volatility spillovers are positive, the medium-term and long-term components are negative. And the absolute value of the medium-term net spillover is even greater than the short-term net spillover at some extreme moments. This suggests that the negative net spillovers during 2013 and 2015 in **Figure 6** are mainly attributable to the medium-term and long-term net spillovers. Therefore, uncertain financial factors such as China's market-oriented reform in 2013 and China's 2015 stock disaster will affect the net oil-commodity volatility spillovers through the medium-term components (week to month) and long-term components (month to year). In addition, the dynamic net volatility fluctuated considerably during the whole sample period for the three time-frequency components, suggesting that crafting well-diversified portfolios with oil and oil-related assets (such as commodities) is an arduous and complicated task. Those frequency results may help investors and portfolio managers with different investment horizons to implement better portfolio diversification.

Heterogeneous Spillovers From the Crude Oil Market to China's Commodities Sectors

The empirical analysis above has examined the dynamic spillovers of the international oil market and China's commodity sectors in a rolling window. To help the investors make informed decisions about asset allocation, and to help policymakers make effective macroeconomic policies about stabilizing commodity markets, we turn to study whether the oil market poses heterogeneous spillovers to different commodity sectors in China. We examine the pairwise volatility spillovers for the entire sample period. **Table 3** displays the values of the volatility spillovers of the DY(2012). When the net spillover value is positive, it means that the particular commodity sector under consideration is a risk contributor: it passes the net volatility spillover to other commodity sectors. On the other hand, if the net spillover value is negative, it means that a particular commodity sector is a net risk receiver; that is, it receives spillovers from other commodity markets. During the full sample period, WTI is the most critical risk contributor to our system, with a net volatility spillover of 0.71. Nonferrous metals (NFFI) and the nonmetal building materials (NMBM) are the other two main risk contributors, with the net volatility spillover of 0.15 and 0.62, respectively. Energy (ENFI), petrochemicals (CIFI), and the agriculture commodity sectors in China (including CRFI, OOFI, and SOFI) are spillover receivers.

To obtain more detailed information about the volatility spillovers from the oil market to China's different commodity sectors, we calculate the net pairwise spillover results in **Table 4**. For one thing, most of the values in the table are positive, indicating that the international crude oil market has a significant positive volatility spillover to China's commodities sectors, and the volatility spillover is mainly caused by short-term components because the values of short-term frequency components are mostly larger than those of the medium-term and long-term components. This result is consistent with the conclusion of *Dynamic Spillovers Between Crude Oil Prices and China's Bulk Commodity Sectors*. For another thing, the spillover effects from the crude oil market to different commodity sectors are heterogeneous. Specifically, the crude oil market has the strongest volatility spillover effects on nonferrous metals (NFFI), coal coke and steel ore (JJRI), energy (ENFI), and precious metals (NMFI) commodity sectors; followed by petrochemicals, nonmetal building materials, and oils and fats; and the least on grains and soft commodities. For the nonferrous metals sector, some nonferrous metals (e.g., aluminum) have to go through the energy-intensive primary processing. Fluctuations in crude oil prices are often related to inflationary pressures, and expectations for demand for precious metals will change. Therefore, international crude oil prices have a large net spillover effect on China's metals commodity sector. For the energy sector, this result is evident since crude oil and belongs to the energy asset class; therefore, shocks from both oil supply and demand have severely affected the energy sector (Caporale et al., 2015). This reason applies to the coal coke and steel ore sector, as it also belongs to the energy class. Comparing with other sectors, we find that the net spillover effect of oil prices on the agriculture commodity is relatively weak, which may be associated with their less strong and indirect industry correlations. Although the shocks of oil price may be transmitted to the agricultural market by affecting the prices of transportation and agricultural inputs (Du et al., 2011), this spillover effect is relatively insignificant. The results for the agricultural sector are similar to the research of Kaltalioglu and Soytas (2011), who do not find any volatility spillovers from oil to agricultural raw materials. The heterogeneous sectoral impact depends on various factors, such as whether oil or oil-related products are inputs or outputs to the sector, the degree of concentration of the sectors, and the indirect impact of oil prices on the sector (Arouri et al., 2011).

CONCLUSIONS

This paper seeks to shed new light on the dynamic spillovers between the crude oil market and China's bulk commodity sectors from the time-frequency perspective of SV. We utilized the SV model of Kastner and Frühwirth-Schnatter (2014) to measure the volatility of oil prices and China's commodity sector price indices, and then we investigate the time-frequency dynamic spillovers under the GFEVD framework of Diebold and Yilmaz (2012) and the corresponding spectral representation of Baruník and Krehlík (2018). The key findings of this study can be summarized as follows. First, we find that there are significant return and volatility spillover effects between the international crude oil market and China's commodity sectors and that the volatility spillovers react more violently to extreme geopolitical or financial events than the return spillovers. For instance, the European sovereign debt crisis in 2010–2011, Iran's geopolitical tensions in 2012, and the international oil crisis in 2014 cause a significant increase in volatility spillovers. Second, the total return and volatility spillovers are driven mainly by short-term spillovers (within a week), which means that China's commodity markets process information of international oil market rapidly. Third, the net volatility spillovers between international oil market and commodity sectors in China are almost positive, indicating that the international oil market is almost a net risk transmitter of China's commodity market. Fourth, uncertain financial factors from China such as the market-oriented reform in 2013 and the stock disaster in 2015 will also transmit risk to international oil market, and this risk transmission is attributable to medium-term (week to month) and long-term (month to year) components. Furthermore, there exists heterogeneity in net pairwise spillovers between oil and different China's commodity sectors. International crude oil market has the most potent volatility spillover effects on nonferrous metals (NFFI), coal coke and steel ore (JJRI), energy (ENFI), and precious metals (NMFI) commodity sectors in China; followed by petrochemicals, nonmetal building materials, and oils and fats; and the least on grains and soft commodities. This heterogeneous sectoral impact depends on various factors, such as whether oil or oil-related products are inputs or outputs to the sector, the degree of concentration of the sectors, and the indirect impact of oil prices on the sector (Arouri et al., 2011). Comparing with other sectors, we find that the net spillover effect of oil prices on the agriculture commodity is relatively weak, which may be associated with their less strong and indirect industry correlations.

Our outcomes implement important implications for investors and policymakers. For one thing, it is not appropriate to form short-term investors to combine large amounts of crude oil and related stocks into one investment portfolio. Because volatility is directly converted into risk, huge fluctuations in volatility and its spillover effects in commodity sectors will have a negative impact on risk-averse investors. For another, when formulating effective macroeconomic policies, Chinese policymakers need to consider the heterogeneous impact of the international oil market on different commodity sectors in order to stabilize China's commodity market. It is necessary to introduce regulatory and institutional rules to reduce the cross-market impact of excessive price volatility, especially in the short run.

There are some possible extensions of this study. For example, on the one hand, this paper neglected the breakpoints on oil-commodity spillovers. Breakpoint analysis is also an effective method to explore the impact of financial, economic, and geopolitical events on the dynamic spillovers of oil commodities. Besides, this article does not predict the volatility spillovers, which can provide more accurate tools for policymakers and investors. What is more, the asymmetries of the time-frequency dynamic spillovers between the international oil market and China's commodity sectors would also be of great interest.

DATA AVAILABILITY STATEMENT

The datasets generated for this study are available on request to the corresponding author.

AUTHOR CONTRIBUTIONS

ZL and YS made substantial contributions to the conception or design of the work; acquired, analyzed, or interpreted of data for the work; drafted the work or revised it critically for important intellectual content; and provided approval for publication of the content.

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REFERENCES

Acharya, V. V., Pedersen, L. H., Philippon, T., and Richardson, M. (2017). Measuring systemic risk. *The Review of Financial Studies* 30, 2–47. doi: 10.1093/rfs/hhw088

Adams, Z., and Glück, T. (2015). Financialization in commodity markets: a passing trend or the new normal? *J. Bank. Finance* 60, 93–111. doi: 10.1016/j.jbankfin.2015.07.008

Adrian, T., and Brunnermeier, M. K. (2011). *CoVaR (No. w17454)*. National Bureau of Economic Research. doi: 10.3386/w17454

Ahmadi, M., Behmiri, N. B., and Manera, M. (2016). How is volatility in commodity markets linked to oil price shocks?. *Energy Econ.* 59, 11–23. doi: 10.1016/j.eneco.2016.07.006

Apergis, N., Cooray, A., and Rehman, M. U. (2018). Do energy prices affect US investor sentiment?. *J. Behav. Finance* 19, 125–140. doi: 10.1080/15427560.2017.1373354

Arouri, M. E. H., Jouini, J., and Nguyen, D. K. (2011). Volatility spillovers between oil prices and stock sector returns: implications for portfolio management. *J. Int. Money Finance* 30, 1387–1405. doi: 10.1016/j.jimonfin.2011.07.008

Bai, S., and Koong, K. S. (2018). Oil prices, stock returns, and exchange rates: Empirical evidence from China and the United States. *North Am. J. Econ. Finance* 44, 12–33. doi: 10.1016/j.najef.2017.10.013

Balli, F., Naeem, M. A., Shahzad, S. J. H., and de Bruin, A. (2019). Spillover network of commodity uncertainties. *Energy Econ.* 81, 914–927. doi: 10.1016/j.eneco.2019.06.001

Baruník, J., and Krehlík, T. (2018). Measuring the frequency dynamics of financial connectedness and systemic risk. *J. Financial Econ.* 16, 271–296. doi: 10.1093/jjfinec/nby0y01

Basak, S., and Pavlov, A. (2016). A model of financialization of commodities. *J. Finance* 71, 1511–1556. doi: 10.1111/jofi.12408

Beckmann, J., and Czudaj, R. (2014). Volatility transmission in agricultural futures markets. *Econ. Model* 36, 541–546. doi: 10.1016/j.econmod.2013.09.036

Bekiros, S. D., and Georgoutsos, D. A. (2008). Direction-of-change forecasting using a volatility-based recurrent neural network. *J. Forecasting* 27, 407–417. doi: 10.1002/for.1063

Bildirici, M. E., and Turkmen, C. (2015). Nonlinear causality between oil and precious metals. *Resour. Policy* 46, 202–211. doi: 10.1016/j.resourpol.2015.09.002

Caporale, G. M., Ali, F. M., and Spagnolo, N. (2015). Oil price uncertainty and sectoral stock returns in China: a time-varying approach. *China Econ. Rev.* 34, 311–321. doi: 10.1016/j.chieco.2014.09.008

Chen, P. (2015). Global oil prices, macroeconomic fundamentals and China's commodity sector comovements. *Energy Policy* 87, 284–294. doi: 10.1016/j.enpol.2015.09.024

Chen, P. F., Lee, C. C., and Zeng, J. H. (2014). The relationship between spot and futures oil prices: do structural breaks matter? *Energy Econ.* 43, 206–217. doi: 10.1016/j.eneco.2014.03.006

Cheng, D., Shi, X., Yu, J., and Zhang, D. (2019). How does the Chinese economy react to uncertainty in international crude oil prices? *Int. Rev. Econ. Finance* 64, 147–164. doi: 10.1016/j.iref.2019.05.008

Choi, K., and Hammoudeh, S. (2010). Volatility behavior of oil, industrial commodity and stock markets in a regime-switching environment. *Energy Policy* 38, 4388–4399. doi: 10.1016/j.enpol.2010.03.067

Creti, A., Joëts, M., and Mignon, V. (2013). On the links between stock and commodity markets' volatility. *Energy Econ*. 37, 16–28. doi: 10.1016/j.eneco.2013.01.005

de Nicola, F., De Pace, P., and Hernandez, M. A. (2016). Co-movement of major energy, agricultural, and food commodity price returns: a time-series assessment. *Energy Econ.* 57, 28–41. doi: 10.1016/j.eneco.2016.04.012

Diebold, F. X., Liu, L., and Yilmaz, K. (2017). *Commodity Connectedness*. National Bureau of Economic Research (No. w2w3685). doi: 10.3386/w2w3685

Diebold, F. X., and Yilmaz, K. (2009). Measuring financial asset return and volatility spillovers, with application to global equity markets. *Econ. J.* 119, 158–171. doi: 10.1111/j.14688-0297.2008.02208.x

Diebold, F. X., and Yilmaz, K. (2012). Better to give than to receive: predictive directional measurement of volatility spillovers. *Int. J. Forecast* 28, 57–66. doi: 10.1016/j.ijforecast.2011.02.006

Diebold, F. X., and Yilmaz, K. (2014). On the network topology of variance decompositions: measuring the connectedness of financial firms. *J. Econometrics* 182, 119–134. doi: 10.1016/j.jeconom.2014.04.012

Du, L., and He, Y. (2015). Extreme risk spillovers between crude oil and stock markets. *Energy Econ.* 51, 455–465. doi: 10.1016/j.eneco.2015.08.007

Du, X., Cindy, L. Y., and Hayes, D. J. (2011). Speculation and volatility spillover in the crude oil and agricultural commodity markets: a Bayesian analysis. *Energy Econ.* 33, 497–503. doi: 10.1016/j.eneco.2010.12.015

Efimova, O., and Serletis, A. (2014). Energy markets volatility modelling using GARCH. *Energy Econ.* 43, 264–273. doi: 10.1016/j.eneco.2014.02.018

Engle, R. F. (1982). Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation. *Econometrica* 50, 987–1007. doi: 10.2307/1912773

Engle, R. F., and Bollerslev, T. (1986). Modelling the persistence of conditional variances. *Econometric Reviews* 5, 1–50. doi: 10.1080/07474938608800095

Ewing, B. T., and Malik, F. (2013). Volatility transmission between gold and oil futures under structural breaks. *Int. Rev. Econ. Finance* 25, 113–121. doi: 10.1016/j.iref.2012.06.008

Fattouh, B., Kilian, L., and Mahadeva, L. (2013). The role of speculation in oil markets: What have we learned so far? *Energy J.* 34, 7–33. doi: 10.5547/01956574.34.3.2

Frahm, G. (2018). How often is the financial market going to collapse? *Quant. Finance Econ.* 2, 590–614. doi: 10.3934/QFE.2018.3.590

Hafner, C. M., and Preminger, A. (2010). Deciding between GARCH and stochastic volatility via strong decision rules. *J. Stat. Plan. Inference* 140, 791–805. doi: 10.1016/j.jspi.2009.09.008

Jebabli, I., Arouri, M., and Teulon, F. (2014). On the effects of world stock market and oil price shocks on food prices: an empirical investigation based on TVP-VAR models with stochastic volatility. *Energy Econ.* 45, 66–98. doi: 10.1016/j.eneco.2014.06.008

Ji, Q., Bouri, E., Roubaud, D., and Kristoufek, L. (2019). Information interdependence among energy, cryptocurrency and major commodity markets. *Energy Econ.* 81, 1042–1055. doi: 10.1016/j.eneco.2019.06.005

Ji, Q., and Fan, Y. (2012). How does oil price volatility affect non-energy commodity markets?. *Appl. Energy* 89, 273–280. doi: 10.1016/j.apenergy.2011.07.038

Jiang, Y., Jiang, C., Nie, H., and Mo, B. (2019). The time-varying linkages between global oil market and China's commodity sectors: evidence from DCC-GJR-GARCH analyses. *Energy* 166, 577–586. doi: 10.1016/j.energy.2018.10.116

Kaltalioglu, M., and Soytas, U. (2011). Volatility spillover from oil to food and agricultural raw material markets. *Modern Econ.* 2:71. doi: 10.4236/me.2011.22011

Kastner, G. (2019). Dealing with stochastic volatility in time series using the R package stochvol. *arXiv preprint arXiv*:1906.12134. doi: 10.18637/jss.v069.i05

Kastner, G., and Frühwirth-Schnatter, S. (2014). Ancillarity-sufficiency interweaving strategy (ASIS) for boosting MCMC estimation of stochastic volatility models. *Comput. Stat. Data Analysis* 76, 408–423. doi: 10.1016/j.csda.2013.01.002

Koirala, K. H., Mishra, A. K., D'Antoni, J. M., and Mehlhorn, J. E. (2015). Energy prices and agricultural commodity prices: testing correlation using copulas method. *Energy* 81, 430–436. doi: 10.1016/j.energy.2014.12.055

Krehlík, T., and Baruník, J. (2017). Cyclical properties of supply-side and demand-side shocks in oil-based commodity markets. *Energy Econ.* 65, 208–218. doi: 10.1016/j.eneco.2017.05.003

Li, Z., Dong, H., Huang, Z., and Failler, P. (2018). Asymmetric effects on risks of virtual financial assets (VFAs) in different regimes: a case of bitcoin. *Quant. Finance Econ.* 2, 860–883. doi: 10.3934/QFE.2018.4.860

Liu, K., Luo, C., and Li, Z. (2019). Investigating the risk spillover from crude oil market to BRICS stock markets based on Copula-POT-CoVaR models. *Quant. Finance Econ.* 3:754. doi: 10.3934/QFE.2019.4.754

Liu, W. H. (2016). A re-examination of maturity effect of energy futures price from the perspective of stochastic volatility. *Energy Econ.* 56, 351–362. doi: 10.1016/j.eneco.2016.03.026

Liu, Y., Dong, H., and Failler, P. (2019). The oil market reactions to OPEC's announcements. *Energies* 12:3238. doi: 10.3390/en1n2173238

Lovcha, Y., and Perez-Laborda, A. (2020). Dynamic frequency connectedness between oil and natural gas volatilities. *Econ. Model* 84, 181–189. doi: 10.1016/j.econmod.2019.04.008

Luo, J., and Ji, Q. (2018). High-frequency volatility connectedness between the US crude oil market and China's agricultural commodity markets. *Energy Econ.* 76, 424–438. doi: 10.1016/j.eneco.2018.10.031

Maslyuk, S., and Smyth, R. (2009). Cointegration between oil spot and future prices of the same and different grades in the presence of structural change. *Energy Policy* 37, 1687–1693. doi: 10.1016/j.enpol.2009.01.013

Mensi, W., Hammoudeh, S., Nguyen, D. K., and Yoon, S. M. (2014). Dynamic spillovers among major energy and cereal commodity prices. *Energy Econ.* 43, 225–243. doi: 10.1016/j.eneco.2014.03.004

Nazlioglu, S., Erdem, C., and Soytas, U. (2013). Volatility spillover between oil and agricultural commodity markets. *Energy Econ.* 36, 658–665. doi: 10.1016/j.eneco.2012.11.009

Ng, A., and Donker, H. (2013). Purchasing reserves and commodity market timing as takeover motives in the oil and gas industry. *Energy Econ.* 37, 167–181. doi: 10.1016/j.eneco.2013.01.010

Reboredo, J. C., Ugolini, A., and Aiube, F. A. L. (2020). Network connectedness of green bonds and asset classes. *Energy Econ.* 86:104629. doi: 10.1016/j.eneco.2019.104629

Shephard, N., and Andersen, T. G. (2009). "Stochastic volatility: origins and overview," in *Handbook of Financial Time Series* (Berlin; Heidelberg: Springer), 233–254. doi: 10.1007/978-3-540-71297-8_10

Shi, X., and Sun, S. (2017). Energy price, regulatory price distortion and economic growth: a case study of China. *Energy Econ.* 63, 261–271. doi: 10.1016/j.eneco.2017.02.006

Tiwari, A. K., Nasreen, S., Shahbaz, M., and Hammoudeh, S. (2020). Time-frequency causality and connectedness between international prices of energy, food, industry, agriculture and metals. *Energy Econ.* 85:104529. doi: 10.1016/j.eneco.2019.104529

Toyoshima, Y., and Hamori, S. (2018). Measuring the time-frequency dynamics of return and volatility connectedness in global crude oil markets. *Energies* 11:2893. doi: 10.3390/en11112893

Uddin, G. S., Rahman, M. L., Shahzad, S. J. H., and Rehman, M. U. (2018). Supply and demand driven oil price changes and their non-linear impact on precious metal returns: a Markov regime switching approach. *Energy Econ.* 73, 108–121. doi: 10.1016/j.eneco.2018.05.024

Vivian, A., and Wohar, M. E. (2012). Commodity volatility breaks. *J. Int. Financial Markets Inst. Money* 22, 395–422. doi: 10.1016/j.intfin.2011.12.003

Wang, X., and Wang, Y. (2019). Volatility spillovers between crude oil and Chinese sectoral equity markets: evidence from a frequency dynamics perspective. *Energy Econ.* 80, 995–1009. doi: 10.1016/j.eneco.2019.02.019

Wang, Y., Wu, C., and Yang, L. (2014). Oil price shocks and agricultural commodity prices. *Energy Econ.* 44, 22–35. doi: 10.1016/j.eneco.2014.03.016

Yang, L., and Hamori, S. (2018). Modeling the dynamics of international agricultural commodity prices: a comparison of GARCH and stochastic volatility models. *Annals Financial Econ.* 13:1850010. doi: 10.1142/S2S010495218500100

Yang, L., and Hamori, S. (2018). Modeling the dynamics of international agricultural commodity prices: a comparison of GARCH and stochastic volatility models. *Annals of Financial Economics* 13:1850010. doi: 10.1142/S2010495218500100

You, W., Guo, Y., Zhu, H., and Tang, Y. (2017). Oil price shocks, economic policy uncertainty and industry stock returns in China: asymmetric effects with quantile regression. *Energy Econ.* 68, 1–18. doi: 10.1016/j.eneco.2017.09.007

Youssef, M., Belkacem, L., and Mokni, K. (2015). Value-at-Risk estimation of energy commodities: a long-memory GARCH–EVT approach. *Energy Econ.* 51, 99–110. doi: 10.1016/j.eneco.2015.06.010

Zhang, Y. J., Chevallier, J., and Guesmi, K. (2017). "De-financialization" of commodities? Evidence from stock, crude oil and natural gas markets. *Energy Econ.* 68, 228–239. doi: 10.1016/j.eneco.2017.09.024

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The Prospect of New Provincial Renewable Portfolio Standard in China Based on Structural Data Analysis

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The new renewable portfolio standard policy issued by China on May 2019 stipulates a specific promotion scheme of a quota obligation mainly on power supply companies and power consumers to sell or buy an increasing proportion of their electricity from renewable energy sources. The quota is essentially switched from the supply side to the demand side and will be provincially distributed and assessed, consequently motivating the provincial power system to accommodate a more renewable energy power. This paper proposes a prospect analysis by assessing the completion pressure of a newly modified quota in 30 provinces across Mainland China. The results show that 17 provinces enjoy the challenging completion pressure, while 10 provinces make it relatively easy to complete. Structural data analysis toward the provincial power supply structure and electricity balance is then put forward and reveals unfavorable factors for activating completion potential. Systematical measures are correspondingly introduced from the supply side, grid side, and demand side of the power system, with accompanying policy implications toward the core position of the power grid corporation and coordinated market-based mechanism simultaneously proposed.

Keywords: renewable portfolio standard, renewable energy, accommodation, prospect analysis, structural data analysis

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INTRODUCTION

According to the International Renewable Energy Agency (IRENA), high curtailment has been reported in China in parallel with the rapid deployment of variable renewable energy over the past decade, while a set of actions has contributed to accommodating increasing shares of solar and wind, substantially decreasing the curtailment levels as a result. The curtailment rate from 2015 to 2016 achieves its highest level and typically reflects many problems for China's power system in integrating and accommodating renewable energy. Though the average curtailment rates of solar and wind have dropped to 1.9 and 4.2%, respectively, by the end of September 2019, the penetration rate of renewables is still 18.4% lower than its target in 2035 (60%), while the non-fossil energy consumption rate is 5.7% away from its target in 2030 (20%). To integrate more than half of generation from renewables and support further sustainable development of a renewable energy, a more powerful plan-oriented policy, together with a coordinating market-oriented mechanism, is needed (He et al., 2016).

Renewable portfolio standard (RPS) policy is the main promotion scheme of a quota obligation on electricity suppliers to supply an increasing proportion of their electricity from renewable sources, usually structured as a quantity regulation and, in most cases, accompanied with tradable green certificates (TGC) created by the government to track the fulfillment of quotas (Zhang et al., 2017). It was first carried out in 1983, and about 25 countries, including Australia, the United States, Italy, Britain, the Netherlands, Belgium, Denmark, and Japan, have implemented different forms of RPS. It has been proven to be one of the most compulsive policy tools toward promoting the development of renewable energy, especially throughout the representative implementation of California and Texas in the United States. Rouhani et al. (2016) and Bento et al. (2018) evaluated the main effects of introducing RPS from electricity prices, greenhouse gas (GHG) emissions, criteria pollutant emissions, the electricity generation mix, the labor market, renewable investment decisions, and social welfare. Similarly, great changes that will happen to China's power supply structure, emissions reduction, and governmental expenditure on subsidies when RPS together with TGC is practically adopted were illustrated by Feng et al. (2018) and Zhang et al. (2018). The special effect toward cutting curtailment and promoting the accommodation of photovoltaic (PV) and wind power in China was also separately proven by Zhang et al. (2017).

Evolution for the introduction and localization of RPS in China could be divided into two stages. It was firstly introduced in 2007, beginning with assessing electricity suppliers on the quota of renewable energy's installed capacity and generating electricity and had delivered large construction booms on the supply side. However, its effect toward accommodating renewable energy power was undesirable because of the mismatch between construction and accommodation. Then, the assessment subject and index were switched from the supply side to the demand side during evolution of the RPS scheme from NEA (2018a,b,c). In May 2019, the final amendment issued as "*Notice on guarantee mechanism of renewable energy power accommodation*" was published (NEA, 2019a). It stipulated that the RPS target will be annually distributed, provincially implemented, and assessed. The assessment subjects will turn to the power supply company together with power users, and the assessment index will directly concentrate on the accommodation rate of renewable energy power (REP) and non-hydro renewable power (NREP) in the total provincial electricity consumption. The newest notice announced the official launch of the demand side-based provincial RPS in China.

After the quota obligation was imposed on the demand side, studies mainly focused on analyzing the impacts of the policy portfolio concerning RPS, TGC, emission trading, carbon trading, and feed-in tariff (FIT), represented by Zuo et al. (2019) and Li et al. (2018). Yet, rare detailed research drew attention to the following three questions. Which provinces in China are possible to complete their obligated quota while other provinces are under a relatively high completion pressure? How many unfavorable factors against activating the accommodation potential hide behind a complicated provincial power supply structure and electricity balance? What kinds of measures are suitable for different provinces in order to release the accommodation potential? This paper aims to answer these questions and seek out a pathway for ensuring effective implementation of the new provincial non-hydro renewable portfolio standard in China. Besides, the background of RPS implementation in China is quite different from other countries thanks to the characteristics of the supply side, grid side, and demand side of the power system (Chen et al., 2018). The RPS in China must be fulfilled within unique ways regarding the lessons learned from the South Korean government's failure in deploying its RPS policy due to blindly copying international experience (Yoon and Sim, 2015). The unique pathway proposed in this paper also provides references for all responsible or related subjects, including the provincial government, the central government, the provincial power grid corporations and their power supply companies, independent power supply companies, enterprises which possess captive power plants, and all kinds of electricity suppliers, to form their RPS completion schemes.

This paper presents a prospect analysis beginning with illustrating an assessment index of provincial RPS completion and highlights in overviewing provincial completion pressure, then proposes a structural data analysis framework to find out favorable factors hiding behind the provincial power supply structure and electricity balance structure, describes how to improve completion conditions for the obligated quota in different or similar provinces, and provides practical experiences from China to optimally integrate the RPS scheme with the physical power system and other energy policies. This paper focuses on the RPS completion in 30 provincial administrative regions (Tibet is not contained in the assessment) across Mainland China and is organized as follows. Section framework and Prospect Analysis introduces the assessment mechanism for provincial RPS completion and then overviews its implementation prospect by analyzing provincial completion pressure. Section Unfavorable Factors Against RPS Completion identifies several unfavorable factors for RPS completion from structural data analysis toward provincial electricity balance and provincial power supply structure. Section Practical Experience From China empirically illustrates the measures closely related to raising the assessment index of RPS or activating accommodation potential, with their measure characteristics and applicable provinces simultaneously listed. Section Conclusions concludes the paper.

FRAMEWORK AND PROSPECT ANALYSIS

Framework of This Paper

The major analysis framework consists of two important parts. One is prospect analysis based on the completion pressure for the obligated quota. The other one is unfavorable factor analysis based on structural data related to NREP accommodation, provincial power supply structure, and electricity balance. The data availability and validity, together with the feasibility and rationality of the analysis methods proposed in this paper, are simply explained. The estimated completion prospect reveals differences among the provinces across the Chinese Mainland and further leads to finding out the unfavorable factors against activating the accommodation potential. Based on the results of these two analyses, this paper further summarizes empirical measures from the supply side, grid side, and demand side of China's physical power system and illustrates a unique pathway for future RPS implementation combined with experiences from China's practice and other countries.

Assessment Mechanism for Provincial RPS Completion[1]

Provincial Quota Distribution

The distributed quota T_i^t for province i in assessment year t will be annually calculated and determined 1 year before using Equation (1).

$$T_i^t = \frac{\mathrm{PL}_i^{t-1} + \mathrm{PE}_i^{t-1}}{\mathrm{PC}_i^{t-1}} \tag{1}$$

where PL_i^{t-1} is the predictable amount of the locally absorbed accommodation 1 year before which will be generated inside province i in year t; PE_i^{t-1} is the predictable amount of the locally absorbed accommodation which will be imported outside province i in year t; and PC_i^{t-1} is the predictable amount of electricity consumption for province i in year t.

Overall Assessment for a Province

According to the newest RPS scheme issued in May 2019, the overall completion progress of the obligated quota for a province is defined as RPS completion. Both amount index and proportion index of RPS completion are assessed by Equations (2) and (3).

$$\mathrm{Com}_i^t = A_i^t + \mathrm{RPS}_i^t + \mathrm{TGC}_i^t - w_i^t \tag{2}$$

$$\mathrm{Ind}_i^t = \frac{\mathrm{Com}_i^t}{\left(C_i^t - w_i^t\right)} \tag{3}$$

where Com_i^t is the amount index of RPS completion for province i in year t; Ind_i^t is the proportion index of RPS completion for province i in year t; A_i^t is the physical accommodation of renewable energy electricity for province i in year t, which is reflected in the provincial electricity balance; RPS_i^t is the total assigned amount of tradable accommodation purchased by all subjects located in province i; TGC_i^t is the total equivalent amount of accommodation corresponding to the voluntary green certificates purchased by all subjects located in province i; w_i^t is the part of electricity consumption which is closely related to public welfare and declared to be out of assessment for province i in year t; and C_i^t is the annual electricity consumption in the whole province i for year t.

Single Assessment for a Responsible Subject

The provincial quota distributed by the NEA will be further undertaken by all responsible subjects located in the same province. The responsible subjects involved in this demand side-based assessment can be divided into two categories. One is collectively called the power supply company, including the independent power supply company that possesses no operation right of the distribution network and the dependent one which belongs to a power grid corporation and directly supplies power to end users. The other one is collectively called the power consumer, including those who directly purchase electricity through a wholesale electricity market and enterprises that possess their captive power plants. All the involved subjects must correspondingly buy (or sell) the same or higher proportion of renewable energy power in their total power purchase (or sale) as the obligated quota for their located province. All the identified RPS completion of a single responsible subject contributes to the total RPS completion of a province.

In particular, the tradable part accompanying the physical assessment consists of two alternatives. One is to purchase the surplus accommodation from market entities whose physical RPS completion has exceeded their obligated one. The other is to voluntarily purchase TGC from green power suppliers with its correspondingly equivalent amount of accommodation be recorded as supplementary RPS completion.

The completion progress of the obligated quota for a single responsible subject is assessed using Equations (4) and (5).

$$\mathrm{com}_j^t = \tau \cdot B_j^t + (1-\tau) \cdot S_j^t + B\mathrm{RPS}_j^t + \mathrm{BTGC}_j^t + Z_j^t - w_j^t \tag{4}$$

$$\mathrm{ind}_j^t = \frac{\mathrm{com}_j^t}{\left(\tau \cdot \mathrm{TB}_j^t + (1-\tau) \cdot \mathrm{TS}_j^t - w_j^t\right)} \tag{5}$$

where com_j^t is the amount index of RPS completion for subject j in year t; ind_i^t is the proportion index of RPS completion for subject j in year t; B_j^t is the actual purchases of renewable energy electricity for power user j in year t; S_j^t is the actual sales of renewable energy electricity for power supply company j in year t; BRPS_j^t is the assigned amount of directly purchased accommodation for subject j in year t; BTGC_i^t is the equivalent amount of accommodation corresponding to the voluntary green certificates purchased by subject j in year t; Z_j^t is the part of electricity which is generated and simultaneously consumed by subject j itself in year t; w_j^t is the part of electricity which is declared to be out of assessment for subject j in year t; and TB_j^t and TS_j^t are the total purchases and TS_j^t the total sales of electricity, respectively, for subject j in year t. τ is set to be 0 when subject j is a power supply company and set to be 1 when subject j is a power user.

Relationships Between RPS and TGC

TGC is usually considered as the certificate for consuming renewable energy and provides the only market-oriented alternative for subjects to complementarily complete their obligated quota. However, this RPS scheme issued in China provides two market-oriented alternatives for RPS completion, voluntary TGC to RPS is not as important as public imagination. The relationship between RPS and TGC seems to be more independent.

Besides, due to the relatively unenforceable TGC, joint administrative punishment and bad credit record substitute

[1]RPS completion and the related parameters used in all equations were all non-hydro ones by default, and hydropower was not assessed unless separately mentioned in this paper.

the economic compensation that is once forced to be paid, for those provinces which can neither absorb enough physical accommodation nor finally buy or sell enough tradable accommodation. This characteristic further reduces TGC's economic influence on RPS, making RPS implementation less reliable to TGC. Last but not least, TGC is still an important part of this RPS scheme because provinces would either raise actual accommodation capability and physically accommodate more NREP, or encourage responsible subjects to purchase enough amount of tradable RPS completion whether through a direct assigned transaction of accommodation or a voluntary subscription of TGC to complete or exceed the obligated quota.

Assessment Index for Completion Pressure

The NEA has been monitoring and evaluating the provincial accommodation of renewable energy power in China for 4 years, which means that the available official data of the total provincial accommodation and its proportion in electricity consumption from 2015 to 2018[2] can be directly quoted from the "*Report on the monitoring and evaluation of national renewable energy and electricity development*" annually issued by the NEA. Equation (6), defined according to these annual reports, is used here to estimate the changing trend of the important parameters in the overall assessment for provincial RPS completion, such as A_i^t and C_i^t.

$$I_i^t = \frac{A_i^t}{C_i^t} \tag{6}$$

where I_i^t is the accommodation rate of non-hydro renewable energy electricity for province *i* in year *t*.

These reports reveal a fact that the most serious curtailment problem appears in 2015 and 2016 and begins to decline in 2017. Our investigation toward Inner Mongolia, Qinghai Province, and Gansu Province was also organized in 2016 and 2017. In addition, data for some provinces in 2018 were calculated using a different statistical method. Therefore, the data from 2015 to 2017 are the most representative for reflecting problems. Data in 2018 are used here to compare with our prediction. Both the amount and proportion data for the provincial accommodation of non-hydro renewable energy electricity from 2015 to 2017 are listed in **Table 1**.

The assessment index for completion pressure is defined to reflect the difficulty in completing the obligated quota. Analysis in this section chooses data from 2015 to 2017 as a representative. Though provincial electricity consumption and the corresponding accommodation rate 2 years later could not be precisely predicted via data in 2015 due to various uncertainties, Equation (7) might simply be used here to similarly reflect the completion pressure of the provincial RPS target.

$$M_i^{\text{pre}} = \frac{T_i^{\text{Nov}} - I_i^{2017}}{T_i^{\text{Nov}}} \tag{7}$$

where M_{pre} is the provincial completion pressure, T_i^{Nov} is the newest non-hydro RPS target, and I_i^{2017} is the accommodation rate of the non-hydro renewable energy electricity for province *i* in 2017.

The prospect analysis based on the assessment index of completion pressure is a practical and direct way to simply find out the distance from the present circumstances to the obligated one across Mainland China. The basic change trend of RPS completion could be inferred by the estimation results and verified by the actual data in 2018. However, the fluctuation led by the newly added accommodation and the excess one led by synergism among policy portfolios are not included in this paper. Nevertheless, the estimation results of the completion pressure that is calculated from the most related actual data are rational enough to be regarded as part of the key indexes in organizing the following prospect overview.

Prospect Overview for Provincial RPS Completion

The provinces in **Table 1** were sorted using M_{pre} in ascending order and were divided into three categories according to the completion pressure of the RPS target. Provinces in class A completed their targets at the end of 2017, including Yunnan, Ningxia, and Inner Mongolia Province. Ten provinces in class B made it relatively easy to complete, while 17 provinces in class C had to complete another 20% or more challenging rate of the RPS target before 2020[3].

A higher provincial RPS target means more expectations on absorbing a non-hydro renewable energy power, potentially resulting in more completion pressure. On one hand, there were a total of 10 provinces possessing an RPS target no <15%, and five of these provinces were classified as class C, and over half of them had at least a quarter of RPS completion remaining to be finished. On the other hand, most provincial targets of the provinces in classes B and C dropped or remained stable from the firstly distributed one to the newly modified one, except Beijing, Tianjin, Hebei, Jiangsu, Zhejiang, Guangdong, Liaoning, Shaanxi, Gansu, Xinjiang, and Guizhou Province. These 11 provinces, together with three provinces classified as class A, possessed either a huge electricity consumption or abundant non-hydro renewable energy resources, which probably led to their relatively high potentials and expectations for raising the assessment index of RPS completion.

Provinces in the "Three North" region were the main producers and exporters of non-hydro renewable energy power thanks to their abundant resources of wind and solar energy. These 12 provinces or regions, shown in **Figure 1**[4] ought to bear more responsibility in RPS completion under their relatively high RPS target. The provinces or regions in **Figure 1** were

[2]The report for 2019 is not yet published.

[3]The boundary value between classes B and C was set to be 20% considering the stipulation that the regulated monitoring and evaluation will be removed when the overall assessment index (including hydropower) exceeds 80% of the target (NEA, 2018c). Thus, it was more challenging for the non-hydro one to exceed this level.

[4]Specially, **Figure 1** used "Jingjinji" to represent Beijing–Tianjin–Hebei region because Beijing, Tianjin, and Hebei Province possessed the same RPS target and were set to be an integral region when involved in RPS assessment. AH_i^t is the provincial accommodation amount of hydropower.

TABLE 1 | Evolution of the non-hydro RPS target and accommodation rate, 2015–2017[a].

Class	Province	M_i^{pre} (%)	T^{Mar}	T^{Sep}	T^{Nov}	I_i^{2015}	I_i^{2016}	I_i^{2017}	I_{Ave}^{inc}	C_i^{2017}	C_{Ave}^{inc} (%)	A_i^{2017}	A_{Ave}^{inc} (%)
A	Yunnan	−23.5	10	12	11.5	5.1	12.5	14.2	4.6	154.2	3.7	21.9	82.8
	Ningxia	−5.0	21.5	20	20	13.4	19.1	21	3.8	98.1	5.8	20.6	32.6
	Inner Mongolia	−1.7	13	18	18	12	15.3	18.3	3.1	288.5	6.6	52.8	31.4
B	Jilin	0.6	20	17	16.5	12.1	13.7	16.4	2.1	70.1	3.7	11.5	20.8
	Chongqing	4.0	3.5	2.5	2.5	1.4	1.6	2.4	0.5	100	6.9	2.4	42.5
	Sichuan	5.7	4.5	3.5	3.5	1.4	2.3	3.3	0.9	221.2	5.4	7.3	61.8
	Hainan	6.0	5	5	5	4	4.5	4.7	0.3	29.8	4.7	1.4	12.9
	Shanghai	10.0	3.5	3	3	1.6	2	2.7	0.5	151.9	4.0	4.1	33.6
	Liaoning	12.4	9	10.5	10.5	7.7	8.6	9.2	0.8	214.1	3.9	19.7	13.9
	Guizhou	14.0	4.8	5	5	2	4.6	4.3	1.2	137.2	8.1	5.9	75.7
	Shanxi	17.2	15	15	14.5	7	10	12	2.5	198.3	6.9	23.8	40.4
	Xinjiang	18.1	14.5	21	16	7.8	11.1	13.1	2.6	200.8	−2.5	26.3	25.0
	Jiangxi	18.8	14.5	8	8	2.2	3.8	6.5	2.1	129.2	9.1	8.4	87.1
C	Guangdong	20.0	3.8	4.5	4	1.8	1.9	3.2	0.7	590.6	5.5	18.9	44.5
	Henan	22.9	13.5	11	10.5	2.3	4.4	8.1	2.9	314.8	4.6	25.5	95.1
	Heilongjiang	22.9	22	20.5	20.5	11.2	12.4	15.8	2.3	92.4	3.1	14.6	23.0
	Anhui	23.5	14.5	13	11.5	3.9	6.1	8.8	2.4	192	8.2	16.9	62.8
	Fujian	25.0	7	7	6	3.4	3.7	4.5	0.5	211.1	6.8	9.5	22.9
	Qinghai	26.0	25.5	25	25	13.5	18.3	18.5	2.5	68.6	2.3	12.7	20.0
	Gansu	27.4	15	20	19	11.4	12.5	13.8	1.2	115.9	2.9	16	13.4
	Jiangsu	28.0	6.5	7.5	7.5	3.3	4.2	5.4	1	585.2	7.0	31.6	36.8
	Beijing	30.7	13	15	15	7.6	9	10.4	1.4	106.7	5.8	11.1	24.2
	Tianjin	30.7	13	15	15	7.6	9	10.4	1.4	80.8	0.4	8.4	17.3
	Hebei	30.7	13	15	15	7.6	9	10.4	1.4	343.3	4.0	35.7	21.7
	Hubei	32.0	11	10	10	3.7	4.7	6.8	1.5	186.8	5.9	12.7	43.4
	Shandong	34.3	10.5	11	10.5	5	5.6	6.9	0.9	539.1	2.7	37.2	20.3
	Shaanxi	35.8	11.5	12	12	2.7	3.8	7.7	2.5	149.4	10.6	11.5	90.8
	Guangxi	40.0	5	5	5	1	1.3	3	1	146.7	4.9	4.4	86.5
	Zhejiang	44.0	6	7.5	7.5	2.4	3.6	4.2	0.9	419	8.6	17.6	45.9
	Hunan	44.6	19	17.5	13	2.8	4.1	7.2	2.2	159.7	5.0	11.5	68.4

Calculated by the authors from NEA (2016, 2018a,b,c), and NEA (2018d).

[a] *The descriptions for headers remain the same with their definitions right after related Equations. Specially, provincial quotas are distributed three times in March, September and November in 2018. I_{Ave}^{inc} is the average annual increasing percentage of accommodation rate from 2015 to 2017. C_{Ave}^{inc} and A_{Ave}^{inc} are the average annual increasing rate of provincial electricity consumption and accommodation, respectively, from 2015 to 2017.*

sorted by completion pressure from left to right and top to bottom, based on summarized data from NEA (2016, 2017a), and NEA (2018d).

Higher RPS completion pressure for these provinces meant more motivation for promoting nearby accommodation inside the "Three North" region because more completion would be preferentially done by local accommodation while the export of redundant RPS completion would be less. This ought to be a more economical way for accommodation compared with long-distance trans-regional transmission. It has been proven that there remained much potential for absorbing uncertain green electricity inter-provincially or trans-regionally throughout the "Three North" region by activating nearby accommodation regardless of a saturated electricity consumption market. For instance, trans-regional accommodation between the North–West China Grid (NWCG), the North China Grid (NCG), and the North–East China Grid (NECG) totally achieved 9.64 TWh, as illustrated in **Figure 2**. And inter-provincial accommodation achieved 2.07 TWh among provinces in the NWCG and 5.2 TWh in NECG. Though there were still rough accommodation problems in the "Three North" region, the accommodation rate of non-hydro renewable energy power, shown as I_i^t in **Figure 1**, had risen from 2016 to 2017, especially in Xinjiang, Ningxia, Inner Mongolia, Heilongjiang, and Jilin Provinces. However, completion pressure was quite different from each other in the "Three North" region. Whether the first five provinces illustrated in **Figure 1**, which were classified as class C, had more potential to achieve the RPS target through nearby accommodation remained uncertain.

The excessively high completion pressure for provinces in the "Three North" region might reduce the supply in the trading market for RPS completion and act against a nationwide accommodation of non-hydro renewable energy power. Compared with the low increase of the provincial electricity consumption from 2015 to 2017, some provinces

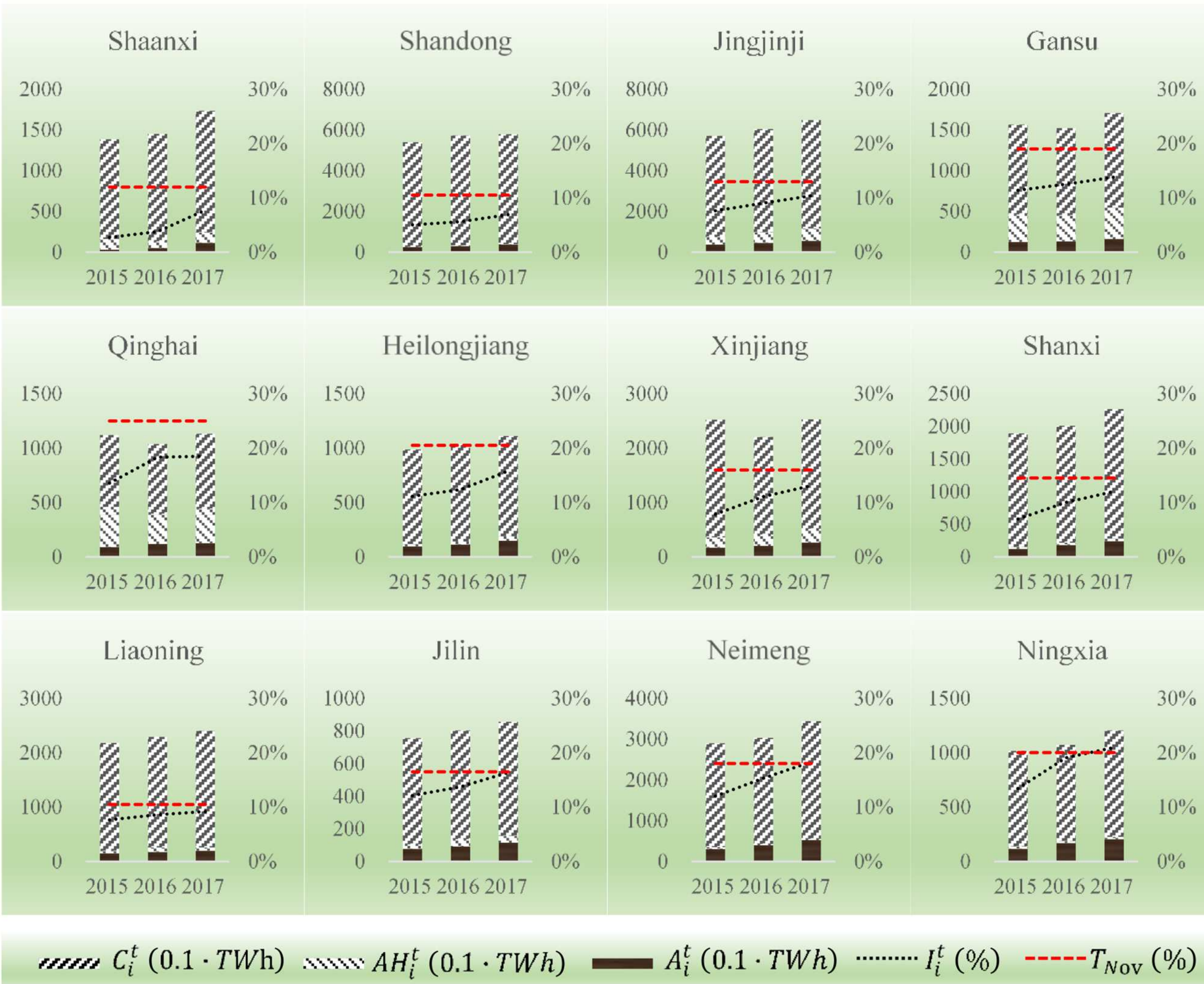

FIGURE 1 | Evolution of the provincial accommodation rate in the "Three North" region, 2015–2017.

such as Shaanxi achieved an extremely high growth rate of accommodation amount, while provinces such as Qinghai and Gansu had a weak growth especially from 2016 to 2017. The distributed target might be too high for them. Even worse, the obvious increase of RPS completion in some provinces was more likely led by the sacrifice of hydropower, which was also green renewable energy power. A comparison between the accommodation of non-hydro renewable energy power and hydropower, illustrated as a histogram in **Figure 1**, also revealed this problem. It was not limited to the "Three North" region and was particularly serious in Shaanxi, Gansu, Qinghai, Guangxi, and Yunnan Provinces in 2016. The accommodation of hydropower electricity decreased by 43.8 TWh, while the total accommodation of wind and PV simultaneously increased by 16 TWh in these five provinces. Presumably, a large part of hydropower curtailment occurred in order to transfer more accommodation space for non-hydro renewable energy power thanks to excessive pressure. Yet, this over-optimistic rising data of accommodation was basically set to be a reference for further dynamic modification of the RPS target and will lead to more excessive completion pressure.

In contrast, provinces in the East China Grid (ECG) and the Central China Grid (CCG) should have played a more important role in RPS completion considering their large electricity consumption market, but the completion pressure for some of them were not motivated enough to completely develop their potentials for absorbing green power especially through trans-regional accommodation. There were six provinces in China possessing electricity consumption over 300 TWh, and five of them are located in ECG and CCG. A relatively high completion pressure is beneficial for guiding these provinces to bear more RPS obligation that is equivalent to their electricity consumption. Nearby accommodation is

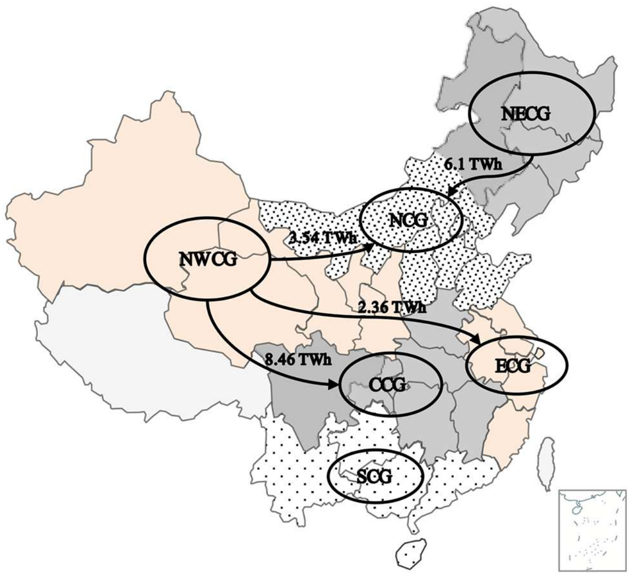

FIGURE 2 | Trans-regional accommodation of non-hydro renewable energy power in China.

also preferentially encouraged, but restricted by limited nearby installation of wind or solar power. Alternatively, trans-regional accommodation should be further utilized to absorb more uncertain green power through transmission lines. For instance, trans-regional accommodation between the NWCG and CCG achieved 8.46 TWh in 2016, as illustrated in **Figure 2**, which only occupied 0.8% in total electricity consumption and 14.1% in total accommodation of the provinces located in CCG. The same two percentages between NWCG and ECG were 0.2% and 4.1%, which were also extremely low. On the contrary, the total export electricity of wind and PV in NWCG only achieved 14.4 TWh, merely occupying 17.7% in the total production of non-hydro renewable energy electricity. These five low percentages simultaneously revealed the fact that these provinces could enjoy a better balance between supply and demand of green power through motivating trans-regional accommodation.

Further Discussion

In 2018, the actual accommodation rate of 10 provinces exceeds their obligated targets for 2020, according to NEA (2019b). Eight of them are located in class B before. Yunnan and Ningxia Provinces are still located in class A, while Inner Mongolia declined to locate in class B. This could partially verify the rationality of the prospect analysis method proposed in this paper. The difference between the actual circumstance in 2018 and the estimated assessment results is possibly led by the impacts of parameter uncertainties. These uncertainties mainly come from the newly added accommodation gained in increasing consumption market and further accommodation of decentralized NREP.

The experience of implementing the RPS scheme in California, Japan, and Britain, is to conduct accommodation cost to end users by a compulsory TGC market and a mature electricity market. Whether responsible subjects are actively involved in RPS implementation depends on the price signal of these two markets. China has reformed its power system, but the electricity market is far from mature. Therefore, there is much more potential for RPS completion that could be developed from a market-oriented transition.

Besides, enterprises are more willing to consuming NREP either through a direct purchase or certificates subscription (Zhang and Ji, 2019). This has become a global trend due to social responsibility or customer demand (Xu et al., 2019). With future green financial tools, China will motivate more potential for absorbing green power, as illustrated in Ji and Zhang (2019) and Zhang et al. (2019). In addition, technological revolution in block chain will further remove obstacles to the certificate trade and release more completion possibility for the obligated quota (Ji et al., 2019).

UNFAVORABLE FACTORS AGAINST RPS COMPLETION

Structural Data Analysis

The structural data analysis proposed in this paper is based on three "structures." The structure of accommodation, the power supply structure, and the structure of provincial electricity balance. The first structure is closely related to complex components, including locally produced and accommodated NREP, a locally accommodated one but is produced outside, and the dispersedly absorbed one. The second one is about the amount and proportion data for all kinds of power suppliers, especially for thermal power units. The third one reflects detailed provincial electricity balance, including trans-provincial export or import of NREP and total power exchange, local electricity production, and consumption. All the complicated data are collectively illustrated together to directly reveal unfavorable factors against activating accommodation potential and RPS completion. The structural data analysis framework is applied to find out the data relationship hiding behind these three "structures."

The data used in this section were collectively quoted from several yearbooks for 2015 issued by the China Electricity Council (CEC) and the National Statistical Bureau of China (NSBC). Besides, the valid data in 2015 reflected China's most common curtailment problem in recent years. The influence factors related to NREP accommodation could be either estimated in the simulation system based on unit commitment and an economic dispatch model or analyzed based on a macroscopic economic model with a detailed module of the electricity department (Li et al., 2018). The method applied in this section avoids the complicated calculation of the former and the strict economic conditions of the latter and is feasible and rational due to the close relationships among the core parameters inside the three "structures."

Provincial Electricity Balance and Insufficient Interconnection of the Power Grid

The following subsection identifies unfavorable factors for RPS completion which hide behind the complex relationships between the structural data of electricity balance and the accommodation in 2015. Every province fulfills its electricity balance by consuming electricity that is generated locally or imported outside. The provincial electricity balance, together with the structural parameters of accommodation and generation, are listed as Equations (8–10).

$$G_i^t + \mathrm{Imp}_i^t = C_i^t \tag{8}$$

$$A_i^t = L_i^t + E_i^t \tag{9}$$

$$G_i^t = \mathrm{GN}_i^t + \mathrm{GH}_i^t + \mathrm{GT}_i^t \tag{10}$$

where G_i^t is the total provincial electricity generated locally; Imp_i^t is the final imported or exported electricity outside a province (it is set to be negative if the province finally exported power); C_i^t is the provincial electricity consumption; A_i^t is the provincial accommodation of non-hydro renewable energy power; L_i^t is the locally generated and absorbed part of accommodation; E_i^t is the imported part of accommodation (it is also set to be negative if the province finally exported non-hydro renewable energy power); and GN_i^t, GH_i^t, and GT_i^t, respectively, refer to the locally generated electricity from non-hydro renewable energy power, hydropower, and thermal power.

It is well-known that the development of the electricity industry in China is strictly plan-oriented. At present, nearly all provinces across Mainland China have published their provincial 13th 5-Year Plan (FYP) not only for the development of the electricity industry but also for the utilization of renewable energy. As the first year of the 13th FYP, 2015 was chosen to be the representative year, with its structural data illustrated in **Table 2** in this paper. Provinces were sorted by the amount of Imp_i^t.

Nearly every province exports locally generated power to others and meanwhile imports power outside to flexibly achieve a real-time power balance and electricity balance. Among those 30 provinces across Mainland China, there were 14 provinces finally exporting power to others and 16 provinces finally importing power from others in 2015.

The relationships between Imp_i^t and E_i^t, concluded from **Table 2**, showed that not all provinces which finally exported power to others simultaneously possessed export of non-hydro renewable energy power. It was assumed that locally generated electricity was preferentially accommodated so that the column illustrated as L_i^t was set to be the same as GN_i^t. Only five provinces which are famous for their rapid development of centralized PV and wind power stations finally exported non-hydro renewable energy power when exporting electricity to others. The final Imp_i^t in the other nine exporting provinces was more probably occupied by hydropower and thermal power. As for those 16 importing provinces, another relationship was illustrated from **Table 2** that all provinces which finally imported power from others simultaneously possessed some but extremely little import for non-hydro renewable energy power.

Notably, the amount of total import of non-hydro renewable energy electricity was far more than that of the total export shown as E_i^t in **Table 2**, which was away from the realistic balance of supply and demand in the inter-provincial or trans-regional trading market for green electricity. In fact, there was another important part which should also be contained in L_i^t yet not being assessed in this section. It is usually the accommodation of electricity generated by a distributed system of PV or wind power. The amounts in the column illustrated as L_i^t in **Table 2** were far lower than the realistic ones due to the absent electricity generated by distributed solar or wind power station. However, two basic relationships illustrated in the previous paragraph were still reasonable, though the absent calculations of distributed systems, the effects from absent four provinces of China, and the international export or import were not assessed. These two relationships between the structural data of electricity balance and accommodation revealed a tough circumstance that neither the supply side nor the demand side of the inter-provincial or trans-regional electricity trading market had a high proportion of NREP.

Once the RPS was strictly implemented, it would be another structure of electricity balance and decomposition of accommodation, where A_i^t and E_i^t rose before a new balance between G_i^t, Imp_i^t, and C_i^t formed, especially in those provinces with high completion pressure no matter they finally exported or imported electricity. More provinces classified in class B would be likely to complete their RPS target and then become suppliers of surplus RPS completion. By then, the total supply of RPS completion, which was calculated by the electricity consumption and RPS target of the provinces that had completed their targets, would be enough to support a sustainable trading market.

However, several obstacles must be overcome in the way provinces are improving conditions for completing RPS.

NREP installations in China were concentrated in the "Three North" region, large in scale, far away from the load center, and difficult to be locally absorbed, while NREP installations in Europe, America, and other countries were dispersedly distributed and absorbed nearby. Transmitting green power generated from the "Three North" region to the load center seemed to be one of the few available alternatives for China to improve tough accommodation. Yet, neither the technological delivering capacity of the trans-regional transmission lines nor the benefits distribution between the importing and the exporting provinces of green electricity transaction was ideal.

The total trans-regional power transmission capacity had achieved 93.42 million kW till the end of 2018, merely accounting for 26% of the total installed capacity of PV and wind power, which was far from enough in contrast to the rapid development of arranged PV and wind power bases in recent years. As a comparison, the transmission capacity between Denmark, Norway, Sweden, and other countries was 1.6 times the domestic wind power installations, and Portugal

TABLE 2 | Structural data of the provincial electricity balance and accommodation, 2015.

Province	Imp_i^t	GN_i^t	GH_i^t	GT_i^t	G_i^t	C_i^t	A_i^t	E_i^t	L_i^t	M_i^{pre} (%)
Inner mongolia	−138	31.4	3.6	342.2	392.3	254.3	30.6	−0.8	31.4	−1.7
Sichuan	−121.6	1.2	276.7	42.9	320.8	199.2	2.8	1.6	1.2	5.7
Yunnan	−111.4	10	217.7	27.6	255.3	143.9	7.3	−2.7	10	−23.5
Guizhou	−75.7	3.3	82.7	107.1	193.1	117.4	2.3	−1	3.3	14.0
Shanxi	−72.1	10.8	3.1	231.9	245.8	173.7	12.1	1.3	10.8	17.2
Hubei	−69.1	2.3	130.3	103	235.6	166.5	6.2	3.9	2.3	32.0
Anhui	−42.2	2.4	4.9	198.9	206.2	164	6.4	4	2.4	23.5
Xinjiang	−31.8	20.8	20.3	206.7	247.8	216	16.9	−3.9	20.8	18.1
Ningxia	−28.8	12.4	1.6	102.6	116.6	87.8	11.8	−0.6	12.4	−5.0
Gansu	−12.9	18.6	33.6	70.6	122.8	109.9	12.5	−6.1	18.6	27.4
Shaanxi	−9.9	2.3	8.3	121.5	132.1	122.2	3.3	1	2.3	35.8
Jilin	−5.2	6.1	5.3	59	70.4	65.2	7.9	1.8	6.1	0.6
Fujian	−3.1	4.5	43.9	110.9	188.3	185.2	6.3	1.8	4.5	25.0
Heilongjiang	−2.6	7.2	1.9	80.4	89.5	86.9	9.7	2.5	7.2	22.9
Guangxi	1.5	0.7	76.2	54.4	132	133.4	1.4	0.7	0.7	40.0
Hainan	1.7	0.8	0.9	23.4	25.5	27.2	1.1	0.3	0.8	6.0
Qinghai	8.5	8.2	37.1	12	57.3	65.8	8.9	0.7	8.2	26.0
Jiangxi	10.5	1.4	17.1	79.7	98.2	108.7	2.4	1	1.4	18.8
Chongqing	19.3	0.3	22.9	45	68.2	87.5	1.2	0.9	0.3	4.0
Hunan	19.5	2.3	52	71	125.3	144.8	4.1	1.8	2.3	44.6
Tianjin	20	0.7	0	59.4	60.1	80.1	6.1	5.4	0.7	30.7
Henan	32.1	1.5	10.9	243.5	255.9	288	6.7	5.2	1.5	22.9
Liaoning	36.6	11.3	3.2	132.9	161.9	198.5	15.2	3.9	11.3	12.4
Shandong	49.8	12.8	0.7	448.4	461.9	511.7	25.7	12.9	12.8	34.3
Beijing	53.1	0.3	0.7	41.2	42.2	95.3	7.2	6.9	0.3	30.7
Zhejiang	58.3	2.4	22.9	222.2	297.1	355.4	8.4	6	2.4	44.0
Shanghai	58.5	1.1	0	81	82.1	140.6	2.3	1.2	1.1	10.0
Jiangsu	68.9	9.6	1.2	415.2	442.6	511.5	16.9	7.3	9.6	28.0
Hebei	87.5	17.1	1.1	210.6	230.1	317.6	24.1	7	17.1	30.7
Guangdong	152.2	4.5	28.4	285.4	378.9	531.1	9.7	5.2	4.5	20.0

Compiled by the authors from NSBC (2016) and CEC (2016).

connected more than a half of the installed capacity of NREP to neighboring countries. Long-distance transmission was mainly supported by ultra-high-voltage (UHV) transmission lines in China. The following eight UHV alternative current (UHVAC) and 13 UHV direct current (UHVDC) transmission lines listed in **Table S1** in the **Supplementary Material** available online and in **Figure 3** were also the backbone channel of the nationwide power grid. Nevertheless, only four lines were designed to transmit NREP; three lines had been approved for auxiliary power suppliers generated from wind or PV. Only two of them, illustrated as No. 13 and No. 15 in **Table S2**, had a reasonable transmission proportion of NREP (near 30%) on the limited technological conditions that an uncertain power output of PV and wind installations could not be solely delivered. Even worse, these lines had to undertake the external power transmission task of the coal-fired power generation bases, which further compressed the conveying space of NREP. In a word, limited trans-provincial or trans-regional transmission capacity determined the insufficient interconnection of the power grid, and even low capacity for delivering NREP restricted nationwide accommodation.

The receiving province of the trans-regional or inter-provincial transmission toward green power had to compress the generating space of local power suppliers thanks to the non-adjustable and plan-oriented output of importing power. And the price of a long-distance import of green power was usually more expensive than the local ones. It was not economically motivated enough for receiving provinces to agree on the transactions, unless the economic compensation mechanism was reasonable. Inter-provincial barriers still existed in China, while Europe has formed a unified electricity market. This compensation mechanism was harder for China to design mostly due to the low marketization degree of the electricity market.

Provincial Power Supply Structure and Limited Flexibility of the Supply Side

With high penetration of NREP integrated, the randomness and fluctuation of its output increase the burden of peak

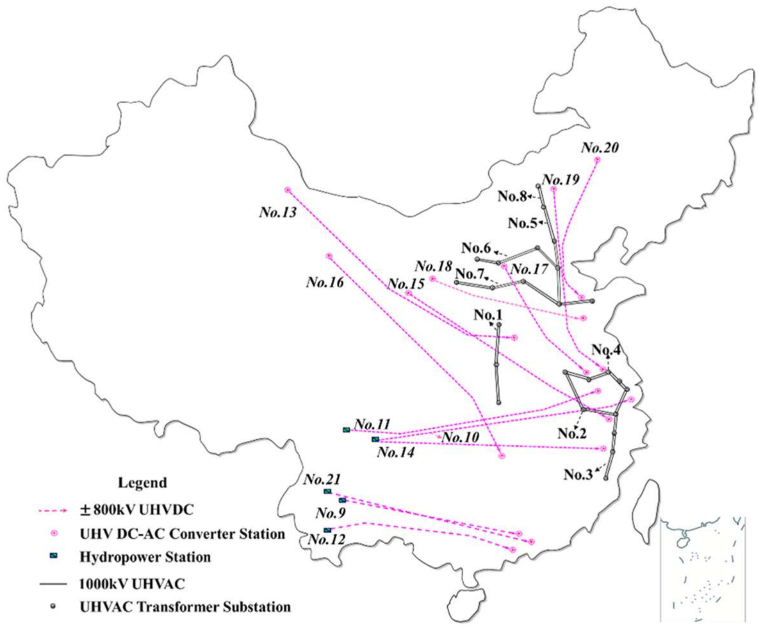

FIGURE 3 | Distribution map of the completed eight ultra-high-voltage alternative current (UHVAC) and 13 ultra-high-voltage direct current (UHVDC) transmission lines (Shu and Chen, 2018).

regulation, and more flexibility of the power system is required. Conventional power suppliers not only need to follow the load changes but also need to flexibly balance the output fluctuation of PV and wind power. When the power output of NREP exceeds the regulation range of the power system, the output must be controlled to ensure a dynamic balance, resulting in the curtailment of PV and wind power. Yet, not only the lack of flexible regulated power supplies and the limited flexibility of the conventional power units, especially those coal-fired units, but also the negative participation of captive power plants in peak regulation, made the power system in China inflexible to accommodate more NREP, which was to the disadvantage of completing the RPS target.

China's power supply structure is still dominated by coal-fired power, especially in the "Three North" region. The average national proportion of flexible regulated power supplies, such as pumped storage and gas-fired power, is only 6%, while the inflexible thermal units account for over 70%. **Table S2** illustrated the proportion of flexible unit in a power supply structure in the "Three North" region, which was far lower than that of Spain, Germany, America, and Portugal.

The peak regulation task of the power system is also mainly undertaken by thermal power in China. Unfortunately, the coal-fired units, which account for the majority in thermal power throughout China, are too inflexible to undertake the task of peak regulation due to the less adjustable load range, lower climbing rate, and longer start–stop time compared with flexible units. Generally, the minimum technical output of units above 0.3 GW usually lies between 40 and 50 % of the rated capacity, while the same index of units below 0.1 GW lies over 80% in China. **Table S3** lists the adjustable load range of different coal-fired units, among which a 600-MW unit and a 1,000-MW unit had a relatively high adjustable range. The type of thermal power was mainly covered by 300 to 1,000-MW units in most provinces, as illustrated in **Table S4**. However, some provinces still possessed a high proportion of units below 300 MW, such as Shandong, Xinjiang, and Hainan Provinces. The more restricted flexibility of units in these three provinces partially contributed to their low increase of accommodation toward NREP. Hence, raising the peak regulation capability of the coal-fired units is a feasible though uneconomical way of meeting the pressing need of system flexibility in China, which means the deeper peak regulation coal-fired units participated, the more accommodation reserved for non-hydro renewable energy power.

The installed capacity of thermal power in most provinces in 2015, which was much more than the maximum load of power generation, as illustrated in **Table S4**, was relatively excessive considering the weak growth expectations of electricity consumption during the 13th FYP (Zhao et al., 2017). The redundant coal-fired power units in those red-warning provinces shaded in **Table S4** had pressed the generation space of PV and wind power (NEA, 2017b)[5]. Besides, limited regulation performance of thermal power, which occupied the power supply structure, affected the flexibility of the power system and further restricted the accommodation of uncertain green power. In contrast, provinces where thermal power was not the leading power supplier, such as Hubei, Hunan, Sichuan, Qinghai, and Yunnan, either possessed a high increasing rate of accommodation or a high increasing percentage of

[5]The installation of coal-fired units in red-warning provinces is quite redundant considering the provincial reasonable system reserve rate.

accommodation rate, as illustrated in **Table 1**, partially revealing the relationship between the completion conditions of RPS and the provincial power supply structure.

Particularly, heating units, also known as cogeneration units or combined heat and power (CHP), were usually not used as the peak regulation power supplier because they had to meet the heating load demand while producing electric power, which further restricted their regulation performance. For instance, when the heating load gradually increased, a 300-MW CHP unit enlarged the capacity of suction; consequently, the minimum technical output rose while the maximum technical output dropped, and its adjustable load range varied from 51.1 to 7.1%, lower than that of the non-cogeneration units listed in **Table S3**. However, heating units accounted for an enormous share of thermal power, especially in the "Three North" region. There are nine provinces listed in **Table S4** where the proportion of heating units was above 50%, and eight of them came from the "Three North" region. These heating units had to take part in peak regulation thanks to conflicts between the limited adjustable load range and the incremental demand of accommodation. Huge curtailment of wind power occurred when the strong wind period overlapped with the heating period during the winter and spring. Those representative provinces, including Gansu, Heilongjiang, Liaoning, Jilin, Hebei, Tianjin, Shandong, and Shanxi, must improve the limited adjustable load range of heating units to accommodate more green power and speed up RPS completion.

Whether the captive power plants participated in peak regulation makes a difference to the system flexibility as well. The most captive power plants belonged to high-electricity-consuming enterprises. They supplied power to "selfishly" meet their own relatively fixed load and did not join the unified peak regulation of the power system. It could be inferred from **Table S5** that the rising installed capacity and power generation of captive power plants had forced public power plants and non-hydro renewable energy power suppliers to further press their power output. This was another obstacle for speeding up RPS completion, especially in Xinjiang, Shandong, Gansu, Ningxia, Inner Mongolia, Heilongjiang, and Liaoning.

The limited flexibility of the power system is not only closely related to the provincial power supply structure but is also influenced by the marketization degree of the electricity market. China is still dominated by a traditional plan-oriented management of power generation and utilization, and the economical compensation mechanism for auxiliary services of peak regulation and frequency modulation is not perfect. In contrast, Europe has established a market-oriented mechanism that is conducive to mobilizing the flexible regulation of power supply and active response of the demand side to participate in peak regulation. More accompanying measures are needed to match the implementation of RPS and create a better condition for RPS completion. These measures, which cover the supply side, grid side, together with the demand side of the power system, containing but not limited to those that have been adopted during the past 4 years, were empirically analyzed in the following section.

PRACTICAL EXPERIENCE FROM CHINA

Activating Flexibility of the Supply Side

Flexibility Modification of Thermal Power Units

Flexibility modification means the minimum operation mode and minimum technical output of thermal power units approved by the government must be strictly implemented to optimize startup arrangement and accommodate more green power. It was especially suitable for those provinces where the power supply structure was mainly occupied by thermal power and was proven to be a feasible measure to maximize peak regulation capacity. For example, thermal power in NECG operated on the minimum technical output in 2016; 6.372 billion kWh of wind power was additionally absorbed. Seven provinces, including Liaoning and Jilin, had completed the preliminary work till the end of 2017. A total of 26 units had completed flexibility modification, and 930 million kWh of non-hydro renewable energy electricity was additionally absorbed by the end of 2017. Minimum output of thermal power could further drop and the adjustable load range would be further enlarged when mature technology in deep peak regulation was applied in more power units.

Strictly controlling the startup mode and power output of CHP units according to the minimum operation mode has been particularly implemented in some provinces. For instance, Jilin Province relied on the "peak-load character management system of thermoelectricity unit" to timely monitor heating information in real time, dynamically calculate the peak regulation capacity, and arrange units to participate to the furthest in deep peak regulation. This model could be popularized in NC and NEC, where the heating load demand was enormous in winter.

Thermoelectric decoupling of CHP units was proven to be another effective measure especially in those provinces which possessed huge installations of heating units. The adjustable load range of CHP units would be extended mainly through four methods, which are equipment of heat storage tank, installation of electric heat storage boiler, cooling and decompression of main steams, and integration of the pumping condensation unit and back pressure unit. The first two measures were relatively mature and had been widely adopted abroad, which could be promoted and applied in China. It should be selected according to the heating requirements of power plants and characteristics of the power system (Pei et al., 2017).

Substitution Trade Toward Captive Power Plants

Substitution trade between NREP suppliers and captive power plants was an effective measure before the unified peak regulation management was fully developed. The substitution electricity in Shaanxi, Gansu, Qinghai, Ningxia, and Xinjiang achieved 390 million kWh, 1.89 billion kWh, 540 million kWh, 1.22 billion kWh, and 7.9 billion kWh, respectively, in 2016. This measure could be similarly applied in Shandong, Inner Mongolia, Heilongjiang, and Liaoning Provinces, which also possessed a huge installed capacity and proportion of captive power plants. Once the unified peak regulation management was completely established, the supplementary adjustable capacity of captive power plants would further raise the peak regulation capability of the supply side.

Unified Planning of Power Generation

Unified planning of power generation is a feasible yet not adopted measure aiming to optimize the distribution and guide the construction of NREP projects in an orderly manner and make room for the accommodation of uncertain green power by strictly controlling new coal-fired power in the provinces regulated by the CCG and ECG.

Enhancing Interconnection of Power Grid

Timely Construction of Provincial Supporting Power Grid

The approval of power grid projects usually lags that of non-hydro renewable energy projects; thus, there was a lack of supporting grid project during the rapid development of PV and wind power bases these years, which leads to a less timely integration of uncertain green power. Consequently, timely construction of provincial supporting power grid was an effective measure toward those provinces where PV or wind power far away from the grid center could not be timely connected to the power grid. For instance, Qinghai had speeded up the resolution of the cross-section restriction caused by the lagging construction of the collection and delivery lines in regions where wind resources are rich. Xinjiang had also increased its delivery capacity by 5 million kW through the operation of a new inter-provincial transmission channel in 2017. Shanxi also alleviated the blockage of wind power, reducing curtailment by 400 million kWh in 2017. Till now, the structure of the inter-provincial power grid has been greatly improved and is friendlier to the integration of NREP. This ongoing measure will sequentially optimize and intellectualize the provincial power grid to face more challenges led by the higher penetration of PV and wind power.

Further Improvement of Inter-provincial Transmission Channels

Inter-provincial transmission is one of the available alternatives for enlarging the configuration range of non-hydro renewable energy power, which contributes to regional accommodation. It is easier for neighboring provinces in the same region to connect with each other than trans-regional ones. Therefore, the orderly construction of inter-provincial transmission channels had become a relatively feasible and effective measure for absorbing more green power. For instance, the total amount of inter-provincial transaction of PV and wind power achieved 49.2 billion kWh in 2017, and the "Three North" region increased accommodation for 6.19 billion kWh through this measure. This measure was proven to be especially suitable for the regional power grid, where inside provinces could integrate their advantages both in adjacent locations and complementary characters in regulation performance, and should be further continued to achieve a more stable structure of the regional electricity balance so that more uncertain green power could be regionally absorbed.

Full Utilization of Trans-regional UHV Transmission Lines

It has been proven that trans-regional UHV transmission could resolve curtailment problems in the "Three North" region, to some extent. For instance, the No. 13 line, listed in **Table S1**, transmitted 32.26 billion kWh electricity in 2016, of which 7.34 billion was from non-hydro renewable energy, accounting for 23% of the total. The external power supply of the No. 15 line was 7.28 billion kWh in 2016, of which 2.08 billion kWh was from wind power, accounting for 29% of the total. Since the No. 16 line was put into operation in June 2017, more than 2 billion kWh of non-hydro renewable energy power had been delivered. China had built eight UHVAC and 13 UHVDC transmission lines across China, yet these trans-regional channels were not fully utilized corresponding to their transmission capacity. Other existing UHV transmission lines similarly had much room for the effective allocation of NREP and remained to be further developed, and more trans-regional UHV transmission lines used for specially transmitting NREP in the "Three North" region should be timely built and put into operation considering the distribution map, illustrated as **Figure 3**.

Enlarging Accommodation Market of the Demand Side

The demand side of the power system determines the maximum limit of the accommodation market. Enlarging the overall scale of the electricity consumption market and increasing the accommodation rate of non-hydro renewable energy power are the basic ways for the realization of RPS. The growth of power demand was slowing down in recent years, while various types of power generators, including non-hydro renewable energy sources, maintained a rapid growth. The more non-hydro renewable energy power accommodated in additional consumptive market, the earlier the RPS target will be completed.

Electric power substitution was proven to be effective in lessening the apparent imbalance between power supply and demand. It was comprehensively carried out in China by separately increasing the electricity consumption on the condition that the newly added electricity market could not support the requirement of accommodation. In 2016, 41,000 key projects of electric power substitution, including electric heating, electric kiln, port shore power, and APU alternative on airport bridges, were implemented, and 103 billion kWh of substitution electricity was completed. In 2017, 115 billion kWh of substitution electricity was completed. With this measure, Xinjiang, Sichuan, and Hebei increased accommodation for 7.9 billion kWh, 1.49 billion kWh, and 47.3 million kWh, respectively, by encouraging PV or wind power suppliers to directly trade with electricity consumers point to point. Gansu had set up a trading platform which offered timely information about electric power supply and demand, so that non-hydro renewable energy power generation enterprises, electric boiler enterprises, and electric heating residential districts could build a closer relationship. This mode could also be applied to other provinces where the heating demand in the winter was stable and the regulation performance was relatively flexible for supporting electric heating by uncertain green power.

Power users should have the market-oriented option of purchasing non-hydro renewable energy power across provinces, either via a trans-regional spot market or through an improved trading system that focuses on medium- or long-term trading and supplementary electricity trading. The market rules and non-hydro renewable energy power trading mechanism should be improved as soon as possible during the construction of a unified national electricity market. Enterprise and an individual's social responsibility and enthusiasm should be improved and encouraged to change the way in using power. Terminal energy efficiency should be improved mainly by introducing an active response, interruptible load control, or other forms of demand side management (DSM). DSM measures also contribute to the overall flexibility of the power system and could be further implemented by market reform (including pricing mechanism reform, in particular).

Strengthening the Core Position of Power Grid Corporations

Power grid corporations should not only bear the responsibility of implementing RPS in their business areas and assisting the government in formulating plans but also act as a technical supporter to assist in determining RPS distribution. Meanwhile, their power supply companies must bear the obligations of completing RPS. As mentioned above, there were a sea of troubles during the implementation of RPS completion in China, mainly due to characteristics in contradiction between the centralized development and provincial accommodation of NREP, limited flexibility of the power system, and the low marketization degree of the electricity market. Consequently, this powerful plan-oriented policy urgently needed a strong executive organizer and an experienced technical supporter. The power grid corporation happened to be a combination of the two mainly due to its centralized management mode, comprehensive data support, and mature technology accumulation, which decided its core position not only in implementing RPS but also in creating better conditions for RPS completion.

Power dispatching is the core work of power grid corporations; optimal dispatching aims to maximize the generating space for uncertain NREP based on the current peak regulation capability under the premise of ensuring a safe and reliable power supply, which is a direct way to tap potentials for RPS completion.

For those provinces with huge installations of PV and wind power in the "Three North" region, more dispatching technologies could be intellectually integrated in the provincial dispatching system to positively maximize the local accommodation of uncertain green power without a huge improvement in provincial peak regulation capability. For instance, Ningxia, Gansu, and Qinghai Provinces used a coordinated and intelligent operation control system, incorporating formulation of power generation, prediction of power output, and implementation of automatic gain control (AGC) into a closed-loop management to adjust the output of thermal power in time, which promoted the consumption of NREP. For those provinces which possessed huge installations of hydropower, the dispatching system could be further improved to achieve a smooth and stable power generation curve since the hydropower station could be used to track uncertain power output and complementarily adjust active power output relying on the rapid response of hydro-turbine and adjustment capability of reservoirs. For those provinces which lack the peak regulation capacity, signing an inter-provincial mutual aid contract of peak regulation could be a complementary measure. Under this agreement, one provincial power grid corporation was obligated to provide daily peak regulation power or electricity to help the other one supplement the absent capacity in peak regulation. With this measure, NECG and NWCG had increased accommodation of non-hydro renewable energy electricity for 1.15 and 8.59 billion kWh, respectively, till the end of 2016.

Organization of electricity transactions is another important work for power grid corporations in China. More active participation in inter-provincial or trans-regional electricity transactions uniformly organized by the electricity trade center of power grid corporations also contributes to speeding up RPS completion. Those measures taken on the grid side were also mainly fulfilled by power grid corporations, which had invested, constructed, and possessed huge power grid assets.

Coordinating Market-Based Mechanism With Plan-Oriented RPS

Judging from the implementation of RPS in other countries, it is extremely important to establish a clearly regulated green certificate trading market for successfully realizing the RPS target. The successful operation of the green electricity trading market requires the government to clearly designate the obligor and the regulatory agency, and the regulatory agency should design clear trading rules such as trading times, storage time limit, and rewards and punishments according to the characteristics of the electricity market. The government should have the ability to regulate the certificate market, especially the means to mediate between the supply and demand of certificates.

China had already done fruitful work not only in the design and distribution of RPS but also in the exploration of market-oriented mechanism. Market-oriented mechanism here mainly referred to TGC or other forms of transaction for RPS completion, which was another direct way to raising the assessment index of RPS and supplemented all measures taken from the three sides of the power system. According to the notice promulgated in November 2018, the market-oriented mechanism in China was going to be implemented from 1 January 2019, but a green certificate would not be solely involved in the assessment. Both a directly purchased RPS completion from overfulfilled provinces and a calculated one corresponding to purchased tradable green certificates could be assessed as RPS completion. This market-oriented mechanism with Chinese characteristics was expected to reduce the overlapping of the policies and seems easier to operate, but the implementation effect would not be guaranteed considering facts that the TGC was provided to be purchased voluntarily while the economic punishment of RPS and detailed incentive scheme were not clearly announced. There remained somewhere to be further improved toward this core accompanying market-oriented mechanism of RPS in China in order to accelerate the true implementation of TGC or RPS completion trading market. It was important for the successful implementation of RPS in China to coordinate the activation of a market-oriented mechanism with the execution of a plan-oriented policy.

Not only do TGC or other forms of transaction for RPS completion need coordination, but also many other market-oriented mechanisms which accompany measures taken on the supply side, grid side, and demand side of the power system need to coordinate with this plan-oriented policy. A nationwide peak regulation auxiliary service market should be further improved to economically motivate active participation in peak regulation. A compensation mechanism between the importing and exporting provinces of NREP should also be established to effectively break down the inter-provincial barriers for accommodation.

CONCLUSIONS

Inevitably, the implementation of China's newly modified provincial RPS will maintain a significant role in energy revolution to provide more than half of the electricity from renewables. Although China has achieved certain progress in the mechanism design and target distribution, great challenges remain not only in further improvement of the completion conditions but also their effective implementation.

This paper focuses on the completion prospect of a new provincial renewable portfolio standard in 30 provincial administrative regions across Mainland China. The prospect analysis specifically introduces a newly modified demand side-based assessment mechanism toward both a single responsible subject and the overall province and then proposes a prospect analysis framework based on an assessment index of the completion pressure. The estimation results indicate that 17 provinces now enjoy an extremely high completion pressure while 10 provinces make it relatively easy to complete, which are partially verified by the actual data in 2018. Unfavorable factors for raising the assessment index are revealed from the structural data analysis on the provincial electricity balance and power supply structure. These factors can be mainly summarized into the contradiction between the centralized development and provincial accommodation of NREP, the limited flexibility of the power system, and the low marketization of the electricity market. However, a greater completion potential could be acquired by the active introduction of systematical measures. This paper empirically analyzes these measures taken from three sides of the power system, which mainly aims to develop a nationwide and provincial flexible power system either by activating the regulation performance of power units from the supply side, enlarging the configuration range of green power accommodation via a more sufficiently interconnected power grid, or by guiding active response and interruptible load control from the demand side. Meanwhile, the unique pathway for ensuring an effective RPS implementation in China simultaneously highlights the accompanying market-based mechanism and core position of power grid corporations. Both introducing a more market-based mechanism to coordinate with a plan-oriented RPS and encouraging the provincial power grid corporation to bear the core responsibility of not only improving the completion conditions of RPS but also in leading, organizing, assessing, and regulating responsible subjects will contribute more in the future implementation of RPS.

DATA AVAILABILITY STATEMENT

Publicly available datasets were analyzed in this study. This data can be found here: http://zfxxgk.nea.gov.cn/auto87/201803/t20180323_3131.htm, http://www.nea.gov.cn/2018-11/15/c_137607356.htm, http://zfxxgk.nea.gov.cn/auto87/201608/t20160823_2289.htm, http://zfxxgk.nea.gov.cn/auto87/201704/t20170418_2773.htm, http://zfxxgk.nea.gov.cn/auto87/201805/t20180522_3179.htm.

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AUTHOR CONTRIBUTIONS

YB collected the research data and wrote the total paper. XZ revised the paper and gave several suggestions.

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SUPPLEMENTARY MATERIAL

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REFERENCES

Bento, A. M., Garg, T., and Kaffine, D. (2018). Emissions reductions or green booms? general equilibrium effects of a renewable portfolio standard. *J. Environ. Econ. Manage.* 90, 78–100. doi: 10.1016/j.jeem.2018.05.006

CEC (2016). [In Chinese]. *China Electric Power Industry Statistical Yearbook 2015*. Beijing: China Electricity Council.

Chen, X., Mcelroy, M. B., Wu, Q., Shu, Y., and Xue, Y. (2018). Transition towards higher penetration of renewables: an overview of interlinked technical, environmental and socio-economic challenges.

J. Mod. Pow. Syst. Clean Energy 7, 1–8. doi: 10.1007/s40565-018-0438-9

Feng, T., Yang, Y., and Yang, Y. (2018). What will happen to the power supply structure and CO_2 emissions reduction when TGC meets CET in the electricity market in China? *Renew. Sustain. Energy Rev*. 92, 121–132. doi: 10.1016/j.rser.2018.04.079

He, Y., Xu, Y., Pang, Y., Tian, H., and Wu, R. (2016). A regulatory policy to promote renewable energy consumption in China: review and future evolutionary path. *Renew. Energy* 89, 695–705. doi: 10.1016/j.renene.2015.12.047

Ji, Q., Li, J. P., and Sun, X. L. (2019). New challenge and research development in global energy financialization. *Emerg. Mark. Finance Trade* 55, 2669–2672. doi: 10.1080/1540496X.2019.1636588

Ji, Q., and Zhang, D. Y. (2019). How much does financial development contribute to renewable energy growth and upgrading of energy structure in China? *Energy Policy* 128, 114–124. doi: 10.1016/j.enpol.2018.12.047

Li, W., Liu, L., Zhang, S., and Zhang, H. (2018). Will the tradable green certifications and renewable portfolio standard policy work well in China: a recursive CGE analysis. *J. Renew. Sustain. Energy* 10:055904. doi: 10.1063/1.5019756

NEA (2016). [In Chinese]. *Report on the Monitoring and Evaluation of National Renewable Energy and Electricity Development in 2015[EB/OL]*. Available online at: http://zfxxgk.nea.gov.cn/auto87/201608/t20160823_2289.htm

NEA (2017a). [In Chinese]. *Report on the Monitoring and Evaluation of National Renewable Energy and Electricity Development in 2016[EB/OL]*. Available online at: http://zfxxgk.nea.gov.cn/auto87/201704/t20170418_2773.htm

NEA (2017b). [In Chinese]. *Notice on Issuing Early Warning of Coal and Electricity Planning and Construction Risks in 2020[EB/OL]*. Available online at: http://zfxxgk.nea.gov.cn/auto84/201705/t20170510_2785.htm

NEA (2018a). [In Chinese]. *Notice on Soliciting Opinions of Renewable Portfolio Standard and Assessment Measures*. Available online at: http://zfxxgk.nea.gov.cn/auto87/201803/t20180323_3131.htm

NEA (2018b). [In Chinese]. *Notice on Soliciting Opinions of Renewable Portfolio Standard and Assessment Measures*. Available online at: http://huanbao.bjx.com.cn/news/20180926/930338-2.shtml

NEA (2018c). [In Chinese]. *Notice on Trial Implementation of Renewable Portfolio Standard and Assessment Measures*. Available online at: http://www.nea.gov.cn/2018-11/15/c_137607356.htm

NEA (2018d). [In Chinese]. *Report on the Monitoring and Evaluation of National Renewable Energy and Electricity Development in 2017[EB/OL]*. Available online at: http://zfxxgk.nea.gov.cn/auto87/201805/t20180522_3179.htm

NEA (2019a). [In Chinese]. *Notice on Guarantee Mechanism of Renewable Energy Power Accommodation*. Available online at: http://zfxxgk.nea.gov.cn/auto87/201905/t20190515_3662.htm

NEA (2019b). [In Chinese]. *Report on the Monitoring and Evaluation of National Renewable Energy and Electricity Development in 2018[EB/OL]*. Available online at: http://zfxxgk.nea.gov.cn/auto87/201906/t20190610_3673.htm

NSBC (2016). *China Energy Statistical Yearbook 2015*. National Statistics Bureau of China.

Pei, Z., Wang, X., Dong, C., Xing, Y., and Liang, Z. (2017). [In Chinese]. Analysis of impact of CHP plant on renewable energy accommodation in Northeast China and thermoelectric decoupling measures. *Pow. Syst. Technol*. 41, 1786–1792. doi: 10.13335/j.1000-3673.pst.2016.2178

Rouhani, O. M., Niemeier, D., Gao, H. O., and Bel, G. (2016). Cost-benefit analysis of various California renewable portfolio standard targets: is a 33% RPS optimal? *Renew. Sustain. Energy Rev*. 62, 1122–1132. doi: 10.1016/j.rser.2016.05.049

Shu, Y., and Chen, W. (2018). Research and application of UHV power transmission in China. *High Volt*. 3, 1–13. doi: 10.1049/hve.2018.0003

Xu, X. F., Wei, Z. F., Ji, Q., Wang, C., and Gao, G. (2019). Global renewable energy development: influencing factors, trend predictions and countermeasures. *Resour. Policy* 63:101470. doi: 10.1016/j.resourpol.2019.101470

Yoon, J., and Sim, K. (2015). Why is South Korea's renewable energy policy failing? a qualitative evaluation. *Energy Policy* 86, 369–379. doi: 10.1016/j.enpol.2015.07.020

Zhang, D. Y., and Ji, Q. (2019). Energy finance: frontiers and future development. *Energy Econ*. 83, 290–292. doi: 10.1016/j.eneco.2019.07.003

Zhang, D. Y., Zhao, R., and Ji, Q. (2019). Green innovation and firm performance: evidence from listed companies in China. *Resour. Conserv. Recycl*. 144, 48–55. doi: 10.1016/j.resconrec.2019.01.023

Zhang, Q., Wang, G., Li, Y., Li, H., McLellan, B., and Chen, S. (2018). Substitution effect of renewable portfolio standards and renewable energy certificate trading for feed-in tariff. *Appl. Energy* 227, 426–435. doi: 10.1016/j.apenergy.2017.07.118

Zhang, Y. Z., Zhao, X. G., Ren, L. Z., and Yi, Z. (2017). The development of the renewable energy power industry under feed-in tariff and renewable portfolio standard: a case study of China"s wind power industry. *J. Clean. Prod*. 168, 1262–1276. doi: 10.1016/j.jclepro.2017.09.102

Zhao, C. R., Zhang, W. R., Wang, Y., Liu, Q., Guo, J., Xiong, M., et al. (2017). The economics of coal power generation in China. *Energy Policy* 105, 1–9. doi: 10.1016/j.enpol.2017.02.020

Zuo, Y., Zhao, X. G., Zhang, Y. Z., and Ying, Z. (2019). From feed-in tariff to renewable portfolio standards: an evolutionary game theory perspective. *J. Clean. Prod*. 213, 1274–1289. doi: 10.1016/j.jclepro.2018.12.170

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Analysis of Residential Lighting Fuel Choice in Kenya: Application of Multinomial Probability Models

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Safe, clean, and affordable modern lighting services are crucial for improving the socio-economic welfare of the underprivileged people in developing countries. However, many of the Kenyan households are deprived of this service, and they continue to use traditional lighting devices to meet their lighting demand. It is essential to understand the determinants which influence the household energy choice to promote the household energy transition from traditional to modern lighting fuels. Therefore, this study examines the determinants of household lighting fuel choice with multinomial probability models using the survey data collected by the Kenya National Bureau of Statistics (KNBS) in 2015/16. The key findings of this study are as follows. First, the results of this study have empirically proven the energy ladder hypothesis as the probability of choosing modern lighting fuel increases with a female household head, and with improvements in income, wealth and education. The energy ladder hypothesis has been confirmed in both cases of the household with and without the choice of grid electricity. Second, different socio-economic determinants for on- and off-grid household fuel choice are identified, which are the location of household, marital status, and household size. This is an important finding which shows that different policy designs are required to promote energy transition in on- and off-grid households.

Keywords: energy transition, energy ladder hypothesis, household fuel choice, multinomial probability analysis, Kenya

INTRODUCTION

Modern lighting services are crucial for improving the socio-economic welfare of underprivileged people in developing countries. Those without access to modern lighting services tend to use hazardous and inefficient lighting devices (such as kerosene lamps) to meet their energy demands (Lam et al., 2012). Hence, this paper aims to examine the ways to improve the household energy consumption by promoting energy transition from traditional fuels to modern fuels.

Previous studies examining the household energy transition follow two theoretical approaches, which are the energy ladder hypothesis and energy stacking hypothesis. These two hypotheses have been empirically tested over decades, but similar models have been tested with changes in the independent variables or target country. However, previous studies have not examined the different natures of on- and off-grid households. As the government is responsible for establishing the grid, the grid electricity should not be considered as a choice of a household. Hence, this study challenges the common assumption that the grid electricity is a household choice by hypothesizing that the socio-economic determinants which influence the household lighting fuel choice for on- and off-grid household would be different.

A case study on Kenyan households is conducted to examine the various socio-economic determinants, which influences the Kenyan household's lighting fuel choice by using the multinomial probability models. The total household energy demand is a sum of the day-to-day decisions made by households. Thus, it is crucial to have a good understanding of the driving factors which influence a household's lighting fuel choice to promote the energy transition.

Developing countries face a similar challenge from a low electrification rate, and households tend to rely heavily on fossil fuels. Kenya also faces similar difficulties, but it has the potential to overcome the issue and can serve as a role model for other developing countries if well-designed policies are successfully implemented. Moreover, the limited data availability poses a barrier to academic studies in developing countries, but the Kenyan government, with the support of international organizations, has been keeping a good record of the household survey.

The contribution of this study to the existing literature is 2-fold. First, the results of this study have empirically proven the energy ladder hypothesis as the probability of choosing modern lighting fuel increases with a female household head, and with improvements in income, wealth and education. This has been confirmed in both cases of the household with and without the choice of grid electricity. Second, different socio-economic determinants for on- and off-grid household fuel choice are identified, which are the location of household, marital status, and household size. This is an important finding which shows that different policy designs are required to promote energy transition in on- and off-grid households. The robustness of the results has been tested with different model specifications. The primary model employed is the multinomial logit model (MNL), but this has the limitation of imposing the independence of irrelevant alternatives (IIA) assumption. Thus, the multinomial probit model (MNP) and the alternative-specific MNP are used to check that the IIA assumption is not violated.

The rest of this study is structured as follows. section Literature Review presents the previous studies, and then section Methodology presents the data and model specification. Afterward, section Results and Analysis discusses the results with the robustness check, and section Conclusion and Policy Recommendations concludes with policy suggestions for Kenya and other developing countries.

LITERATURE REVIEW

The critical conceptual framework of this study is the household energy transition, which is dealt with by two key hypotheses: the energy ladder hypothesis; and the energy stacking hypothesis. The energy ladder hypothesis assumes that as the income rises, the household would make a transition (stepping up the energy ladder) from traditional fuels to modern fuels (Leach, 1992; van der Kroon et al., 2013). At the household level, empirical studies have repeatedly confirmed that income is a crucial component of fuel choice (Farsi et al., 2007; Hiemstra-Van der Horst and Hovorka, 2008; Danlami et al., 2017). Thus, socio-economic determinants other than income need to be examined to test the energy ladder hypothesis empirically.

On the other hand, the energy ladder hypothesis has been criticized as energy transition is not a step by step process, but rather an overlapping process with multiple fuels being used simultaneously. This is known as fuel stacking, and the energy stacking hypothesis assumes that the households would adopt modern fuels as the income rises, but also continue to use traditional fuels as well. Several empirical studies have tested and confirmed the fuel stacking behaviors in developing countries (Masera et al., 2000; Heltberg, 2004, 2005; Mekonnen and Köhlin, 2009; Andadari et al., 2014; Cheng and Urpelainen, 2014; Ruiz-Mercado and Masera, 2015; Alem et al., 2016).

Given the importance of household energy consumption, a large pool of literature exists for household cooking fuel choice, but only a handful of researches have been conducted on household lighting fuel choice (Lay et al., 2013; Olang et al., 2018; Choumert-Nkolo et al., 2019). Also, Giri and Goswami (2017) report household location, gender, education level, family size, size of dependent families, and market distance as the significant determinants for the household choice of electricity as the main lighting fuel. Danlami et al. (2017) present income, age of the household head, urban location, number of rooms, and access to electricity to have a positive influence on the adoption of electricity as the main lighting fuel. Rahut et al. (2017) examine the determinants of the household's electricity use in four African countries (Ethiopia, Malawi, Tanzania, and Uganda). The results show that female-headed households, education level, household location, wealth, and access to infrastructure are common determinants that influence the household's use of electricity as the main lighting fuel. Martey (2019) examines the Ghanaian household's lighting and cooking fuel choice using the linear probability model and the bivariate probit model. The estimated result identified several components influencing household fuel choices, such as basic demographics (age and education), poverty, household expenditure, saving, remittances, and housing characteristics.

This study contributes to the existing literature in two ways. First, the energy ladder hypothesis is empirically tested. The previous studies have shown that multinomial probability models using cross-sectional dataset is unsuitable for examining the fuel stacking behavior, which requires a panel data[1]. However, the energy ladder hypothesis and the determinants of household lighting fuel choice can still be examined using the cross-sectional dataset. Therefore, this study will examine whether income and other socio-economic determinants show the behaviors discussed in the energy ladder hypothesis.

Second, the socio-economic determinants for the off-grid household fuel choice are identified. The previous studies have assumed that grid electricity is a choice of equal value to other alternative lighting fuel choices. This study challenges this

[1]Kenyan households do use secondary lighting fuels in case they cannot use the main lighting fuel, but no meaningful analysis can be conducted without seeing a change in the fuel stacks. Other studies examining the fuel stacking behavior analyzes the difference between before and after of household fuel stacks [e.g. (Andadari et al., 2014)].

assumption by arguing that the households have no control over grid electricity; thus, it should not be treated as a choice like other alternative fuels. The government needs to build the necessary infrastructure and supply adequate electricity for the household to benefit from this service. In other words, the off-grid households should not have the choice of grid electricity. Therefore, a new sample (excluding the households with grid connection) is used to examine the determinants of the household lighting choice.

METHODOLOGY

Theoretical Framework

MNL is a frequently used regression technique for assessing discrete choice data, such as the household lighting fuel choice. van der Kroon et al. (2013) provide a list of studies that have used MNL to examine the energy transition and fuel switching behavior. In this study, MNL is used to analyze the Kenya Integrated Household Budget Survey (KIHBS) 2015/16. The dependent variable includes four distinct unordered alternatives (grid electricity, solar panel, kerosene and battery torch) used for lighting purposes[2]. The basic equation for the MNL is as follows:

$$Prob(Y_i = j) = \frac{\exp(\beta_j x_i)}{\sum_{k=1}^{j} \exp(\beta_k x_i)} \quad with\ j = 1, 2, 3, 4 \tag{1}$$

Where Y_i is the household's lighting fuel choice and takes the value of 1 to 4 if alternative fuels are chosen instead of the reference fuel. x_i is the vector of independent variables that affect the household fuel choice. β_j is the vector of estimated coefficients. Afterward, the outcome is shown in odds ratios, which are the ratios of the probability of choosing an alternative fuel over the reference fuel. The equation for the odds ratios is as follows:

$$l_n \left[\frac{P_{ij}}{P_{ik}} \right] = X_i \left(\beta_j - \beta_k \right) = X_i \beta_j \ \ if\ k = 1 \tag{2}$$

A positive ratio means that the probability of a household choosing an alternative fuel than the reference fuel increases relative to the probability of a household choosing the reference fuel than the alternative fuel, and vice versa. The reference fuel could be any fuel type, but in this study, kerosene is the reference fuel as it is the most commonly used lighting fuel.

Data and Descriptive Statistics

This study uses a cross-sectional survey data collected by the Kenya National Bureau of Statistics (KNBS) in 2015/16 across Kenya. This data is processed to select the household's main lighting fuels and the key determinants which influence the household's lighting fuel choice, as discussed in section Literature Review. The dependent variable is a set of lighting fuels which are available to the Kenyan households. The independent variables are chosen based on previous studies and data availability.

[2]This is the full list of available household lighting fuel choices, but the choices vary for different estimation models.

TABLE 1 | Descriptive statistics.

Variables	Full sample		No grid sample	
	Observation	Mean	Observation	Mean
Lighting fuels	20,605		13,190	
• Grid electricity	6,881	33.39	n/a	n/a
• Solar panel	3,501	16.99	3,038	23.03
• Kerosene	8,247	40.02	8,187	62.07
• Battery torch	1,976	9.59	1,965	14.90
Age [scaled by 100]	21,161	44.54	14,287	46.40
Income	18,870	11,310.41	12,629	6820.40
Rooms	21,145	2.21	14,269	2.16
Household size	21,187	4.25	14,306	4.63
Dwelling type dummy	21,195		14,314	
• Modern	18,331	86.49	11,553	80.71
• Traditional	2,864	13.51	2,761	19.29
Location dummy	21,195		14,314	
• Urban	8,637	40.75	3,559	24.86
• Rural	12,558	59.25	10,755	75.14
Marital status dummy	21,195		14,314	
• Married	6,221	29.35	4,185	29.24
• Not married	14,974	70.65	10,129	70.76
Gender dummy	21,195		14,314	
• Male	14,088	66.47	9,229	64.48
• Female	7,107	33.53	5,085	35.52
Education dummy	21,195		14,314	
• No education	4,067	19.19	3,633	25.39
• Primary school	9,279	43.78	7,230	50.51
• Secondary school	5,151	24.30	2,706	18.90
• Tertiary school	2,698	12.73	745	5.20
Kerosene price	20,767	93.23	13,940	96.60
Electrification rate	21,195	32.43	n/a	n/a

The unit of mean is in percentage, except for age, income, rooms, household size, and kerosene price variables.

The descriptive statistics of the selected variables are presented in **Table 1**.

As this study examines two different samples (a full sample and a sample excluding households with grid connection), separate descriptive statistics are presented for each sample. The lighting fuels are organized into a categorical variable representing the household's fuel choice. The age variable represents the age of the household head, which is scaled by 100. Income variable represents the household's monthly income, which is transformed using the natural log. The rooms variable represents the number of rooms available for the household, while the household size variable represents the number of people in the household. The dwelling type dummy represents the housing style with a modern style as 1.

The location dummy represents the location of the household with urban as 1. The marital status dummy represents the marital status of the household head with married being 1 and the gender dummy represents the gender of the household head with a female as 1. The education dummy represents the final level of

TABLE 2 | Household's monthly lighting fuel expenditure in Kenyan shillings (KSh).

Lighting fuel	Observation	Mean	S.D.	Median
Grid electricity	4,822	579.67	843.23	380.00
Kerosene	9,821	170.76	183.08	120.00
Dry cell battery	2,124	117.47	151.08	80.00
Lead cell battery	181	125.14	387.63	50.00

Source: KIHBS 2015/16.

education received by the household head with no education as the reference. The kerosene price variable is the price paid by each household to purchase a liter of kerosene, and the average kerosene price of each county is used for the households without a survey response. Lastly, the electrification rate is the proportion of electrified (grid-connected) households in each cluster. The correlation matrix of the independent variables is provided in **Table A1**.

Kerosene is the most commonly used lighting fuel as it is reliable and relatively cheap, with the average price of 84.04 KSh/liter (about 0.83 USD/liter[3]) in 2014. **Table 2** presents the average monthly expenditure of kerosene, which is 170.76 KSh (about 1.69 USD). Grid electricity is the second most used lighting fuel but has a high average price of 691 KSh (about 6.84 USD) for 50 kWh in 2014. The average monthly expenditure is 579.67 KSh (about 5.73 USD).

Harper et al. (2013) present the price of off-grid lighting devices in three Kenyan towns of Kericho, Brooke, and Talek. Many different types of battery torches exist, but for most of the products, the prices were usually below 300 KSh (about 2.97 USD) in 2012. A caveat is that this is the price of the device only, and the average monthly expenditure of batteries is in the range of 117.47–125.14 KSh (about 1.16–1.24 USD).

The advantage of solar panel products is that there is no monthly expenditure, but it has a high upfront cost. Furthermore, the quality of solar panel products is not guaranteed in Kenya, so the household may have to pay an additional maintenance fee (Harper et al., 2013).

TABLE 3 | Average marginal effects of household lighting fuel choice (Full sample).

	Grid electricity	Solar panel	Kerosene	Battery torch
Age	−1.054***	−0.00378	1.055***	0.00324
	(0.17)	(0.15)	(0.19)	(0.044)
Age^2	1.052***	−0.00625	−1.007***	−0.0386
	(0.18)	(0.15)	(0.19)	(0.044)
Location	0.0247**	−0.0265***	0.0103	−0.00856***
(Urban =1)	(0.01)	(0.01)	(0.01)	(0.003)
Gender	0.0323***	−0.00316	−0.0126	−0.0166***
(Female = 1)	(0.01)	(0.01)	(0.01)	(0.003)
Marital status	−0.0771***	−0.0393***	0.114***	0.00267
(Married = 1)	(0.01)	(0.01)	(0.01)	(0.003)
Household size	−0.0149***	0.00917***	0.00475**	0.000955*
	(0.002)	(0.001)	(0.002)	(0.001)
Primary education	0.0245	0.0487***	−0.0288*	−0.0443***
	(0.02)	(0.01)	(0.02)	(0.004)
Secondary education	0.128***	0.0844***	−0.171***	−0.0419***
	(0.02)	(0.02)	(0.02)	(0.003)
Tertiary education	0.366***	0.0388*	−0.376***	−0.0290***
	(0.03)	(0.02)	(0.02)	(0.003)
Dwelling type	0.149***	0.0335***	−0.124***	−0.0587***
(Modern = 1)	(0.02)	(0.01)	(0.02)	(0.007)
Rooms	0.0627***	0.0305***	−0.0695***	−0.0237***
	(0.004)	(0.003)	(0.005)	(0.002)
ln(income)	0.0152***	0.00129	−0.0163***	−0.000191
	(0.002)	(0.001)	(0.002)	(0.0003)
ln(kerosene price)	0.251***	0.181***	−0.475***	0.0432***
	(0.01)	(0.01)	(0.02)	(0.004)
ln(electrification rate)	1.571***	−0.592***	−0.888***	−0.0913***
	(0.03)	(0.02)	(0.03)	(0.008)
Observations		18,840		
Pseudo R^2		0.4067		
Log-likelihood		−13,211.69		

*No education is the reference for education dummies, Standard errors in parentheses, ***p < 0.01, **p < 0.05, *p < 0.1.*

RESULTS AND ANALYSIS

Estimation Results

Initially, the full sample (including households with grid connection) is estimated to examine whether the results are similar to previous studies. The estimated coefficients for alternative lighting fuels are compared with kerosene, which is the reference fuel in this model. **Table 3** presents the anticipated results. If a household has a grid connection, grid electricity will be the most preferred lighting fuel choice. The estimated coefficients of most of the variables show positive and statistically significant results for grid electricity. On the contrary, the estimated coefficients of most of the variables tend to show negative and statistically significant results for other alternative fuel types.

The result empirically confirms the energy ladder hypothesis; when income rises, the probability of a household choosing grid electricity as the main lighting fuel also increases. The estimated coefficient of income shows that a one-unit increase in the monthly income of the household would increase the probability of choosing grid electricity by 1.5%. Other variables (dwelling type and the number of rooms) that indicate the wealth of the household also support the energy ladder hypothesis. The estimated coefficients of dwelling type and the number of rooms are positive and statistically significant for grid electricity. On the contrary, when a household lives in a modern style house, the probability of choosing kerosene and battery are reduced by 12.4 and 5.9%, respectively, compared to a household living in a traditional style house. Similarly, the results show that a one-unit increase in the number of rooms would reduce the probability of choosing kerosene and battery by 7.0 and 2.4%, respectively.

[3]Exchange rate of 1 USD to 101.1 KSh (15 May 2019) is used in this study. The conversion is to compare the price of the goods in terms of USD, and serves no other purpose.

Another important variable regarding the energy ladder hypothesis is education. Different educational levels are reflected as dummies in the model to examine the effect of education in detail. As expected, the estimated coefficients are positive and statistically significant for grid electricity. When the household head has received secondary and tertiary education, the probability of choosing grid electricity is increased by 12.8 and 36.6%, respectively, compared to other educational levels. It is interesting to note that as the household head receives higher education, the probability of choosing modern fuel type is increased by the interval of around 20%. This result shows the importance of education in designing policies regarding household energy transition.

The estimated coefficient of a household with a female household head is positive and statistically significant at a 5% confidence level. The result indicates that when the household head is female, the probability of a choosing grid electricity is increased by 3.2% than the male counterpart. Furthermore, a one-unit increase in the electrification rate of the cluster increases the probability of choosing grid electricity as the main lighting fuel by 157%, which shows the importance of grid accessibility.

The determinants of household lighting fuel choice identified above are similar to the results of Lay et al. (2013)[4]. Therefore, the first model is well-designed with relevant independent variables. However, the main question of this study is to examine whether the determinants of household lighting fuel choice is the same for both the households with and without grid connections.

Previous studies have assumed that grid electricity is a choice of equal value to other alternative lighting fuel choices. This study challenges this assumption by arguing that the households have no control over grid electricity; thus, it should not be treated as a choice like other alternative fuels. The government needs to build the necessary infrastructure and supply adequate electricity for the household to benefit from this service. In other words, the off-grid households should not have the choice of grid electricity. Therefore, a new sample (excluding the households with grid connection) is used to examine the determinants of the household lighting choice.

The expected result was that all variables would be positive and statistically significant for solar panels, which is the next modern energy to grid electricity. However, the result is quite interesting as the determinants for lighting fuel choice are divided between the solar panel and kerosene (see **Table 4**).

The energy ladder hypothesis is once again empirically confirmed as the probability of the household choosing the solar panel as the main lighting fuel increases when the income rises. The estimated coefficient of income shows that a one-unit increase in the monthly income would increase the probability of choosing a solar panel by 0.7% while decreasing the probability of choosing kerosene by 0.7%.

Afterward, the proxy variables for the wealth of the household also support the energy ladder hypothesis. The estimated coefficients of the dwelling type and the number of rooms are positive and statistically significant for the solar panel. The modern style house increases the probability of choosing a solar panel by 6.7% compared to the traditional style house. The number of rooms is related to the wealth of a household as more rooms often mean a larger house. A one-unit increase in the number of rooms would increase the probability of choosing a solar panel by 5.2% but decreases the probability of choosing kerosene by 1.6%.

TABLE 4 | Average marginal effects of household lighting fuel choice (No grid sample).

	Solar Panel	Kerosene	Battery torch
Age	−0.360** (0.179)	0.428** (0.186)	−0.069 (0.072)
Age^2	0.360** (0.179)	−0.364* (0.186)	0.0036 (0.073)
Location (Urban =1)	−0.0449*** (0.0097)	0.064*** (0.01)	−0.019*** (0.004)
Gender (Female = 1)	0.0181* (0.011)	0.0098 (0.011)	−0.0278*** (0.0042)
Marital status (Married = 1)	−0.0789*** (0.011)	0.079*** (0.012)	−0.0005 (0.005)
Household size	0.011*** (0.002)	−0.0118*** (0.002)	0.0007 (0.001)
Primary education	0.0636*** (0.014)	0.0196 (0.015)	−0.0832*** (0.006)
Secondary education	0.146*** (0.019)	−0.085*** (0.02)	−0.062*** (0.004)
Tertiary education	0.257*** (0.029)	−0.222*** (0.029)	−0.035*** (0.004)
Dwelling type (Modern = 1)	0.067*** (0.013)	0.0093 (0.015)	−0.077*** (0.009)
Rooms	0.0515*** (0.004)	−0.016*** (0.0045)	−0.036*** (0.002)
ln(income)	0.0069*** (0.0013)	−0.007*** (0.0015)	0.001 (0.0005)
ln(kerosene price)	0.260*** (0.013)	−0.342*** (0.015)	0.0821*** (0.0051)
Observations		11,489	
Pseudo R^2		0.1915	
Log-likelihood		−8,112.65	

*No education is the reference for education dummies, Standard errors in parentheses, ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.*

The estimated coefficients of education variables are positive and statistically significant for the solar panel. When the household head has received primary, secondary, and tertiary education, the probability of choosing solar panel is increased by 6.3, 14.6, and 25.7%, respectively, compared to other educational levels. Therefore, once again, the education variables support the energy ladder hypothesis.

The result gets interesting as location and marital status are positive and statistically significant for kerosene, but negative and statistically significant for solar panel. The result shows that for a household living in an off-grid urban area, the probability of choosing kerosene would increase by 6.4% compared to a household living in an off-grid rural area.

[4]The authors used the survey data of KIHBS 2005/06 to examine the determinants of household lighting fuel choice.

The reason for this is because the price and accessibility of kerosene serve as a barrier for households in the rural areas. For example, the distance to the urban center from the rural villages are about 8 km for Kisumu city, and in the range of 16–46 km for Meru city. Also, the median price per liter of kerosene was 46% higher in rural villages than in the urban center in 2011 (Tracy and Jacobson, 2012). On top of this, the households living in urban areas tend to have a higher demand for kerosene as it is used for both lighting and cooking (Ngeno et al., 2018). Therefore, kerosene is a cheap source of lighting for the urban households, but relatively expensive for the rural households. Furthermore, there is no incentive for urban households to use expensive solar panels when a cheaper alternative exists.

When the household head is married, the probability of choosing kerosene as the main lighting fuel increases by 7.9% compared to the single household heads. Married couples tend to have higher monthly expenditure than a single household, and the high upfront cost of solar panels may be unbearable for some households. In addition, a solar panel provides the most benefit when there is a high demand for electricity, but this is not the case for most of the Kenyan households. Therefore a one-unit increase in the household size would increase the probability of choosing a solar panel by 1.1%, while decreasing the probability of choosing kerosene by 1.2%.

The results have empirically proven the energy ladder hypothesis as the probability of choosing modern lighting fuel increases with a female household head, and with improvements in income, wealth and education. This has been confirmed in both cases of the household with and without the choice of grid electricity. However, some socio-economic determinants show varied results, which are location of household, marital status, and household size. This is an important finding which shows that the households in the off-grid setting would require different policy designs to promote the energy transition from traditional to modern energy types and to improve the household energy consumption.

Robustness Tests

The results in the previous subsection would be biased and inconsistent if the errors are found in the model assumptions. The MNL assumes the IIA assumptions, meaning that no

TABLE 5 | Average marginal effects of the multinomial probit model.

	Solar panel	Kerosene	Battery torch
Age	−0.363**	0.449**	−0.087
	(0.175)	(0.184)	(0.088)
Age^2	0.374**	−0.375**	0.001
	(0.175)	(0.184)	(0.089)
Location	−0.049***	0.071***	−0.022***
(Urban =1)	(0.01)	(0.01)	(0.005)
Gender	0.018*	0.017	−0.036***
(Female = 1)	(0.011)	(0.011)	(0.005)
Marital status	−0.076***	0.077***	−0.0014
(Married = 1)	(0.011)	(0.012)	(0.006)
Household size	0.012***	−0.012***	0.0004
	(0.002)	(0.002)	(0.001)
Primary education	0.061***	0.044***	−0.105***
	(0.0131)	(0.014)	(0.007)
Secondary education	0.135***	−0.058***	−0.0767***
	(0.018)	(0.018)	(0.004)
Tertiary education	0.246***	−0.199***	−0.0478***
	(0.026)	(0.026)	(0.004)
Dwelling type	0.066***	0.044***	−0.11***
(Modern = 1)	(0.013)	(0.015)	(0.011)
Rooms	0.053***	−0.015***	−0.0384***
	(0.004)	(0.005)	(0.003)
ln(income)	0.006***	−0.007***	0.001
	(0.001)	(0.001)	(0.0017)
ln(kerosene price)	0.205***	−0.291***	0.0856***
	(0.011)	(0.011)	(0.005)
Observations		11,489	
Wald chi2		2,889.54	
Prob>chi2		0.0000	
Log-likelihood		−8,172.05	

*No education is the reference for education dummies, Standard errors in parentheses, ***p < 0.01, **p < 0.05, *p < 0.1.*

TABLE 6 | Average marginal effects of the alternative-specific multinomial probit model.

	Solar panel	Kerosene	Battery torch
Age	−0.374*	0.463**	−0.089
	(0.192)	(0.199)	(0.094)
Age^2	0.393**	−0.407*	0.014
	(0.193)	(0.199)	(0.095)
Location	−0.067***	0.098***	−0.031***
(Urban =1)	(0.011)	(0.012)	(0.006)
Gender	0.018	0.012	−0.0302***
(Female = 1)	(0.012)	(0.012)	(0.006)
Marital status	−0.076***	0.079***	−0.0037
(Married = 1)	(0.013)	(0.014)	(0.007)
Household size	0.01***	−0.009***	0.00008
	(0.002)	(0.002)	(0.0011)
Primary education	0.074***	0.012	−0.087***
	(0.016)	(0.016)	(0.007)
Secondary education	0.162***	−0.055***	−0.107***
	(0.018)	(0.019)	(0.009)
Tertiary education	0.247***	−0.167***	−0.079***
	(0.024)	(0.025)	(0.012)
Dwelling type	0.064***	0.018	−0.082***
(Modern = 1)	(0.018)	(0.019)	(0.007)
Rooms	0.067***	−0.03***	−0.037***
	(0.005)	(0.005)	(0.003)
ln(income)	0.006***	−0.007***	0.001
	(0.001)	(0.001)	(0.0007)
ln(kerosene price)	0.26***	−0.346***	0.086***
	(0.02)	(0.021)	(0.007)
Observations		31,602	
Number of cases		10,534	
Wald chi2		747.39	
Prob>chi2		0.0000	
Log simulated-likelihood		−7,980.02	

*No education is the reference for education dummies, Standard errors in parentheses, ***p < 0.01, **p < 0.05, *p < 0.1.*

correlation exists between the residuals of each alternative. Hence, the suest-based Hausman test and Small-Hsiao test of IIA assumptions are performed, but one test passes while the other fails, which is not a solid evidence that the IIA assumption is not violated. Therefore, MNP and alternative-specific MNP is used to test the robustness of the results. MNP relaxes the IIA assumption by grouping similar subsets, while alternative-specific MNP removes the IIA assumption by estimating the full correlation matrix of the residuals.

The results of MNP and alternative-specific MNP are shown in **Tables 5**, **6**. The sign and coefficient of the three models (MNL, MNP, and alternative-specific MNP) are similar, which suggests that the IIA assumption has not been violated in the MNL. Therefore, the results are robust in different model specifications.

CONCLUSION AND POLICY RECOMMENDATIONS

The importance of lighting is often shadowed by other energy demands, such as cooking. However, modern lighting services are crucial for improving the socio-economic welfare of underprivileged people in developing countries. It is important to have a good understanding of the driving factors which influence a household's lighting fuel choice to promote the energy transition. Therefore, this study examines the various socio-economic determinants of the Kenyan household's lighting fuel choice using multinomial probability models.

This study conducts a case study on Kenya, but many other developing countries also face similar challenges from the low electrification rates, and the households tend to rely heavily on fossil fuels. Therefore, the policy insights drawn from the findings would be useful for the Kenyan government as well as other developing countries. The policy implications regarding the key determinants (income, education, and wealth of a household) of the energy ladder hypothesis have been discussed numerous times in previous studies; hence, will not repeated in this paper.

The first policy suggestion is to empower women and enhance their bargaining power in household decision making process. In developing countries, microfinancing is a method widely used to assist individuals in starting small businesses and relieving their credit constraints. A survey shows that once women were able to purchase mobile phones, they had access to more professional opportunities, and their income increased (Quak, 2018). Also, studies have suggested that women's employment has enhanced their bargaining power at home, and the probability of the household purchasing modern lighting devices have increased (Pachauri and Rao, 2013). Therefore, educating and opening opportunities for women would have a positive influence on the household energy transition.

Second, the government should make substantial public investments in constructing community-level solar power plants. The result has shown that urban households have better access to kerosene at a lower price than rural households. This is an opportunity for rural households to leapfrog from traditional lighting fuel to modern lighting fuel. Instead of subsidizing kerosene, it would be more beneficial in the long term if the government could construct community-level solar power plants and subsidize the electricity tariffs.

These are the four reasons for suggesting community-level solar power plants over household solar panels. First, solar panels need to be subsidized by the government for most of the rural households even to attempt a purchase of the system, which in total, would be more expensive than constructing utility power plants. Second, solar panels requires constant maintenance, but it is likely that technicians will not live in small villages, and the household would continue to use fossil fuels as a safety net. On the other hand, if independent power producers (IPP) are contracted, these companies will manage and maintain a stable supply of electricity to make a profit. Third, the cost of renewable energy technologies is constantly declining, which would greatly reduce the investment cost soon (Baek et al., 2019). Lastly, as the population density is increasing, it would be more effective to deal with the rising demand at a community-level (Quak, 2018). Therefore, substantial government funding and political support are crucial for successful rural electrification and household energy transition.

DATA AVAILABILITY STATEMENT

Publicly available datasets were analyzed in this study. This data can be found here: https://www.knbs.or.ke/.

AUTHOR CONTRIBUTIONS

YB was responsible for data curation, investigation, analysis, original draft, review, and editing. TJ was responsible for conceptualization, methodology, review, and editing. SK was responsible for analysis, review, and editing.

REFERENCES

Alem, Y., Beyene, A. D., Köhlin, G., and Mekonnen, A. (2016). Modeling household cooking fuel choice: a panel multinomial logit approach. *Energy Econ.* 59, 129–137. doi: 10.1016/j.eneco.2016.06.025

Andadari, R. K., Mulder, P., and Rietveld, P. (2014). Energy poverty reduction by fuel switching. Impact evaluation of the LPG conversion program in Indonesia. *Energy Policy* 66, 436–449. doi: 10.1016/j.enpol.2013.11.021

Baek, Y. J., Jung, T. Y., and Kang, S. J. (2019). Low carbon scenarios and policies for the power sector in Botswana. *Climate Policy* 19, 219–230. doi: 10.1080/14693062.2018.1490243

Cheng, C. Y., and Urpelainen, J. (2014). Fuel stacking in India: changes in the cooking and lighting mix, 1987–2010. *Energy* 76, 306–317. doi: 10.1016/j.energy.2014.08.023

Choumert-Nkolo, J., Motel, P. C., and Le Roux, L. (2019). Stacking up the ladder: a panel data analysis of Tanzanian household energy choices. *World Dev.* 115, 222–235. doi: 10.1016/j.worlddev.2018.11.016

Danlami, A. H., Applanaidu, S. D., and Islam, R. (2017). Movement towards the adoption of non-traditional household lighting fuel energy in developing areas. *Biofuels* 10, 623–633. doi: 10.1080/17597269.2017.1338125

Farsi, M., Filippini, M., and Pachauri, S. (2007). Fuel choices in urban Indian households. *Environ. Dev. Econ.* 12, 757–774. doi: 10.1017/S1355770X07003932

Giri, M., and Goswami, B. (2017). Determinants of households' choice of energy for lighting in Nepal. *Econ. Business Lett.* 6, 42–47. doi: 10.17811/ebl.6.2.2017.42-47

Harper, M., Alstone, P., and Jacobson, A. (2013). *A Growing and Evolving Market for Off-grid Lighting.* Available online at: https://www.lightingglobal.org/resource/a-growing-and-evolving-market-for-off-grid-lighting-market-presence-of-off-grid-lighting-products-in-the-kenyan-towns-of-kericho-kapkugerwet-brooke-and-talek/ (accessed April 11, 2019).

Heltberg, R. (2004). Fuel switching: evidence from eight developing countries. *Energy Econ.* 26, 869–887. doi: 10.1016/j.eneco.2004.04.018

Heltberg, R. (2005). Factors determining household fuel choice in Guatemala. *Environ. Dev. Econ.* 10, 337–361. doi: 10.1017/S1355770X04001858

Hiemstra-Van der Horst, G., and Hovorka, A. J. (2008). Reassessing the "energy ladder": household energy use in Maun, Botswana. *Energy Policy* 36, 3333–3344. doi: 10.1016/j.enpol.2008.05.006

Lam, N. L., Smith, K. R., Gauthier, A., and Bates, M. N. (2012). Kerosene: a review of household uses and their hazards in low-and middle-income countries. *J. Toxicol. Environ. Health B Crit. Rev.* 15, 396–432. doi: 10.1080/10937404.2012.710134

Lay, J., Ondraczek, J., and Stoever, J. (2013). Renewables in the energy transition: evidence on solar home systems and lighting fuel choice in Kenya. *Energy Econ.* 40, 350–359. doi: 10.1016/j.eneco.2013.07.024

Leach, G. (1992). The energy transition. *Energy Policy* 20, 116–123. doi: 10.1016/0301-4215(92)90105-B

Martey, E. (2019). Tenancy and energy choice for lighting and cooking: evidence from Ghana. *Energy Econ.* 80, 570–581. doi: 10.1016/j.eneco.2019.02.008

Masera, O. R., Saatkamp, B. D., and Kammen, D. M. (2000). From linear fuel switching to multiple cooking strategies: a critique and alternative to the energy ladder model. *World Dev.* 28, 2083–2103. doi: 10.1016/S0305-750X(00)00076-0

Mekonnen, A., and Köhlin, G. (2009). *Determinants of Household Fuel Choice in Major Cities in Ethiopia.* Available online at: http://efdinitiative.org/sites/default/files/publications/efd-dp-13-12.pdf (accessed April 20, 2019).

Ngeno, G., Otieno, N., Troncoso, K., and Edwards, R. (2018). *Opportunities for Transition to Clean Household Energy in Kenya: Application of the Household Energy Assessment Rapid Tool (HEART).* Available online at: https://apps.who.int/iris/handle/10665/311281 (accessed May 10, 2019).

Olang, T. A., Esteban, M., and Gasparatos, A. (2018). Lighting and cooking fuel choices of households in Kisumu City, Kenya: a multidimensional energy poverty perspective. *Energy Sustain. Dev.* 42, 1–13. doi: 10.1016/j.esd.2017.09.006

Pachauri, S., and Rao, N. D. (2013). Gender impacts and determinants of energy poverty: are we asking the right questions?. *Curr. Opin. Environ. Sustain.* 5, 205–215. doi: 10.1016/j.cosust.2013.04.006

Quak, E. J. (2018). *Lighting and Electricity Services for Off-Grid Populations in Sub-Sahara Africa.* Available online at: https://assets.publishing.service.gov.uk/media/5af96657ed915d0df4e8cdea/Costs_Benefits_Off-Grid_Electricity_Lighting_Systems.pdf (accessed May 10, 2019).

Rahut, D. B., Behera, B., Ali, A., and Marenya, P. (2017). A ladder within a ladder: understanding the factors influencing a household's domestic use of electricity in four African countries. *Energy Econ.* 66, 167–181. doi: 10.1016/j.eneco.2017.05.020

Ruiz-Mercado, I., and Masera, O. (2015). Patterns of stove use in the context of fuel–device stacking: rationale and implications. *EcoHealth* 12, 42–56. doi: 10.1007/s10393-015-1009-4

Tracy, J., and Jacobson, A. (2012). *The True Cost of Kerosene in Rural Africa.* Available online at: https://www.lightingafrica.org/publication/true-cost-kerosene-rural-africa/ (accessed April 24, 2019).

van der Kroon, B., Brouwer, R., and van Beukering, P. J. (2013). The energy ladder: theoretical myth or empirical truth? Results from a meta-analysis. *Renew. Sustain. Energy Rev.* 20, 504–513. doi: 10.1016/j.rser.2012.11.045

Conflict of Interest: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

APPENDIX

TABLE A1 | Correlation matrix of independent variables.

	Age	Age^2	Location	Gender	Marital status	HH size	Primary education	Secondary education	Tertiary education	Dwelling type	Rooms	Income	Kerosene price
Age	1												
Age^2	0.9839	1											
Location	−0.1995	−0.1918	1										
Gender	0.101	0.1056	−0.0466	1									
Marital status	0.0752	0.1044	0.0537	0.4772	1								
HH size	0.1398	0.0846	−0.2063	−0.1121	−0.3645	1							
Primary education	−0.0072	−0.0143	−0.1294	−0.0103	−0.005	0.0653	1						
Secondary education	−0.157	−0.1604	0.134	−0.085	−0.0525	−0.078	−0.5504	1					
Tertiary education	−0.1013	−0.1043	0.1706	−0.0581	−0.0401	−0.0827	−0.3604	−0.2303	1				
Dwelling type	0.0176	0.0169	0.1696	0.0136	0.0489	−0.1139	0.0663	0.1151	0.0951	1			
Rooms	0.29	0.2601	−0.1389	0.0261	−0.1166	0.2351	−0.0087	0.0206	0.1097	0.2419	1		
Income	−0.2398	−0.251	0.2483	−0.1908	−0.0652	−0.0877	−0.1077	0.1036	0.2059	0.091	−0.0682	1	
Kerosene price	−0.0145	−0.0181	−0.0493	−0.0311	−0.0621	0.1364	−0.0866	−0.0725	0.0019	−0.2145	−0.101	−0.0294	1

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Installed Hydropower Capacity and Carbon Emission Reduction Efficiency Based on the EBM Method in China

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This study employs 29 provincial-level administrative regions in China from 2013 to 2017 to evaluate the overall efficiency score of hydropower electricity generation in the three main regions of China. The EBM (Epsilon-based Measure) model with the DEA (Data Envelopment Analysis) method uses installed capacity data, labor force data, and equipment utilization hours as input indicators and electricity generation and CO_2 emission reduction as output indicators. By comparing the efficiency values of the two indices of installed capacity and CO_2 emission reduction, we are able to analyze the differences between installed hydropower electricity generation capacity efficiency and carbon emission reduction efficiency in various provinces and cities. The findings show that the western region is the best, followed by the central region and then the eastern region in terms of the input-output index level, total efficiency score of hydropower, and comparison of installed capacity-carbon emission reduction efficiency. Natural water resources and geographical advantages have a great positive effect on hydropower efficiency, while economic development has little effect on it. China should promote the sustainable development of hydropower according to local conditions and formulate and adopt countermeasures in line with the different circumstances between regions.

Keywords: EBM model, efficiency, hydropower in China, renewable energy, CO_2 emission reduction

INTRODUCTION

As the global economy grows and the international community attaches increasing importance to sustainable development, a common consensus has formed over issues such as energy security, ecological environment, and climate change that are accelerating the development of renewable energy utilization and improving energy efficiency. Hydropower is the conversion of water energy into electricity. As a form of clean energy, it is inexhaustible, renewable, pollution-free, convenient to carry out peak regulation of electricity, conducive to improving the utilization rate of resources, and has comprehensive economic and social benefits and low operating costs. Hydropower is presently the most mature technology and offers the most stable supply of renewable clean energy.

China is rich in hydropower resources, ranking first in the world both in terms of the amount of proven hydropower resources and those that can be developed. In 2018, China's hydropower electricity generation reached 6.8 trillion kilowatt-hours, up 6.8% year-on-year and accounting for 25.49% of the global total. China's hydropower has a total installed capacity of about

350 million kilowatts, making its installed capacity, and electricity generation the highest in the world. Affected by climate, topography, and other factors, China's water resources have the prominent characteristics of steep rivers and huge drops, which are very beneficial to the development of hydropower.

In China, hydropower is the second largest power resource after coal. As a form of clean energy, its development can save coal resources, reduce the emissions of greenhouse gases and various pollutants, and play an important role in the rise of low-carbon and sustainable development. The China government has targeted hydropower resources as an active extension of its energy strategy and energy security. Therefore, quantitative research on hydropower energy efficiency can help optimize its domestic energy structure, reduce greenhouse gas emissions, prevent and mitigate floods, and disasters, achieve energy conservation and emission reduction targets, and promote sustainable development.

Compared with developed countries, China's degree of hydropower development leaves still a lot of room for improvement in the future. Specifically, the degree of hydropower development in Switzerland, France, and Italy exceeds 80%, and the degree of hydropower development in Germany, Japan, and the United States is over 67%, whereas for China it is only 37% (by generating capacity),[1] which is only slightly higher than the global average level. This study thus takes installed capacity data, labor force data, and equipment utilization hours of 29 provincial-level administrative regions in China from 2013 to 2017 as input indicators and electricity generation and CO_2 emission reduction as output indicators. Via the EBM (Epsilon-based Measure) model, we divide these 29 provincial-level administrative areas of China into 3 regions and compute their overall efficiency score and 5 years of hydropower investment capacity and output of carbon emission reduction. We then compare two index efficiency values in order to offer a more precise and effective policy for hydropower development in China and to put forward useful suggestions.

Many scholars have made fruitful achievements in the research field of energy efficiency related to hydropower, with five major directions. First, many scholars have focused on the area of renewable energy development, trying to find how it is affected by other factors within a specific area, such as Ohler and Fetters (2014), Xu et al. (2019), and Wang et al. (2020). Second, studies have looked at what drives or influences the efficiency of carbon emissions in an area, such as Kim et al. (2015), Cheng et al. (2018), Harlan (2018), Xian et al. (2018), Wang et al. (2019), and Zhao et al. (2020). The third strand looks into the comprehensive utilization of renewable energy from the perspective of the constraints of climate and other objective environments on hydropower, such as Ehrbar et al. (2018), Koch et al. (2018), Li et al. (2018), Mosquera-Lopez et al. (2018), Ranzani et al. (2018), and Zapata et al. (2018). The fourth channel covers a comparative study and method innovation of renewable energy efficiency—for example, Scheel (2001), Fare et al. (2007), Sozen et al. (2010), Sueyoshi and Goto (2011), Zanella et al. (2015), and Calabria et al. (2018). The fifth area is the comprehensive analysis and research on carbon emission reduction potential, low-carbon technology, and electricity energy production—for example, Ang et al. (2011), Zhou et al. (2012), Zhou et al. (2014), Viebahn et al. (2015), Herrera-Estrada et al. (2018), Fernandes et al. (2019), Firth et al. (2019), Severnini (2019), and Kumar et al. (2019).

Most of the above research results focus on the positive impact of hydropower as a form of clean energy on the economy, society, and the environment, such as conducting a comprehensive analysis from the perspective of power policy and renewable energy structure. At present, research on energy efficiency and its quantification level only takes hydropower stations or power plants as the sample. Moreover, CO_2 emission reduction efficiency is not included in the evaluation of clean energy in the above literature, but rather traditional radial data envelopment analysis (DEA) is the main method used therein.

The main innovation of this paper has the following three aspects. Firstly, taking specific provinces of China as units and according to their economic and geographical factors, we divide the country into the east, central, and west regions and include CO_2 emissions as an important output. This helps to measure the contribution of hydropower as an important clean energy source to CO_2 emissions reduction. Secondly, the EBM model is able to overcome the double defects in which the traditional radial DEA model ignores non-radial relaxation and non-radial DEA ignores the proportional relationship with radial DEA. Thirdly, the analysis of the factors affecting the efficiency of hydropower in China adopts the comparison of economic conditions and geographical location. It can help regions and provinces to rely on objective conditions based on their active development of hydropower, to efficiently improve the equipment utilization rate of their resources.

LITERATURE REVIEW

Hydropower electricity generation is one of the most mature and cleanest forms of renewable energy power with large-scale development conditions and commercial prospects for related industries. Ever since the world's first hydropower station was built in France in 1878, hydropower has gradually become the second largest power source after thermal power generation. With the wave of sustainable, green, and low-carbon development in recent years, countries are now shifting their focus to hydropower. As such, many scholars have also shown strong interest in the efficiency of the power industry, focusing on five aspects below.

(1) Many scholars have targeted the area of renewable energy development, trying to find how it is affected by other factors within a specific area, such as Wang et al. (2020), who carried out a comprehensive evaluation on regional renewable energy development in China, concluding that better economic conditions help renewable energy development in a region to exhibit good performance, such as Beijing, Shanghai, and Guangdong. Xu et al. (2019) divided the world into seven regions and proposed a comprehensive prediction model to analyze the situation of renewable energy from

[1] International clean energy industry development report (2018).

the political, technical, economic, and social perspectives. Ohler and Fetters (2014) examined the causal relationship between economic growth and renewable energy generation in 20 OECD (Organization for Economic Cooperation and Development) countries between 1990 and 2008, finding that increases of endogenous substances and wastes in the short term have a negative impact on GDP, while renewable energy and hydropower electricity generation are beneficial to GDP growth.

(2) Some scholars have narrowed their research to analyze what drives or influences the efficiency of carbon emissions in an area. For example, Wang et al. (2019) used the panel Tobit model to analyze the negative correlation between the abundance of natural resources and emission efficiency. Economic scale indirectly affects carbon emission efficiency via emission reduction potential. These findings suggest that resource-based regions should make improving emission efficiency and exploring emission reduction potential the top priorities of any low-carbon transformation actions and promote industrial restructuring to reap double dividends in sustainable development and carbon efficiency.

Resource endowment, economic scale, and other external factors such as policies and technologies all impact a region's carbon emission reduction. Zhao et al. (2020) found that the decline in carbon intensity of electricity (CIE) generation is concentrated in three provinces: those with a large economic scale, strong policy support, and strong clean energy implementation. Xian et al. (2018) presented that regional technology heterogeneity exists in the process of electricity generation and related CO_2 emission reduction, which means it is necessary to formulate more differentiated regulations and policies on emission reduction and inter-regional technology transfer in the various regions of China.

Government policies can affect the energy mix and energy efficiency domestically, which in turn influence the efficiency of carbon reduction. Kim et al. (2015) took the DEA method to evaluate the investment efficiency of three new electricity-generating sources in South Korea: wind power generation, photovoltaic power generation, and fuel cell. In terms of government investment, wind power is the most efficient renewable energy source there. Cheng et al. (2018) pointed out that China's Yunnan Province, as a pilot market for power reform, provides a reference for future market reforms and renewable energy policies in the country as well as other regions through its integration and experience in low-carbon construction, inter-provincial competition, power grid security, and development goals. Harlan (2018) analyzed the policies that promote the transformation of small hydropower (SHP) in China and believed that SHP's transformation into a privatized low-carbon industry would make it easier to industrialize.

(3) Some scholars also analyzed the comprehensive utilization of renewable energy from the perspective of the constraints of climate and other objective environments on hydropower. Zapata et al. (2018) took Colombia as an example and analyzed the scenario of 100% renewable energy supply via a simulation model, concluding that both energy efficiency improvement and supply security can be achieved through a gradual adjustment and transformation of energy structure. Li et al. (2018) employed the world's largest hydropower photovoltaic hybrid power system, the Longyangxia project in China, as a case study and proposed a multi-objective optimization model of a hydropower system that considers both power generation and energy consumption. Mosquera-Lopez et al. (2018) mentioned that below freezing temperatures in cold weather force hydropower systems to cease operations, and so more renewable energy should be included in countries dependent on hydropower to eliminate price spikes. Koch et al. (2018) established a model system for simulating wind power electricity generation and hydroelectric power electricity generation and analyzed their complementarity based on climate change. Ranzani et al. (2018) proposed that climate change is changing the seasonality and exploitable capacity of hydropower. Ehrbar et al. (2018) set up an evaluation matrix for the systematic analysis of 16 economic, environmental, and social criteria for hydropower potential in the glacial edges of the Swiss Alps.

(4) Power production efficiency evaluation and method innovation research is noteworthy. Sozen et al. (2010) analyzed the electricity generation efficiency of China's state-owned thermal power plants with two DEA models: returns to scale (RTS or CCR) and various returns scale (VRS or BCC). Zanella et al. (2015) offered a new comprehensive index model based on the directional distance function to improve the shortcomings of traditional data envelopment analysis (DEA) and the directional distance function model. Calabria et al. (2018) constructed a new method based on the composite index of the directional distance function model to evaluate the efficiency of hydropower stations in Brazil, presenting underperforming hydropower stations and quantifying their improvement potential. Wang et al. (2018) proposed a new meta-frontier framework for measuring the heterogeneity of technology, which may provide help for investigating the heterogeneity among regions.

For application research of efficiency methods, Scheel (2001) discussed various methods to deal with unsatisfactory output under the DEA framework and compared the effective frontier generated from this. Fare et al. (2007) calculated the technical efficiency and pollution emission reduction cost by using data of coal-fired power plants, providing an empirical basis for the comparison of the environmental production function and the environmental direction distance function. Sueyoshi and Goto (2011) included input separation (dividing the input into energy and non-energy parts) in the calculation framework of DEA non-radial measurement as well as output separation (ideal and non-ideal outputs).

(5) Some studies have focused on carbon emission reduction potential, low carbon technology, and integrated research of electricity generation. Using data from 2005 for 129 countries and their total CO_2 intensity of electric power production, production efficiencies of coal, oil, and natural gas, and non-fossil fuels' electricity share as five

national-level performance indicators, Ang et al. (2011) studied the potential for reducing global energy-related CO_2 emissions from electricity production through simple benchmarking. Zhou et al. (2014) analyzed the energy efficiency and carbon dioxide emission reduction of thermal power electricity generation in China's seven regional power grids from 2004 to 2010 through the logarithmic average decomposition index (LMDI). They determined that energy intensity and energy combination have positive impacts on CO_2 emission reduction, but the influences of structure and CO_2 emission factors are not significant.

Using a kind of radial direction distance function on more than 100 countries in the process of generating energy and CO_2 emissions, Zhou et al. (2012) found OECD countries have better carbon emission and comprehensive energy-carbon performances in electricity generation than non-OECD countries, but there is no significant difference of energy performance between them. Firth et al. (2019) noted that the modification of carbon capture and storage in power plants can reduce the radiation force of carbon dioxide. Viebahn et al. (2015) used a comprehensive evaluation method covering five evaluation dimensions to evaluate carbon capture and storage (CCS) technology, proving that the economic, ecological, and social feasibilities of CCS in a low-carbon policy environment may be completely effective. Fernandes et al. (2019) combined field sampling and gas chromatography with geostatistics and remote sensing methods, proposing that hydropower reservoirs promote the greenhouse effect in the atmosphere through the emissions of methane and carbon dioxide and suggesting more measurements and observations.

Due to environmental constraints on hydropower development, Severnini (2019) showed that each additional megawatt of fossil-fuel electricity generation capacity adds about 1,400 tons of carbon dioxide emissions per year. Kumar et al. (2019) collected data from 12 hydropower reservoirs in China and input them into the GHG risk assessment tool model to predict the long-term greenhouse gas (CO_2 & CH_4) risk of hydropower reservoirs and their related life cycle, concluding that the Three Gorges reservoir is currently at high-risk CH_4 and medium-risk CO_2 levels. Herrera-Estrada et al. (2018) used multiple linear regressions to study the impact of droughts on electricity generation and found that they positively correlate with the increase of natural gas electricity generation in California, Idaho, Oregon, and Washington.

Based on the above literature, one can see that hydropower is mainly used as an auxiliary object in the research of energy structure or renewable energy electricity generation, so as to understand the positive impact of hydropower as a form of clean energy on the economy, society, and the environment. There are few regional comparative studies targeting hydropower efficiency, especially from the perspective of inter-provincial differences. Therefore, this paper aims to solve how to subjectively and efficiently develop a hydropower industry in a region or province based on objective conditions, uses the EBM model to evaluate the energy efficiency of the hydropower industry among provinces in China, and makes a comparative analysis of regional differences, focusing on the installed capacity and CO_2 emission reduction efficiencies of various regions.

RESEARCH METHOD

Both CCR (A. Charnes & W. W. Cooper & E. Rhodes) and BCC (Banker & Charnes & Cooper) are radial DEA models that ignore non-radial slacks when evaluating efficiency values. While SBM (Slacks-Based Measure) is a non-radial DEA model, it fails to consider the radial characteristics; that is, it ignores those characteristics that have the same radial proportions. To address and resolve the shortcomings in both the radial and non-radial models, Tone and Tsutsui (2010) proposed the Epsilou-Based Measure (EBM) DEA model, which is input-oriented, output-oriented, and non-oriented.

Since the EBM model which considers both radial and non-radial factors is more in line with the actual situation of China's hydropower input and output, and the conclusion obtained will be more objective and accurate in evaluating China's hydropower efficiency. So, this paper thus uses Tone and Tsutsui (2010) EBM Non-oriented DEA to calculate and evaluate the overall efficiency score of hydropower electricity generation in three main regions of China, including east, central, and west. The non-oriented EBM DEA description for the basic model and solution goes as follows.

Non-oriented EBM

With n DMU, where $DMU_j = (DMU_1, DMU_2, ..., DMU_k, ..., DMU_n)$, m kinds of inputs $X_j = \left(X_{1j}, X_{2j}, ..., X_{mj}\right)$, and soutputs $Y_j = \left(Y_{1j}, Y_{2j}, ..., Y_{sj}\right)$, the efficiency value of a DMU is:

$$K^* = \min_{0,\eta,\lambda,s^-,s^+} \frac{\theta - \varepsilon_x \sum_{i=1}^{m} \frac{w_i^- s_i^-}{x_{i0}}}{\eta + \varepsilon_y \sum_{i=1}^{s} \frac{w_i^+ s_i^+}{y_{i0}}} \tag{1}$$

Subject to $\theta X_0 - X_\lambda - S^- = 0, \qquad \eta Y_0 - Y_\lambda + S^+ = 0,$
$\lambda_1 + \lambda_2 + \ldots + \lambda_n = 1$
$\lambda \geq 0, \quad S^- \geq 0, \quad S^+ \geq 0.$
Y: DMU output,
X: DMU input,
S^-: slack variable,
S^+: surplus variable,
W^-: weight of input I, $\sum W_i^- = 1 \ \left(\forall_i \ W_i^- \geq 0\right)$,
W^+: weight of output S, $\sum W_i^+ = 1 \ \left(\forall_i \ W_i^+ \geq 0\right)$,
$\mathcal{E}_x$: set of radial θ and non-radial slack,
$\mathcal{E}_y$: set of radial η and non-radial slack.

If DMU0 $K^* = 1$ is the best efficiency for a non-oriented EBM, and if an inefficient DMU wants to achieve an appropriate efficiency goal, then the following adjustments are needed:

$$X^{0*} = X\lambda^* = \theta^* X_0 - S^{-*} \tag{2}$$

$$Y_0^* = Y\lambda^* = \eta^* y_0 + S^+ \tag{3}$$

Generating Equipment Availability Hour, Installed Capacity, Electricity Generation, and CO_2 Emission Reduction Production Efficiency Indices

This research uses the total-factor energy efficiency index to overcome any possible bias in the traditional energy efficiency indicators. For each specific evaluated municipality or province, the generating equipment availability hour (GEAH), installed capacity, electricity generation and CO_2 emission reduction (CO2 ER) are calculated using Equations (4)–(7):

$$\text{GEAH} = \frac{\text{Target GEAH input (i, t)}}{\text{Actual GEAH input (i, t)}} \tag{4}$$

$$\text{Installed capacity} = \frac{\text{Target Installed capacity input (i, t)}}{\text{Actual Installed capacity input (i, t)}} \tag{5}$$

$$\text{Electricity generation} = \frac{\text{Actual EEP desirable output (i, t)}}{\text{Target EEP desirable output (i, t)}} \tag{6}$$

$$\text{CO2 ER} = \frac{\text{Actual CO2 ER desirable output (i, t)}}{\text{Target CO2 ER desirable output (i, t)}} \tag{7}$$

If the target GEAH and installed capacity input equal the actual input, then GEAH and installed capacity efficiencies equal 1, indicating overall efficiency. If the target GEAH and installed capacity input are less than the actual input, then their efficiencies are <1, indicating overall inefficiency.

If the target electricity generation and CO_2 ER desirable output are equal to the actual electricity generation and CO_2 ER desirable output, then electricity generation and CO_2 ER efficiencies equal 1, indicating overall efficiency. If the actual electricity generation and CO_2 ER desirable output are less than the target electricity generation and CO_2 ER desirable output, then electricity generation and CO_2 ER efficiencies are <1, indicating overall inefficiency.

Data Sources and Description

This study utilizes panel data from 29 municipalities/provinces in the most developed areas of China spanning 2013–2017. The labor data are from the Chinese Statistical Yearbooks and the Demographics and Employment Statistical Yearbook of China. Electricity data come from the China Energy Administration annual report and China Electric Power yearbook. As the 29 municipalities/provinces have different populations, industries, natural resources, meteorological conditions, and geographical positions, they are fairly representative of the status quo, efficiency, and contribution of hydropower in China for examining carbon dioxide reduction. The input indicator variables used in this study are labor, generating equipment availability hour, and installed capacity, while the output indicators are electricity generation and CO_2 emission reduction (**Table 1**).

TABLE 1 | Input and output variables.

Inputs	Outputs	Data sources
Labor Generating equipment availability hour Installed capacity	Electricity generation CO_2 emission reduction	China Electric Power yearbook 2014–2017 China's National Bureau of Statistics China clean development mechanism network Other related journals and websites

Input Variables

Labor input (lab): Employees. Since there are no separate statistics on the number of employees in the hydropower industry, we instead use the employment of urban units in the production and supply industries of electricity, gas, and water. This study takes the number of employees in each municipality/province at the end of each year. Unit = 10,000 people.

Generating equipment availability hour: the number of operating hours, calculated by dividing the generating capacity of the reporting period by equipment capacity. Unit = hours.

Installed capacity: the sum of the rated effective electricity of the generator set actually installed. Unit = MKW.

Output Variables

Electricity generation: the amount of electrical energy produced by a generator through energy conversion. Unit: KWH.

CO_2 emission reduction: Hydropower is clean because it produces electricity without the need for conventional energy (unless the small number of ancillary equipment). In this paper, the contribution of hydropower to CO_2 emission reduction is calculated by using the standard coal consumption required for the same power generation. Based on CO_2 generated by thermal electricity under the same generating capacity, this capacity is converted into standard coal, where one degree of electricity consumes 360 grams of standard coal; 1 ton of raw coal = 0.714 tons of standard coal. The carbon dioxide emission coefficient per ton of raw coal is 1.9003 kg-co2/kg. Therefore, the formula is CO_2 emission reduction = electricity generation* 0.36/0.714*1.9003/10. Unit: Mt.

EMPIRICAL ANALYSES

Statistical Analysis of Input-Output Indicators

This paper divides 29 provincial-level administrative regions into the east, central, and west. The eastern coastal areas include Beijing, Hebei, Liaoning, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, and Hainan. The central inland includes Shanxi, Inner Mongolia, Jilin, Heilongjiang, Anhui, Jiangxi, Henan, Hubei, Hunan, and Guangxi. The western frontier includes Sichuan, Guizhou, Yunnan, Tibet, Shaanxi, Gansu, Qinghai, Ningxia, Xinjiang, and Chongqing. In order to compare the energy efficiency and hydropower environment of these three regions, we analyze their efficiency indices. In **Table 2** we see from 2013 to 2017 that there is a small difference in the amount of hydropower employment in the eastern and central regions, while the western region has the lowest amount.

Figure 1 shows the index level and its change trend for the 5 years in each area. In regard to the input index of installed capacity, the eastern, central, western, and national trends have the same change, growing steadily from 2013 to 2016 and falling back in 2017, whereas the hydropower installed electricity capacity of the western region is more than twice that of the eastern region.

TABLE 2 | Average situation of each indicator by region from 2013 to 2017.

	Area	2013	2014	2015	2016	2017
Labor (10,000 people)	East	15.95	15.63	15.06	14.98	14.98
	Central	15.64	15.53	15.43	14.97	14.37
	West	9.48	9.87	9.74	9.44	9.02
	Total	13.69	13.67	13.41	13.13	12.79
Utilization time (h)	East	1666.67	1801.11	1537.44	2305.22	1990.67
	Central	2660.00	2539.00	2500.70	2648.10	2615.89
	West	3552.80	3642.30	3615.50	3355.70	3817.85
	Total	2626.49	2660.80	2551.21	2769.67	2808.14
Installed capacity (10,000 KW)	East	494.40	498.53	501.54	528.37	460.12
	Central	862.64	882.60	897.18	915.32	901.85
	West	1496.70	1712.00	1846.60	1930.00	1924.69
	Total	951.25	1031.04	1081.77	1124.56	1095.56
Generated energy (100 million KWH)	East	119.30	119.39	134.63	176.38	120.17
	Central	266.85	300.55	312.84	320.81	317.35
	West	537.41	656.52	696.25	713.82	764.33
	Total	307.85	358.82	381.24	403.67	400.62
CO_2 emission reduction (10,000 tons)	East	1142.92	1143.80	1289.72	1689.68	1151.27
	Central	2556.43	2879.24	2997.01	3073.38	3040.19
	West	5148.40	6289.46	6670.11	6838.38	7322.25
	Total	2949.25	3437.50	3652.28	3867.14	3837.91

In terms of utilization time, the level and change in trend of the three regions are different. The change in trend of the central region is relatively gentle, while the change in trend of the eastern and western regions is unstable, rising and falling at random. In terms of output index and electricity generation, the western region is at a high level, which is about 4 times and 2 times that of the eastern and central regions, respectively, and it has been continuously increasing in the past 5 years. However, hydropower electricity generation in the eastern and central regions is basically unchanged and declined in 2017. Generally speaking, the development momentum of the hydropower industry in various regions of China has slowed down in recent years. Moreover, hydropower development has not reached any standard, which may relate to the difficulty of such development and poor consumption of hydropower.

Total Efficiency Score and Ranking Analysis

Table 3 exhibits the total efficiency score and ranking in different regions. The western region as a whole performed significantly better, while the eastern and central regions rarely had the most efficient provinces. For example, Sichuan and Yunnan both have a total efficiency score of 1, and their energy efficiency of hydropower is 1 from 2013 to 2017. Fujian, Hubei, Gansu, and Shaanxi have a total efficiency value ranging from 0.8 to 1.0.

As seen from **Figure 2**, the total efficiency of hydropower is west > central > east from high to low overall. The ratio of the number of top-10 provinces in the three regions is 1:3:6, while 13 cities with a total efficiency value <0.5 are distributed in the eastern and central regions, indicating that hydropower energy efficiency in these two regions is far below that of the western region.

From **Figure 3** we can see the geographical distribution in the three regions. In terms of the whole country, the hydropower

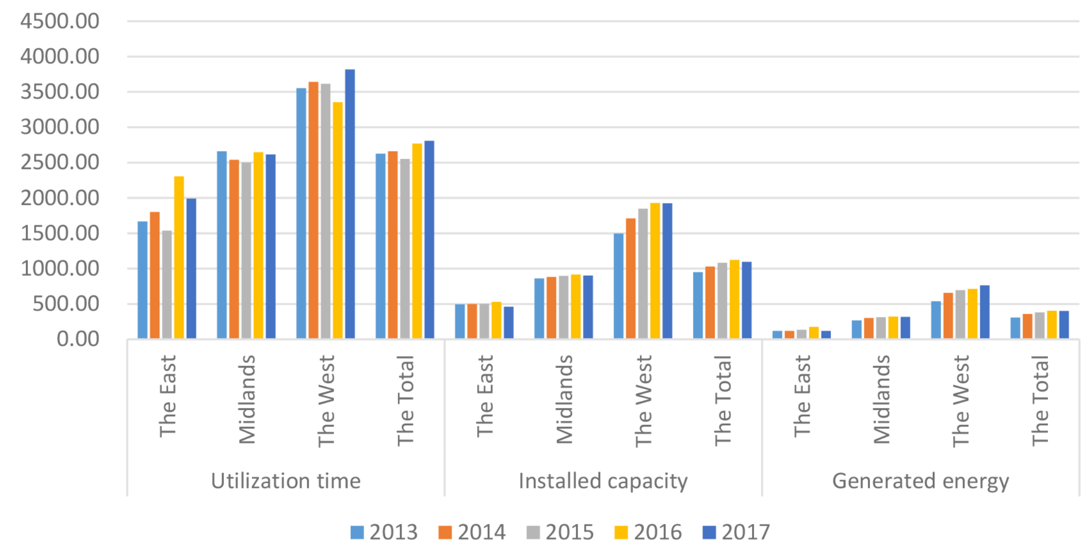

FIGURE 1 | Comparison of the average situation of each indicator by region from 2013 to 2017.

TABLE 3 | The total efficiency score and ranking in different regions.

DMU		2013	2014	2015	2016	2017	Score	Rank
East	Beijing	0.0882	0.1376	0.1183	0.1652	0.2057	0.1430	27
	Hebei	0.1162	0.1245	0.1032	0.1724	0.1830	0.1399	28
	Liaoning	0.4028	0.2981	0.2056	0.2331	0.2214	0.2722	23
	Jiangsu	0.1743	0.1973	0.1746	0.1972	0.1997	0.1886	26
	Zhejiang	0.3717	0.3858	0.4820	0.4230	0.3846	0.4094	19
	Fujian	0.6699	0.7096	0.7609	1	0.8979	0.8077	6
	Shandong	0.0610	0.0977	0.1251	0.1676	0.1106	0.1124	29
	Guangdong	0.6212	0.6105	0.6636	0.6323	0.5799	0.6215	14
	Hainan	0.5061	0.5924	0.3114	0.2826	0.5787	0.4543	18
	AVE	0.3346	0.3504	0.3272	0.3637	0.3735	0.3499	
Central	Shanxi	0.3012	0.2775	0.2168	0.2233	0.3208	0.2679	24
	Inner Mongolia	0.2961	0.3820	0.2676	0.1735	0.1505	0.2539	25
	Jilin	0.5084	0.3988	0.2924	0.3296	0.3402	0.3739	20
	Heilongjiang	0.5039	0.3908	0.2737	0.2075	0.3410	0.3434	21
	Anhui	0.2266	0.2989	0.3061	0.3139	0.3908	0.3073	22
	Jiangxi	0.5435	0.5711	0.6572	0.5220	0.6272	0.5842	15
	Henan	0.5411	0.4908	0.4854	0.3530	0.4699	0.4681	17
	Hubei	0.8434	0.9125	0.8471	0.8190	0.7899	0.8424	5
	Hunan	0.7610	0.7751	0.7851	0.7164	0.8688	0.7813	9
	Guangxi	0.6670	0.8497	1	0.7146	0.7669	0.7997	7
	AVE	0.5192	0.5347	0.5132	0.4373	0.5066	0.5022	
West	Chongqing	0.5480	0.7874	0.6803	0.6171	0.7608	0.6787	11
	Gansu	1	1	0.7704	0.6076	0.8949	0.8546	3
	Guizhou	0.5855	0.7822	0.8439	0.6779	0.6892	0.7157	10
	Ningxia	0.7013	0.7668	0.5915	0.4001	0.6533	0.6226	13
	Qinghai	1	1	0.7977	0.5770	0.5656	0.7881	8
	Shaanxi	0.7908	1	1	0.6406	0.8100	0.8483	4
	Sichuan	1	1	1	1	1	1	1
	Tibet	0.6102	0.6153	0.5711	0.5585	0.4919	0.5694	16
	Xinjiang	0.7529	0.5913	0.6877	0.5579	0.6519	0.6483	12
	Yunnan	1	1	1	1	1	1	1
	AVE	0.7989	0.8543	0.7943	0.6637	0.7518	0.7726	

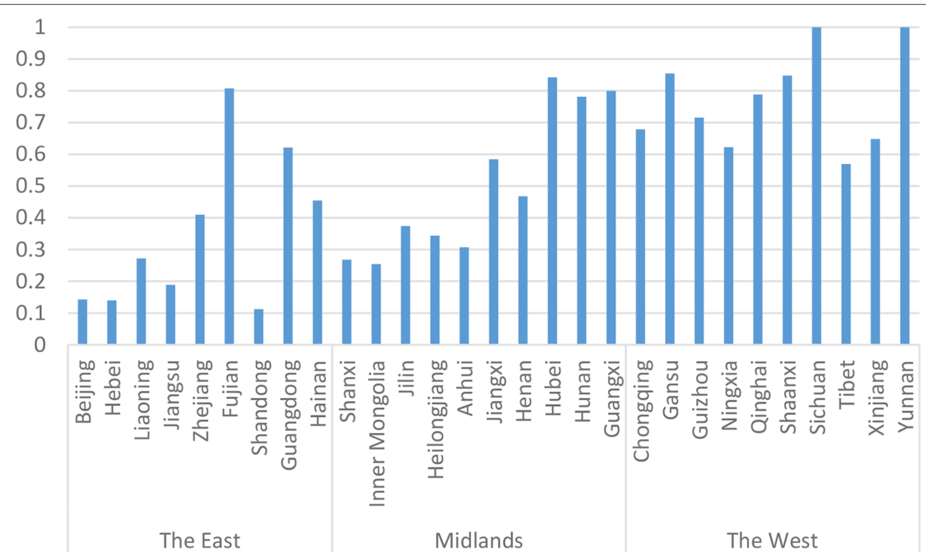

FIGURE 2 | Total efficiency scores among provinces by region from 2013 to 2017.

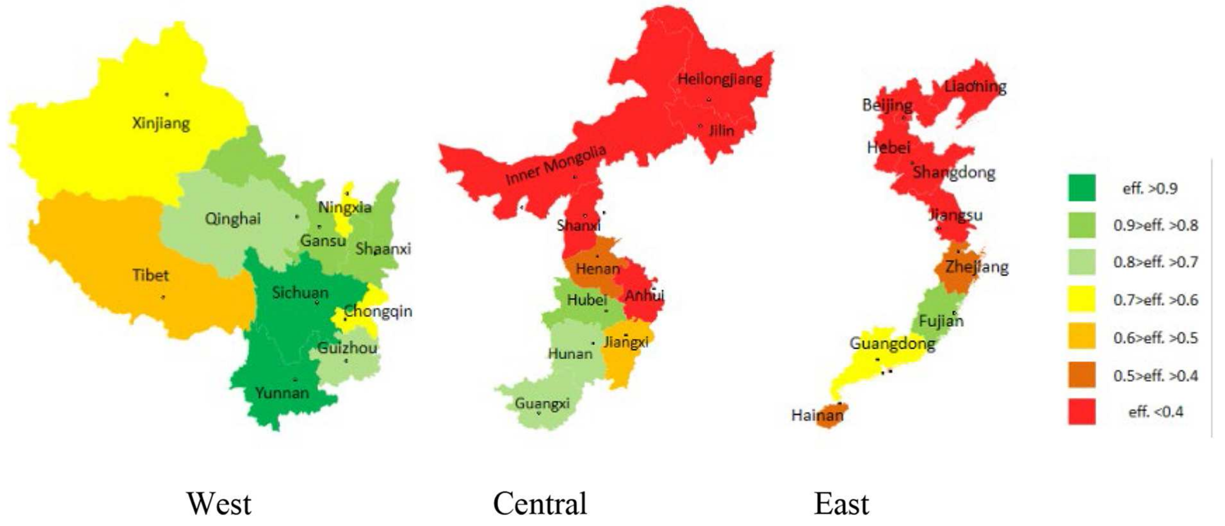

FIGURE 3 | Map of regional total efficiency.

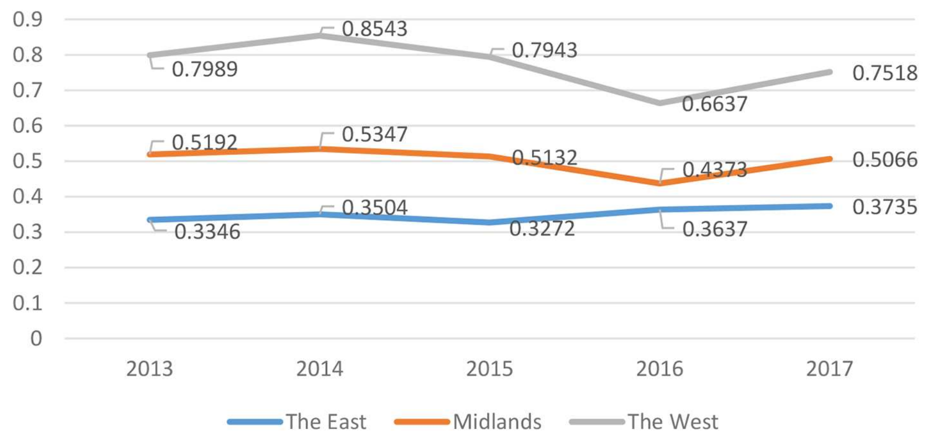

FIGURE 4 | Variation trend of total efficiency by regions from 2013 to 2017.

efficiency of the southwest region is obviously better than that of northeast. There is still much room for hydropower efficiency improvement in the central and eastern regions.

Under multiple factors and from regional differences in hydropower energy efficiency, further analysis concludes that the level of economic development has a weaker influence on hydropower energy efficiency, and that the level of this efficiency is more likely to depend on the resource endowment of a region. Moreover, policy support also plays a significant role to a certain extent, because with the development of clean energy in recent years, the government is more and more encouraging the western region with its rich water resources to exploit hydropower in order to improve its energy structure and achieve carbon reduction benefits. Under a multilateral support policy, hydropower enterprises in the western region have accumulated rich experience and advanced technology, and so regions with hydropower energy efficiency are more efficient than other areas.

It is obvious from **Figure 4** that, first, the total efficiency of hydropower energy varies greatly in the three regions, with the highest in western remote areas, followed by central inland areas, and the lowest in eastern coastal areas. Second, the trend of hydropower energy efficiency in the three regions varies from time to time. The western and central regions both increased in 2017, while the eastern region declined slightly. Compared to 2013, the hydropower energy efficiency in western China decreased slightly in 2017, which is the key region for hydropower development and includes many large hydropower complexes. In recent years, China has invested heavily in the development and construction of hydropower, but the expected effect has not been achieved. Generally speaking, the economic effects of hydropower development are fading. Thus, the government should identify the bottleneck problems of hydropower development in various regions as soon as possible, measure the long-term and short-term costs and benefits of

TABLE 4 | Average score of installed electricity capacity and CO_2 emission reduction efficiency.

DMU		Installed electricity capacity	CO_2 emission reduction
East	Beijing	0.3081	0.5920
	Hebei	0.2967	0.5879
	Liaoning	0.4942	0.6675
	Jiangsu	0.3845	0.6195
	Zhejiang	0.6698	0.7540
	Fujian	0.9564	0.9594
	Shandong	0.2548	0.5745
	Guangdong	0.8755	0.8928
	Hainan	0.7085	0.7789
Central	Shanxi	0.5024	0.6688
	Inner Mongolia	0.4724	0.6591
	Jilin	0.6279	0.7341
	Heilongjiang	0.6092	0.7249
	Anhui	0.5493	0.6900
	Jiangxi	0.8333	0.8579
	Henan	0.7413	0.7975
	Hubei	0.9642	0.9668
	Hunan	0.9784	0.9793
	Guangxi	0.9614	0.9647
West	Sichuan	1	1
	Guizhou	0.9121	0.9235
	Yunnan	1	1
	Tibet	0.8369	0.8645
	Shaanxi	0.9790	0.9800
	Gansu	0.9748	0.9761
	Qinghai	0.8791	0.9164
	Ningxia	0.8951	0.9094
	Xinjiang	0.8937	0.9071
	Chongqing	0.9119	0.9215
AVE		0.7404	0.8230

hydropower development, formulate more effective targeted policies, and attain environmental and economic double benefits by replacing traditional fossil energy with clean energy.

Comparison of Installed Electricity Capacity and Carbon Emission Reduction Efficiencies

From **Table 4**, the efficiency score of installed electricity capacity is generally lower than that of the CO_2 emission reduction index. This shows that installed electricity capacity in many areas is underutilized and there is redundant investment, especially in the eastern coastal areas. The number of provinces with installed electricity capacity and CO_2 emission reduction efficiency close to the production frontier (above 0.9) is 1, 3, and 6 for the east, central and west regions, respectively. These provinces have achieved better carbon emission reduction benefits from hydropower. The efficiency value is divided into three gradients: Above 0.85, 0.45–0.85, and below 0.45. The ratio of the number

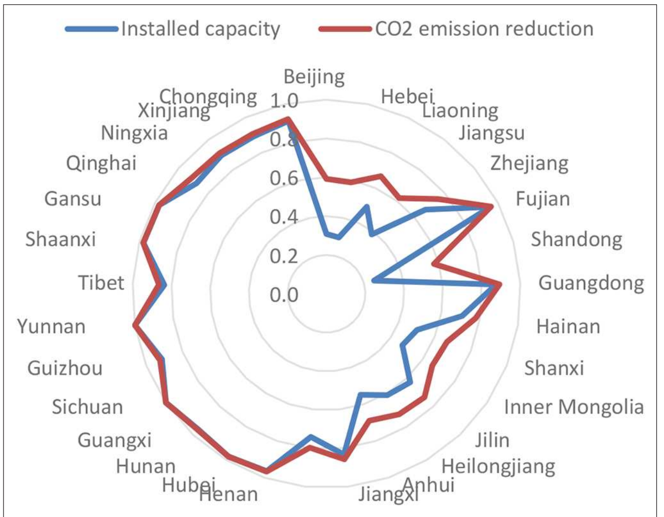

FIGURE 5 | Radar contrast chart of installed capacity and CO_2 emission reduction.

of provinces whose efficiency value of hydropower installed electricity capacity is distributed in the same three gradients is 14:11:4. Beijing, Hebei, Jiangsu, and Shandong have an efficiency value lower than 0.45, indicating that their hydropower electricity capacity is weak, and they are all located in eastern coastal areas. Provinces with more electricity generation have a greater contribution to CO_2 emission reduction, whereas provinces whose efficiency of CO_2 emission reduction is >0.9 are also outstanding at generating electricity. Thus, most areas with resource endowment can exert their advantages and vigorously develop clean energy; these areas are mostly in the west. The eastern coastal region has had rapid economic development, but needs to improve its hydropower industry efficiency for the reduction of carbon emissions.

From the contrast analysis of the two indicators' efficiency value in **Figure 5**, Fujian, Sichuan, and Yunnan have the same efficiency score for the two indices. In the other provinces, their installed capacity efficiency scores are lower than the values of CO_2 emission reduction efficiency. Shandong, Hebei, Jiangsu, and Shanxi have bigger differences amongst themselves. While the input efficiency of the four provinces is low, they perform relatively well at carbon emission reduction, and so improving installed electricity capacity efficiency is not an ideal way to increase carbon reduction efficiency.

We can divide those provinces with smaller difference between the two indices above into two categories. The first one covers those with a high efficiency value, whereby both efficiencies of installed electricity capacity and CO_2 emissions reduction are close to the frontier. From the radar contrast chart, they are mostly distributed in the western region, and their room for improvement of installed electricity capacity and carbon emission reduction efficiencies is not large. The second category is provinces with relatively low efficiency values, which are all located in the eastern and central regions. These regions need to focus on improving the efficiency of installed electricity capacity or the hours of equipment utilization to indirectly promote the growth of carbon emission reduction efficiency.

There are large inter-provincial differences in the efficiency values of the two indices in the eastern and central regions, especially for installed electricity capacity. The curves of the efficiency values of installed electricity capacity and CO_2 emission reduction are basically in line with each other and very close to the production frontier in the western region, which also reflects the mature development of hydropower in this region. The differences in central China are moderate. The curves of the efficiency values of installed electricity capacity and CO_2 emission reduction there exhibit a high degree of agreement, being close to the production frontier for Guangdong, Hunan, and Hubei. In the eastern region, the difference is more obvious. Except for Fujian and Guangdong, the provinces here have low installed electricity capacity and low investment efficiencies. In fact, most places in the eastern region have flat terrain and scarce water energy resources, and so governments have invested in the construction of many pumped-storage hydropower stations. Although such hydropower stations have a high number of hours of equipment utilization, the initial investment is large, and the machinery and equipment in the production process release carbon dioxide, leading to insufficient contribution of hydropower to carbon emission reduction. Hence, local governments in the eastern region could consider developing other clean energy sources, such as photovoltaic, wind, and tidal power to reach carbon reduction targets.

Cause Analysis of Efficiency Difference

Clean energy development in China is affected by the withdrawal of the United States from the Paris agreement and the expansion of fossil energy exports. Moreover, in China the current shortage of clean energy consumption and the long overdue and widening gap of renewable energy subsidies are restricting the future development of its clean energy industry.

In China the eastern and western regions have key roles in the country's hydropower development. The eastern region has a high level of economic development, which can provide many convenient conditions for the development of the hydropower industry. The western region has the natural advantages of hydropower development, rich resources, and sparse population, which is suitable for the establishment of large- and medium-sized hydropower facilities. The inefficiency factors of the western region mainly come from its fragile ecological environment, poor traffic conditions, long electricity transmission distance, high costs of engineering construction and electricity transmission, and increasing resettlement and ecological environmental protection investment. In addition, the demand for comprehensive utilization of hydropower is becoming greater, and insufficient investment subsidies and allocation mechanisms have increased the economic burden and construction cost of hydropower. In recent years, the growth rate of electricity consumption has decreased, and the supply in the electricity market has exceeded demand, leading to the problem of "abandoning water" (the amount of water used to generate electricity under the generating capacity of a hydropower station that is not actually used for generating electricity due to various reasons) in western China.

TABLE 5 | Kruskal-Wallis test score of total efficiency.

Year	Ave. Score of East	Ave. Score of Central	Ave. Score of West	Kruskal-Wallis Test Score
2013	0.3346	0.5192	0.7989	0.001***
2014	0.3504	0.5347	0.8543	0.001***
2015	0.3272	0.5132	0.7943	0.003***
2016	0.3637	0.4373	0.6637	0.028***
2017	0.3735	0.5066	0.7518	0.011***

****Significant confidence interval of 0.05 (two-tailed test).*
The data in this table are calculated with SPSS Statistics 25 Software (IBM Corporation, Armonk, New York, U.S.A.).

The high proportion of pumped storage electricity stations in east and central China leads to a low utilization rate of hydropower equipment. Moreover, hydropower projects in the eastern region are mostly saturated, and to some extent they rely on the "west-east gas transmission" for electricity supply, resulting in additional electricity costs and poor efficiency. The input-output efficiency scores of various indices are lower in the central regions than in the western region due to geographical location and non-disadvantages of water energy resources.

It is therefore recommended that the central government establish a "dynamic comprehensive hydropower cost evaluation system" to understand the significance of developing the clean energy hydropower industry from the four dimensions of energy, environment, economy, and social benefits. China should complete an investment subsidy mechanism as soon as possible and vigorously support the development of hydropower in the western region.

Table 5 shows the Wilcoxon test score for the average technology gap. In 2013–2017, the average total efficiency of the three regions passes the significance test.

CONCLUSIONS AND POLICY RECOMMENDATIONS

Conclusions

This study divides 29 provincial-level administrative areas in China into eastern, central, and western regions. We then evaluate and analyze their hydropower energy efficiency, inter-provincial differences, and improvement space in 2013–2017 in order to discuss the level of hydropower efficiency, influencing factors, and improvement direction of each region. The empirical results are as follows.

(1) In terms of the level of input and output indicators, the western region is higher than the central region, and the eastern region is at the bottom. In terms of the change in trend over the past 5 years, many indicators in most provinces and cities have fallen back. Generally speaking, the development momentum of the hydropower industry in China has slowed down in recent years.

(2) The total energy efficiency of hydropower in order from high to low is west, central, and east. The ratio of the top-ten provinces among the three regions of east, central, and west is 1:3:6. Moreover, the provinces and cities whose total efficiency value is <0.5 are all distributed in the eastern and central regions, indicating that the hydropower energy efficiency of these two regions is far away from that of the western region.

(3) From a comparison of installed electricity capacity efficiency and carbon emission reduction efficiency, the performance of the three regions is consistent with the order of the total efficiency score, no matter for the efficiency value or inter-provincial difference. The overall levels of installed electricity capacity and CO_2 emission reduction efficiencies in the east are significantly lower, and inter-provincial differences are large. The curves of installed electricity capacity efficiency and CO_2 emission reduction efficiency in the west are basically identical and very close to the production frontier. The differences in the central region are between these two regions.

(4) In terms of the energy efficiency of hydropower, we conclude that the western region is the best, followed by the central region and then the eastern region. Moreover, natural water resources and geographical advantages have a great positive effect on hydropower efficiency, while economic development has little effect on it.

This shows that in China, the improvement of hydropower efficiency mainly depends on the more economical and rational use of hydropower resources. It is an effective measure to make full use of water head, reasonable operation of reservoirs and reasonable number of power stations in the western region to ensure the operation of hydropower in the high-efficiency area. With the rapid development of economy and the increasing energy shortage, small hydropower and pumped storage power stations can become the important channels for hydropower development in eastern China. On the one hand, small hydropower and pumped storage power stations can overcome the weak natural conditions of hydropower in the eastern region. On the other hand, they can meet the elastic needs of peak adjustment, frequency modulation and phase adjustment of power grid in the developed eastern region.

Policy Recommendations

With the development of technology and the concept of ecological and environmental protection, China should consolidate its leading position as a powerful hydropower country in the world, actively promote the concept and innovation of hydropower development, and attach equal importance to development, protection, construction, and management. Based on the above conclusions, provinces, cities, and regions should solve their problems according to local conditions and formulate and adopt strategies and countermeasures in line with their own actual circumstances.

Eastern Coastal Area

(1) The basic development of hydropower resources is complete, but there is still room for improvement in their installed electricity capacity. In particular, the efficiency of equipment utilization hours should be improved, which requires the region to increase investment in hydropower construction, make full use of existing equipment, and increase its contribution to carbon emission reduction.

(2) This region should cultivate and rationalize the allocation of relevant human resources, reduce waste, and improve efficiency in the number of employees.

Central Inland Area

(1) This region should target deeper development, control the growth of small- and medium-sized hydropower stations, and realize the optimal allocation of resources. Hydropower development here is at the top level, yet some provinces and cities in the region are similar to the western region, while others are only slightly better than the eastern region. A "one-to-one" pull coordinated development within the region can be adopted to achieve centralized control and optimized operations, so as to drive the provinces and cities at the bottom of the rankings to keep pace with the western region.

(2) By integrating the experiences and measures of the eastern and western regions, learning from each other, and complementing each other, this region can pay equal attention to both construction and operation management and combine project development with personnel training. Relying on the construction of large-scale hydropower projects can help cultivate various hydropower construction talents and teams with leading professional levels and outstanding scientific and technological innovation abilities.

Western Outlying Area

(1) Some provinces and cities still have great development potential and continue to expand the scale of "west-to-east electricity transmission." On the one hand, the energy potential of the western electricity supply area can be fully developed; on the other hand, the range of hydropower consumption can be effectively expanded to solve the problem of water abandonment here.

(2) As for the constraints of hydropower development in the western region, authorities can help strengthen infrastructure construction, promote ecological restoration of small- and medium-sized river basins, improve external traffic conditions, reduce construction difficulties, continually enhance the technical level of hydropower construction and the manufacturing capacity of mechanical and electrical equipment, and target technological innovation.

(3) This region can also increase investment in hydropower, promote poverty alleviation, improve the land acquisition mechanism, and reduce development costs. Each province

should boost hydropower investment subsidies and the hydropower station compensation mechanism, strengthen the coordination of departments, meet the demand for hydropower construction land, and improve the work of land applications and approvals. Governments here can do a better job at compensation and resettlement of land expropriated for hydropower construction, earnestly safeguard the rights and interests of farmers whose land is expropriated, and implement "land in advance" to ensure timely construction of hydropower projects.

DATA AVAILABILITY STATEMENT

All datasets generated for this study are included in the article/supplementary material.

AUTHOR CONTRIBUTIONS

ZT and DL: conceptualization. FR: writing—original, writing—review, and editing, methodology and formal analysis. ZT: software, data curation, draft preparation, project administration, and funding acquisition. DL: validation, resources, and visualization. JP: investigation and supervision.

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REFERENCES

Ang, B. W., Zhou, P., and Tay, L. P. (2011). Potential for reducing global carbon emissions from electricity production-A benchmarking analysis. *Energy Policy* 39, 2482–2489. doi: 10.1016/j.enpol.2011.02.013

Calabria, F. A., Camanho, A. S., and Zanella, A. (2018). The use of composite indicators to evaluate the performance of Brazilian hydropower plants. *Int. 0Transact. Operat. Res.* 25, 1323–1343. doi: 10.1111/itor.12277

Cheng, C., Chen, F., and Li, G. (2018). Reform and renewables in China: the architecture of Yunnan's hydropower dominated electricity market. *Renew. Sustain. Energy Rev.* 94, 682–693. doi: 10.1016/j.rser.2018.06.033

Ehrbar, D., Schmocker, L., and Vetsch, D. F. (2018). Hydropower potential in the periglacial environment of switzerland under climate change. *Sustainability* 10:2794. doi: 10.3390/su10082794

Fare, R., Grosskopf, S., and Pasurka, C. A. (2007). Environmental production functions and environmental directional distance functions. *Energy* 32, 1055–1066. doi: 10.1016/j.energy.2006.09.005

Fernandes, G., Lima Gomes, L., Teixeira Brandão, L. E. (2019). Mitigating hydrological risk with energy derivatives. *Energy Econ.* 81, 528–535. doi: 10.1016/j.eneco.2019.05.001

Firth, A., Zhang, B., and Yang, A. (2019). Quantification of global waste heat and its environmental effects. *Appl. Energy* 235, 1314–1334. doi: 10.1016/j.apenergy.2018.10.102

Harlan, T. (2018). Rural utility to low-carbon industry: small hydropower and the industrialization of renewable energy in China. *Geoforum* 95, 59–69. doi: 10.1016/j.geoforum.2018.06.025

Herrera-Estrada, J. E., Diffenbaugh, N. S., and Wagner, F. (2018). Response of electricity sector air pollution emissions to drought conditions in the western United States. *Environ. Res. Lett.* 13:124032. doi: 10.1088/1748-9326/aaf07b

Kim, K.-T., Lee, D. J., and Park, S.-J. (2015). Measuring the efficiency of the investment for renewable energy in Korea using data envelopment analysis. *Renew. Sustain. Energy Rev.* 47, 694–702. doi: 10.1016/j.rser.2015.03.034

Koch, H., Chaves Silva, A. L., and Goncalves de Azevedo, J. R. (2018). Integrated hydro-and wind power generation: a game changer towards environmental flow in the Sub-middle and Lower Sao Francisco River Basin? *Regional Environ. Change* 18, 1927–1942. doi: 10.1007/s10113-018-1301-2

Kumar, A., Yang, T., and Sharma, M. P. (2019). Long-term prediction of greenhouse gas risk to the Chinese hydropower reservoirs. *Sci. Total Environ.* 646, 300–308. doi: 10.1016/j.scitotenv.2018.07.314

Li, F.-F., Qiu, J., and Wei, J.-H. (2018). Multiobjective optimization for hydro-photovoltaic hybrid power system considering both energy generation and energy consumption. *Energy Sci. Eng.* 6, 362–370. doi: 10.1002/ese3.202

Mosquera-Lopez, S., Uribe, J. M., and Manotas-Duque, D. F. (2018). Effect of stopping hydroelectric power generation on the dynamics of electricity prices: an event study approach. *Renew. Sustain. Energy Rev.* 94, 456–467. doi: 10.1016/j.rser.2018.06.021

Ohler, A., and Fetters, I. (2014). The causal relationship between renewable electricity generation and GDP growth: a study of energy sources. *Energy Economics* 43, 125–139. doi: 10.1016/j.eneco.2014.02.009

Ranzani, A., Bonato, M., and Patro, E. R. (2018). Hydropower future: between climate change, renewable deployment, carbon and fuel prices. *Water* 10:1197. doi: 10.3390/w10091197

Scheel, H. (2001). Undesirable outputs in efficiency valuations. *Eur. J. Operational Res.* 132, 400–410. doi: 10.1016/S0377-2217(00)00160-0

Severnini, E. (2019). The unintended impact of ecosystem preservation on greenhouse gas emissions: Evidence from environmental constraints on hydropower development in the United States. *PLoS ONE* 14:10483. doi: 10.1371/journal.pone.0210483

Sozen, A., Alp, I., and Ozdemir, A. (2010). Assessment of operational and environmental performance of the thermal power plants in Turkey by using data envelopment analysis. *Energy Policy* 38, 6194–6203. doi: 10.1016/j.enpol.2010.06.005

Sueyoshi, T., and Goto, M. (2011). DEA approach for unified efficiency measurement: assessment of Japanese fossil fuel power generation. *Energy Economics* 33, 292–303. doi: 10.1016/j.eneco.2010.07.008

Tone, K., and Tsutsui, M. (2010). An epsilon-based measure of efficiency in DEA - A third pole of technical efficiency. *Euro. J. Oper. Res.* 207, 1554–1563. doi: 10.1016/j.ejor.2010.07.014

Viebahn, P., Vallentin, D., and Hoeller, S. (2015). Prospects of carbon capture and storage (CCS) in China's power sector - An integrated assessment. *Appl. Energy* 157, 229–244. doi: 10.1016/j.apenergy.2015.07.023

Wang, K., Wu, M., Sun, Y., Shi, X., Sun, A., and Zhang, P. (2019). Resource abundance, industrial structure, and regional carbon emissions efficiency in China. *Resourc. Policy* 60, 203–214. doi: 10.1016/j.resourpol.2019.01.001

Wang, N., Chen, J., Yao, S., and Chang, Y.-C. (2018). A meta-frontier DEA approach to efficiency comparison of carbon reduction technologies on project level. *Renew. Sustain. Energy Rev.* 82, 2606–2612. doi: 10.1016/j.rser.2017.09.088

Wang, Y., Zhang, D.-Y., Ji, Q., and Shi, X.-P. (2020). Regional renewable energy development in China: a multidimensional assessment. *Renew. Sustain. Energy Rev*. 124:109797. doi: 10.1016/j.rser.2020.109797

Xian, Y., Wang, K., Shi, X., Zhang, T., Wei, Y., and Huang, Z. (2018). Carbon emissions intensity reduction target for China's power industry: an efficiency and productivity perspective. *J. Cleaner Product.* 197, 1022–1034. doi: 10.1016/j.jclepro.2018.06.272

Xu, X.-F., Wei, Z.-F., Ji, Q., Wang, C.-, and l., Gao, G.-W. (2019). Global renewable energy development: influencing factors, trend predictions and countermeasures. *Resources Policy* 63:101470. doi: 10.1016/j.resourpol.2019.101470

Zanella, A., Camanho, A. S., and Dias, T. G. (2015). Undesirable outputs and weighting schemes in composite indicators based on data envelopment analysis. *Eur. J. Operational Res.* 245, 517–530. doi: 10.1016/j.ejor.2015.03.036

Zapata, S., Castaneda, M., and Jimenez, M. (2018). Long-term effects of 100% renewable generation on the Colombian power market. *Sustain. Energy Tech. Assess.* 30, 183–191. doi: 10.1016/j.seta.2018.10.008

Zhao, Y., Cao, Y., Shi, X., Li, H., Shi, Q., and Zhang, Z. (2020). How China's electricity generation sector can achieve its carbon intensity reduction targets? *Sci. Total Environ*. 706:135689. doi: 10.1016/j.scitotenv.2019.135689

Zhou, G., Chung, W., and Zhang, Y. (2014). Carbon dioxide emissions and energy efficiency analysis of China's regional thermal electricity generation. *J. Cleaner Produc.* 83, 173–184. doi: 10.1016/j.jclepro.2014.06.047

Zhou, P., Ang, B. W., and Wang, H. (2012). Energy and CO_2 emission performance in electricity generation: a non-radial directional distance function approach. *Eur. J. Operat. Res.* 221, 625–635. doi: 10.1016/j.ejor.2012.04.022

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METHODS
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How Can China Achieve Its Non-fossil Energy Target? An Effective Allocation of China's Renewable Electricity Consumption Obligation

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Promoting the consumption of renewable energy is an important way to optimize power structure, control greenhouse gas emissions and fulfill Intended Nationally Determined Contributions (INDCs) in the Paris Agreement. China's INDCs is to reduce carbon intensity by 60–65% in 2030 (compared to 2005) and promote non-fossil energy consumption proportion in primary energy consumption to 20%. On one hand, China has accomplished its 2020 carbon intensity target in 2017; on the other hand, China also faces certain difficulties achieving the target of 15% non-fossil energy consumption proportion in 2020 and 20% in 2030. Setting appropriate annual overall renewable electricity consumption (REC) and allocating it at sub-national scales can help China reach both carbon intensity and non-fossil energy consumption proportion targets. To this end, we couple the "top-down" and "zero sum gains-data envelopment analysis (ZSG-DEA)" models to form a comprehensive model for the appropriate allocation of REC. First, the "top-down" model was used to calculate the annual overall REC based on the non-fossil energy proportion target. Second, we applied the multi-principle "ZSG-DEA" model to allocate the overall REC effectively among provinces. Based on our analysis, the total REC which can be reached by Chinese government's policy of renewable electricity consumption guarantee mechanism (REC guarantee mechanism) still needs to increase by 15.36 to 20.25% compared with the overall REC calculated by our effectiveness model. In order to achieve non-fossil energy target, 26 provinces need to increase the consumption of renewable electricity compared to their initial shares required by the REC mechanism, most of which are developed coastal areas. Our empirical results provide a scientific basis for the Chinese government to achieve its non-fossil energy targets through the REC guarantee mechanism. We also provide policy makers with ideas for determining the total amount of REC and adjusting the province's consumption responsibility.

Keywords: Intended Nationally Determined Contributions (INDCs), Zero sum gains-data envelopment analysis (ZSG-DEA), renewable electricity consumption, allocation, top-down model

INTRODUCTION

The development and utilization of non-fossil energy has become an important way for countries around the world to ensure energy security, protect the environment, and respond to climate change (National Development and Reform Commission, 2017). China, as the world's largest greenhouse gas emitter (Zhou et al., 2012), announced its INDCs in 2015, which proposed that its carbon dioxide emissions peak around 2030, striving to reach the peak as soon as possible; the intensity of CO_2 emission reduces by 60% to 65% in 2030 compared to the level of 2005; the proportion of non-fossil energy in primary energy consumption increases to about 20%; the 2030's volume of forest reserves increases by 4.5 billion m^3 compared with 2005 (Ye et al., 2017; Mo et al., 2018). In 2017, China's carbon intensity decreased by about 46% compared with 2005. It had exceeded the target of 40–45% reduction in carbon intensity in 2020 three years in advance. However, achieving the target of 15% non-fossil energy in 2020 and 20% in 2030 is still a challenge (Shan et al., 2012; Ye et al., 2017). "The China Energy Development Report 2018" shows that in 2018, non-fossil energy accounts for 14.3% of total primary energy consumption, which means that China needs to increase its non-fossil energy share by at least 0.7% to achieve the 2020 non-fossil energy target. However, as shown in **Figure 1**, the growth of China's non-fossil energy share has significantly slowed down in recent years. Compared with 2016, the non-fossil energy share increased by only 0.3 percentage points in 2017. "China Electric Power Development Report 2017" pointed out that the construction period of nuclear power is extended, and the scale of installed capacity is not expected to meet the planning expectations, which will affect the proportion of non-fossil energy consumption by about 0.2 percentage points.

Non-fossil energy power generation is the main means to increase the proportion of non-fossil energy (Cheng et al., 2010; Shan et al., 2012; Zhou et al., 2012). Studies have shown that the contribution rate of the non-fossil energy power industry to the realization of China's non-fossil energy target is about 80% (Cheng et al., 2010; Ouyang, 2010). Under the influence of the Japanese nuclear leak accident, the development of nuclear power in China has slowed down, which means the realization of non-fossil energy target will mainly depend on the development of renewable energy in the near future (Cheng et al., 2011). Promoting renewable energy generation and consumption requires a balance between top-level design and the underlying foundation. In terms of top-level design, it is necessary to strengthen national legislation, formulate, and improve a series of policy systems related to renewable energy development, such as green power systems, green energy labeling systems, quota systems, renewable energy generation price mechanisms, and preferential investment, and financing mechanism (Yu, 2013; Liu, 2019), etc. In terms of the underlying foundation, it is necessary to coordinate the construction of renewable energy power generation facilities and renewable energy power transmission channels among provinces and regions (Xu et al., 2015; Wang, 2017), and develop renewable energy power generation technologies and large-scale energy storage technologies (Zhao, 2019), etc.

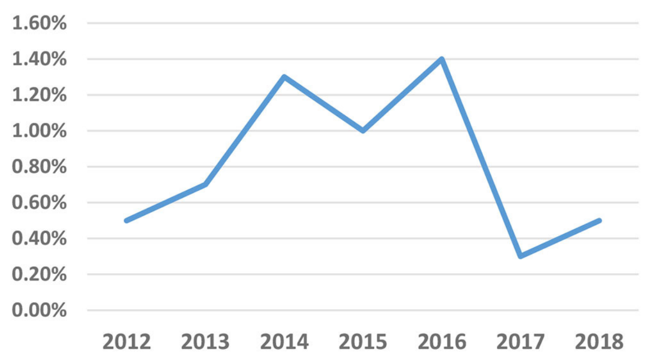

FIGURE 1 | Growth of non-fossil energy proportion in 2012–2018 (China Electric Power Planning and Engineering Institute, 2013, 2014, 2015, 2016, 2017, 2018, 2019).

Since the Renewable Energy Law was officially implemented in 2006, China's renewable energy power industry has developed rapidly. In 2018, the installed capacity of renewable energy was 729 million kilowatts, accounting for 38.4% of the total installed power capacity, and renewable energy power generation reached 1.87 trillion kWh, the share of renewable electricity in total electricity increased from 20% in 2012 to 26.7% in 2018 (Zhao, 2019). However, curtailment of renewable electricity generation -i.e., the abandonment of electricity generation of effective power capacity-is becoming part of the "New Normal"[1] as wind and solar installation expand across the country (Qi et al., 2018). For example, from 2010 to 2018, 219.9 terawatt hours (TWh), or as much as 13 percent of overall wind generation, was abandoned. In order to further promote the consumption of renewable energy, China's National Development and Reform Commission and the National Energy Administration issued the "Notice on Establishing and Perfecting a renewable electricity consumption Guarantee Mechanism"[2] (referred to as the "REC guarantee mechanism") in May 2019, marking China's renewable portfolio standard policy was formally introduced (Li, 2019). The "REC guarantee mechanism" is one of the most important supporting policies in the renewable energy development process following the Renewable Energy Law (Wang, 2019). According to the experience of renewable portfolio standard in other countries, the "REC guarantee mechanism" can effectively achieve China's non-fossil energy target and establish a long-term mechanism to promote the development and consumption of renewable energy (Jin, 2019). As China's main and most restrictive renewable energy policy in the short term, its design plays a decisive role in achieving China's non-fossil energy goals.

The renewable portfolio standard has been widely used in the energy policy design of many countries and regions in the world. Up to now, more than 100 countries or

[1]China Daily, "The 'new normal' means the Chinese economy has entered a new phase that is different from the high-speed growth pattern exhibited in the past. It is a new trend that features more sustainable, mid- to high-speed growth with higher efficiency and lower costs." http://www.chinadaily.com.cn/opinion/2014-10/10/content_18716671.htm.

[2]https://www.ndrc.gov.cn/xxgk/zcfb/tz/201905/t20190515_962446.html

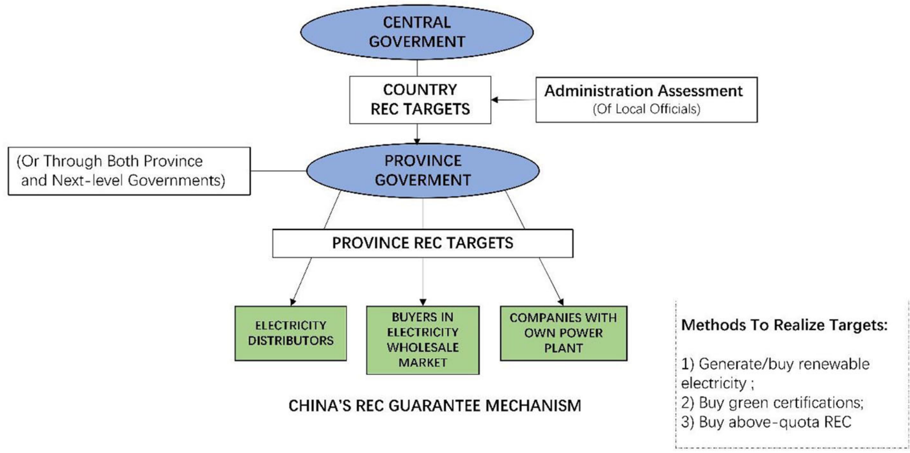

FIGURE 2 | China's REC guarantee mechanism.

federal states (provinces) have implemented different forms of renewable portfolio standard (RPS) (Heeter et al., 2019). The design of the RPS mechanism differs in terms of target, compliance entities, eligible resources, operating mechanisms, and penalties (Ringel, 2006; Li and Chen, 2008; Huang et al., 2013; Linnerud and Simonsen, 2017), etc. The renewable portfolio standard related research is also numerous. The research topics include implementation obstacles, implementation effects, and comparison with clean energy subsidy policies (e.g., Feed-in-Tariff) (Yin and Powers, 2010; Zhao et al., 2014; Chang and Li, 2015; Kwon, 2015; Siddiqui et al., 2016; Wiser et al., 2017; Anguelov and Dooley, 2019). However, it needs to be clear that China's REC guarantee mechanism (**Figure 2**) is different from the RPS in other countries and regions. China's REC guarantee mechanism is that the national-level government places an obligation on provinces to consume a specified fraction of their electricity from renewable electricity, and the provincial government organizes compliance entities to consume renewable electricity in various ways, while other countries' RPS do not set binding goals for the next-level administrative regions (Heeter et al., 2019). The obligatory proportion of renewable electricity (referred to as OP) for each province is the core design of China's REC guarantee mechanism. The OP is set according to renewable power installed capacity, power generation, society's electricity consumption in each province and electricity transmission among provinces, which fully takes the implementation capabilities of provinces into account. However, there are two problems of OP setting: on the one hand, the OP setting is independent of the INDCs, and it remains to be discussed whether the REC guarantee mechanism can achieve the guidance and motivation it should have. On the other hand, only the feasibility of OP is considered, and the principles of equity and efficiency are not taken into account. In view of the above two issues, this paper intends to optimize the allocation of REC in two levels. First, the total amount of REC can effectively achieve the INDCs; second, the inter-provincial allocation takes the principles of equity, efficiency, and achievability into account.

The related research on the allocation of the constant total amount is more common in the allocation of carbon emission allowance, energy consumption, and so on among regions (Vaillancourt and Waaub, 2004; Miketa and Schrattenholzer, 2006; Wei et al., 2012; Wang H. et al., 2016; Wu H. et al., 2016; Wu J. et al., 2016; Wang Y. et al., 2017) and industries (Mu et al., 2016; Yang et al., 2017; Chastas et al., 2018). Common allocation methods include weighting method (Zhao R. et al., 2017; Chastas et al., 2018; Fang et al., 2018), scenario analysis method (Chen and He, 2016; Zhao Q. et al., 2017), and zero sum gains-data envelopment analysis (ZSG-DEA) (Gomes and Lins, 2008; Lin and Ning, 2011; Sun et al., 2012; Pan et al., 2015; Qian et al., 2015; Xiong et al., 2017). Among them, the ZSG-DEA model does not need to set weights manually, which largely avoids subjectivity and arbitrariness (Fang et al., 2019). It also can improve the technical efficiency of the entire system (Charnes et al., 1978; Banker et al., 1984), and overcome the unreasonable assumptions that the input or output variables of the decision making units (DMU) in the traditional DEA method are not restricted and unrelated to each other (Lins et al., 2003). More and more studies use ZSG-DEA as a reasonable and powerful means to ensure the allocation of resources and emissions. The principles that allocation should follow are also the focus of academic debate. Although the allocation methods used in the previous studies are different, most studies consider the principle of equity to be the primary principle of allocation (Fang et al., 2019). The literature quantifies the principle of equity from different perspectives such as egalitarianism (e.g., carbon emissions per capita; Pan and Zheng, 2009; Raupach et al., 2014), ability to pay (e.g., GDP per capita; Pan et al., 2014), and grandfather rights (e.g., historical carbon emissions; Wang L. et al., 2017). The allocation principles of efficiency (Miao et al., 2016; Zhao R. et al., 2017) and feasibility (Wang et al., 2011) are also increasingly taken into consideration. Including multiple distribution principles can consider the differences between provinces comprehensively, and ultimately promote the effective implementation of allocation plans (Fang et al., 2019).

Existing literatures on the overall REC allocation mostly use renewable energy potential and consumption as allocation indicators, and the choice of indicators is relatively similar. Wu Rui and He Yongxiu used a top-down decomposition method to construct a target forecasting model for the total amount of renewable electricity and a quota index decomposition model based on renewable energy potential and consumption (Wu and He, 2014). Liu Zhen et al. introduced the EU renewable energy planning model and target decomposition process in detail, and proposed that when the overall target is decomposed into provinces, the renewable energy development potential, economic development level, and the status of renewable energy development should be considered. According to the actual situation in China (Liu et al., 2009), Liu Zhen proposed a target decomposition model based on renewable energy potential and energy consumption (Liu et al., 2011). Since China's REC guarantee mechanism has just been implemented, related research is still at the level of theoretical conception. Actually, there is not much research on the internal logical relationship between China's INDCs and REC allocation. In order to improve the scientific and political relevance of inter-provincial allocation of REC, this paper designs a comprehensive model for the effective allocation of renewable energy consumption based on the INDCs. The model includes two parts: the "Top-down" overall renewable electricity consumption model and a multi-principle allocation model based on "ZSG-DEA." In general, the contributions of this paper are: (1) we consider the differences between provinces comprehensively, and incorporate multiple principles and corresponding indicators into the allocation model of REC; (2) The comprehensive model for the effective allocation of REC clarifies the internal logical relationship among China's INDCs, the overall REC and allocation method, and provides a new perspective for the future related research; (3) The model can actually calculate the effective overall REC and inter-provincial allocation value, to compare the gap between policies and targets, which can be a reference for determining the renewable electricity consumption allocation in each region in the future.

The rest of the paper is structured as follows. In Section model, the renewable electricity consumption allocation model is designed. Section data and parameter settings describes the model data and parameter settings. Section results shows the results. Conclusions and recommendations are provided in Section conclusions and discussion.

MODEL

In addition to solving the problems of curtailment of wind power, solar power and hydro, the REC guarantee mechanism is also a main method for the Chinese government to increase the proportion of non-fossil energy in the short term. In order to ensure the realization of China's non-fossil energy targets, the allocation of REC needs to be considered from two aspects. The first one is to calculate an effective overall consumption. The primary task is to clarify the quantitative relationship between the overall REC and non-fossil energy targets. This article uses the renewable electricity market 's contribution rate (Formula 9) to the national non-fossil energy target to reflect this quantitative relationship. The higher contribution rate is, the more effective the renewable electricity market is. The second one is to allocate the overall REC effectively among provinces. We define effective distribution under the principles of "efficiency, equity, and feasibility" and apply a multi-principal ZSG-DEA model to adjust the allocation to reach an optimal state. The model design framework is shown in **Figure 3**.

"Top-Down" Overall Renewable Electricity Consumption Model

The design of the "top-down" overall renewable electricity consumption model is as follows:

First, we assume that the three indicators of non-fossil energy consumption at the national level are: Q_n^0 represents the overall non-fossil energy consumption nationwide at the beginning of the planning period, and Q_n^t represents the overall non-fossil energy consumption after t years of implementation of the REC guarantee mechanism. Q_{nBAU}^t indicates the overall non-fossil energy consumption nationwide under the BAU (Business As Usual) scenario at the end of year t. The BAU scenario refers to the non-fossil energy consumption under the assumptions that no new policies will be introduced and non-fossil energy technologies remain at the old-previous, which means the non-fossil energy will maintain the original speed of development and the ratio of non-fossil energy in primary energy consumption will not change. n denotes non-fossil energy, 0 denotes the beginning of planning period and t denotes it is the t year of planning period. As a result, the three indicators of non-fossil energy consumption can be expressed as:

$$Q_n^0 = E^0 R^0 \tag{1}$$

$$Q_n^t = E^t R^t = E^0(1+\eta)R^0(1+\xi) \tag{2}$$

$$Q_{nBAU}^t = E^t R^0 = E^0(1+\eta)R^0 \tag{3}$$

E refers to the national overall primary energy consumption, R represents the ratio of non-fossil energy in primary energy consumption, η denotes the growth rate of national primary energy consumption during the planning period, ξ represents the growth rate of non-fossil energy ratio during the planning period. All these indicators are non-negative. The relationships among these three indicators are shown in **Figure 4**.

Therefore, the difference between non-fossil energy consumption with the application of the REC guarantee mechanism and non-fossil energy consumption under the BAU scenario in the planning period can be expressed as:

$$\begin{aligned} \Delta Q_n &= Q_n^t - Q_{nBAU}^t = E^t R^t - E^t R^0 \\ &= E^0\,(1+\eta)\,R^0\,(1+\xi) - E^0\,(1+\eta)\,R^0 \\ &= E^0 R^0 (1+\eta)\xi = Q_n^0(1+\eta)\xi \end{aligned} \tag{4}$$

Similarly, we assume that the three indicators of renewable electricity consumption at the national level are: Q_m^0 denotes

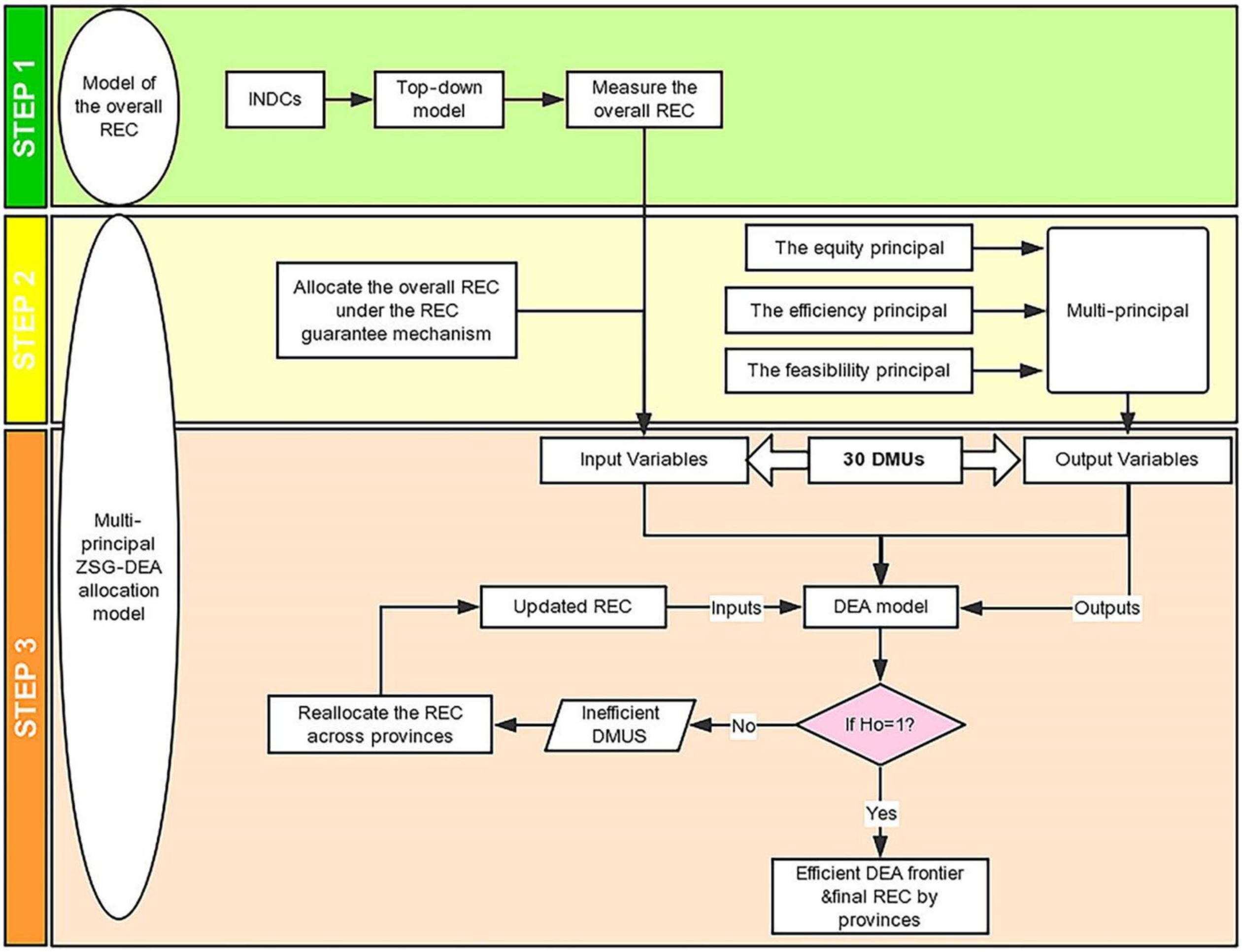

FIGURE 3 | The model design framework.

the overall REC when the planning period starts, Q_m^t denotes the overall REC after t years implementation of the REC guarantee mechanism (the implementation of this mechanism can encourage the innovation of power producers to develop cost-efficient renewable power generation technologies, which may lead to increase in ratio of REC to total electricity consumption) and Q_{mBAU}^t represents the overall REC under the BAU scenario at the end of year t.

Hence, these indicators of renewable electricity consumption can be written as:

$$Q_m^0 = C^0\boldsymbol{\alpha}^0 \tag{5}$$

$$Q_m^t = C^t\boldsymbol{\alpha}^t = C^0(1+\boldsymbol{\beta})\boldsymbol{\alpha}^0(1+\boldsymbol{\gamma}) \tag{6}$$

$$Q_{mBAU}^t = C^t\boldsymbol{\alpha}_{BAU}^t = C^0(1+\boldsymbol{\beta})\boldsymbol{\alpha}^o(1+\boldsymbol{\gamma}_{BAU}) \tag{7}$$

Where m refers to renewable electricity that differs from n, C denotes the national electricity consumption, α represents the proportion of renewable electricity in total electricity consumption, [[Inline Image]]refers to the growth rate of the country's electricity consumption, γ refers to the growth rate of renewable electricity consumption ratio under the implementation of the REC guarantee mechanism and γ_{BAU} represents the growth rate of renewable electricity consumption ratio under the BAU scenario. The relationships among these three indicators can be expressed as in **Figure 5**:

Similarly, the difference between renewable electricity consumption with the application of the REC guarantee mechanism and renewable electricity consumption under the BAU scenario in the planning period can be expressed as:

$$\begin{aligned} \Delta Q_m &= Q_m^t - Q_{mBAU}^t = C^t\alpha^t - C^t\boldsymbol{\alpha}_{BAU}^t \\ &= C^0\,(1+\boldsymbol{\beta})\,\boldsymbol{\alpha}^o\,(1+\boldsymbol{\gamma}) - C^0\,(1+\boldsymbol{\beta})\,\boldsymbol{\alpha}^0\left(1+\boldsymbol{\gamma}_{BAU}\right) \\ &= Q_m^0\,(1+\boldsymbol{\beta})\,(\boldsymbol{\gamma}-\boldsymbol{\gamma}_{BAU}) \end{aligned} \tag{8}$$

We define the contribution rate of the REC guarantee mechanism to national non-fossil energy target as (Unit is unified as standard coal):

$$\boldsymbol{\delta} = \frac{\boldsymbol{\Delta}Q_m}{\boldsymbol{\Delta}Q_n} = \frac{Q_m^0(1+\boldsymbol{\beta})(\boldsymbol{\gamma}-\boldsymbol{\gamma}_{BAU})}{Q_n^0(1+\boldsymbol{\eta})\xi} = m^0\frac{(1+\boldsymbol{\beta})\,(\boldsymbol{\gamma}-\boldsymbol{\gamma}_{BAU})}{(1+\boldsymbol{\eta})\boldsymbol{\xi}} \tag{9}$$

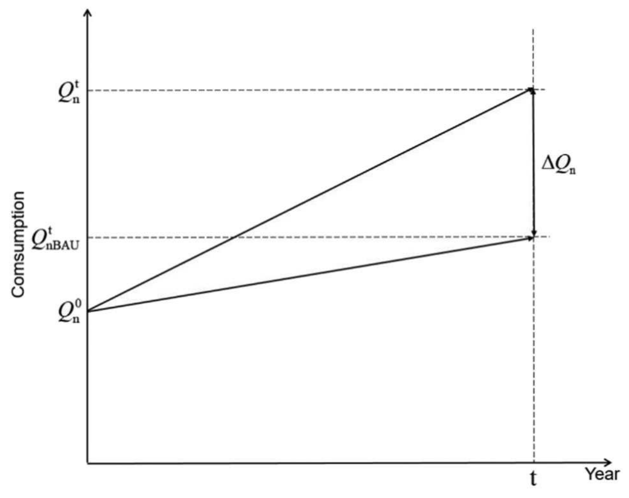

FIGURE 4 | Relationships among Q_n^0, Q_n^t, and Q_{nBAU}^t.

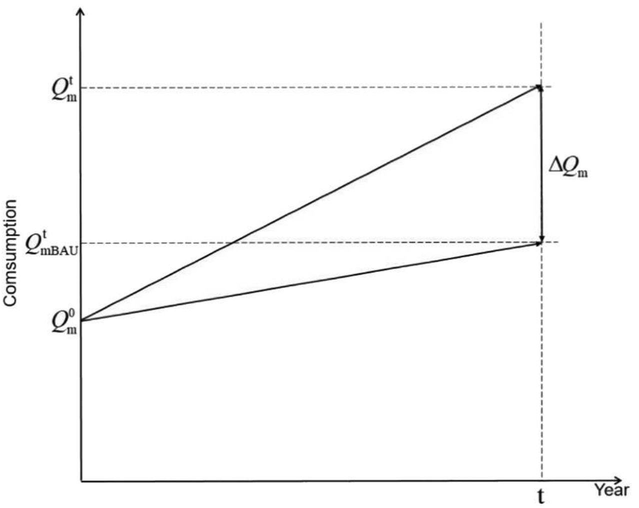

FIGURE 5 | Relationships among Q_m^0, Q_m^t, and Q_{mBAU}^t.

m^0 denotes the proportion of national renewable electricity consumption in the national non-fossil energy consumption at the beginning of the REC guarantee mechanism's implementation.

After rearranging the formula (9), the growth rate of the renewable electricity consumption ratio after the implementation of REC guarantee mechanism can be expressed as:

$$\boldsymbol{\gamma} = \frac{\boldsymbol{\delta}(1+\boldsymbol{\eta})\boldsymbol{\xi}}{m^0(1+\boldsymbol{\beta})} + \boldsymbol{\gamma}_{BAU} \tag{10}$$

Then, the overall REC after t years implementation of the REC guarantee mechanism can be expressed as:

$$Q_m^t = Q_m^0 (1+\boldsymbol{\beta})(1+\boldsymbol{\gamma}_{BAU} + \frac{\boldsymbol{\delta}(1+\boldsymbol{\eta})\boldsymbol{\xi}}{m^0(1+\boldsymbol{\beta})}) \tag{11}$$

ZSG-DEA Model for REC Allocation

Data envelopment analysis (DEA), proposed by Charnes et al. (1978), can estimate production frontier and measure productive efficiency of decision making units (DMUs) through the ratio of multiple inputs to outputs (Banker et al., 1984). Assume that we allocate the overall renewable electricity consumption to N provinces (Each province is a DMU) and each DMU has an input factor $\times$ (Renewable electricity consumption) and P output factors y. Using the classic input-oriented BCC model (Banker et al., 1984), we can evaluate the efficiency of each province, as shown in formula (12):

$$\min h_o \quad s.t. \begin{cases} \sum_{i=1}^{N} \lambda_i y_{ip} \geq y_{op}, \mathrm{p} = 1, 2, 3, \ldots, P \\ \sum_{i=1}^{N} \lambda_i \mathrm{x}_i \leq \mathrm{h_o x}_o \\ \sum_{\mathrm{i}=1}^{N} \lambda_\mathrm{i} = 1, \mathrm{i} = 1, 2, 3, \ldots, \mathrm{N} \\ \lambda_i \geq 0 \end{cases} \tag{12}$$

Where h_o represents the efficiency of province o, λ_i denotes the weight of DMU of i.

Although the classical DEA model can measure DMUs' efficiency, it is unable to bring each DMU together into the DEA frontier. What's more, the classical DEA model holds the hypothesis that all DMUs can freely produce input and output variables without influencing each other, which does not remain true when it comes to REC allocation, as the overall REC is a constant value. The reduced REC of one province must be distributed to other provinces, which means there is a zero-sum game. To deal with the constant constraint of total input or output, Lins et al. (2003) proposed the ZSG-DEA model. The ZSG-DEA model for renewable electricity consumption allocation is formulated as follows:

Provinces with an efficiency score of one are efficient units, while other provinces with a score of <1 are inefficient units. In order to improve the efficiency of inefficient units and make them reach the DEA frontier together, it is necessary to reduce the REC of provinces with an efficiency score of <1. The reduction volume of province o is:

$$d_o = x_o(1-h_{Ro}) \tag{13}$$

Where x_o refers to the REC of province o, h_{Ro} is the efficiency value under the condition that the total amount of input is constant. Lins et al. (2003) proved that there is a linear correlation between h_o and h_{Ro}, which can be expressed as:

$$h_{Ro} = h_o \left[1 + \frac{\sum_{i \in W} x_i (1 - \boldsymbol{\rho}_{io} h_{Ro})}{\sum_{i \notin W} x_i} \right] \tag{14}$$

W is a set of provinces with the DEA efficiency <1. $\rho_{io} = \frac{h_i}{h_o}$ denotes the DEA efficiency ratio between province i and province o.

To make sure the overall REC remains constant, the reduction volume d_o has to be divided proportionally to other provinces. As a result, the REC that province i will get from province o is:

$$r_{io} = \frac{x_i}{\sum_{i\neq o} x_i} d_o = \frac{x_i}{\sum_{i\neq o} x_i} x_o (1-h_{Ro}) \tag{15}$$

As all provinces are adjusting REC simultaneously, the REC of province i will finally be adjusted to:

$$x'_i = \sum_{i\neq o} r_{io} - d_i = \sum_{i\neq o}\left[\frac{x_i}{\sum_{i\neq o} x_i} x_o (1-h_{Ro})\right] - x_i\left(1-h_{Ri}\right), \quad i = 1,2,3,\ldots,N \tag{16}$$

Some provinces can't reach the DEA frontier after first reallocation, which means we need to reallocate REC again. After several round of reallocation, the efficiency of all provinces will finally reach one. The input oriented ZSG-DEA model is formulated as follows:

$$\min \mathrm{h_{Ro}}$$
$$s.t.\begin{cases} \sum\limits_{i=1}^{N} \lambda_i y_{ij} \geq y_{oj}, j = 1, 2, 3, \ldots, P \\ \sum\limits_{i=1}^{N} \lambda_i \mathrm{x}_i \left[1 + \frac{\mathrm{x_o}(1-h_{Ro})}{\sum\limits_{i\neq o} \mathrm{x_i}}\right] \leq \mathrm{h_{Ro}} \mathrm{x}_o \\ \sum\limits_{i=1}^{N} \lambda_\mathrm{i} = 1, \mathrm{i} = 1, 2, 3, \ldots, \mathrm{N} \\ \lambda_i \geq 0 \end{cases} \tag{17}$$

DATA AND PARAMETER SETTINGS

Parameters in the Overall REC Model

According to Formula (11), in order to calculate the overall REC, we need to know the following five parameters:

(1) ξ:the growth rate of non-fossil energy consumption proportion;
(2) m^0: the proportion of renewable electricity consumption in non-fossil energy consumption;
(3) η:the growth rate of national energy consumption;
(4) β:the growth rate of national electricity consumption;
(5) γ_{BAU}: the growth rate of renewable electricity consumption proportion under the BAU scenario;
(6) δ: the contribution rate of the REC guarantee mechanism to 2020 non-fossil energy target.

First, according to three official documents published by the Chinese government (the "13th 5-Years Plan" for Renewable Energy Development, the "13th 5-Years Plan" for Energy Development, and the "Strengthening Action on Climate Change-China's Intended Nationally Determined Contributions"), the non-fossil energy target can be expressed as "Non-fossil energy accounts for 15 and 20% of primary energy consumption in 2020 and 2030 respectively". We set the end of 2018 as the beginning of the planning period, and the end of 2020 as the end of the planning period. This is because the REC guarantee system designed the obligatory renewable electricity proportion of the provinces by 2020, and has not yet specified each province's OP in 2030. The end of 2020 is selected as the end of the planning period of the model in this paper, which can better compare our results with the design of the REC guarantee mechanism. In 2018, China's non-fossil energy proportion in primary energy consumption was 14.3%, which means, in order to achieve the 2020 target, non-fossil energy proportion has to reach an annual growth rate of 2.42% at least. According to the calculation formula of $(1 + 2.42\%)^2$-1, resulting in a total growth rate of 4.90% (ξ) in non-fossil energy proportion within the planning period of 2018 to 2020.

Second, China consumed 1815.90 TWh (Equivalent to 223.17 million tons of standard coal)[3] renewable electricity in 2018, while non-fossil energy consumption was 663.52 million tons of standard coal (Mtce) (China Electric Power Planning and Engineering Institute, 2019). Thus, m^0 is 33.63% at the early stage of the planning period.

In this article, we use the elastic coefficient method (Xue and Zhang, 2013) to predict the national energy consumption (Wu and Huang, 2016) and national electricity consumption (Yang and Wang, 2018) in 2020 under three scenarios, and then derive their corresponding growth rates. Under the planned GDP growth rate of the 13th 5-Years Plan, the growth rate of national energy consumption is 4.8% and that of national electricity consumption is 10.59%. The average GDP growth rate in 2015–2018 is 6.7%. Considering that the larger the national economic base, the more difficult it is to grow. During the planning period of 2018–2020, we set the GDP growth rate in the pessimistic scenario to 6.0%. The GDP growth rate under the optimistic scenario is 6.7%. Under the pessimistic scenario, the growth rate of national energy consumption is 4.16% and that of national electricity consumption is 5.06%. Under the optimistic scenario, the growth rate of national energy consumption is 9.10% and that of national electricity consumption is 11.19%. The parameters of η and β are shown in **Table 1**.

Since only 4 years of renewable electricity consumption proportion data are available (2015–2018) (NEA, 2016, 2017, 2018, 2019), a gray prediction model GM(1,1) (Deng, 1982; Hamzacebi and Es, 2014) suitable for small data volume is used to predict the 2020 renewable electricity consumption proportion. The calculation result is 27.71%. According to the National Renewable Energy Development Report, the proportion of renewable energy electricity consumption in 2018 is 26.50%, and the growth rate of renewable electricity consumption ratio in 2018–2020 under the BAU scenario is calculated as 4.57% (γ_{BAU}).

At last, we set three contribution rates δ based on what may happen in the future. First of all, it is assumed that no new policies to promote the consumption of non-fossil energy will be introduced in the future, and the old policies will not promote the consumption of non-fossil energy further more. The growth of non-fossil energy consumption is entirely stimulated by the REC guarantee mechanism, which means the contribution rate of the REC guarantee mechanism to

[3] According to the Energy Conversion Standard Coal Reference Coefficient Table of the China Energy Statistics Yearbook, the conversion standard power coefficient of electricity is 0.1229 kg standard coal / kWh.

TABLE 1 | The growth rate of national energy consumption and electricity consumption under three scenarios.

	2017	2018	Elasticity coefficient (%)	Scenario hypothesis	The growth rate of GDP	2018E	2020E	Growth rate during the planning period
National energy consumption (Mtce)	4485.29	4640.00	0.42	Pessimistic hypothesis	6.0%	4598.31	4876.80	4.16% (η_1)
				13th 5-years plan	6.5%	4607.74	4862.76	4.80% (η_2)
				Optimistic scenario	6.7%	4611.51	4874.69	5.06% (η_3)
National electricity consumption (TWh)	6363.60	6900.20	0.96	Pessimistic hypothesis	6.0%	6730.01	7527.78	9.10% (β_1)
				13th 5-years plan	6.5%	6760.70	7630.75	10.59% (β_2)
				Optimistic scenario	6.7%	6772.90	7672.19	11.19% (β_3)

The data comes from the China Statistical Yearbook.

TABLE 2 | Parameters setting of the overall REC model.

Scenario hypothesis			ξ	m^0	η	β	γ_{BAU}
Scenario number	Economic growth hypothesis	Contribution rate hypothesis (δ)					
1	6.0%	80%	4.90%	33.63%	4.16%	9.10%	4.57%
2		90%	4.90%	33.63%	4.16%	9.10%	4.57%
3		100%	4.90%	33.63%	4.16%	9.10%	4.57%
4	6.5%	80%	4.90%	33.63%	4.80%	10.59%	4.57%
5		90%	4.90%	33.63%	4.80%	10.59%	4.57%
6		100%	4.90%	33.63%	4.80%	10.59%	4.57%
7	6.7%	80%	4.90%	33.63%	5.06%	11.19%	4.57%
8		90%	4.90%	33.63%	5.06%	11.19%	4.57%
9		100%	4.90%	33.63%	5.06%	11.19%	4.57%

the realization of the non-fossil energy goal is 100% in the planning period; Second, assuming that no new policies to promote the consumption of non-fossil energy will come out in the future, and because of the lag in the role of policies, the old policies continue to promote the increase of the non-fossil energy proportion, but the REC guarantee mechanism still plays a major role due to its strong binding force. We assume that contribution rate of the REC guarantee mechanism to the achievement of the non-fossil energy target is 90% under the second situation; Finally, assuming that the old policies still play a role and new policies will come out in the future, however, it is clear that there will be no policies that are more restrictive than the REC guarantee mechanism. We assume that the REC guarantee mechanism plays a major role and contributes 80% to the achievement of non-fossil energy goal under the third situation.

As analyzed above, here we set the parameters as **Table 2**.

Indicators and Data of the ZSG-DEA Model

Input Variable of the ZSG-DEA Model

In order to better compare the results of this article with the design of the REC guarantee mechanism, we use the ratio (φ) of the achievable consumption of each province under the REC guarantee mechanism requirements divided by the sum of provinces' achievable consumption as the basis for the initial allocation. We can get the province *i's* achievable consumption (x_i^0) through multiplying the OP of province i required by the REC guarantee mechanism and the predicted electricity consumption of province i in 2020. The initial allocation coefficient is $\varphi_i = \frac{x_i^0}{\sum_i^N x_i^0}$. Considering that the development of nuclear energy and biomass energy has a certain contribution to the non-fossil energy target, here we demonstrate the allocation under the scenario of economic growth of 6.5% and contribution rate of 90% without loss of generality. The initial allocation of province i is $x_i = Q_m^t \varphi_i$, which is the input variable of the ZSG-DEA model.

Output Variables of the ZSG-DEA Model

In this paper, we consider the principle of equity, efficiency and feasibility when we determine allocation indicators. Historical renewable electricity consumption, total electricity consumption, and energy consumption gap are selected as output variables for REC allocation. They are expected to reflect the principle of feasibility, equity and efficiency respectively. An analysis of the reasons for choosing output variables is as follows:

When decomposing the overall REC, comprehensive consideration should be given to the renewable energy resource endowment status, renewable energy development potential, economic development status, and grid development status of each province (Liu et al., 2009; Wu and He, 2014). The historical renewable electricity consumption in the province can reflect the renewable power resource endowment and grid development in the region to a certain extent (Lv et al., 2019). Based on data availability, we choose average historical renewable electricity consumption of each province as the embodiment of the regional renewable power resources endowment status. Historical renewable electricity consumption data comes from annual "National Renewable Energy Development Monitoring Evaluation Reports."

From the perspective of equity, the higher the total electricity consumption is in a province, the more renewable electricity should be consumed. And the total electricity consumption is linked to GDP to a certain extent, it can also reflect the economic development of the region (Yang and Wang, 2018). Therefore, we chose the total electricity consumption as an indicator of

TABLE 3 | Each province's energy consumption constraints and energy consumption gap (Mtce).

Province	Total energy consumption in 2015	Incremental energy consumption control target by the 13th 5-years plan	Total energy consumption constraint in 2020	Predicted total energy consumption in 2020	Energy consumption gap
Beijing	685.30	80.00	765.30	743.91	21.39
Tianjin	826.00	104.00	930.00	868.45	61.55
Hebei	2939.50	339.00	3278.50	3099.82	178.68
Shanxi	1938.40	301.00	2239.40	2013.90	225.50
Inner Mongolia	1892.70	357.00	2249.70	2162.03	87.67
Liaoning	2166.70	355.00	2521.70	2168.55	353.15
Jilin	814.20	136.00	950.20	739.31	210.89
Heilongjiang	1212.60	188.00	1400.60	1310.78	89.82
Shanghai	1138.70	97.00	1235.70	1227.64	8.06
Jiangsu	3023.50	348.00	3371.50	3391.34	−19.84
Zhejiang	1961.00	238.00	2199.00	2266.69	−67.69
Anhui	1233.20	187.00	1420.20	1449.22	−29.02
Fujian	1218.00	232.00	1450.00	1477.25	−27.25
Jiangxi	844.00	151.00	995.00	1050.33	−55.33
Shandong	3794.50	407.00	4201.50	3912.90	288.60
Henan	2316.10	354.00	2670.10	2511.74	158.36
Hubei	1640.40	250.00	1890.40	1805.55	84.85
Hunan	1546.90	238.00	1784.90	1704.96	79.94
Guangdong	3014.50	365.00	3379.50	3499.71	−120.21
Guangxi	976.10	184.00	1160.10	1181.02	−20.92
Hainan	193.80	66.00	259.80	246.68	13.12
Chongqing	893.40	166.00	1059.40	1183.11	−123.71
Sichuan	1988.80	302.00	2290.80	2187.27	103.53
Guizhou	994.80	185.00	1179.80	1151.64	28.16
Yunnan	1035.70	194.00	1229.70	1155.78	73.92
Shaanxi	1171.60	217.00	1388.60	1458.31	−69.71
Gansu	752.30	143.00	895.30	793.73	101.57
Qinghai	413.40	112.00	525.40	478.16	47.25
Ningxia	540.50	150.00	690.50	718.67	−28.17
Xinjiang	1565.10	354.00	1919.10	2011.21	−92.11

The data comes from the "13th 5-years plan for comprehensive energy conservation and emission reduction" (lack of data for Tibet).

economic development. The total electricity consumption in 2020 is predicted by the electricity elasticity coefficient method (Xue and Zhang, 2013) and the data comes from each province's statistical yearbooks.

In addition, we also select energy consumption gap as an indicator. The energy consumption gap is the difference between the energy constraint that required by the "13th 5-Years Plan" and the predicted energy consumption in 2020. The smaller the province's energy consumption gap is, the more difficulty the province has in achieving the energy control target. The reason for choosing energy consumption gap is that currently more than 10 provinces across the country have proposed that the energy consumption target of the "13th 5-Years Plan" cannot be achieved[4]. According to China's "13th 5-Years Plan for Energy Conservation and Emission Reduction," renewable energy is not included in the scope of energy consumption control[5]. Provinces that are not expected to meet their energy control goals can meet the energy needs of economic development by using more renewable energy. We hold the view that allocating more REC quota to areas with less energy consumption gap can loosen energy constraints on the economic development of provinces, which means each unit of renewable electricity produces more economic output. Based on the total energy consumption of each province from 2010 to 2017 (data from each province's statistical yearbooks), we use the GM(1,1) model (Deng, 1982; Hamzacebi and Es, 2014) to predict the total energy consumption of each province in 2020, and compare the predicted value with the energy consumption constraints of the "13th 5-Years Plan," the differences are energy consumption gap for provinces (**Table 3**). The DEA model requires inputs

[4]http://www.qstheory.cn/dukan/qs/2019-12/15/c_1125346157.htm

[5]http://www.gov.cn/zhengce/content/2017-01/05/content_5156789.htm

TABLE 4 | Input and output indicators for each province in 2020.

Province	Initial allocation of each province (TWh)	Historical REC (TWh)	Total electricity consumption (TWh)	Energy consumption gap (Mtce)
Beijing	21.33	11.72	120.24	331.76
Tianjin	16.08	8.13	90.66	291.60
Hebei	73.09	36.11	412.05	174.47
Shanxi	42.46	25.13	217.61	127.65
Inner Mongolia	79.95	49.01	365.47	265.47
Liaoning	35.33	26.06	239.00	0.01
Jilin	21.62	14.64	83.12	142.26
Heilongjiang	30.60	15.92	99.53	263.33
Shanghai	65.67	47.88	168.29	345.09
Jiangsu	116.55	76.42	704.04	372.98
Zhejiang	104.94	76.65	479.71	420.84
Anhui	40.18	24.23	234.35	382.17
Fujian	59.52	53.97	258.14	380.39
Jiangxi	55.66	31.07	162.33	408.47
Shandong	74.77	39.49	632.28	64.54
Henan	69.12	40.28	365.33	194.79
Hubei	111.21	72.12	235.11	268.30
Hunan	113.86	73.70	196.52	273.21
Guangdong	238.93	191.79	684.95	473.35
Guangxi	98.92	74.38	167.31	374.07
Hainan	5.11	3.66	37.55	340.02
Chongqing	61.62	46.97	115.80	476.86
Sichuan	245.65	179.38	251.19	249.62
Guizhou	64.44	49.81	173.01	324.98
Yunnan	172.22	127.42	182.05	279.22
Shaanxi	46.61	21.55	183.32	422.85
Gansu	78.31	52.34	140.90	251.58
Qinghai	73.43	47.06	88.71	305.90
Ningxia	30.85	20.43	118.59	381.32
Xinjiang	101.53	46.66	381.61	445.26

and outputs indicators to be positive, but there are negative values in some provinces' energy consumption gap. Based on the consideration that allocating more REC quota to areas with less energy consumption gap, we use the maximum value of the energy consumption gap minus the value of each province's energy consumption gap.

Table 4 displays the input and output variables for each province.

RESULTS

The Overall REC

According to the "National Renewable Energy Power Development Monitoring and Evaluation Report 2018," the total amount of renewable electricity consumption in China (excluding Tibet) in 2018 (Q_m^0) was 1815.90 TWh. The achievable overall REC under the constraint of REC guarantee mechanism is $Q_p^t = \sum_i^N x_i^0$ (1986.97 TWh). Using Q_m^0 and parameters in **Table 2**, we can calculate overall RECs (Q_m^t) that can achieve the non-fossil energy target under nine scenarios base on Formula (11). We can know whether the current REC mechanism can achieve the non-fossil energy target by simply comparing Q_m^t and Q_p^t.

China needs to consume 2292.16 TWh to 2389.34 TWh renewable electricity to accomplish the 2020 non-fossil energy target (**Figure 6**). The expected REC under the constraint of the REC guarantee mechanism still needs to increase by 15.36–20.25% to achieve the non-fossil energy target.

The Allocation of Overall REC

Figure 7 shows the evolution of the DEA efficiency value of the initial allocation and reallocation. It needs to be clear that in the allocation of REC, provinces with high efficiency values tend to have insufficient obligatory REC and need to increase their REC quota. Among the 30 provinces, Fujian, Shandong, and Hainan reach the DEA boundary in the beginning with their initial efficiency values equal to one. There are 14 provinces, whose initial DEA efficiency are higher than the average initial efficiency (0.794). Xinjiang 's DEA initial efficiency is the lowest, at 0.590. After the first reallocation, the average DEA efficiency increase to 0.960. The most effective provinces are still Fujian, Shandong, and Hainan. The DEA efficiency value in Xinjiang increase to 0.913 and the lowest value (Shaanxi) is 0.905. After the third reallocation, the overall DEA efficiency value reach one, and six provinces (Shanxi, Inner Mongolia, Heilongjiang, Guizhou, Shaanxi, and Gansu) are weakly effective with an efficiency value of 0.999, while other 24 provinces reach the DEA frontier. After the fifth reallocation, all provinces achieve the maximum DEA efficiency of one.

Figure 8 compares the REC adjusted by the ZSG-DEA model of each province (x_i') with the REC calculated based on the OP required by the REC guarantee mechanism (x_i^0).

It can be seen that in order to achieve the non-fossil energy target more efficiently, 26 provinces need to increase the consumption of renewable electricity, and four provinces can appropriately reduce the REC quota. Guangdong Province's REC increase the most, which is 63.09 TWh, and it also has the biggest amount of the REC after reallocation, at 265.15 TWh. Xinjiang province experiences the biggest reduction of 10.77 TWh. With the lowest reallocated REC (6.41 TWh), Hainan province has the highest increase rate of 48.33%. The five provinces with the highest increase rate are Hainan (48.33%), Fujian (48.33%), Shandong (48.33%), Liaoning (46.13%), and Guangdong (31.22%). The provinces that are reduced allocation are Xinjiang (−12.55%), Shaanxi (−10.84%), Heilongjiang (−8.92%), and Jiangxi (−6.70%).

By looking deeper at the direction of electricity flow (**Figure 9**), one may notice that most provinces and autonomous regions that increase the REC significantly are in developed coastal areas and belong to the receiving end of power transmission. In contrast, most of the provinces and regions whose consumption is reduced or increased slightly belong to

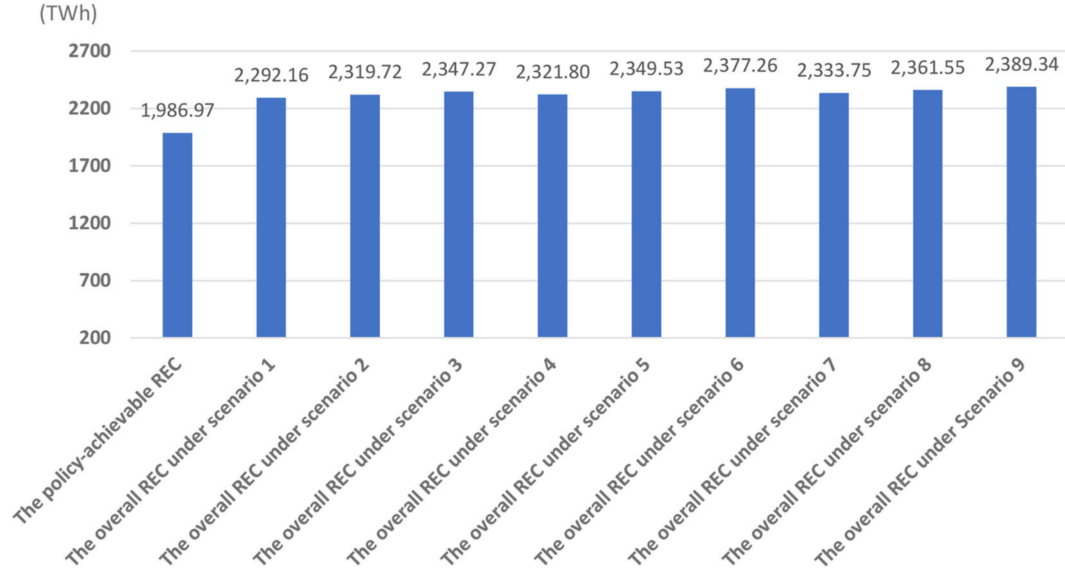

FIGURE 6 | Comparison of Q_m^t and Q_p^t.

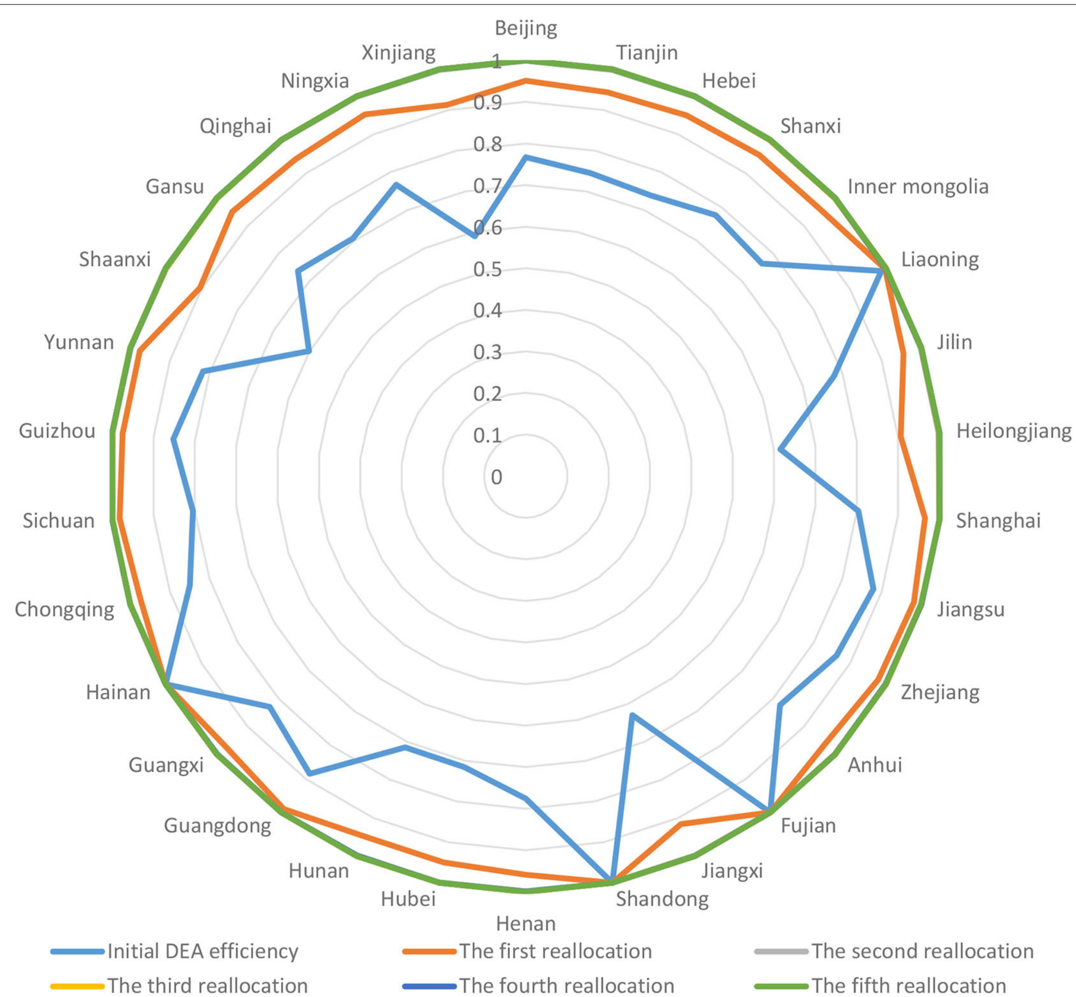

FIGURE 7 | The evolution of the DEA efficiency value.

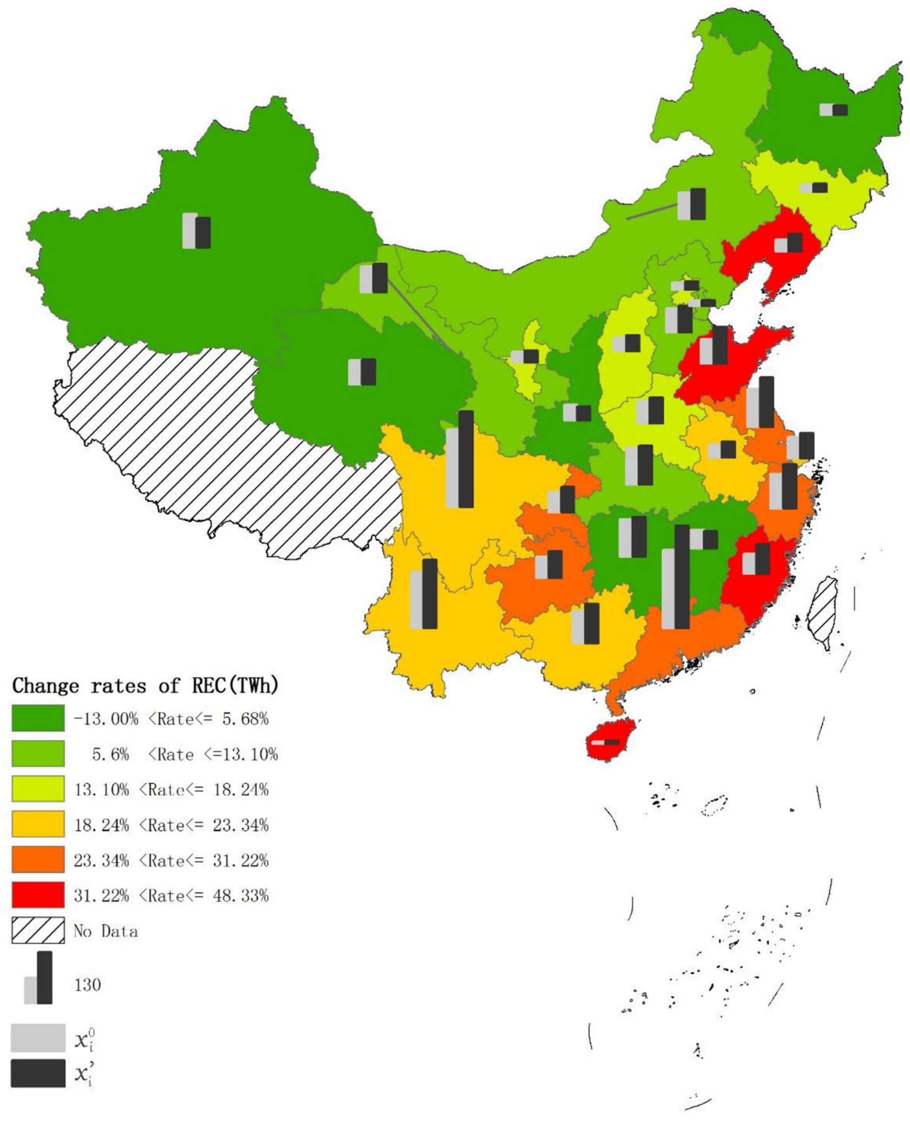

FIGURE 8 | Geographical distribution of provincial REC through reallocation. All the provinces are marked on the basis of the increase rate from x_i^0 to x_i'. Tibet, Taiwan, Hong Kong, and Macau are not displayed due to the lack of data.

the supply end of power transmission. This adjustment reflects the principle of equity, also known as "who uses electricity, who bears responsibility." Slight changes occur mostly in northern China, and the change rate of REC quotas in the central region is smaller than that of the national level (18.24%). Although Hubei, Hunan, and Jiangxi are power receiving areas, their OP settings in the REC guarantee mechanism are inherently high, so the rate of increase is relatively low.

Table 5 shows the comparison between the OP in the REC guarantee mechanism and the adjusted proportion values. It can be seen that, in order to meet the non-fossil energy target, under the principles of equity, efficiency, and achievability, 26 provinces need to increase the proportion of REC by an average of 5.46%. Ten provinces' increase rates are higher than the average increase rate. Sichuan needs to increase the proportion value the most (18.68%)[6], while Xinjiang has the highest proportion to reduce (−6.32%)[7]. Although Guangdong needs to increase the biggest amount of the REC, the increase in

[6]The predicted total electricity consumption in Yunnan province is relatively small in 2020. Based on equation *Proportion* = REC/total electricity consumption, the adjustment of consumption results in relatively big changes in proportion value.

[7]Part of the reason why Xinjiang province has big reduction in consumption is that its historical elastic coefficient is 2.07, resulting in higher volume of total electricity consumption and original allocation (93.35 TWh). Xinjiang's renewable electricity consumption in 2018 is just 5.73 TWh. The proportion value of Xinjiang is reduced by 30.41%, however, the consumption volume is increased by 20.4% to 6.90 TWh compared to 2018, which is rather more reasonable. According to historical data, the electricity consumption elasticity value in Xinjiang has been gradually reducing, with the last 3-years average of 1.34, so we believe the actual total electricity consumption of Xinjiang in 2020 could be much lower than predicted.

FIGURE 9 | National power transmission.

the proportion value is just 9.21% as it has the second highest total electricity consumption.

CONCLUSIONS AND DISCUSSION

This article takes the non-fossil energy targets of 2020 and 2030 in China's INDCs as the starting point to discusses the issue of the REC allocation. We formed an analysis framework for renewable electricity consumption allocation, which can provide some references for policy makers. In this framework, the "contribution rate" reflects the quantitative relationship between the renewable electricity consumption and the non-fossil energy target. The higher contribution rate is, the more effective the allocation is. We calculated the overall REC which can realize the non-fossil energy target under nine scenarios. China needs to consume 2292.16–2389.34 TWh renewable electricity to accomplish the 2020 non-fossil energy target, while the REC guarantee mechanism can only reach 1986.97 TWh. In other words, current policy needs to increase the REC by 15.35–20.25% to achieve the non-fossil energy target. Allocation of the overall REC is another important problem. We adjusted the original allocation requested by current policy under the principles of equity, efficiency, and feasibility using a ZSG-DEA model to make sure all provinces reached the DEA frontier. Our empirical results show that to realize the non-fossil energy target under the scenario of economic growth of 6.5% and contribution rate of 90%, 26 provinces need to increase renewable electricity consumption. The general trend of adjusting is that coastal, developed provinces located in receiving end of power transmission should take more responsibility for renewable electricity consumption while policy makers could reduce the obligatory REC quota of some central provinces and provinces at supplying end of power transmission relatively.

The results of this paper not only assist policy makers to scientifically determine the total amount of REC and adjust the REC allocation plans among provinces, but also provide

TABLE 5 | The OP values in the REC guarantee mechanism and adjusted proportion values of each province.

Province	The OP values in the REC guarantee mechanism	Adjusted proportion value	Gap	Province	The OP values in the REC guarantee mechanism	Adjusted proportion value	Gap
Beijing	15.00%	17.06%	2.06%	Henan	16.00%	18.39%	2.39%
Tianjin	15.00%	16.56%	1.56%	Hubei	40.00%	42.39%	2.39%
Hebei	15.00%	16.43%	1.43%	Hunan	51.50%	51.79%	0.29%
Shanxi	16.50%	18.95%	2.45%	Guangdong	29.50%	38.71%	9.21%
Inner Mongolia	18.50%	20.92%	2.42%	Guangxi	50.00%	61.39%	11.39%
Liaoning	12.50%	18.27%	5.77%	Hainan	11.50%	17.06%	5.56%
Jilin	22.00%	25.41%	3.41%	Chongqing	45.00%	56.65%	11.65%
Heilongjiang	26.00%	23.68%	−2.32%	Sichuan	80.00%	98.68%	18.68%
Shanghai	33.00%	39.39%	6.39%	Guizhou	31.50%	39.80%	8.30%
Jiangsu	15.00%	18.22%	3.22%	Yunnan	80.00%	96.63%	16.63%
Zhejiang	19.00%	23.65%	4.65%	Shaanxi	21.50%	19.17%	−2.33%
Anhui	14.50%	17.68%	3.18%	Gansu	47.00%	51.32%	4.32%
Fujian	22.00%	28.92%	6.92%	Qinghai	70.00%	73.35%	3.35%
Jiangxi	29.00%	27.06%	−1.94%	Ningxia	25.00%	25.02%	0.02%
Shandong	10.50%	14.83%	4.33%	Xinjiang	26.00%	19.68%	−6.32%

certain insights for future power grid pattern planning. To meet the needs of renewable energy consumption and large-scale transmission of power across regions, it is urgent to scientifically plan the layout of the power grid, strengthen the construction of inter-regional and inter-provincial interconnected power grids. With adjustments of each province's obligatory REC in this paper, the key construction areas of the interconnected power grid can be determined.

To achieve the non-fossil energy targets, we hold the view that the primary problem that needs to be handled with is the consumption of renewable electricity. China has not yet established an national electricity market and there are serious inter-provincial barriers. Based on the interests of GDP and local employment, the province government prefers to use local thermal power rather than accept renewable electricity from other provinces. However, in the wet season, some regions' abundant renewable energy cannot be fully absorbed by the local market alone. There are still many surpluses that can and need to be consumed in a larger market. Many provinces with large scale installed capacity of renewable energy can consume a large proportion of renewable energy for a long time, indicating that technically renewable electricity can meet the daily electricity demand. For example, more than 80% of Yunnan's electricity comes from hydropower (NEA, 2016), Qinghai provinces whose area equivalents to two Japan has been able to use only renewable energy to supply electricity for 15 consecutive days (Xia, 2019). Therefore, if China can accelerate the construction and improvement of the unified national electricity market where provinces can freely allocate electricity, and with the development, and improvement of smart grids, and energy storage technologies, then consumption market of renewable electricity will be expanded. In conclusion, we reckon that China will eventually be able to achieve its non-fossil energy targets of 2020 and 2030.

We have to admit that there are certain limitations of this paper: (1) The assumption of constant growth rate we made while setting parameters for the model and predicting output variables is relatively strong. However, since this article discusses the short-term REC allocation planning, the growth rates of parameters and variables are more certain in the near future, so constant growth rate has little effect on the model's results. (2) The DEA method or ZSG-DEA model itself has some shortcomings. The DEA method emphasizes that the decision-making units are comparable, but the situation in different regions is often different, and this method may overemphasize the technical efficiency and ignore other principles. There are papers are discussing the question of DMU heterogeneity (Belotti and Ilardi, 2018), and we are also working toward this question, but we do not discuss it in this article. (3) This method is only suitable for short-term studies with relatively definite future conditions, not for long-term dynamic growth scenarios.

DATA AVAILABILITY STATEMENT

The datasets generated for this study are available on request to the corresponding author.

AUTHOR CONTRIBUTIONS

JZ was responsible for the specific work of this paper optimized the structure and tone of this article. RG developed the model, carried out some of the calculation work, and wrote the manuscript. NX and CX contributed to the manuscript.

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REFERENCES

Anguelov, N., and Dooley, W. F. (2019). Renewable portfolio standards and policy stringency: an assessment of implementation and outcomes. *Rev. Policy Res.* 36, 195–216. doi: 10.1111/ropr.12322

Banker, R. D., Charnes, A., and Cooper, W. W. (1984). Some models for estimating technical and scale inefficiencies in data envelopment analysis. *Manag. Sci.* 30, 1078–92. doi: 10.1287/mnsc.30.9.1078

Belotti, F., and Ilardi, G. (2018). Consistent inference in fixed-effects stochastic frontier models. *J. Econometr.* 202:5. doi: 10.1016/j.jeconom.2017.09.005

Chang, Y., and Li, Y. (2015). Renewable energy and policy options in an integrated ASEAN electricity market: quantitative assessments and policy implications. *Energy Policy* 85, 39–49. doi: 10.1016/j.enpol.2015.05.011

Charnes, A., Cooper, W. W., and Rhodes, E. (1978). Measuring the efficiency of decision making units. *Eur. J. Operat. Res.* 2, 429–44. doi: 10.1016/0377-2217(78)90138-8

Chastas, P., Theodosiou, T., Kontoleon, K. J., and Bikas, D. (2018). Normalising and assessing carbon emissions in the building sector: a review on the embodied CO2O emissions of residential buildings. *Build. Environ.* 130, 212–26. doi: 10.1016/j.buildenv.2017.12.032

Chen, W., and He, Q. (2016). Intersectoral burden sharing of CO 2 mitigation in China in 2020. *Mitigat. Adapt. Strategies Glob. Change* 21, 1–14. doi: 10.1007/s1027-014-9566-3

Cheng, L., Bai, J., and Jia, D. (2011). Influence of nuclear power on the 15% non-fossil energy target for 2020 and power system. *Energy Technol. Econ.* 23, 10–3. doi: 10.3969/j.issn.1674-8441.2011.07.003

Cheng, L., Jiang, L., Bai, J., Jia, D., and Xin, S. (2010). Research on developing route to achieve the 15% non-fossil energy target by 2020 in China. *China Energy* 32:11-14+26.

China Electric Power Planning and Engineering Institute (2013). *China Energy Development Report 2012*. Beijing: China Electric Power Press.

China Electric Power Planning and Engineering Institute (2014). *China Energy Development Report 2013*. Beijing: China Electric Power Press.

China Electric Power Planning and Engineering Institute (2015). *China Energy Development Report 2014*. Beijing: China Electric Power Press.

China Electric Power Planning and Engineering Institute (2016). *China Energy Development Report 2015*. Beijing: China Electric Power Press.

China Electric Power Planning and Engineering Institute (2017). *China Energy Development Report 2016*. Beijing: China Electric Power Press.

China Electric Power Planning and Engineering Institute (2018). *China Energy Development Report 2017*. Beijing: China Electric Power Press.

China Electric Power Planning and Engineering Institute (2019). *China Energy Development Report 2018*. Beijing: China Electric Power Press.

Deng, J. (1982). Control problems of grey systems. *Syst. Control Lett.* 1, 288–94. doi: 10.1016/S0S167-6911(82)80025-X

Fang, K., Zhang, Q., Long, Y., Yoshida, Y., Sun, L., Zhang, H., et al. (2019). How can China achieve its intended nationally determined contributions by 2030? A multi-criteria allocation of China's carbon emission allowance. *Appl. Energy* 241, 380–9. doi: 10.1016/j.apenergy.2019.03.055

Fang, K., Zhang, Q., Ye, R., and Zhou, Y. (2018). Allocating China's carbon emission allowance to the provincial quotas in the context of the Paris Agreement. *Acta Scientiae Circumstantiae* 38, 1224–34. doi: 10.13671/j.hjkxxb.2017.0402

Gomes, E. G., and Lins, M. P. (2008). Modelling undesirable outputs with zero sum gains data envelopment analysis models. *J. Operat. Res. Society* 59, 616–23. doi: 10.1057/palgrave.jors.2602384

Hamzacebi, C., and Es, H. A. (2014). Forecasting the annual electricity consumption of Turkey using an optimized grey model. *Energy* 70, 165–71. doi: 10.1016/j.energy.2014.03.105

Heeter, J., Speer, B., and Glick, M. B. (2019). *International Best Practices for Renewable Portfolio Standard (RPS) Policies*. Golden, CO: National Renewable Energy Laboratory. Available online at: https://www.nrel.gov/docs/fy19osti72798.pdf

Huang, B., Li, Q., Xie, G., and Wang, Q. (2013). Renewable portfolio standard in Italy and its enlightenment for China. *Wind Energy* 54–9. doi: 10.3969/j.issn.1674-9219.2013.11.039

Jin, R. (2019). Electricity market is the main direction of future renewable energy consumption. *China Power Enterprise Manag.* 18–22.

Kwon, T. (2015). Is the renewable portfolio standard an effective energy policy? Early evidence from South Korea. *Utilities Policy* 36, 46–51. doi: 10.1016/j.jup.2015.09.002

Li, J., and Chen, G. (2008). International experience and China's renewable portfolio standard design. *Pacific J.* 44–51. doi: 10.14015/j.cnki.10044-8049.2008.10.013

Li, Q. (2019). Consumption and guarantee mechanism promotes high-quality development of renewable energy in China. *China Power Enterprise Manag.* 23–25.

Lin, T., and Ning, J. (2011). Study on allocation efficiency of carbon emission permit in EUETS based on ZSG—DEA model. *J. Quantitat. Tech. Econ.* 28, 36–50. doi: 10.13653/j.cnki.jqte.2011.03.002

Linnerud, K., and Simonsen, M. (2017). Swedish-Norwegian tradable green certificates: Scheme design flaws and perceived investment barriers. *Energy Policy* 106, 560–78. doi: 10.1016/j.enpol.2017.04.012

Lins, M. P. E., Gomes, E. G., Mello João Carlos, C. B., Soares de, M., and Adelino José, R. (2003). Soares de. Olympic ranking based on a zero sum gains DEA model. *Eur. J. Operat. Res.* 148, 312–22. doi: 10.1016/S0S377-2217(02)006877-2

Liu, J. (2019). China's renewable energy law and policy: a critical review. *Renew. Sustain. Energy Rev.* 99, 212–9. doi: 10.1016/j.rser.2018.10.007

Liu, Z., Zhang, X., Gao, H., Tang, C., Qi, T., and Zhang, D. (2011). A target disintegration model based on renewable energy potential and energy consumption. *Renew. Energy Resourc.* 29, 78–83. doi: 10.13941/j.cnki.21-1469/tk.2011.03.017

Liu, Z., Zhang, X., and Zhang, D. (2009). The target decomposition of renewable energy in Europe Union and its inspiration to China′s provincial planning. *China Mining Magazine* 18, 66–70. doi: 10.3969/j.issn.1004-4051.2009.09.017

Lv, J., Sun, W., Han, D., Zuo, Y., Yang, J., and Liu, P. (2019). Medium and long term electricity forecasting based on GDP-electricity consumption coupling relationship. *Power Syst. Clean Energy* 35, 1–7. doi: 10.3969/j.issn.1674-3814.2019.01.001

Miao, Z., Geng, Y., and Sheng, J. (2016). Efficient allocation of CO2 emissions in China: a zero sum gains data envelopment model. *J. Clean. Prod.* 112, 4144–50. doi: 10.1016/j.jclepro.2015.07.035

Miketa, A., and Schrattenholzer, L. (2006). Equity implications of two burden-sharing rules for stabilizing greenhouse-gas concentrations. *Energy Policy* 34, 877–91. doi: 10.1016/j.enpol.2004.08.050

Mo, J., Duan, H., Fan, Y., and Wang, S. (2018). China's energy and climate targets in the paris agreement: integrated assessment and policy options. *Econ. Res. J.* 53, 168–81.

Mu, H., Li, L., Li, N., Xue, Z., and Li, L. (2016). Allocation of carbon emission permits among industrial sectors in Liaoning province. *Energy Procedia* 104, 449–55. doi: 10.1016/j.egypro.2016.12.076

National Development and Reform Commission (2017). 13th five-year plan for renewable energy development (part 1). *Solar Energy* 5–11. doi: 10.3969/j.issn.1003-0417.2017.02.001

NEA (2016). *[In Chinese] Report on the Monitoring and Evaluation of National Renewable Energy and Electricity Development in 2015[EB/OL]*. Available online at: http://zfxxgk.nea.gov.cn/auto87/201608/t20160823_2289.htm

NEA (2017). *[In Chinese] Report on the Monitoring and Evaluation of National Renewable Energy and Electricity Development in 2016[EB/OL]*. Available online at: http://zfxxgk.nea.gov.cn/auto87/201704/t20170418_2773.htm

NEA (2018). *[In Chinese] Report on the Monitoring and Evaluation of National Renewable Energy and Electricity Development in 2017[EB/OL]*. Available online at: http://zfxxgk.nea.gov.cn/auto87/201805/t20180522_3179.htm

NEA (2019). *[In Chinese] Report on the Monitoring and Evaluation of National Renewable Energy and Electricity Development in 2018[EB/OL]*. Available online at: http://zfxxgk.nea.gov.cn/auto87/201906/t20190610_3673.htm

Ouyang, C. (2010). Planning ahead: achieving "15% non-fossil energy" by 2020. *China Power Enterprise Manag.* 16–18. doi: 10.3969/j.issn.1007-3361.2010.10.004

Pan, J., and Zheng, Y. (2009). Responsibility and individual equity for carbon emissions rights. *World Econ. Politics* 6–16.

Pan, W., Wu, T., and Wang, F. (2015). Study on the efficiency of carbon emission allocation in Chinese industries. *Statist. Dec.* 142—4. doi: 10.13546/j.cnki.tjyjc.2015.18.039

Pan, X., Teng, F., and Wang, G. (2014). Sharing emission space at an equitable basis: Allocation scheme based on the equal cumulative emission per capita principle. *Appl. Energy* 113, 1810–8. doi: 10.1016/j.apenergy.2013.07.021

Qi, Y., Lu, J., and Zhu, M. (2018). *Wind Curtailment in China and Lessons from the United States*. Beijing. Available online at: https://www.brookings.edu/wp-content/uploads/2018/03/wind-curtailment-in-china-and-lessons-from-the-united-states1.pdf

Qian, M., Lu, Z., and Wang, J. (2015). Analysis of carbon emissions allocation in industrial sectors based on ZSG-DEA model. *J. Indus. Technol. Econ.* 97–104. doi: 10.3969/j.issn.10044-910X00XX.2015.11.012

Raupach, M. R., Davis, S. J., Peters, G. P., Andrew, R. M., Canadell, J. G., Ciais, P., et al. (2014). Sharing a quota on cumulative carbon emissions. *Nat. Climate Change* 4:873. doi: 10.1038/nclimate2e384

Ringel, M. (2006). Fostering the use of renewable energies in the European Union: the race between feed-in tariffs and green certificates. *Renew. Energy* 31, 1–17. doi: 10.1016/j.renene.2005.03.015

Shan, B., Xu, M., Zhu, F., and Zhang, C. (2012). China's energy demand scenario analysis in 2030. *Energy Procedia* 14, 1292–8. doi: 10.1016/j.egypro.2011.12.1091

Siddiqui, A., Tanaka, M., and Chen, Y. (2016). Are targets for renewable portfolio standards too low? The impact of market structure on energy policy. *Eur. J. Operat. Res.* 250, 328–41. doi: 10.1016/j.ejor.2015.10.063

Sun, Z. R., Zhou, D. Q., Zhou, P., and Miao, Z. (2012). Quota allocation of China's energy conservation based on environmental ZSG-DEA. *Syst. Eng.* 30, 84–90.

Vaillancourt, K., and Waaub, J-P. (2004). Equity in international greenhouse gases abatement scenarios: a multicriteria approach. *Eur. J. Operat. Res.* 153, 489–505. doi: 10.1016/S0S377-2217(03)00170-X

Wang, H., Liu, H., He, X., and Zeng, W. (2016). Allocation of carbon emissions right based on the intergenerational equity. *China Environ. Sci.* 36, 1895–1904. doi: 10.3969/j.issn.1000-6923.2016.06.044

Wang, J., Cai, B., Cao, D., Zhou, Y., and Liu, L. C. (2011). Scenario study on regional allocation of CO2 emissions allowance in China. *Acta Scientiae Circumstantiae* 31, 680–5. doi: 10.13671/j.hjkxxb.011.04.012

Wang, L., Chen, W., Zhang, H., and Ma, D. (2017). Dynamic equity carbon permit allocation scheme to limit global warming to two degrees. *Mitigat. Adapt. Strategies Glob. Change* 22, 609–28. doi: 10.1007/s11027-015-9690-8

Wang, S. (2017). Analysis of the status and problems of non-fossil energy power generation in China. *Environ. Protect.* 45, 52–4. doi: 10.14026/j.cnki.02533-9705.2017.21.010

Wang, X. (2019). Consumption guarantee mechanism escorts renewable energy consumption. *Energy* 30–33.

Wang, Y., Jia, W., and Bi, Y. (2017). Provincial decomposition of China's 2030 carbon dioxide emission peak target from the perspective of efficiency: Research on the zero sum gains DEA model. *Acta Scientiae Circumstantiae* 37, 4399–408. doi: 10.13671/j.hjkxxb.2017.0348

Wei, C., Ni, J., and Du, L. (2012). Regional allocation of carbon dioxide abatement in China. *China Econ. Rev.* 23, 552–65. doi: 10.1016/j.chieco.2011.06.002

Wiser, R., Mai, T., Millstein, D., Barbose, G., Bird, L., Heeter, J., et al. (2017). Assessing the costs and benefits of US renewable portfolio standards. *Environ. Res. Lett.* 12:94023. doi: 10.1088/17488-9326/aa8a7bd

Wu, H., Cheng, Y., Zhang, N., Zhou, B., Lu, S., and Kang, C. (2016). A study on power carbon emission quota allocation in interprovincial carbon trading mechanism. *Power System Technol.* 40, 3440–3445. doi: 10.13335/j.1000-3673.pst.2016.11.024

Wu, J., Zhu, Q., and Liang, L. (2016). CO2 emissions and energy intensity reduction allocation over provincial industrial sectors in China. *Appl. Energy* 166, 282–91. doi: 10.1016/j.apenergy.2016.01.008

Wu, Q., and Huang, W. (2016). Study on the dynamic relationships between energy consumption and economic growth. *Energy China* 38, 30–32. doi: 10.3969/j.issn.10033-2355.2016.07.005

Wu, R., and He, Y. (2014). Optimal allocation model of renewable energy quota. *Electric Power Construct.* 35, 147–52. doi: 10.3969/j.issn.1000-7229.2014.06.028

Xia, Y. (2019). Why this wind power project has set multiple records. *Wind Energy* 22–26.

Xiong, S., Tian, Y., Ji, J., and Ma, X. (2017). Allocation of energy consumption among provinces in China: a weighted ZSG-DEA model. *Sustainability* 9:2115. doi: 10.3390/su9u112115

Xu, W., Tang, Q., Wang, Y., and Dai, S. (2015). Power planning implementation deviation influence on non-fossil energy development goal. *Electric Power Construct.* 36, 61–5. doi: 10.3969/j.issn.10000-7229.2015.08.010

Xue, J., and Zhang, L. (2013). Comparison of elastic coefficient method and regression analysis method prediction. *Shanxi Architecture* 39, 199–201. doi: 10.13719/j.cnki.cn1n4-1279/tu.2013.05.071

Yang, B., Liu, C., Su, Y., and Jing, X. (2017). The allocation of carbon intensity reduction target by 2020 among industrial sectors in China. *Sustainability* 9:148. doi: 10.3390/su9010148

Yang, S., and Wang, T. (2018). Analysis of electricity consumption elasticity coefficient of some countries in ASEAN. *Tourism Manag.* 1, 18–24. doi: 10.23977/tmte.2018.11004

Ye, B., Jiang, J., Li, C., Miao, L., and Tang, J. (2017). Quantification and driving force analysis of provincial-level carbon emissions in China. *Appl. Energy* 198, 223–38. doi: 10.1016/j.apenergy.2017.04.063

Yin, H., and Powers, N. (2010). Do state renewable portfolio standards promote in-state renewable generation? *Energy Policy* 38, 1140–9. doi: 10.1016/j.enpol.2009.10.067

Yu, X. (2013). Research on consumption prospects of non-fossil energy in China. *Consumer Econ.* 29, 94–97.

Zhao, P. (2019). *Research on Power Transmission Direction and Scale of Interconnected Grid Considering Uncertainty*. Master. Beijing: North China Electric Power University.

Zhao, Q., Yan, Q., Cui, H., and Zhao, H. (2017). Scenario simulation of the industrial sector carbon dioxide emission reduction effect. *Polish J. Environ. Stud.* 26:e74403. doi: 10.15244/pjoes/74403

Zhao, R., Min, N., Geng, Y., and He, Y. (2017). Allocation of carbon emissions among industries/sectors: an emissions intensity reduction constrained approach. *J. Clean. Prod.* 142, 3083–94. doi: 10.1016/j.jclepro.2016.10.159

Zhao, X., Feng, T., Cui, L., and Feng, X. (2014). The barriers and institutional arrangements of the implementation of renewable portfolio standard: a perspective of China. *Renew. Sustain. Energy Rev.* 30, 371–80. doi: 10.1016/j.rser.2013.10.029

Zhou, S., Tong, Q., Yu, S., Wang, Y., Chai, Q., and Zhang, X. (2012). Role of non-fossil energy in meeting China's energy and climate target for 2020. *Energy Policy* 51, 14–9. doi: 10.1016/j.enpol.2012.05.083

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Economic Analysis of Renewable Energy in the Electricity Marketization Framework: A Case Study in Guangdong, China

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Along with China's rapid advancement of electricity market reform, market-oriented policies in promoting renewable energy development and accommodation are foreseeing. Assessing the economics of renewable energy under electricity marketization is an important issue worthy of study. In this paper, we firstly employ merit order method to establish an electricity market clearing model of the electricity trading by modeling 48 hypothetical scenarios. Then we simulate the market clearing prices at 15-min intervals to discuss the economics of renewable energy in a benchmark feed-in tariff (FIT) scenario and a market-oriented scenario with the historical data of Guangdong, China. Further, the study exams the economic interrelationship between the outputs of wind and solar power in different load scenarios. The results demonstrate that the consumption of renewable energy is greatly improved in the market-oriented situation. However, in this scenario, renewable energy generation is unprofitable and uneconomic compared with in the benchmark FIT scenario. In the high-load scenarios, the changes in wind power output have a negative impact on the economics of solar power, while the mixed effects exist in the low-load scenarios. Based on these findings, conclusions and policy implications are drawn at the end of the paper.

Keywords: renewable energy, marketization, clearing price, LCOE, economic analysis

INTRODUCTION

As an alternative to mitigating climate change, developing renewable energy has become a general consensus all over the world (Liu W. et al., 2019). Developing renewable energy sector and upgrading energy structure have strategically important role in China's commitments against climate changes (Ji and Zhang, 2019). The ambitious development plan of renewable energy and significant progress have been achieved in recent years in China. With the large-scale expansion of renewable energy, the cost of renewable energy has dropped considerably. China is accelerating the reform of electricity market which was started in Guangdong Province as a crucial pilot. Government plays a large role in facilitating progress in developing renewable energy (Jia et al., 2019; Wang et al., 2020). In the electricity market situation, units with low marginal cost are dominant in the bidding process. It is conducive to promote the accommodation of renewable energy and alleviate the curtailment of wind and solar power. In addition, there emerges a new opportunity for the evolution of renewable energy and it is possible to achieve the transition from a benchmark feed-in tariff (FIT) mechanism to a market-oriented one in the future. Thus, it is of great practical significance to assess the economics of renewable energy in China under the electricity market situation.

In March 2015, the Chinese Communist Party Central Committee and the State Council jointly issued "Document No. 9 – Opinions on Further Deepening the Reform of the Power System" (Zeng et al., 2016). In the following years, a series of companion documents were issued by relevant central government agencies to flesh out an action plan of the reform. Provincial governments developed implementation plans according to the central policy. Eight provinces have moved into pilot runs of wholesale spot markets (Yu, 2020). Because of regional disparity and convergence of electricity consumption in China (Cheong et al., 2019), generation scheduling and dispatch rules have been revised to better incorporate renewable generators into electricity markets. Previous researches have studied Chinese electricity reform from different perspectives. The first perspective is a comprehensive review of Chinese electricity reform. Wang and Chen (Wang and Chen, 2012) discussed China's electricity market-oriented reform from an absolute to a relative monopoly perspective. Ngan (2010) analyzed the three main stages of China's reform in order to trace out the main characteristics of reform measures including those for power investment financing, separation of government and enterprise, and the division between power generation firms and power grids. In addition, poor renewable energy integration is posing a huge challenge to China's electricity sector. Zhang et al. (2018) examined the extent to which China's power sector reforms will assist renewable energy integration, and issues to effective implementation. The policy suggestions to promote the integration of renewable energy in the power market were concluded. The second is the specific study of typical provinces. Liu S. et al. (2019) analyzed the progress of Yunnan electric power market reform, resource allocation and renewable energy integration. The main contributions of this paper lie in the extension of the existing understanding of electricity reforms in Yunnan and China. Cheng (2018) reviewed four elements in the reformed market architecture including market pricing rules, transitional quantity controls, the generation rights market, and inter-provincial trade in Yunnan and concluded on six insights regarding the role of the grid operator, security checks on trade, integration of cascade hydropower, the inclusion of renewables in the generation rights market, price controls, and market participant price uncertainty. In general, market is playing an increasingly significant role in China's electricity industry.

With respect to the economic evaluation of renewable energy, it is generally analyzed and presented in three related indicators: the per watt capital cost of renewable energy modules (typically expressed as CNY/W), the levelized cost of electricity (LCOE) (typically expressed as CNY/kWh), and the concept of "grid parity" (Bazilian et al., 2013). The indicator of per watt capital cost has the disadvantages that module costs do not translate automatically into full installed system costs. While LCOE is a popular metric which is widely used as a metric to rank the competitiveness of power generation technologies (Limmanee et al., 2017; Tran and Smith, 2018; Sarasa-Maestro et al., 2019). Many literatures have studied the application of traditional LCOE calculation methods. Firstly, some of them aim to evaluate the LCOE of specific energy technologies and analyze the factors affecting the cost of renewable energy. For example, Mulligan et al. (2015) provided the first commercial-scale LCOE estimates for organic photovoltaics (OPVs) by integrating OPV-specific measured and calculated data into the estimates. Abdelhady et al. (2018) attempted to estimate the energy production and LCOE of biomass power plant fed with rice straw in Egypt. Lerch et al. (2018) performed a sensitivity analysis on the LCOE for floating offshore wind farms to obtain maximum and minimum LCOE variation limits and possible cost reduction potentials. Secondly, some of them apply LCOE to compare projects. Zang et al. (2018) provided a techno-economic comparative analysis of biomass integrated gasification combined cycles with and without CO_2 capture through LCOE evaluation. Luo et al. (2017) discussed sensitivity factors of LCOE to capture the impacts of solar multiple on the performance of direct steam generation solar power tower plant with integrated thermal storage. Thirdly, some studies extend the calculation method of LCOE or revise the traditional LCOE calculation approach. Said et al. (2015) presented improved modeling and analysis of the LCOE associated with photovoltaic (PV) power plants in Egypt. The presented model considers the effective lifetime of various PV technologies rather than the usual use of the financial lifetime and the result show that the effective lifetime has a significant impact on the LCOE. Bruck et al. (2018) developed a new cost model to evaluate the LCOE from a wind power source under a Power Purchase Agreement (PPA) contract. The developed cost model can be used as a basis for setting appropriate PPA terms, such as a price schedule and performance metrics. Ling-zhi et al. (2018) developed a new revised LCOE mathematical model based on NPV and discounted cash flows techniques, and analyzes the cost-benefit evolution of concentrated solar power (CSP) technologies by taking the CSP industry of China as an example. Aldersey-williams et al. (2019) developed a new approach and methodology, which uses the United Kingdom (UK) "audited" data published in company accounts, to determine more accurate LCOE estimates. Geissmann (2017) set forth a novel approach to calculate the LCOE using a probabilistic model that accounts for endogenous input parameters. Branker et al. (2011) reviewed the methodology of properly calculating the LCOE for solar PV, correcting the misconceptions made in the assumptions found throughout the literature.

Furthermore, the concept of "grid parity" has emerged as a key competitiveness indicator to evaluate the economics of renewable energy. It refers to the price intersection of renewable and conventional electricity. For example, Bhandari and Stadler (2009) computed the LCOE of a PV power generation system in Germany and compares them to the respective local electricity prices, which gave a suggestion that grid parity will be reached between 2013 and 2014. Li et al. (2016) explored the LCOE of wind, PV and coal power on the utility's transmission and distribution grids. Finding that wind power is approaching the utility cost in 2020 and achieves the grid parity in provinces with favorable wind resources and unfavorable coal electricity costs. Distributed PV stations can reach the grid parity on the retail level for business or even industrial consumers.

In the existing literature, scholars have presented various methods to provide economic analysis for renewable energy. However, the dynamics of economic analysis of renewable energy in market conditions are complex. Most of the literature either examine the economic analysis through the indicator of LCOE on renewable energy, or compare the LCOEs with static local electricity prices to verify the grid parity. Few examples assess the economics of renewable energy between LCOEs and dynamic market clearing prices in a market situation, especially in China. Thus, our goal is to fill this gap. In this paper, the economics of renewable energy is done by comparing the calculation result – the LCOE – with the market clearing price under the electricity marketization background. As one of the first pilot province in the retail electricity market reform process, Guangdong is also one of the developed provinces in China. Therefore, this paper selects Guangdong Province as the case. To the best of our knowledge, this is the first paper to systematically compare the LCOE of renewable energy with market clearing price under the electricity marketization background in Guangdong Province, China. The contributions of this paper are 2-fold. Firstly, the paper not only clearly calculates the LCOEs of renewable energy in Guangdong but also reveals the simulation process of market clearing prices at 15-min intervals through merit order method and the unit commitment constraints. Secondly, the paper studies the economic interrelationship between wind and solar power in different load conditions. The models proposed in this paper can provide a reference for scholars to study the economics of the renewable energy in the electricity marketization framework. Furthermore, it is conducive to facilitating an understanding of the renewable energy power's long-term sustainable development pattern under free market conditions in the future, and helping to provide references for policy-making institutions.

The paper is organized as follows. Section Methodology introduces the Methodology. Section Economic assessment of renewable energy generation: the case of Guangdong Province in China presents the economic calculation of renewable energy generation in Guangdong. The discussion is presented in section Discussion. Section Conclusions and Policy Implications presents the study's conclusions and policy implications.

METHODOLOGY

Generating Unit Commitment Model

The ideal power market is dispatched by the method of merit order according to the principle of increasing marginal cost of the power system. In the idealized situation, the clearing result of the power system at a moment must be able to minimize the marginal cost of the system. Therefore, in this paper, the minimum marginal cost of the power system during the study period is taken as the objective function of the unit commitment in the market-oriented situation, which is written as follows:

$$obj = min\sum_{t}\sum_{i}(OC_{it} + SUC_{it} + SDC_{it}) \tag{1}$$

where OC_{it} is operating cost of unit i at time t, SUC_{it} is start-up cost, and SDC_{it} is shutdown cost.

In the process of electric power dispatching, a series of constraint conditions require to be considered, mainly including power balance constraints, operational standby requirements, unit maximum and minimum output constraints, climbing constraints, start and stop constraints (Geng et al., 2009; Qiuna et al., 2012; Lu et al., 2019).

Power balance constraint:

$$\sum_{i} P_{it} = D_t + L_t \ \ \forall t \tag{2}$$

where P_{it} is the power supply of unit i at time t, D_t is system load and L_t is line loss at time t.

Operational standby requirement:

$$\sum_{i} R_{it} \geq \underline{R_t} \ \ \forall t \tag{3}$$

where R_{it} is operating reserve of unit i at time t, R_t is minimum operational standby requirements at time t.

Unit maximum and minimum output constraint:

$$\begin{gathered} \underline{P_i} u_{it} \leq P_{it} + R_{it} \leq \overline{P_i} u_{it} \\ u_{it} = \begin{cases} 1 \ , \ on \\ 0 \ , \ off \end{cases} \forall i, t \end{gathered} \tag{4}$$

where P_i is the minimum power supply, $\overline{P_i}$ is the maximum power supply, u_{it} is running state of unit i at time t.

Climbing constraint:

$$R^{i}_{down} \leq P_{i(t+1)} - P_{it} \leq R^{i}_{up} \forall i, t \tag{5}$$

where R^{i}_{down} is the downhill climbing constraint of unit i, R^{i}_{up} is the upward climbing constraint of unit i.

Start and stop constraint:

$$\begin{cases} \left(\Delta t^{it}_{on} - \underline{\Delta t^{i}_{on}}\right)(u_{it} - u_{i(t+1)}) \geq 0 \\ \left(\Delta t^{it}_{off} - \underline{\Delta t^{i}_{off}}\right)(u_{i(t+1)} - u_{it}) \geq 0 \end{cases} \forall i, t \tag{6}$$

where Δt^{it}_{on} is cumulative start-up time, and Δt^{it}_{off} is cumulative shutdown duration of unit i as of time t. Δt^{i}_{on} is minimum start-up duration, Δt^{i}_{off} is minimum shutdown duration of unit i.

Economic Assessment Model

LCOE is a common metric for comparing power generating technologies, which measures the economic lifetime electric production and cost. This metric allows comparing the generation costs of conventional plants with variable renewable sources like wind and solar PV, despite their different cost structures (Ueckerdt et al., 2013). The method used to evaluate the economic analysis of renewable energy is to calculate the net economic value of unit electric energy provided by the generation resources through the difference between the average electricity price and LCOE, which is shown in Equation (7).

$$\begin{aligned} NV &= P - LCOE \\ LCOE &= \frac{A(CAPEX)+A(OM)+A(F)+A(T)}{A(E)} \end{aligned} \tag{7}$$

where, NV is the net value of unit electric energy. P is the annual average electricity price, which is the annual average market clearing price. *A(CAPEX)* is the annual levelized capital expenditure, *A(OM)* is the annual value of operating maintenance costs, *A(F)* is the annual value of fuel costs, *A(T)* is the annual value of tax, and *A(E)* is the expected annual value of on-grid electricity.

ECONOMIC ASSESSMENT OF RENEWABLE ENERGY GENERATION: THE CASE OF GUANGDONG PROVINCE IN CHINA

As one of the first pilot province in the retail electricity market reform process, Guangdong is also one of the developed provinces in China. Therefore, this paper selects Guangdong Province as the case and economically assesses the renewable energy in Benchmark pricing scenario and market-oriented scenario.

Benchmark FIT Scenario

In the case of benchmark FIT scenario, 100 MW wind power units and 50 MW solar power units in Guangdong are taken as the sample[1]. Since the marginal cost of wind and solar power is negligible, its marginal contribution is approximately equal to its benchmark FIT. In this paper, we prioritize the dispatch of renewable energy and fulfill the remaining load with coal power by adjusting its output level. Based on the data of 2017, the economic values of wind and solar power in Guangdong Province are calculated under benchmark FIT scenario, as shown in **Table 1**[2].

As can be seen in **Table 1**, no significant differences were found between wind power and solar power for the indicators of initial investment, the number of employees, and materials and other costs. The difference in occupied area per unit capacity, which has a significant impact on the value of tax, between the wind and solar groups was significant. Annual full utilization hours also has a significant impact on the value of on-grid electricity. As a result, the LCOE of solar power is 0.31 CNY/kWh higher than that of wind power. Therefore, the net value of unit energy created by wind power and solar power in the benchmark FIT scenario is positive, and the economic value of wind power is 0.06 CNY/kWh higher than that of solar power.

[1]The 100 MW wind power units and 50 MW solar power units are mainstreams of renewable energy installation in Guangdong Province.

[2]Detailed calculation data are provided upon request. This is true for all results presented in this paper.

TABLE 1 | Parameters setting and LCOEs for wind and solar power generation.

Resource types	Wind power	Solar power
Initial investment (CNY/kW)	6,825	7,000
Annual full utilization hours (hour)	1,900	1,050
Occupied area per unit capacity (m^2/MW)	50,000	28,000
Number of employees (capita)	12	10
Materials and other costs (CNY/kWh)	0.02	0.01
Benchmark FIT (CNY/kWh)	0.60	0.85
LCOE (CNY/kWh)	0.48	0.79
Net value of unit energy (CNY/kWh)	0.12	0.06

The economics of wind power and solar power generation are positively significant under the support of benchmark FIT.

Market-Oriented Scenario

Overview of Power Generation Capacity in Guangdong

Based on the National Electric Power Industry Statistics Express[R] (2017), Renewable Energy Data Sheet[R] (2017), and partial actual survey data of Guangdong, the installed power capacity of Guangdong Province is shown in **Appendix Table A1**. Including indicators of integrated auxiliary power rate, maximum load rate and maximum power supply. In addition, the minimum technical output of coal-fired power units needs to be considered according to the type and scale of the single unit, which is listed separately in **Appendix Table A2**.

The surrounding provinces of Guangdong are rich in hydropower resources, from which Guangdong will imports a large amount of hydropower. Based on the statistics of China Southern Power Grid, inter-provincial transaction hydropower accounted for 24.53% of the whole electricity consumption in Guangdong Province at the end of the "Twelfth Five-Year Plan" period. Therefore, the impact of external hydropower is considered in the output model of this paper. We assume that the external hydropower import is flexible and can be adjusted according to the power load of Guangdong Province. That is, increasing the import output at the peak of electricity consumption and reducing the import output at the valley of power consumption. Due to the principle of increasing marginal cost and uniform clearing price rules, the electricity price changes with the load in the market-oriented situation.

Market Rules in Guangdong Province

According to the *Interim measures for the preparation of priority electricity purchase plans for priority Generation* issued by the State Development and Reform Commission, and combined with the actual situation in Guangdong Province, the dispatch order of priority generators is as follows: 1. Wind, solar, and biomass power generation. 2. External hydropower. 3. Runoff hydropower. 4. Nuclear power. 5. Comprehensive utilization unit. Since there is no mandatory requirement for people's livelihood heating in Guangdong Province, cogeneration is dispatched with the principle of increasing short-term marginal

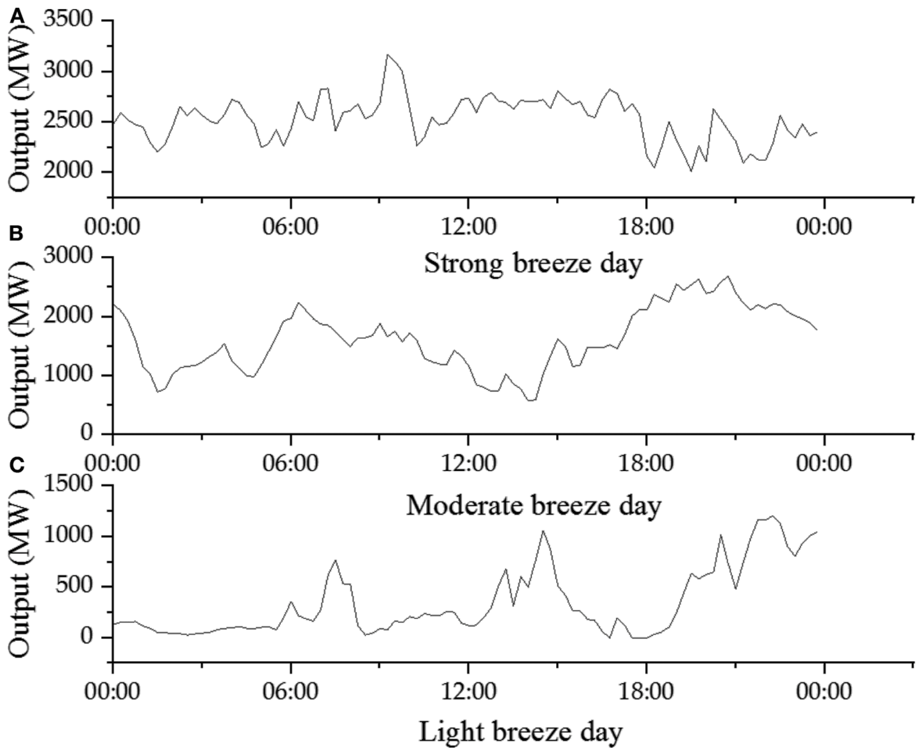

FIGURE 1 | Simulation curve of wind typical daily output of Guangdong in 2017.

cost along with conventional coal-fired power, pumped-storage power generation and natural gas power generation. In addition, the FIT is determined by the uniform clearing price, which is derived from the cost of the marginal generator unit that meets Guangdong's power demand in the market-oriented power system. If the electricity market has already been cleared in a priority generator unit, the unit quoted price with the lowest marginal cost of participation in market bidding is the current clearing price.

Wind and Solar Power Output Characteristics

Based on the historical data of wind power output surveyed in Guangdong Province, the wind power output characteristics are divided into four categories: strong breeze day, moderate breeze day, light breeze day and windless day. The simulation curve of wind typical daily output of Guangdong in 2017 is presented in **Figure 1**. It can be found that the variations and uncertainties occurred in intermittent wind power generation. Specifically, daily wind output ranges from 2013 to 3,168 MW in strong breeze day, from 573 to 2,686 MW in moderate breeze day and from 0 to 12,05 MW in light breeze day.

Solar power generation is significantly correlated with seasons and light intensity. Referring to the output data of roof photovoltaic in Guangdong, it is found that the output curve of solar power is roughly the shape of a downward parabola, and reaches the peak of 1 day at about 12:30. The output time in summer is about at 5: 00–20: 00, spring and autumn at 6: 00–19: 00, winter at 7: 00–18: 00. Combined with the annual photovoltaic power generation of 13,147 MWh (Su et al., 2013) and the solar power generation of 2 million MWh in Guangdong province in 2017, the real-time output curves of solar power generation in different seasons of Guangdong Province in 2017 are simulated (**Figure 2**). The maximum output of solar power will reach 1,643 MW in summer, 1,170 MW in spring and autumn, and 637 MW in winter.

Furthermore, the proportion of light days and no light days is also an important factor in solar power generation. According to **Figure 2**, there are 15 h of light a day in summer, 13 h in spring and autumn, and 11 h in winter. Combined with the annual solar irradiation time of 2,200 h in Guangdong Province, the annual light days of Guangdong Province is about 160.98 days. Hence, the proportion of light days and no light days in 1 year in Guangdong Province is about 160.98: 204.02.

Generating Unit Commitment Constraint in Guangdong

Considering the data availability and the low level of renewable energy penetration in Guangdong Province, the marketization situation has little effect on the climbing and start-stop of the units. Therefore, to simplify, this paper does not consider the climbing and start-stop constraints and its related costs. Operating cost is the main factor in calculating the marginal cost of the coal-fired power unit. Since the fuel cost accounts for a dominant proportion in the operating cost of the coal-fired

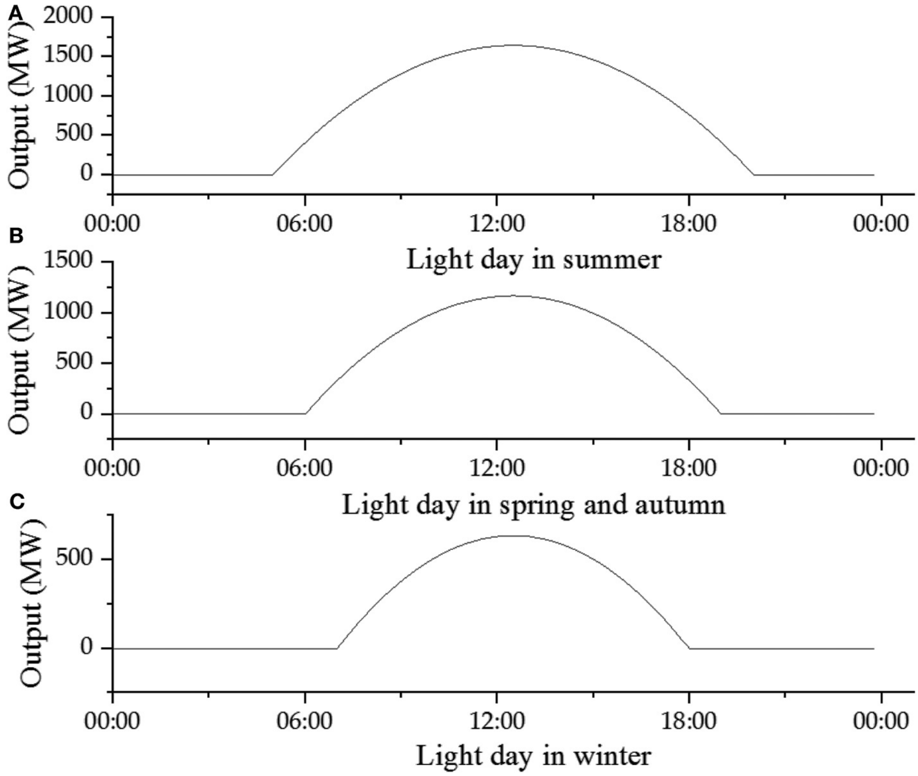

FIGURE 2 | Simulation curve of the solar typical daily output of Guangdong in 2017.

power unit, the unit's marginal cost is simply replaced by the unit's fuel supply cost.

The line loss rate of Guangdong Power Grid Enterprise was 3.25% in 2016[3]. In the market simulation, the power load should be converted into power supply load according to this ratio, and then generator sets are dispatched in combination with power system operation standby requirements. In consideration of the large scale power system of Guangdong, the operating reserve is considered as 5% of the maximum daily power supply load. The maximum power generation resources are determined by the installed capacity, the maximum load rate, and the integrated auxiliary power rate. The minimum power generation mainly considers the minimum technical output of power units, which is assumed to be 45% of installed capacity for the conventional coal power unit and the comprehensive utilization unit, and 50% of installed capacity for the cogeneration unit.

The power balance constraint is based on the 2017 actual electricity load data of Guangdong[4]. The electricity load data on January 28, October 23 and August 9 represent the electricity demand situation in winter weekends, spring and autumn weekdays, and summer weekdays in Guangdong, respectively[5]. According to the electricity load data on October 22 and 25, the corresponding daily electricity consumption in Guangdong is calculated, and the conclusion that the weekends' electricity load in Guangdong is about 0.88 times of the weekdays' electricity load is obtained. Thus, the above typical daily load curves are extended to six situations presented in **Figure 3**: (a) weekdays in winter, (b) weekends in winter, (c) weekdays in spring and autumn, (d) weekends in spring and autumn, (e) weekdays in summer, (f) weekends in summer.

It can be seen from **Figure 3** that the typical daily load curve in Guangdong is roughly the trend of "three peaks and three valleys." According to the criteria for the four seasons of Guangdong and ratio of working days to weekends at 5:2, the annual sustained load curve of Guangdong Province is obtained, as shown in **Figure 4**. It can be seen that the duration of the load of 103,092 MW is only 32.59 h, and the duration of the load that no $<$ 17,955 MW is 8,760 h.

In addition, considering the typical daily load curve, the annual electricity consumption in Guangdong Province is calculated to be 595 billion kWh, which is very close to the actual electricity consumption (595.9 billion kWh) in 2017[6]. It is further verified the rationality of the selected typical daily load curve and the relative simulation hypothesis.

[3]Data Sources: National Electricity Price Supervision Report[R] (2016).
[4]Data sources: China Southern Power Grid.
[5]There is no seasonal difference between spring and autumn seasons in Guangdong. In addition, the electricity load and consumption of the spring and autumn are basically similar according to the statistics. Therefore, seasonal factors are divided into three categories: spring and autumn, summer, winter.
[6]Data Sources: National Electric Power Industry Statistics Express (2017).

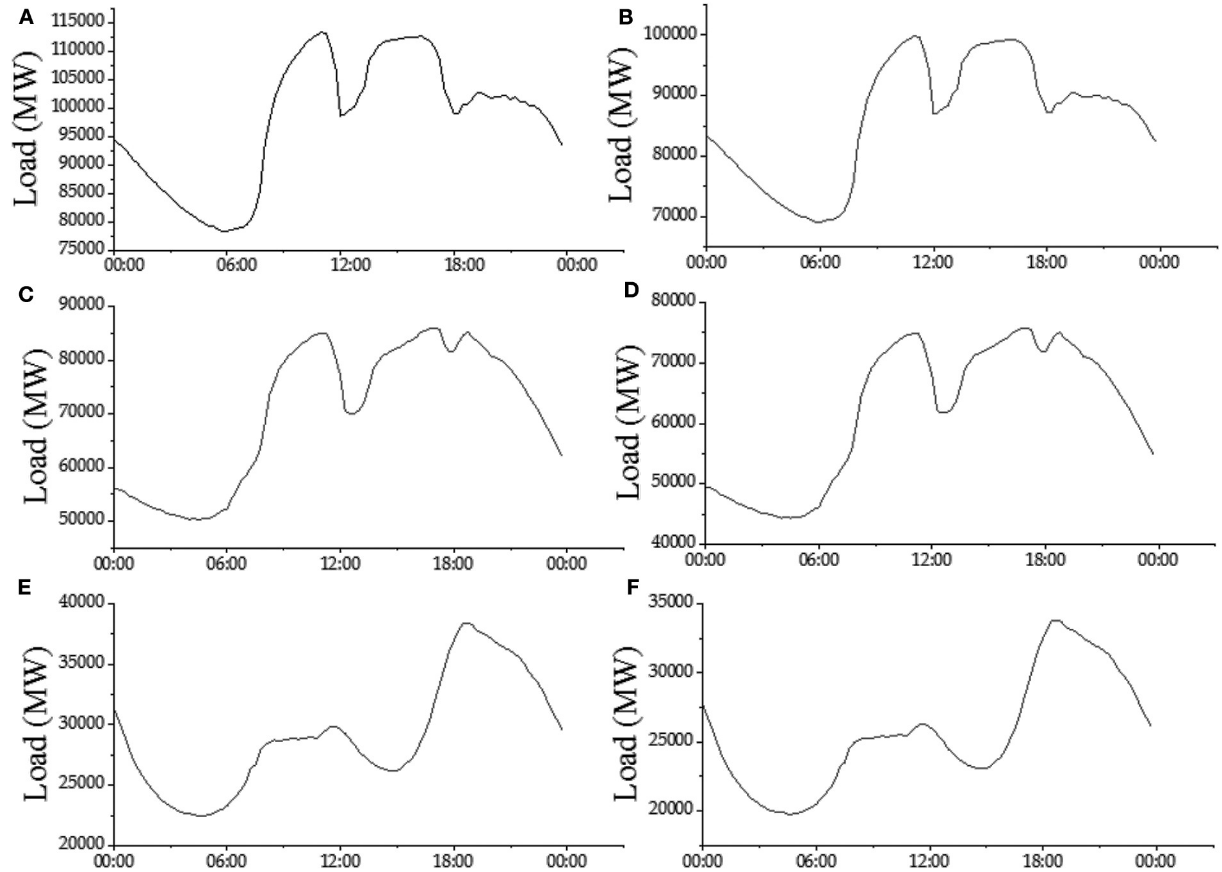

FIGURE 3 | Typical daily load curve of Guangdong in 2017. **(A)** Weekdays in winter. **(B)** Weekends in winter. **(C)** Weekdays in spring and autumn. **(D)** Weekends in spring and autumn. **(E)** Weekdays in summer. **(F)** Weekends in summer.

Power Supply Curve in Guangdong Province

Under the principle of marginal cost increment, the key to simulate the power supply curve in Guangdong is to dispatch the units participating in the market bidding according to the marginal cost. The marginal cost of the coal-fired power supply is determined by coal consumption and coal price. Additionally, the coal consumption of power supply is related to the output of the units. According to the "Guangdong Power Grid Coal Consumption Online Monitoring System Monthly Report (January 2017)," the coal consumption of coal-fired power plants at 80% and 90% load rate is presented, and the power supply of coal-fired power units in Guangdong under various load rates is calculated. In 2017, the coal price index in Guangdong Province ranges from 600.26 to 641.20 CNY/t[7], which is equivalent to 841.00–898.35 CNY/t of standard coal. According to the maximum and minimum coal-fired price in 2017, the high and low coal prices are set, and the coal-fired power generation in Guangdong is used to calculate the marginal power supply cost of the coal-fired power units in Guangdong under various load rates, which are shown in **Table A3**.

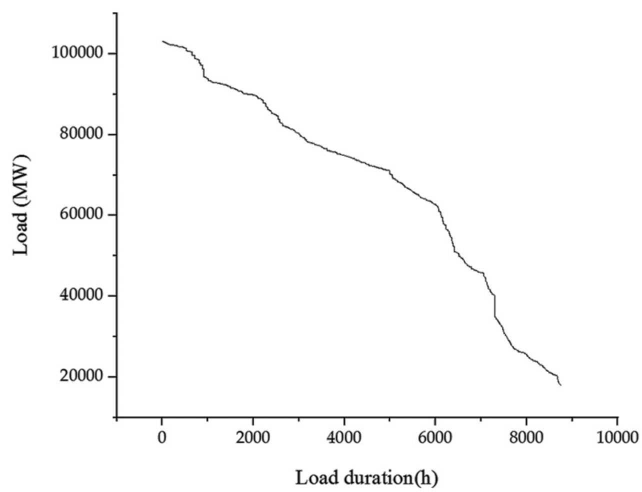

FIGURE 4 | Annual sustained load curve of Guangdong.

Since September 1, 2017, the gas price of Guangdong Natural Gas Pipeline Company has been cut to 2.32 CNY/m^3. Assuming that one unit (1 m^3) natural gas will generate 5.18 kWh

[7]National Development and Reform Commission Price Monitoring Center: http://jgjc.ndrc.gov.cn/zgdmjgzs.aspx?clmId=syjgzs6

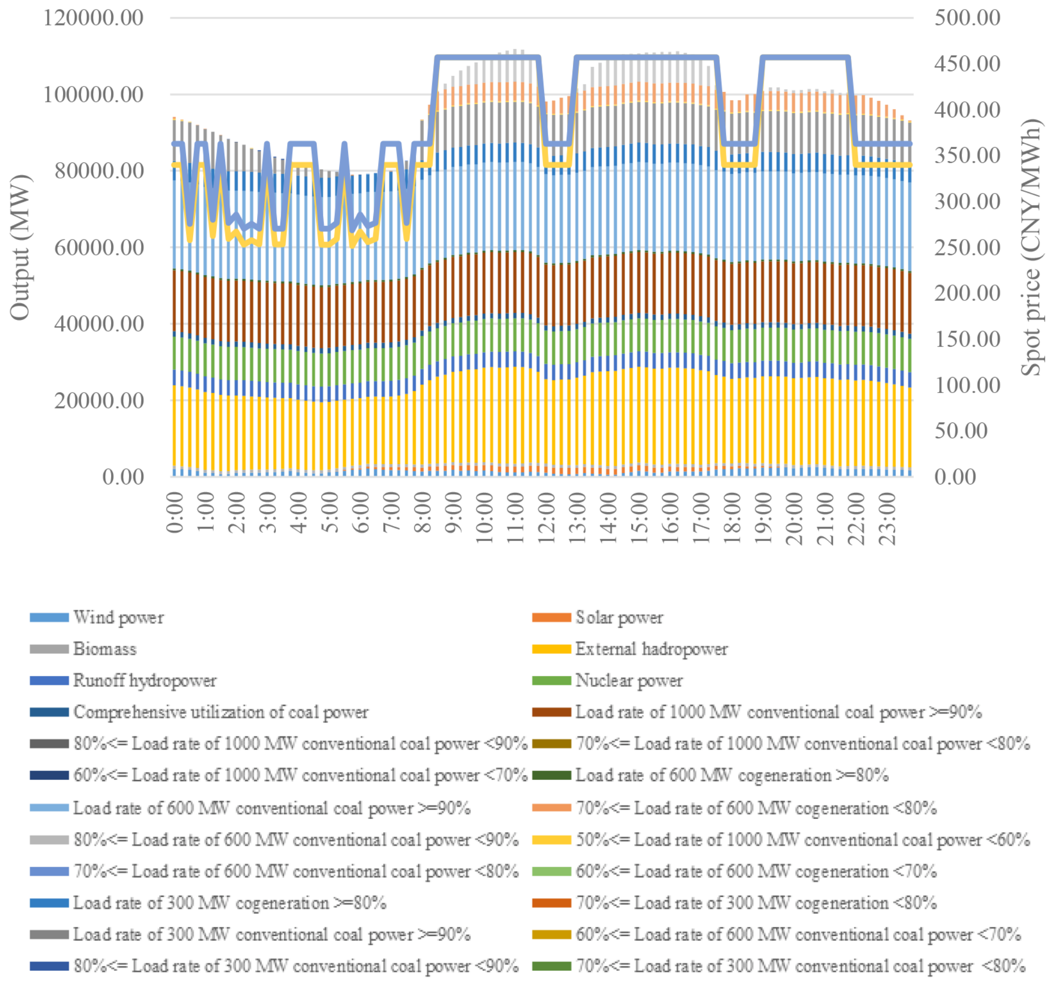

FIGURE 5 | Guangdong power supply curve and clearing electricity price in S1W1WD2L1 scenario.

electricity, combined with the natural gas power generation comprehensive auxiliary power consumption rate of 2.02%, and the marginal cost of natural gas power supply is about 457.11 CNY/MWh.

In ideal circumstances, it is assumed that the pumped storage power station will obtain relevant information about electricity price in a timely and accurate manner, and accordingly make pumping or power generation decisions. So as to minimize the pumping cost and increase the economic benefits of power generation.

According to the market rules described in 3.2.2, wind and solar power output characteristics, the marginal cost above-mentioned resources, and combined with the typical daily load curve of Guangdong Province, the power generation resources of Guangdong are simulated in **Figure 5**. For the sake of simplicity, the season uses S1, S2, S3 instead of summer, spring and autumn, and winter, respectively. Weekdays and weekends are represented by W1 and W2, respectively. WD0, WD1, WD2, and WD3, respectively indicate windless day, light breeze day, moderate breeze day, and strong breeze day. L0 and L1, respectively indicate no light day and light day. We use short-term simulation at 15-min intervals as market clearing results. The power supply curve was obtained in 48 cases of a random combination of the above factors. **Figure 5** shows the power supply curve and the clearing electricity price in the case of S1W1WD2L1, and the others are available on request.

In **Figure 5**, the dispatch order of resource power supply is shown in bottom-up order. Specifically, the order of dispatch is wind power, solar power, biomass power, external hydropower, runoff hydropower, nuclear power and comprehensive utilization of coal power. The generation resources with lower dispatch order are coal generating units with high marginal cost of power supply, pumped storage generation and natural gas power generation. It can be found that due to the high-load in summer weekdays, the natural gas power generation unit is the clearing unit in most cases, the pumped-storage power generation unit in several cases, and the coal-fired power generation price only a few times. In other seasons, the price of coal-fired power plants is mainly cleared, but the electricity price of pumped storage power is cleared in a few cases.

Interestingly, when the natural gas power generation unit is used as the marginal clearing unit, the electricity price curves in the cases of high and low coal prices are coincident. Indicating that the coal price only affects clearing price when coal-fired power and pumped-storage power generation as marginal clearing units. While it will not affect the clearing price when natural gas power generation as marginal clearing units. A possible explanation lies in the fact, that the pumped-storage power station pumps water at the valley price of electricity and generate electricity at a rate of 3/4. While the valley price of electricity is mostly cleared in coal-fired power generation. Hence, the marginal cost of pumped storage power supply will be affected by the coal price.

Economic Analysis of RE Power Generation in Guangdong

According to the simulation results of the power market in Guangdong Province, the daily return of wind and solar power in Guangdong under 48 scenarios are obtained, and shown in **Table 2**.

Generally speaking, the market clearing price is determined by the coal-fired power units in most cases and determined by pumped storage and gas power in a few cases. It can be seen from **Table 2** that the coal price affects the income level of wind and solar power. In the scenario of high coal price, the return of wind power and solar power generation is generally higher than that of low coal price. Reasons for the different effects lie in the different power supply marginal cost of the coal-fired power units which significantly affected by coal prices.

There is an interaction between wind and solar power, and the interaction will change with the load variation. In summer, for the scenarios of S1L1, the higher output level of wind power is, the higher profits it will earn. This is because of the low level of renewable energy penetration in Guangdong, renewable energy generation revenue is positively related to its output. In short, the higher output level of wind power is, the higher income it will get, and vice versa. While the income level of solar power generation decreases with the increase of wind power output. This is due to the increase in wind power output, which will lead the power system to use lower marginal cost generators as clearing units, thus decreasing the clearing price. Hence, in the case of a certain solar power generation, the market income of solar power will decrease. For the scenarios of S1WD3, S1WD2, and S1WD1, wind power has a higher income in the case of no light day than light day. That is the decline in solar power output will cause a higher clearing price. Hence, in the case of a certain wind power generation, the market income of wind power is increased.

However, the above conclusions may not be concluded in spring, autumn, and winter scenarios, where the load is relatively low. For example, in S3W2L1 scenarios, the income level of solar power generation decreases with the reduction of wind power output. In S3W2WD3 scenarios, wind power has a higher income in the case of light day than no light day. This is due to the

TABLE 2 | Typical daily return of wind and solar power generation under the market condition in Guangdong Unit: 10,000 CNY/day.

Resource types	Low coal price		High coal price	
	Wind	Solar	Wind	Solar
S1W1WD3L1	2,149.42	659.49	2, 213.75	670.51
S1W1WD2L1	1,424.50	676.69	1, 466.47	686.74
S1W1WD1L1	328.45	683.64	333.88	691.60
S1W1WD0L1	0.00	689.17	0.00	696.25
S1W1WD3L0	2,204.67	0.00	2,265.25	0.00
S1W1WD2L0	1,438.47	0.00	1,476.35	0.00
S1W1WD1L0	333.61	0.00	338.74	0.00
S1W1WD0L0	0.00	0.00	0.00	0.00
S1W2WD3L1	1, 721.15	492.47	1, 838.54	526.06
S1W2WD2L1	1,072.41	493.08	1, 145.55	526.71
S1W2WD1L1	235.57	499.22	251.64	533.27
S1W2WD0L1	0.00	515.62	0.00	550.79
S1W2WD3L0	1,757.91	0.00	1,877.81	0.00
S1W2WD2L0	1,088.36	0.00	1,162.59	0.00
S1W2WD1L0	240.72	0.00	255.73	0.00
S1W2WD0L0	0.00	0.00	0.00	0.00
S2W1WD3L1	1,634.29	277.59	1,745.76	296.52
S2W1WD2L1	1,048.84	287.72	1,120.38	307.34
S2W1WD1L1	221.50	278.00	236.60	296.96
S2W1WD0L1	0.00	283.78	0.00	303.13
S2W1WD3L0	1,683.70	0.00	1,798.54	0.00
S2W1WD2L0	1,048.20	0.00	1,119.69	0.00
S2W1WD1L0	221.13	0.00	236.21	0.00
S2W1WD0L0	0.00	0.00	0.00	0.00
S2W2WD3L1	1, 630.46	282.73	1,741.66	302.01
S2W2WD2L1	1,059.61	283.51	1,131.88	302.85
S2W2WD1L1	220.16	277.63	235.17	296.57
S2W2WD0L1	0.00	276.68	0.00	295.55
S2W2WD3L0	1,640.74	0.00	1,752.64	0.00
S2W2WD2L1	1,051.18	0.00	1,122.87	0.00
S2W2WD1L1	222.10	0.00	237.24	0.00
S2W2WD0L1	0.00	0.00	0.00	0.00
S3W1WD3L1	1,509.28	117.74	1,612.22	125.77
S3W1WD2L1	958.49	117.77	1,023.87	125.81
S3W1WD1L1	207.19	117.62	221.33	125.65
S3W1WD0L1	0.00	122.70	0.00	131.07
S3W1WD3L0	1,512.08	0.00	1,615.21	0.00
S3W1WD2L0	963.61	0.00	1,029.33	0.00
S3W1WD1L0	209.27	0.00	223.54	0.00
S3W1WD0L0	0.00	0.00	0.00	0.00
S3W2WD3L1	1, 495.83	121.11	1,597.86	129.37
S3W2WD2L1	968.51	118.97	1,034.57	127.08
S3W2WD1L1	200.71	118.95	214.39	127.06
S3W2WD0L1	0.00	115.95	0.00	123.86
S3W2WD3L0	1,476.01	0.00	1,576.68	0.00
S3W2WD2L0	955.90	0.00	1,021.10	0.00
S3W2WD1L0	203.17	0.00	217.02	0.00
S3W2WD0L0	0.00	0.00	0.00	0.00

For the sake of simplicity, the season uses S1, S2, S3 instead of summer, spring and autumn, and winter, respectively. Weekdays and weekends are represented by W1 and W2, respectively. WD0, WD1, WD2, and WD3, respectively, indicate windless day, light breeze day, moderate breeze day, and strong breeze day. L0 and L1, respectively, indicate no light day and light day. For example, S1W1WD3L1 is weekday with strong breeze and light in summer, S2W2WD2L1 is weekend with moderate breeze and light in spring and autumn.

TABLE 3 | Economic value of wind and solar power generation in guangdong province under the market condition.

Economic indicators	Low coal price		High coal price	
	Wind	Solar	Wind	Solar
Annual average electricity price (CNY/kWh)	0.32	0.35	0.33	0.36
Net value of unit energy (CNY/kWh)	−0.16	−0.44	−0.15	−0.43

TABLE 4 | Economic value of wind and solar power generation when the electricity load increased 10% in Guangdong Province under the market condition.

Economic indicators	Low coal price		High coal price	
	Wind	Solar	Wind	Solar
Annual average electricity price (CNY/kWh)	0.42	0.63	0.44	0.64
Net value of unit energy (CNY/kWh)	−0.06	−0.16	−0.04	−0.15

fact that coal-electricity are generally used as marginal clearing units in the power system during the period of low-load scenario. The reduction of wind power output will increase the load rate of coal-fired power units. As a result, the coal consumption and the marginal power supply cost of coal-fired power units are reduced, leading to the reduction of clearing price. Further, the market revenue of solar power generation (or wind power generation) decreased, resulting in its economic deterioration. Therefore, the economic benefits of wind power (or solar power) is dependent on the combined effect of load and wind power (or solar power) output.

In order to better show the economics of wind and solar power between the high and low coal prices, we calculate the economic value of wind and solar power generation based on the economic analysis of resource power generation under the market condition and the simulation results of the power market in Guangdong, as shown in **Table 3**.

As can be seen from **Table 3**, the annual average electricity price of solar power is higher than that of wind power. This is due to the positive correlation between solar power output and load, while the random output of wind power. In the case of light day, the peak of solar power output corresponds to the peak of the load, and the price of electricity is also at its peak. While the output of wind power is uncertain, and even in most cases the output is low. Therefore, the annual average electricity price of solar power is slightly higher than that of wind power. However, since the LCOE of solar power is significantly higher than wind power, under market-oriented condition, the net economic value of unit wind power is higher than that of solar power.

Table 3 also shows that the net value of unit energy of wind and solar power are both negative in the market-oriented scenario. Even if the wind and solar power are all consumed in priority dispatching, they are still uneconomic. Because in most cases, the clearing unit is coal-fired, and occasionally it is gas, in which the cost of wind and solar power are much higher than the clearing price. Indicating that the market benefits of wind and solar power generation are not enough to make up for their fixed costs. However, the utilization level of low marginal cost units has been greatly improved due to the economic dispatching principle adopted in the market-oriented scenario, in which the wind and solar curtailment can be eliminated approximately. According to the comparison between **Tables 1**, **3**, in the market-oriented scenario, the net value of unit energy of wind and solar power is obviously lower than that of the benchmark FIT scenario. With the advancement of retreat subsidy policy, the cost of renewable energy has dropped significantly, the wind and solar power present good economic result under the benchmark FIT scenario. Therefore, to ensure the better economics of renewable energy in the market-oriented scenario, it is essential to adjust policies and measures to promote the survival and development of renewable energy in the context of electricity market reform. One of alternative policy selection for China is to change from FIT to feed-in premium (FIP) gradually. In addition, there is a 0.01 CNY/ kWh difference in the net economic value of unit energy between the cases of high and low coal prices, indicating that the coal price level has a positive impact on the market returns of wind and solar power.

DISCUSSION

The Impact of Load Growth on the Economics of Renewable Energy Generation

With the economic growth of Guangdong Province, its power load will increase significantly. Based on this, this section carries out the following counterfactual simulation: assuming that the electricity load in Guangdong Province increased 10%, while the power installed capacity, wind and solar resources status and other unit commitment constraints remain unchanged. This paper evaluates the impact of load growth on the economics of renewable energy generation in Guangdong Province.

The scarcity pricing rules need to be considered in the counterfactual simulations. When the available power supply fails to meet the system load and 5% operational standby requirements, part of the load needed to be unloaded and an administrative pricing mechanism needed to be implemented. Since there is no scarcity pricing rule in China, it is assumed that the administrative price of 2 CNY/kWh will be implemented at the appointed time.

Based on the economic analysis of the resource generation under the market-oriented condition in part 2.2 and the results of electricity market simulation in Guangdong Province, the market value of wind and solar power generation is obtained in the counterfactual simulation that the electricity load is 10% higher than the current situation, as shown in **Table 4**.

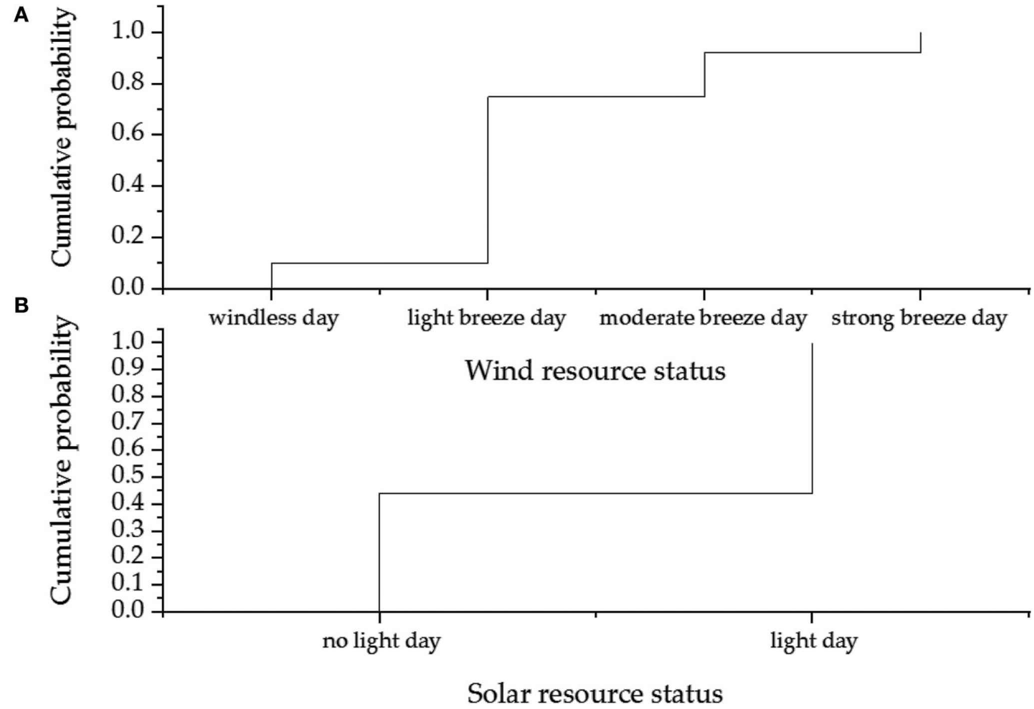

FIGURE 6 | Cumulative probability distribution map of wind and solar resources.

As can be seen from **Tables 3**, **4**, although the market value of wind and solar power is still negative when the electricity load increases 10%, there has been an improvement significantly. Specifically, the annual average electricity price of wind power increases about 0.1 CNY/ kWh, and the annual average electricity price of solar power increases about 0.28 CNY/ kWh. The annual average electricity price of solar power generation has increased by a large margin compared with wind power. The reason might due to the positive correlation between solar power output and load, which will be simulated and verified in section 3.2.6.3. This paper assumes that administrative pricing is implemented at the peak of power consumption, which emphasizes the scarcity value of peak electricity consumption, thus greatly increasing the market revenue of solar power generation.

According to the results of the counterfactual simulation, it can be foreseen that, with the electricity load growth and the rationalization of electricity scarcity pricing in Guangdong, the subsidies required for renewable energy development will decrease gradually and achieve "zero subsidy" possibly. That is to say, the economic feasibility of renewable energy generation projects can be guaranteed only by the complete market mechanism.

Correlation Between Power Generation Output and Load

This section examines the correlation between power output and load through Monte Carlo simulation. We assume a uniform distribution of wind and solar resources. Firstly, according to the proportion of strong breeze day, moderate breeze day, light breeze day and windless day in Guangdong Province, the cumulative probability distribution map of wind resource condition is obtained, which is shown in **Figure 6A**. The cumulative probability distribution of solar resource condition is shown in **Figure 6B** according to the proportion of light days and days without light.

Secondly, two random numbers with uniform distribution from 0 to 1 are generated separately as random values of the cumulative probability of wind and solar resources. Based on the cumulative probability distribution of wind and solar resources, the wind and solar resources of a certain day were determined. Thirdly, according to the typical daily output curve of wind and solar power generation, combined with the division standard of four seasons in Guangdong Province, the output of wind power and solar power generation is obtained 1 day. Finally, this paper repeats the above process until a year of wind and solar output are simulated. We further calculate the correlation coefficient between power output and load. Simulation results are shown in **Figures 7**, **8**.

Simulation results in **Figures 7**, **8** show that the correlation coefficient between wind power output and load is −0.05, and the correlation coefficient between solar power output and load is 0.29. Indicates that there is a slightly negative correlation between wind power output and load, while the solar power output is positively correlated with the load. This is due to the high output of wind power at night and the low output during the day. While the solar power generation reached the peak output at noon, which is consistent with the peak of the power load. Therefore, the peak shaving effect of solar energy has certain

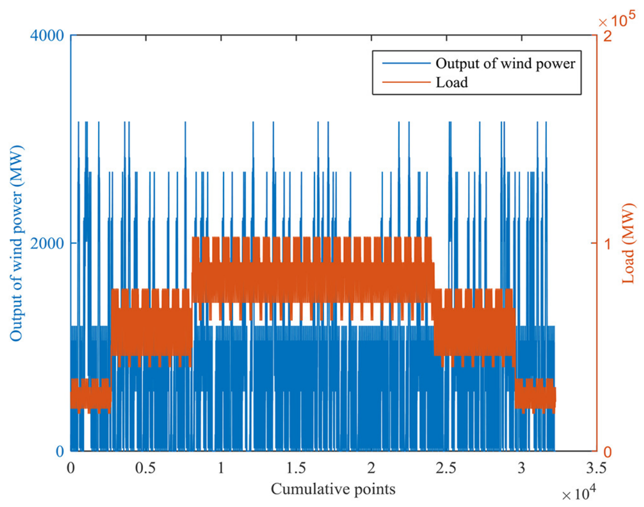

FIGURE 7 | Relationship between Wind Power output and load.

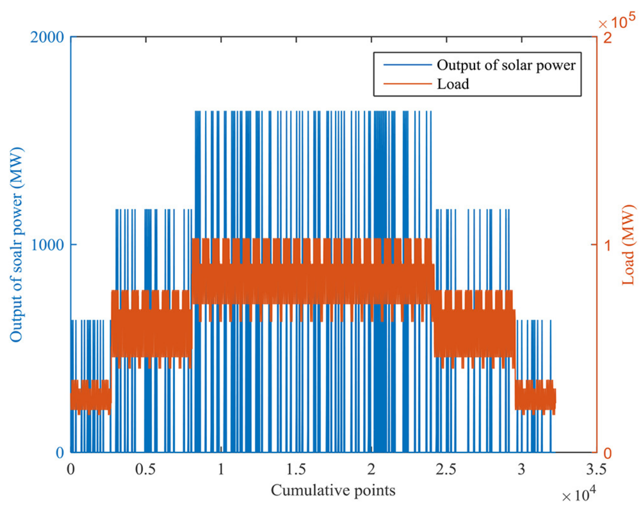

FIGURE 8 | Relationship between Solar Power output and load.

guiding significance for maintaining the safe and stable operation of the power system.

CONCLUSIONS AND POLICY IMPLICATIONS

This paper constructs an electricity market clearing model through the merit order method based on the short-term marginal cost increment principle and the generating unit commitment constraints. Further, the historical data in Guangdong is used to simulate different scenarios in a market-oriented situation to discuss the economics of wind and solar power.

The paper found that under market condition, it effectively promote accommodation of wind and solar energy, and significantly mitigate the serious problem of wind and solar curtailment. However, due to local conditions, coal power is cleared in most cases, and gas power is cleared in a few cases. The LCOE of renewable energy is much higher than the marginal cost of coal power. In such market clearing prices, renewable energy is unprofitable and uneconomic in market scenario compared to the benchmark FIT scenario. Hence, when the clearing price is settled, wind and solar power cannot recover the cost, resulting in the uneconomic results. This is due to the high cost of renewable energy on the one hand, and the lack of subsidy policy support under market conditions on the other hand. Therefore, the continued support policy is required to make renewable energy competitive in the energy market. On the one hand, it is of glorious significance to transfer FIT to FIP. For FIP, the fixed premium subsidies or floating premium subsidies should be implemented according to the technological development maturity. Specifically, it is recommended to adopt a fixed premium subsidy for renewable energy generation with relatively mature technologies such as solar photovoltaic and onshore wind power, while floating premium subsidies are recommended for emerging power generation technologies such as offshore wind power. On the other hand, measures needed to be taken to reduce renewable energy costs from technological and non-technological aspects. First, it is imperative to accelerate technological innovations of renewable energy due to its fundamental role in the long-term reduction of cost. Second, an inventory of non-technological costs should be formulated to regulate related operations and control total cost. The non-technological costs are the investment except the part into facilities, which is expected to be the key source of cost reduction for renewable energy in the future. It is necessary to clarify the management body, the division of responsibilities and related standards for non-technical costs, to provide a legal system for the development of renewable energy. Currently, the government is supposed to clearly define the category of the land occupied by wind farms or solar stations as soon as possible, along with the corresponding standards of land acquisition compensation and taxes, which should be strictly enforced under effective supervision.

In addition, the results show that the economics of renewable energy generation is closely related to the change of coal price and power load under the condition of marketization. Both the coal price and power load have a positive effect on the economics of renewable energy generation. The main reason is that the increase in coal price and load will raise the market's clearing price, which will enhance the economic efficiency of renewable energy generation. In particular, the influence of coal price on the economics of wind power is more significant than that of solar energy. The effect of power load on the economics of solar power is more significant compared to wind power.

DATA AVAILABILITY STATEMENT

All datasets generated for this study are included in the article/ **Supplementary Material**.

AUTHOR CONTRIBUTIONS

WL designed this research and wrote this paper. XZ and YW conducted the simulation. SF prepared data and revised this paper.

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REFERENCES

Abdelhady, S., Borello, D., and Shaban, A. (2018). Techno-economic assessment of biomass power plant fed with rice straw : sensitivity and parametric analysis of the performance and the LCOE. *Renew. Energy* 115, 1026–1034. doi: 10.1016/j.renene.2017.09.040

Aldersey-williams, J., Broadbent, I. D., and Strachan, P. A. (2019). Better estimates of LCOE from audited accounts – a new methodology with examples from United Kingdom o ff shore wind and CCGT. *Energy Policy* 128, 25–35. doi: 10.1016/j.enpol.2018.12.044

Bazilian, M., Onyeji, I., Liebreich, M., MacGill, I., Chase, J., Shah, J., et al. (2013). Re-considering the economics of photovoltaic power. *Renew. Energy* 53, 329–338. doi: 10.1016/j.renene.2012.11.029

Bhandari, R., and Stadler, I. (2009). Grid parity analysis of solar photovoltaic systems in Germany using experience curves. *Sol. Energy* 83, 1634–1644. doi: 10.1016/j.solener.2009.06.001

Branker, K. M., Pathak, J. M., and Pearce, J. M. (2011). A review of solar photovoltaic levelized cost of electricity. *Renew. Sustain. Energy Rev*. 15, 4470–4482. doi: 10.1016/j.rser.2011.07.104

Bruck, M., Sandborn, P., and Goudarzi, N. (2018). A levelized cost of energy (LCOE) model for wind farms that include power purchase agreements (PPAs). *Renew. Energy* 122, 131–139. doi: 10.1016/j.renene.2017.12.100

Cheng, C. (2018). Reform and renewables in China : the architecture of Yunnan's hydropower dominated electricity *market. Renew. Sustain. Energy Rev.* 94, 682–693. doi: 10.1016/j.rser.2018.06.033

Cheong, T. S., Li, V. J., and Shi, X. (2019). Regional disparity and convergence of electricity consumption in China: a distribution dynamics approach. *China Econ. Rev*. 58:101154. doi: 10.1016/j.chieco.2018.02.003

Geissmann, T. (2017). A probabilistic approach to the computation of the levelized cost of electricity. *Energy* 124, 372–381. doi: 10.1016/j.energy.2017.02.078

Geng, J., Xu, F., Yao, J., Gao, Z., Ding, Q, Yang, Z., et al. (2009). Performance analysis of mixed-integer programming based algorithm for security constrained unit commitment. *Autom. Electr. Power Syst*. 33, 24–27. doi: 10.7500/AEPS200906096

Ji, Q., and Zhang, D. (2019). How much does financial development contribute to renewable energy growth and upgrading of energy structure in China? *Energy Policy* 128, 114–124. doi: 10.1016/j.enpol.2018.12.047

Jia, L., Dayong, Z., Jing, C., and John, D. (2019). Legal systems, national governance and renewable energy investment: evidence from around the world. *Br. Manag. J*. 1–32. doi: 10.1111/1467-8551.12377

Lerch, M., De-prada-gil, M., Molins, C., and Benveniste, G. (2018). Sensitivity analysis on the levelized cost of energy for fl oating o ff shore wind farms. *Sustain. Energy Technol. Assessments* 30, 77–90. doi: 10.1016/j.seta.2018.09.005

Li, H., Yu, Y., Xie, Y., and Zhang, J. (2016). Could wind and PV energies achieve the grid parity in China until 2020? *Filomat* 30, 4173–4189. doi: 10.2298/FIL1615173L

Limmanee, A., Songtrai, S., and Udomdachanut, N. (2017). Degradation analysis of photovoltaic modules under tropical climatic conditions and its impacts on LCOE. *Renew. Energy* 102, 199–204. doi: 10.1016/j.renene.2016.10.052

Ling-zhi, R., Xin-gang, Y., Xin-xuan, Z., and Yu-zhuo, Z. (2018). Cost-benefit evolution for concentrated solar power in China. *J. Clean Prod.* 190, 471–482. doi: 10.1016/j.jclepro.2018.04.059

Liu, S., Yang, Q., Cai, H., Yan, M., Zhang, M., and Wu, D. (2019). Market reform of yunnan electricity in southwestern China : practice, challenges and implications. *Renew. Sustain. Energy Rev*. 113:109265. doi: 10.1016/j.rser.2019.109265

Liu, W., Zhang, X., and Feng, S. (2019). Does renewable energy policy work? Evidence from a panel data analysis. *Renew. Energy* 135, 635–642. doi: 10.1016/j.renene.2018.12.037

Lu, S.-D., Wang, M.-H., Kuo, M.-T., Tsou, M.-C., and Liao, R.-M. (2019). optimal unit commitment by considering high penetration of renewable energy and ramp rate of thermal units-A case study in Taiwan. *Appl. Sci*. 9:421. doi: 10.3390/app9030421

Luo, Y., Du, X., Yang, L., Xu, C., and Amjad, M. (2017). Impacts of solar multiple on the performance of direct steam generation solar power tower plant with integrated thermal storage. *Front. Energy* 11, 461–471. doi: 10.1007/s11708-017-0503-5

Mulligan, C. J., Bilen, C., Zhou, X., Belcher, W. J., and Dastoor, P. C. (2015). Levelised cost of electricity for organic photovoltaics. *Sol. Energy Mater. Sol. Cells* 133, 26–31. doi: 10.1016/j.solmat.2014.10.043

National Electric Power Industry Statistics Express[R] (2017). Beijing: China Electricity Council.

National Electricity Price Supervision Report[R] (2016). Beijing: National Energy Administration.

Ngan, H. W. (2010). Electricity regulation and electricity market reforms in China. *Energy Policy* 38, 2142–2148. doi: 10.1016/j.enpol.2009.06.044

Qiuna, C., Fushuan, W., Yusheng, X., and Jianbo, X. (2012). An SCUC-based optimization approach for power system dispatching with plug-in hybrid electric vehicles. *Autom. Electr. Power Syst.* 36, 38–46. doi: 10.3969/j.issn.1000-1026.2012.01.008

Renewable Energy Data Sheet[R] (2017). Beijing: National Energy Administration.

Said, M., EL-Shimy, M., and Abdelraheem, M. A. (2015). Photovoltaics energy: improved modeling and analysis of the levelized cost of energy (LCOE) and grid parity - Egypt case study. *Sustain. Energy Technol. Assessments* 9, 37–48. doi: 10.1016/j.seta.2014.11.003

Sarasa-Maestro, C., Dufo-López, R., and Bernal-Agustín, J. (2019). Evaluating the effect of financing costs on PV grid parity by applying a probabilistic methodology. *Appl. Sci*. 9:425. doi: 10.3390/app9030425

Su, J., Zhou, L., and Li, R. (2013). Cost-benefit analysis of distributed grid-connected photovoltaic power generation. *Zhongguo Dianji Gongcheng Xuebao/Proc. Chin. Soc. Electr. Eng.* 33, 50–57. doi: 10.13334/j.0258-8013.pcsee.2013.34.001

Tran, T. T., and Smith, A. D. (2018). Incorporating performance-based global sensitivity and uncertainty analysis into LCOE calculations for emerging renewable energy technologies. *Appl. Energy* 216, 157–171. doi: 10.1016/j.apenergy.2018.02.024

Ueckerdt, F., Hirth, L., Luderer, G., and Edenhofer, O. (2013). System LCOE: what are the costs of variable renewables? *Energy* 63, 61–75. doi: 10.1016/j.energy.2013.10.072

Wang, Q., and Chen, X. (2012). China's electricity market-oriented reform : from an absolute to a relative monopoly. *Energy Policy* 51, 143–148. doi: 10.1016/j.enpol.2012.08.039

Wang, Y., Zhang, D., Ji, Q., and Shi, X. (2020). Regional renewable energy development in China: a multidimensional assessment. *Renew. Sustain. Energy Rev*. 124:109797. doi: 10.1016/j.rser.2020.109797

Yu, Z. (2020). Beyond the state / market dichotomy : institutional innovations in China's electricity industry reform. *J. Environ. Manage*. 264:110306. doi: 10.1016/j.jenvman.2020.110306

Zang, G., Jia, J., Tejasvi, S., Ratner, A., and Silva, E. (2018). International journal of greenhouse gas control techno-economic comparative analysis of biomass integrated gasi fi cation combined cycles with and without CO 2 capture. *Int. J. Greenh. Gas Control* 78, 73–84. doi: 10.1016/j.ijggc.2018.07.023

Zeng, M., Yang, Y., Wang, L., and Sun, J. (2016). The power industry reform in China 2015 : policies, evaluations and solutions. *Renew. Sustain. Energy Rev*. 57, 94–110. doi: 10.1016/j.rser.2015.12.203

Zhang, S., Andrews-speed, P., and Li, S. (2018). To what extent will China's ongoing electricity market reforms assist the integration of renewable energy. *Energy Policy* 114, 165–172. doi: 10.1016/j.enpol.2017.12.002

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frontiers in Energy Research

ORIGINAL RESEARCH
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The Evolution of Energy Market and Energy Usage: An Application of the Distribution Dynamics Analysis

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There has been a general consensus that greenhouse gas emission is closely related with energy consumption. A systematic and complete investigation of the state and evolution of the energy consumption structure (ECS) of global countries is of great importance to figure out the different positions, responsibilities and missions of each country in the global climate change cooperation. Furthermore, such task is of great policy implications to generate a global reference system for different countries, guiding each one to improve, update and optimize its ECS. However, most existing studies regarding the world ECS neglects the evolutionary trends of ECS and their distributional positions in the global picture. Noting the paucity of studies of convergence in ECS across the world countries, this paper aims to explore the evolution of ECS at the national level and the global level to sharpen understandings on the state of global energy transition by employing the distribution dynamics approach. Three major energy sources were investigated, including coal, oil, and natural gas. The dataset was collected from the Global Trade Analysis Project database whose latest version covers the period from 2004 to 2014. In the second part of the analysis, the dataset is further divided into different income groups so as to evaluate the impacts of income on the distribution dynamics. A distribution dynamics approach is used to analyze the data of almost all the countries and regions in the world. The visualization of global ECS provides an insightful and novel understanding on the underlying trends. This study fills an important gap in the literature by providing several important findings which are not available from traditional econometric techniques. First, many countries would reduce their relative coal and oil consumption in the future but oil would remain to be the most common form of energy source. However, great variability can be observed for the distribution of gas consumption. Second, from the ergodic distribution of the gas market, it can be observed convergence clubs may emerge in the long run as the countries would congregate in certain clusters with similar levels of gas consumption. These findings call for further research and policy planning for the development of gas industry. Third, the distribution dynamics is very different for the four income groups (according to the World Bank), and so it is necessary to take a country's income level into consideration in formulating energy policies. Fourth, our findings reflect the issue of global inequality amongst the countries as the energy consumption of the poor countries are much lower than the

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other countries. Fifth, oil is deemed to be the most popular form of energy sources for the upper-middle-income and high-income countries, while coal is not a preferred energy source for the affluent countries, thereby suggesting the need to provide aid to the poor countries for mitigating the use of coal. Finally, gas consumption seems to have a very high variability and the countries can have very different consumption patterns of gas even if they belong to the same income category, implying that country-specific policies should be formulated for the development of the gas industry. Furthermore, it is observed that for the lower-middle-income and upper-middle-income countries, the big consumers of gas tend to increase their gas consumption further. The findings derived from this study may prove valuable for the policy makers in formulating energy policies for adapting to market changes, and may assist the design of international aid program on mitigating carbon emissions for the poor countries.

Keywords: energy consumption structure (ECS), transitional dynamics approach, global energy transition, transitional dynamics, climate change

INTRODUCTION

Against the backdrop of global warming and the global commitment on mitigating the adverse impacts of climate change, promoting energy consumption transition toward clean and renewable alternatives is an imperative mission. The energy consumption structure (ECS) is defined as the composition and proportion of each type of energy consumed (such as coal, oil, natural gas, nuclear power, and other renewable energy) relative to the total energy consumption (Hu et al., 2018; Yang et al., 2018). In the current global ECS, coal and oil are regarded as the top culprit of carbon emission and other air pollutants (Ozturk and Yuksel, 2016). Undoubtedly, the massive use of coal and oil has led to relentless growth of carbon dioxide emissions in developing countries. Additional environmental challenges on sustainable economic growth has also been brought about (Kahia et al., 2016; Li et al., 2018; Wei et al., 2019a,b). In addition, renewable energy sources generate nearly zero emission in the consumption process, which is the key to promote ECS optimization (Çelikbilek and Tüysüz, 2016). However, the widespread use of renewable energy sources has been impeded by the immaturity of technology and economical unaffordability (Chen et al., 2019). On the contrary, natural gas is considered as clean and transitional energy with the advantages of high unit heat value, low exhaust pollution and good economy. Before the advent of economically viable and technological reliable renewable energy sources, expanding the natural gas consumption is a feasible roadmap to promote the ECS toward a green transition.

While there have been substantial literatures exploring the contributing factors behind energy consumption globally, little attention has been paid on whether differences in ECS among different countries vanish over time, and if convergence can be realized. Convergence research is important in terms of mapping out the current condition and in the formulation of regional policies so as to rationalize the energy structure (Herrerias, 2012). Nevertheless, the existing literature cannot provide policy makers with country-level estimation on the ongoing dynamics of the global energy consumption market. In the absence of this material, this study aims to fill the gap in the literature by examining the unfolding energy consumption market dynamics through performing country-level transitional dynamics analysis. This paper evaluates the evolution and the trend of energy consumption structure, but focusing on three major energy sources i.e., oil, coal, and gas. The data used in the study are based on the Global Trade Analysis Project database which is compiled by Purdue University. The dataset is made up of almost all the countries and regions in the world spanning the period from 2004 to 2014. Distribution dynamics approach is used to explore the evolution and dynamics changes of each country with the distributions in different regional groups. The methodological and practical advantages of the research method are summarized as follows: (1) The estimation on the distribution of ECS among all the countries can help commensurate intergovernmental cooperation plan by prioritizing the energy and subsidy policies across the countries. (2) The research outcome can depict the future development trend of national ECS, thereby guiding the government to allocate capital and technical resources in a more efficient way to promote energy transition. (3) The organizations for climate change cooperation can encourage and prioritize their investment in these countries and regions, and improve knowledge diffusion, particularly for the region with outdated and imbalanced ECS.

The contribution of this study lies in the following three aspects. First, to the best of the authors' knowledge, this is the most comprehensive study ever performed for investigating the evolution and trend of global energy transition by using distribution analysis. Stochastic kernel analyses are performed for the world in order to draw a complete and an in-depth picture of the evolution and convergence of energy transition in the world. Second, distribution dynamics analyses are conducted individually for each of the three main markets, namely, the coal, oil, and gas markets, so as to provide a comprehensive analysis on the overall energy market in the world. Finally, this paper also provides an in-depth investigation on the impact of income on the distribution dynamics of the countries at the global level.

The findings foster better understanding of dynamics of ongoing energy transition and provide policy makers relevant reference for formulation of pertinent energy policies in alleviating climate change impacts.

The rest of the paper is organized as follows. In section Background and Literature Review, background information and literature review of the convergence concept are provided. In sections Data and Method, the research methods and data are introduced. Section Results is a detailed discussion of empirical results. Section Conclusions concludes the research findings and policy recommendations.

BACKGROUND AND LITERATURE REVIEW

The optimization of ECS is beneficial to promoting energy security and environmental conservation. Firstly, the improvement in ECS contributes to the energy security (Augutis et al., 2015; Yang et al., 2018). Optimal ECS can be considered as a mix of different types of energy to minimize the risks caused by the future uncertainties in the energy market (Thangavelu et al., 2015). Ozturk and Yuksel (2016) argued that some renewable and clean energy sources are centrally important to ensure safe and sustainable energy supply. Therefore, improvement in ECS is imperative to guarantee energy security and support economic development (Liang and Zhang, 2009). Secondly, the optimization and green transition of ECS is centrally important to curb global warming and realize sustainable economic development. ECS is also one of the most important monitoring and measurable indicators to evaluate the technological or affluence level of a region or nation (Hu et al., 2018). Besides excessive carbon dioxide emissions, the fossil fuel-based ECS leads to some environment issues such as frequent hazy weather, acid rains, etc. in developing countries. Actually, ECS is rooted in the energy endowment and accessibility condition of a nation (Yang et al., 2018). Since energy sources endowments are diverse, ECS shows varied patterns in different countries. For example, the Middle East countries have natural advantages of rich oil and natural gas endowments, hence their ECSs mainly rely on these two types of fuels. For China and India, the top two developing countries situated in the Asia Pacific regions, they have extremely high proportion of coal in their ECSs, due to their huge coal reserves. On the other hand, ECS is highly related to technological and affluent level of a country (Wu et al., 2018b). In many post-industrial and developed countries, their ECS are transiting rapidly toward low-carbon, high-output structures. The energy-related technologies including clean and renewable energy mix and the end processing technologies of carbon emission are advancing remarkably. For another example, the growing of renewable energies in the energy mix and trade, such as the wide commercialization of shale gas and globalization of liquefied natural gas (LNG) driven by the technological progress is an impetus for energy transition in these countries (Wu et al., 2018b), contributing to a high share of gas in their ECSs. These countries are proactively diversifying and optimizing their ECS (Hu et al., 2018). Therefore, evolutional analyses on the ECS of the global countries is important not only for guiding a country to figure out its ECS, but also for developing an analytic framework within which countries can make cross-sectional comparisons and learn from the cohorts with similar conditions but superior ECS.

Figure 1 shows the historical evolution of energy mix consumption including the consumption volumes of oil, coal, gas and renewable alternatives (e.g., nuclear power, hydropower, solar power, and wind power) and the proportions of fossil energy consumption and non-fossil consumption during 1965 to 2018. According to British Petroleum (BP) statistical data (BP,

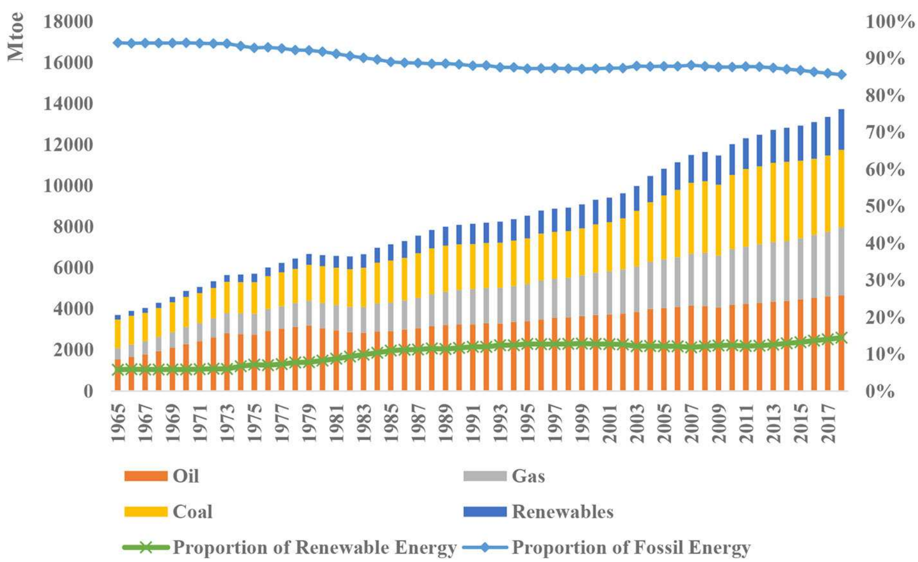

FIGURE 1 | Evolution of global energy mix consumption and ESC structure Note: (Left Axis refer to the unit of Mtoe; Right Axis refer to the unit of percentage) Source: BP (2019).

2019), the total global energy consumption gradually increased from 3699.3 Mtoe in 1965 to 13724.2 in 2018, with an annual growth rate of 6% and a total increment of 10023.9 Mtoe. In terms of ECS, the proportion of global fossil energy consumption decreased steadily from 94.2% in 1965 to 85.6% in 2018. In general, the improvement of ECS is sluggish and less optimistic than expected, showing a mild reduction in the fossil energy proportion by 10% in the past 53 years. The percentage of renewable energy increased from <5% in 1965 to 14% in 2018. Looking into the internal structure of fossil energy consumption, the proportion of oil consumption ranked the top, fluctuating up and down around the level of 40%. In the 1970s, the fluctuation was significant and the proportion of oil reached the peak of more than 50%. Since 1980s, the overall proportion of oil use tends to decline steadily. The proportion of coal consumption varies from 25 to 40%. The proportion of natural gas consumption, as a clean and transitional energy, has been increased year by year, from 14.7% in 1965 to 24.1% in 2018. In views of different countries and regions, the ECS varies greatly. For example, during 2001 to 2018 the average proportion of coal in national primary energy consumption of China has been 68.7% (BP, 2019). This share is substantially higher than that of the Organization for Economic Co-operation and Development (OECD) countries, 19.8% and three of other four BRICS countries, 6.0% in Brazil, 14.2% in Russia, 54.6% in India, and 72.2% in South Africa over the same period. In general, **Figure 1** shows that the global ECS has experienced a gradual improvement. However, different countries are of varied ECS evolution patterns due to different resources and technology conditions. An in-depth investigation on the national level is imperatively needed to understand the distributional patterns of ECS, i.e., whether differences in the ECS is diminishing over time and if convergence can be achieved.

Turning to the literature, there are two major strands of literatures related to this study: (1) Convergence concept (Section The Concept of Convergence), and (2) Related literatures on energy consumption and ECS (Section Related Literatures on Energy Consumption and ECS).

The Concept of Convergence

The concept of convergence, originating from the economic growth theories (Herrerias, 2012), has been widely introduced to various research domains such as energy and environmental economics study (Cheong et al., 2016, 2019). A growing number of studies has attempted to use the convergence concept to understand energy problems and phenomena. For example, Sheng and Shi (2013) explored the issue of how the ongoing integration of regional or global energy market contributes to the economic growth. The estimation results confirmed that a more integrated energy market has a positive effect on the convergence of income for a group of countries, contributing to equitable growth. By integrating the accumulation of physical capital and energy consumption among 50 states of the U.S, Burnett and Madariaga (2017) extended a neoclassical growth model to explore the policy implications for convergence in economic growth and energy intensity. The empirical findings show that energy intensity of the entire panel of 50 states has a convergence pattern over the past four decades. By means of difference in difference estimator (DID) on a panel data for 30 developing and 21 industrialized countries, Jakob et al. (2012) explored the dynamic patterns of energy use in the process of economic development over the period 1971–2005. Estimation results show that there is almost a one-to-one relationship between economic convergence and convergence of energy use patterns for developing countries. The findings indicate that the economic growth of developing countries has recently caught up the global average level and their energy use patterns are changing toward a more energy- or carbon-intensive than those in industrialized ones. Some scholars use this concept to explore various energy economics research themes, including energy intensity convergence, electricity consumption (Cheong et al., 2016, 2019), per capita energy consumption convergence (Fallahi and Voia, 2015; Payne et al., 2017) and energy market convergence in terms of prices (Ma and Oxley, 2012; Sheng and Shi, 2013).

In view of these previous studies, we would like to investigate if the level of income exerts impact on the convergence of energy consumption amongst countries. So our hypothesis is:

Hypothesis 1: *The convergence pattern of energy consumption is not the same for different income groups.*

We will investigate this issue by separating the countries into different income groups. Distribution dynamics analysis will then be conducted separately for each group, so that we can compare the convergence patterns of each group and know if they are the same.

Related Literatures on Energy Consumption and ECS

Compared with related topics such as convergence in per capita energy consumption (Mohammadi and Ram, 2012; Payne et al., 2017), and environment and growth (Le Pen and Sévi, 2010; Herrerias, 2012), the question of whether ESC converges across countries over time or not is a salient topic that has not been well-explored. For example, related studies on the topics of convergence in per capita energy use have emerged recently. Payne et al. (2017) explored the convergence properties of per capita renewable energy consumption across states of the U.S. and found that there is stochastic convergence of per capita renewable energy consumption for a majority of U.S. states. Combining parametric and non-parametric approaches, Mohammadi and Ram (2012) explored if per-capita energy consumption had converged across the states of the U.S. over the period 1970–2013. The estimation results support the lack of convergence in per-capita energy consumption across states of the U.S. and attribute the contributing factors to the significant variations in structural factors. Besides the related studies in the U.S., some study focused on the convergence in per capita energy use among OECD countries. However, there are no consistent findings. Using newly developed LM and RALS-LM (residual augmented least squares regression), Meng et al. (2013) investigated the convergence in per capita energy use among 25 OECD countries during 1960 to 2010. Their empirical findings provided a significant support for convergences existing among

OECD countries. However, by means of different methods and same dataset with different timespan, Fallahi and Voia (2015) offered different findings. By constructing subsampling confidence intervals, they explored the convergence patterns in per capita energy consumption among 25 OECD countries over the period 1960–2012. Their findings reveal that the convergent pattern only exists in a limited number of countries, while other countries show either persistent or divergent patterns.

There has been a limited number of studies focusing on the evolution of ECS particularly at the regional or global level. By means of traditional time series approaches including cointegration tests and Granger causality tests, Feng et al. (2009) found that there is a temporal dynamic and casual relationships among ECS, economy structure and energy intensity during 1980–2006 in China. Proposing a bottom-up accounting model and constructing a long-range energy alternative planning energy modeling tool, Dong et al. (2017) projected the future trajectory of Chinese ECS evolution under multiple policies scenarios. Their research outcomes suggest that natural gas and renewables could develop into important alternatives to traditional fossil-based energy (coal and oil) and provide much more potentials. Lawrence et al. (2013) focused on the issue of the global probability distribution of energy consumption per capita around the world. Their research findings revealed that the Gini coefficient, decreased from 0.66 in 1980 to 0.55 in 2010, indicating a decrease in inequality. Using entropy information approach, Zhang et al. (2011) investigated the changes of China's ECS and found that Chinese ECS only experience slow and limited improvement. However, the links between ECS of different countries have been largely ignored in existing literature, and the evolution of the global ECS requires further investigation.

Given that gas is better than oil and coal in terms of greenhouse gas emission, we would like to investigate if the countries will change their ECS by increasing the use of gas, and reducing the consumption of oil and coal. So our second hypothesis is:

Hypothesis 2: *The consumption of oil and coal will be reduced, and the use of gas will be increased in the future.*

We will investigate this issue by conducting distribution dynamics analysis for the three energy sectors separately by employing ergodic distribution and mobility probability plots, so that we can understand future development of these three markets.

Summary of the Literature Review

A summary of the literature review is provided in **Table 1**. It can be observed that there has been limited research concerns on the dynamic aspects of ECS. Although the strand of parametric method-based study generates a summary of the statistic of interest, it neglects the important information on multimodal distribution, which may containment data and lead to misleading results (Quah, 1990, 1997). In addition, the traditional method cannot derive insightful understandings on the integral shape of the distribution and its dynamics (Quah, 1990, 1997).

TABLE 1 | Major recent findings of relevant literature in this area.

Researchers	Main findings
Sheng and Shi (2013)	A more integrated energy market leads to convergence of income, contributing to equitable growth
Burnett and Madariaga (2017)	There is a convergence in energy intensity over the past four decades for 50 U.S. states
Jakob et al. (2012)	There is almost a one-to-one relationship between economic convergence and convergence of energy use for developing countries
Payne et al. (2017)	There is stochastic convergence of per capita renewable energy consumption for a majority of U.S. states
Mohammadi and Ram (2012)	No convergence in per-capita energy consumption across states of the U.S. can be observed for the period 1970–2013
Meng et al. (2013)	Convergences in per capita energy use can be found among OECD countries
Fallahi and Voia (2015)	Convergent pattern only exists in a limited number of countries, while other countries show either persistent or divergent patterns
Feng et al. (2009)	There are temporal dynamic and casual relationships among ECS, economy structure and energy intensity during 1980-2006 in China
Dong et al. (2017)	Natural gas and renewables could develop into important alternatives to traditional fossil-based energy
Lawrence et al. (2013)	There is a decrease in global inequality in energy consumption per capita from 1980 to 2010
Zhang et al. (2011)	Chinese ECS only experience slow and limited improvement

To fill the gaps, this study applies the distribution dynamics approach. This method provides a lens to the transitional dynamics of ECS across time. This information will improve the understanding of intra-distribution energies across countries by global energy trade. The research findings can provide complete and insightful information on each spatial grouping by uncovering their distinguishing features in terms of ECS. Moreover, this method is powerful to project the shape of the distribution of ECS levels in the long term, which provides rich reference for the improvement of energy policy.

DATA

The preliminary data were extracted from the Global Trade Analysis Project 10 database which is compiled by Purdue University. This is a Computable General Equilibrium model database which covers the years of 2004, 2007, 2011, and 2014. The database has 65 sectors and 141 countries and regions, and it covers almost all the important economies in the world. It is worth noting that the data are available for every year, so that a panel dataset which has no gap can be compiled; and this is a prerequisite for the distribution dynamics analysis which will be employed later in this study.

The main focus of this study is on energy market, therefore, the data of the coal, oil, and gas sectors were extracted from the database for further processing. For each year, total consumption values in the world (which are made up of consumption as intermediate goods and final consumption) of the three sectors were computed. These values were divided by total population in the globe to derive the average world consumption per capita for each sector. After that, total consumption per capita of each sector for each country/region was then divided by the average world consumption per capita of each sector in that particular year to compute the values of relative consumption per capita for the three sectors separately.

The data were used to conduct distribution dynamics analysis for each sector individually so as to provide an overview of the three markets. However, in order to understand the impacts of income level on the distributions of consumption in greater detail, the preliminary dataset was then further divided into smaller datasets according to the income level of the countries. The classification is according to the definition, proposed by the World Bank, which divides countries into four groups, namely, low, lower-middle, upper-middle, and high-income groups. The idea is to conduct distribution dynamics analysis on each of these smaller datasets so that one can fully understand the evolutionary trend within these countries. The analytical results derived from these smaller datasets can offer pertinent policy implications in formulating energy policies for the countries in a more specific way which takes into consideration the income level, and thus the level of economic development of each country. The results can also provide important information on the market changes of the three sectors, so that international co-operation can be properly recommended in mitigating carbon emissions. Please refer to **Table 2** for a summary of the sources of data used.

METHOD

The analysis is based on the transitional dynamics of the relative per capita consumption value of the three sectors in all the countries and regions compiled from the database. The distribution dynamics approach was first proposed by Quah (1993). This is a very useful tool for investigating evolution of distribution across time. Although time series econometrics is commonly used in forecasting, it can only provide information on several important characteristics of a distribution as it can only prepare a forecast of the dependent variable for the future. Given that distribution is a two-dimensional entity, it is impossible to prepare a forecast of the overall shape of the future distribution by relying on time series econometrics. Therefore, one can rely on distribution dynamics analysis which helps generate the shape of future distributions easily. Moreover, this approach can even offer the ergodic distribution which is the steady-state distribution for the future. By employing this analytical technique, one can gain a complete understanding of the underlying trend and also future evolution of the three markets. This analysis not only can fill an important gap in the literature, but also complement the findings from econometrics.

Distribution dynamics analysis can be broadly divided into two kinds, namely, the traditional Markov transition matrix analysis and the stochastic kernel approach. The former has the thorny issue of demarcation of the state which is associated with the selection of grid values. It is notable that this is an arbitrary process and the analytical results are dependent on the selection of grid line. On the contrary, the latter is deemed to be a much better tool since it can circumvent the issue of demarcation, therefore, the stochastic kernel approach is used in this study.

The bivariate kernel estimator is defined as:

$$\hat{f}\left(x,y\right) = \frac{1}{n\,h_1 h_2} \sum\nolimits_{i=1}^{n} K(\frac{x - X_{i,t}}{h_1}, \frac{y - X_{i,t+1}}{h_2}) \qquad (1)$$

where h_1 and h_2 are the bandwidths which are calculated based on the approach suggested by Silverman (1986), K is the normal density function, n is the number of observations, x is a variable representing the relative per capita consumption value of one of the three markets of a country/region at time t, y is a variable representing the relative per capita consumption value of one of the three markets of that country at time t+1, $X_{i,t}$ is an observed value of relative per capita consumption value at time t, and $X_{i,t+1}$ is the observed value of relative per capita consumption at time t+1.

In order to take the sparseness of the data into consideration, an adaptive kernel with flexible bandwidth is employed (Silverman, 1986). Assuming that the process is first order and time invariant, and the distribution at time $t+\tau$ depends on t only and not on any previous distributions, then the relationship between the distributions at time t and time $t+\tau$ is shown as:

$$f_{t+\tau}\left(z\right) = \int_0^{\infty} g_\tau\left(z|x\right) f_t\left(x\right) dx \qquad (2)$$

where $f_{t+\tau}(z)$ is the τ-period-ahead density function of z conditional on x, $g_\tau(z|x)$ is the transition probability kernel which maps the distribution from time t to $t+\tau$, whilst $f_t(x)$ is the kernel density function of the relative per capita consumption distribution of one of the three markets at time t.

TABLE 2 | Sources of data.

Data	Sources
Coal market	Data compiled from sector "coa" of the Global Trade Analysis Project 10 database
Oil market	Data compiled from sector "oil" of the Global Trade Analysis Project 10 database
Gas market	Data compiled from sector "gas" of the Global Trade Analysis Project 10 database
Population	Data compiled from the Global Trade Analysis Project 10 database
Low-income group	Classification of income group defined by the World Bank
Lower-middle-income group	Classification of income group defined by the World Bank
Upper-middle-income group	Classification of income group defined by the World Bank
High-income group	Classification of income group defined by the World Bank

The ergodic density function, given that it exists, can then be calculated by:

$$f_{\infty}(z) = \int_{0}^{\infty} g_{\tau}(z|x) f_{\infty}(x)\, dx \tag{3}$$

where $f_{\infty}(z)$ is the ergodic density function when τ is infinite. This is the steady-state equilibrium distribution in the long run.

Cheong and Wu (2018) developed the mobility probability plot (MPP) for interpreting mobility probability. This is an enhancement of the traditional tools of display of the stochastic kernel approach which are mainly based on the three-dimensional plots and the contour maps. Following the invention of this new tool, the MPP has been employed to analyze transitional dynamics in various research areas, such as industrial output (Cheong and Wu, 2018), energy markets (Wu et al., 2018a; Cheong et al., 2019), and also carbon dioxide emissions (Cheong et al., 2016; Wu et al., 2016).

The MPP can be constructed by computing $p(x)$ which is calculated as the net upward mobility probability which can be represented by the following relationship:

$$p(x) = \int_{x}^{\infty} g_{\tau}(z|x)\, dz - \int_{0}^{x} g_{\tau}(z|x)\, dz \tag{4}$$

The MPP shows the net upward mobility probability against the relative per capita consumption. It is worth noting that a positive value implies that the country will have a net probability of moving upwards in the future; whereas a negative value of net upward mobility probability implies that the country has a net probability of moving downwards within the distribution. Interested readers can refer to Cheong and Wu (2018) for technical details.

The scheme of this study is to calculate the relative per capita consumption of the three energy products for each country, followed by distribution dynamics analysis. Distribution dynamics analysis will be conducted for each market separately. Three-dimensional plot and contour map will be constructed to reveal the trend in the data, while ergodic distribution and MPP will be computed for uncovering the steady-state equilibrium and the movement of the countries within the distribution. After that, the whole dataset will be divided into smaller datasets according to the levels of income of the countries. Distribution dynamics analysis will then be conducted for each group of countries separately. However, in order to save space, only ergodic distribution and MPP will be employed in the analysis.

RESULTS

The analysis results are shown below in two different sections. The first one depicts the transitional dynamics of the three sectors, while the second one illustrates the impacts of income levels on the distribution dynamics.

Overview of the Three Energy Markets and Its Distribution Dynamics

Although many countries have invested a lot of resources in research and development of new energy source and progress have been made; however, the most important energy sources nowadays are still coal, oil, and gas. It is thus important to understand the trend of these three energy markets, so that one can have a better understanding of the future demand in each sector. Distribution dynamics analysis is a suitable tool for this task as it can reveal the distributions of consumption of the three markets in great details.

In this section, the coal market will be discussed first, and the value used in this sub-section is the relative consumption per capita for coal; the second sub-section covers the relative consumption per capita for oil, and the last sub-section is based on the relative consumption per capita for gas.

The Coal Market

The three-dimensional plot of the coal market is shown in **Figure 2A**, while **Figure 2B** is the contour map. It can be observed from both figures that there is a very high peak situated in the region with a relative per capita coal consumption value below 0.2. Since the value of one represents the consumption level which is equal to the world average; therefore, a value much lower than 0.2 suggest that many countries just do not rely on coal but other forms of energy resources in the study period.

In order to provide a forecast into the future, one cannot rely on the three-dimensional plot and contour map alone. One needs to employ the ergodic distribution and the MPP too. **Figure 3** shows the ergodic distribution and the MPP of the coal market. The ergodic distribution shown in **Figure 3A** is a heavily right-skewed one with a peak situated around a value of relative per capita coal consumption of 0.1. Since the ergodic distribution is the steady-state equilibrium distribution of the coal market, while the value of the world average is one, a peak situated at a value of 0.1 suggests that the consumption of coal is very low for a lot of the countries if the distribution dynamics remains unchanged. This is an encouraging finding as carbon dioxide emission per unit of energy output is the highest for the burning of coal, followed by oil, while gas has the lowest emission in the burning process amongst the three energy sources.

Figure 3B shows the MPP of the coal market, one can observe that the MPP crosses the horizontal axis at a relative per capita coal consumption value of 0.1. In fact, it is the same value of the peak of the ergodic distribution. It is noteworthy that this is not a coincidence since a positive value of MPP suggests that the country has a higher probability in increasing the relative consumption of coal, while a negative value of MPP suggests that it has a higher tendency in reducing coal consumption; therefore, countries would gather around the value where the MPP crosses the horizontal axis, thereby creating the peak of the ergodic distribution. Hence the MPP is a very useful tool in analyzing distribution dynamics as it can reveal the trend behind the scene and the mechanics behind the changes in the distribution of consumption.

The MPP reaches the lowest point with a relative per capita coal consumption value of 0.9, as the average world consumption level is one, it means that for a country with coal consumption close to the world average level, it has a very high probability to decrease in its consumption in the future. In fact, it can be observed that the MPP lies under the horizontal axis from 0.14

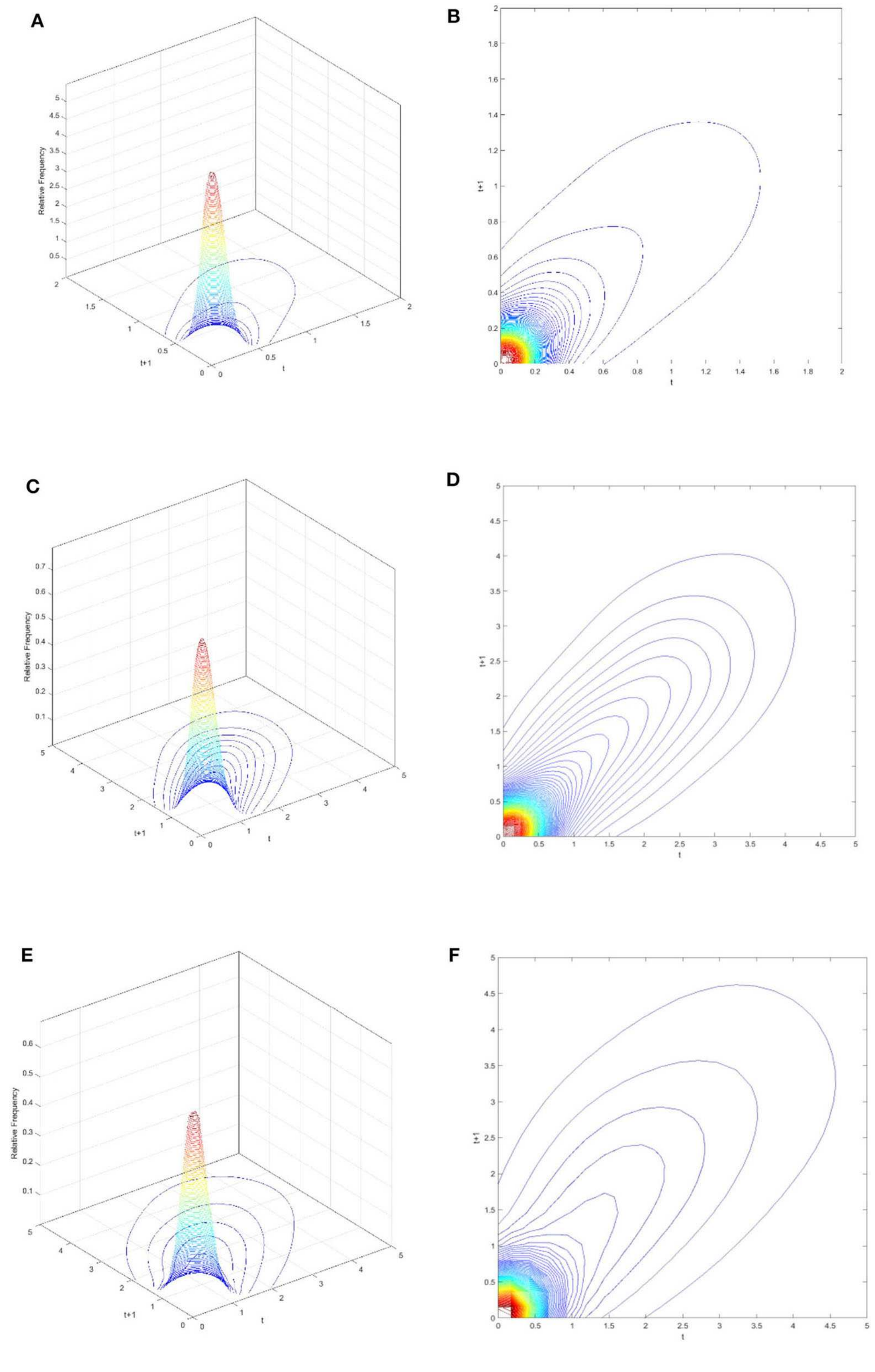

FIGURE 2 | Three-dimensional plots and contour maps of the three markets. Note: **(A,B)** are for the coal market. **(C,D)** are for the oil market. **(E,F)** are for the gas market. For figures **(A,C)**, and **(E)**, the right axis represents time t, left axis represents time t+1, and height represents kernel density. For figures **(B,D,F)**, horizontal axis represents time t, vertical axis represents time t+1. Source: Authors' calculation.

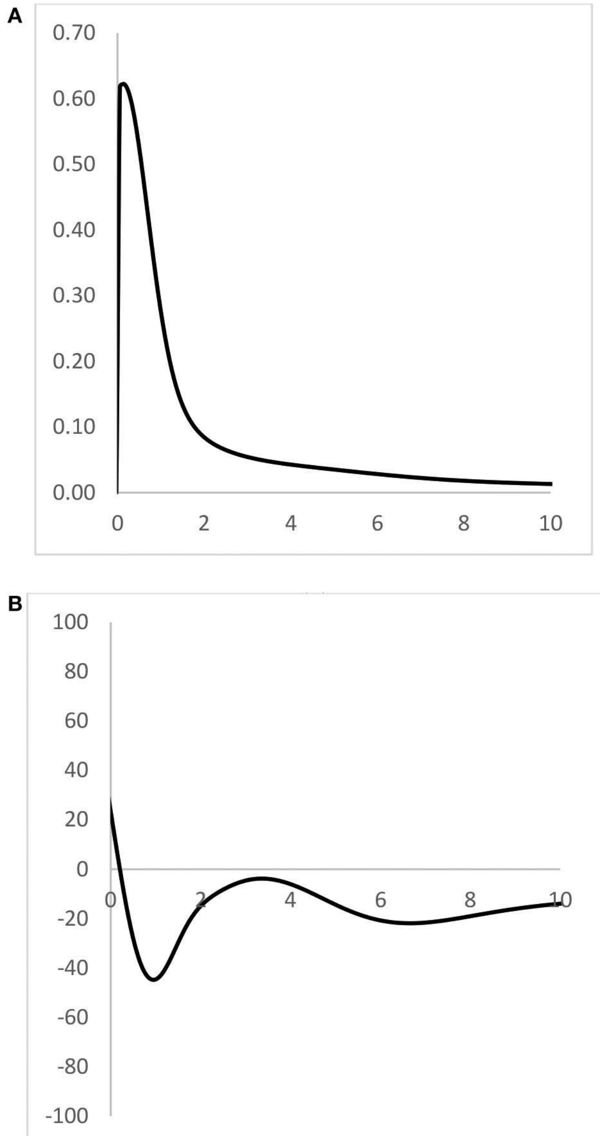

FIGURE 3 | Ergodic distribution and MPP of the coal market for all countries. Note: For **(A)**, horizontal axis represents relative per capita consumption, vertical axis represents proportion. For **(B)**, horizontal axis represents relative per capita consumption, vertical axis represents MPP. Source: Authors' calculation.

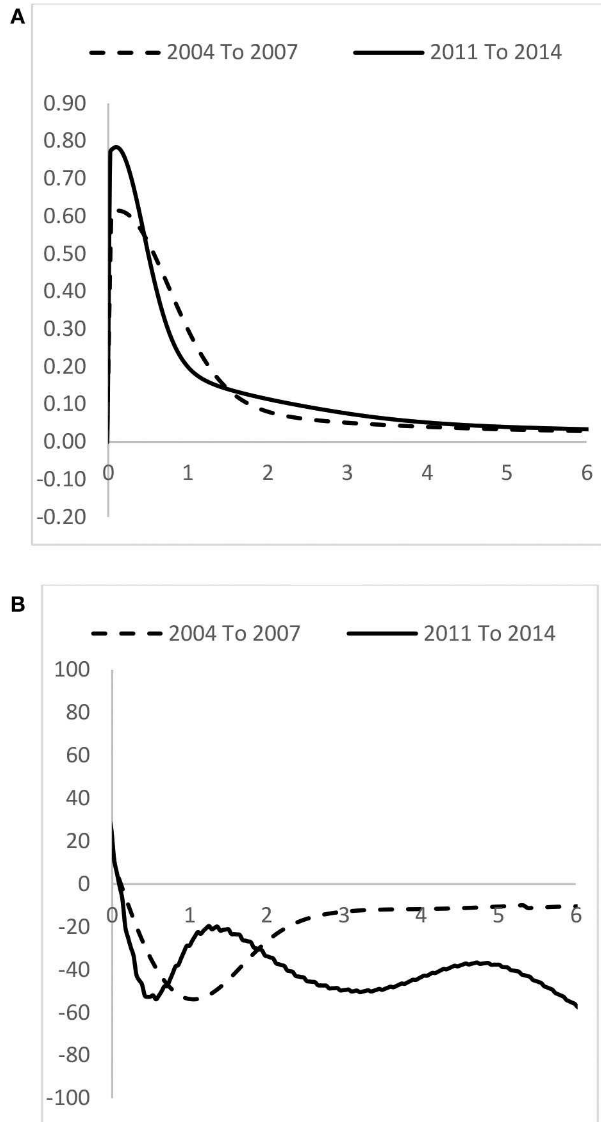

FIGURE 4 | Comparison of the ergodic distributions and MPPs of the coal market for all countries across time. Note: For **(A)**, horizontal axis represents relative per capita consumption, vertical axis represents proportion. For **(B)**, horizontal axis represents relative per capita consumption, vertical axis represents MPP. Source: Authors' calculation.

onwards; it is a good sign as it suggests that many countries would tend to reduce their coal usage in the future. However, it is alarming to note that for the countries with a relative per capita coal consumption value around 3.8, they are very close to the horizontal axis, implying that they have a higher probability of increasing their coal consumption than the other countries even though the net probability is negative.

In order to observe the changes across time, the dataset was divided according to different time periods, so that the changes in the distribution dynamics can be studied in greater details. The results are provided in **Figure 4**. According to **Figure 4A**, the ergodic distribution generated from the data from 2004 to 2007 is observed to be more dispersed than the one based on the data from 2011 to 2014.

The MPPs are shown in **Figure 4B**, by comparing the MPP of the period 2004 to 2007 with the one of the period 2011 to 2014, it can be concluded that the MPP of the second period lies lower than the first period for those countries with a relative per capita coal consumption values from 0 to 0.7 and above 2.0, thereby signifying that many countries would have a higher probability in reducing their consumption. However, the second period shows an increase in probability for a rise in coal consumption for those countries with a relative per capita coal consumption values from 0.7 to 2.0. Combining this observation with the finding derived from the changes of the ergodic distributions across time, one can conclude that there would be a reduction in relative coal consumption for most of the countries. Nevertheless, attention should be paid to those countries with a relative per capita coal consumption value from 0.7 to 2.0 which have demonstrated an upward trend in coal consumption.

The Oil Market

Turning to the oil market, **Figure 2C** shows the three-dimensional plot, and **Figure 2D** shows the contour map. It can be observed that the peak of the distribution also lies in a low value of relative per capita oil consumption, however, it is higher than the one of coal market. Another observation is that the outermost contour line reaches a relative per capita oil consumption value of 4.3 which is much higher than the outermost contour line of the coal market which has only a value of 1.6. The pattern of the oil market is more dispersed, and so it implies that the oil market is made up of countries from a more diverse background, with many countries having above-average consumption. In contrast, the coal market is limited to a few countries with comparatively similar characteristics. Another interesting fact derived from the contour map is that the contour map of the oil market is more dispersed than the one of the coal market, thereby suggesting that the oil market has higher variability in consumption.

The ergodic distribution and the MPP of the oil market are shown in **Figure 5**. Similar to the coal market, the peak of the ergodic distribution also lies in a low value of relative consumption even though the shape of the two distributions are very different. It is interesting to note that the MPP lies under the horizontal axis for almost all the values except for the values close to zero, therefore it suggests that a lot of the countries have a higher tendency to reduce their relative consumption in oil.

The changes across time can be examined by **Figure 6** which shows the ergodic distributions and MPP for the two different time periods. The convergence pattern of the ergodic distribution of the second period is more prominent than the one of the first period. This finding is supported by the fact that the MPP of the second period lies much lower than the MPP of the first period in almost all the values except the values from 0.3 to 0.9, from 2.1 to 2.8, and from 6.7 to 8.7. The two figures show that many countries have reduced their relative consumption in oil across time.

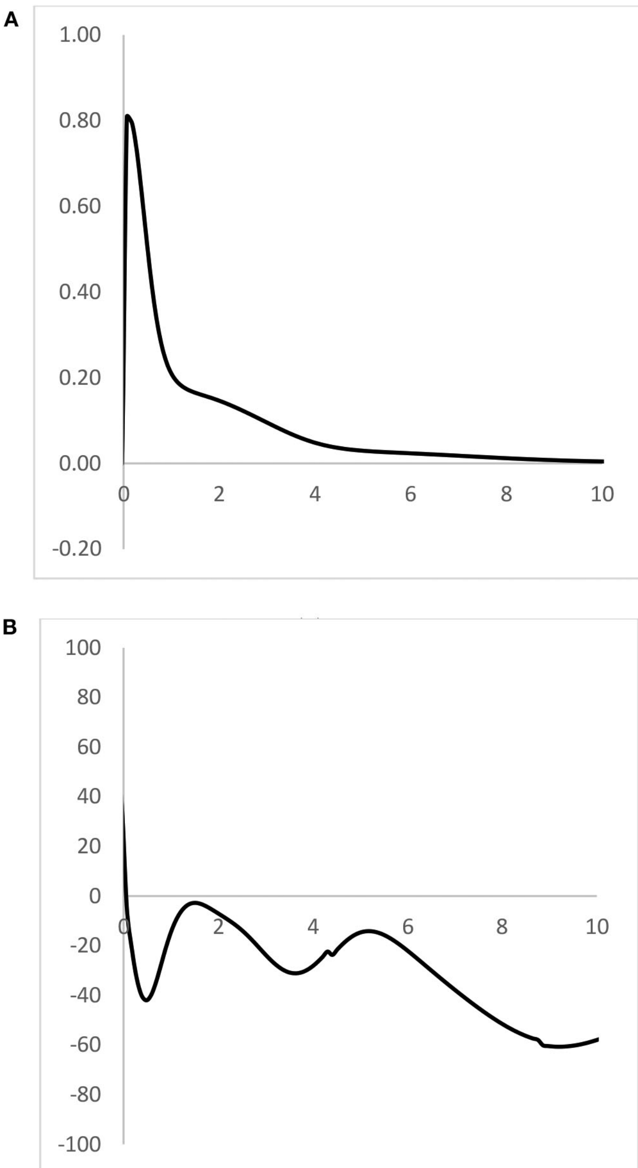

FIGURE 5 | Ergodic distribution and MPP of the oil market for all countries. Note: For **(A)**, horizontal axis represents relative per capita consumption, vertical axis represents proportion. For **(B)**, horizontal axis represents relative per capita consumption, vertical axis represents MPP. Source: Authors' calculation.

The Gas Market

The evolutionary trend of the gas market can be examined from **Figure 2**. The shape of the probability mass as shown in **Figures 2E,F** is very similar to the one of the oil market, however, the shape is much more dispersed than the oil market as the outermost contour line is above the level of 4.5. It means that the constituents of the countries of the gas market are far more diverse and are made up of countries from very different backgrounds. Moreover, by comparing the different markets in **Figure 2**, it can be observed that both the contour maps of the coal market and the oil market are more concentrated around the 45-degree diagonal line than the one of the gas market. It is worth noting that the 45-degree diagonal line represents the case that the country will stay at the same level of relative per capita consumption value before and after the transition as if the t (current) and t+1 (future) values of the contour map are the same, then it is basically the 45-degree diagonal line. Since the shape of the gas market is more dispersed than the others, it suggests that the consumption of gas is subject to much higher variability. In contrast, the consumption levels of coal and oil markets are relatively more stable than the gas market, so that the consumption levels of coal and oil in a country are more similar

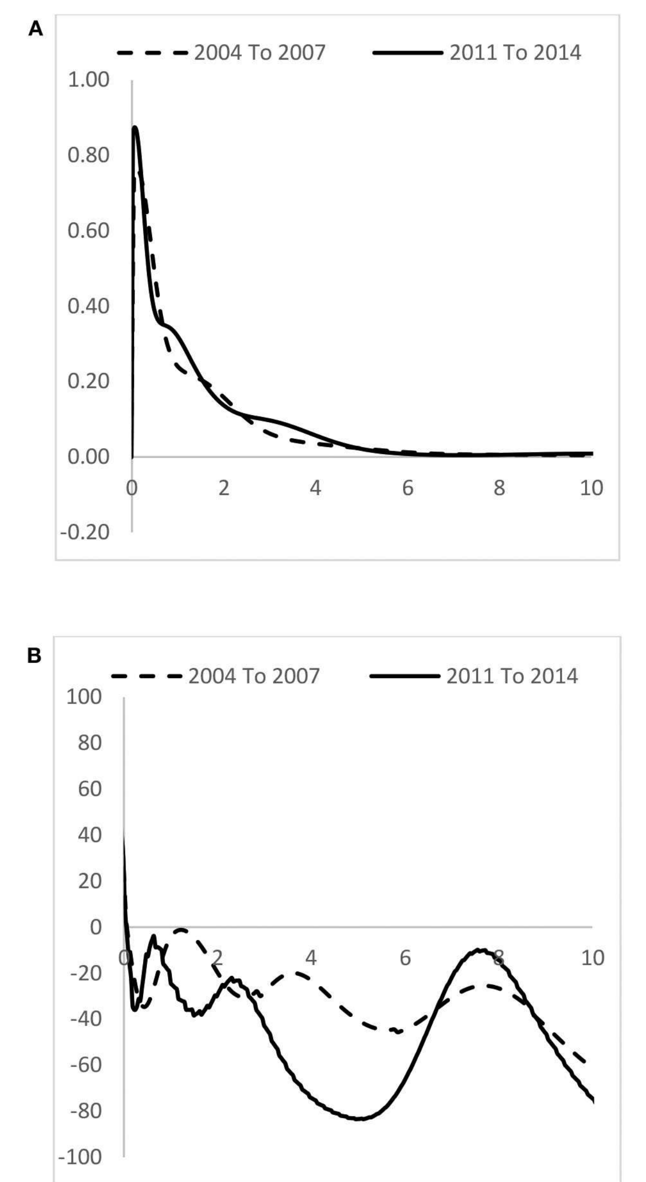

FIGURE 6 | Comparison of the ergodic distributions and MPPs of the oil market for all countries across time. Note: For **(A)**, horizontal axis represents relative per capita consumption, vertical axis represents proportion. For **(B)**, horizontal axis represents relative per capita consumption, vertical axis represents MPP. Source: Authors' calculation.

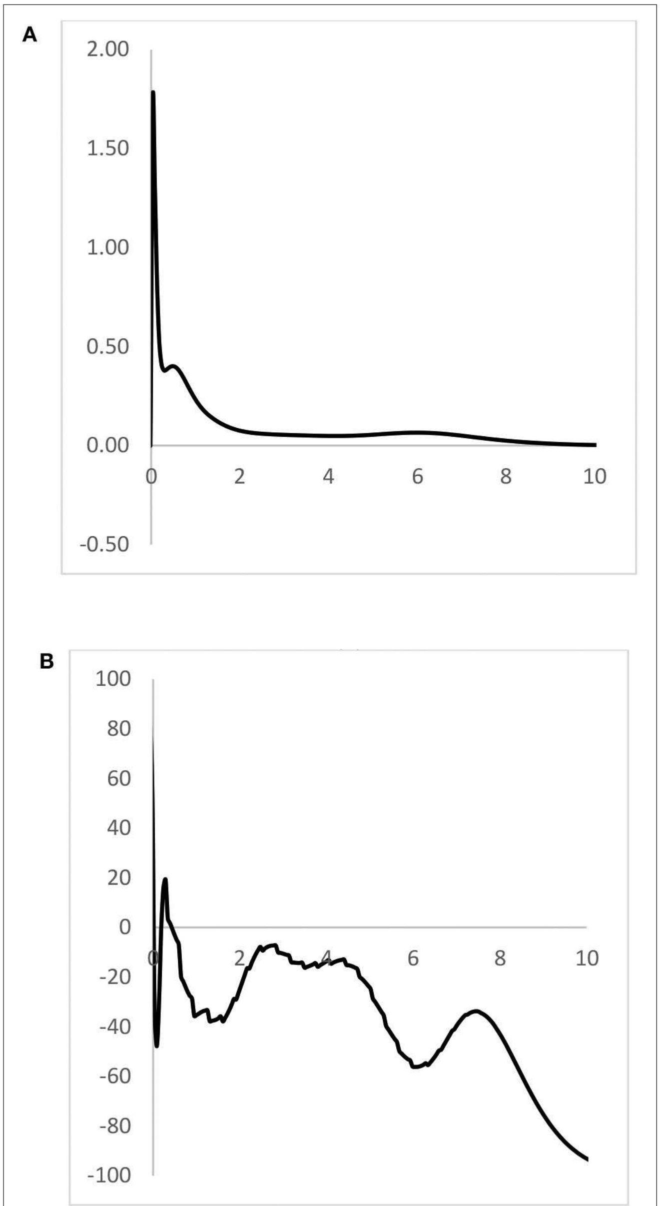

FIGURE 7 | Ergodic distribution and MPP of the gas market for all countries. Note: For **(A)**, horizontal axis represents relative per capita consumption, vertical axis represents proportion. For **(B)**, horizontal axis represents relative per capita consumption, vertical axis represents MPP. Source: Authors' calculation.

to its previous consumption level in the past. This salient finding is important for the policy makers in formulating global policies for mitigating carbon emissions. Given that the gas market has a much variability in consumption, it implies that this market is comparatively more flexible than the coal and oil market. Thus, it is much easier to implement changes in the gas market for reducing carbon emissions.

Figure 7 shows the ergodic distribution and MPP of the gas market for all the countries. Some interesting findings can be derived from the ergodic distribution. First, similar to the other markets, the peak of the ergodic distribution also lies at a very low level of relative per capita gas consumption. Second, it can be observed that there is a smaller peak with a relative per capita gas consumption value of 0.6. Moreover, there is another peak which is situated at a relative per capita gas consumption value around 6. The multi-modal pattern of the ergodic distribution suggests the emergence of convergence clubs in the future. This finding is very important as it implies that the countries will congregate in certain clusters with similar levels of gas consumption.

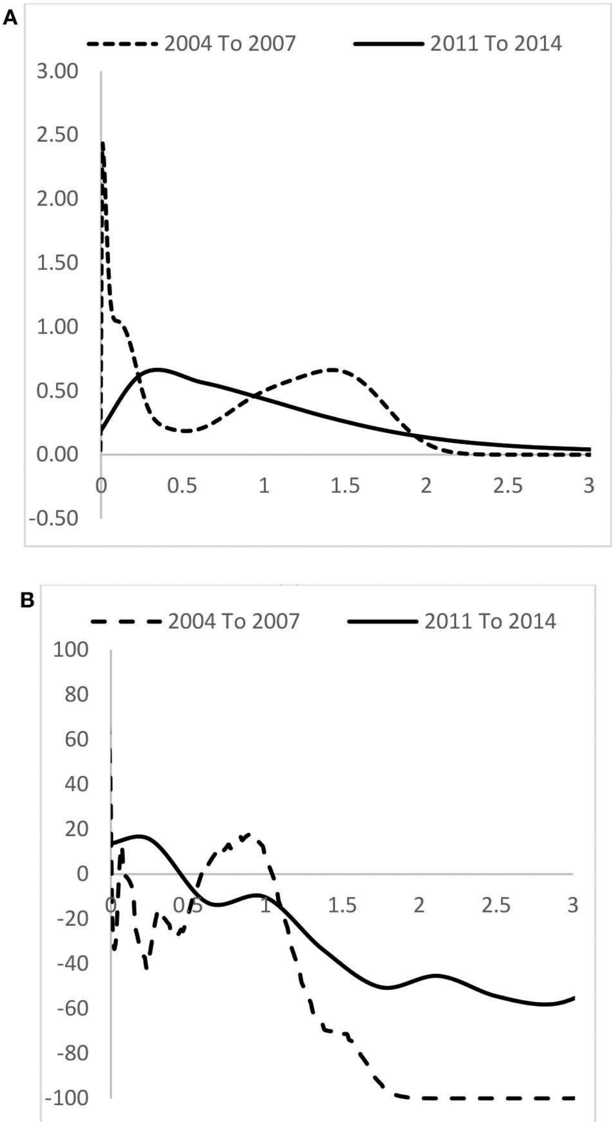

FIGURE 8 | Comparison of the ergodic distributions and MPPs of the gas market for all countries across time. Note: For **(A)**, horizontal axis represents relative per capita consumption, vertical axis represents proportion. For **(B)**, horizontal axis represents relative per capita consumption, vertical axis represents MPP. Source: Authors' calculation.

The MPP of the gas market is also very different from the other markets, the MPP lies above the horizontal axis for the values of relative per capita gas consumption from 0.2 to 0.4. It means that for those countries having a relative consumption level of 0.2 to 0.4 of the world average, would have a higher probability in increasing their consumption of gas. This lends support to the shape of the ergodic distribution and the emergence of the convergence clubs as discussed above. This is an encouraging finding as gas is deemed to be the best energy source out of the three in terms of carbon dioxide emission per unit of energy output.

Figure 8 provides a comparison of the ergodic distributions and MPPs across time. **Figure 8A** shows that there is a significant change across time. The ergodic distribution changes from a two-modal shape into a dispersed one, thereby implying that there is an increase in the variability of the gas market. From **Figure 8B**, it can be observed that the MPP has also changed a lot as the latest period shows that the MPP lies above the horizontal axis for the values from 0 to 0.45, it suggests that the countries with a level of relative per capita gas consumption from 0 to 0.45 of the world average would increase their levels of consumption further in the future. Moreover, the countries with relative per capita gas consumption values from 1.1 and above also tend to have a higher probability in increasing their consumption than before. However, for those countries with relative per capita gas consumption values from 0.6 to 1.2, the MPP fell within the study period; in fact, the disappearance of the second smaller peak of the ergodic distribution in the first period can be explained by the change of MPP from positive values to negative for the range from 0.6 to 1.2.

By examining the MPPs and ergodic distributions of the three markets, we can conclude that hypothesis 2 is true, thereby confirming that the consumption of oil and coal will be reduced, and the use of gas will be increased in the future. Our findings corroborate with prior research findings reported by Dong et al. (2017) that gas will become an important alternative to coal and oil in the future. Moreover, our findings also support the conclusion drawn by Meng et al. (2013) that convergence in per capita energy use can be achieved in the long run; however, it is notable that the research conducted by Meng et al. (2013) only covers the OECD countries, while this study covers almost all the important economies in the world.

This concludes the first part of analysis in this paper by providing an overview of the recent pattern of the three energy markets and a forecast of the ergodic distributions in the long run along with the MPPs. However, in order to formulate effective energy polices for the countries, one has to take economic development into consideration. Therefore, the next subsection will be based on an investigation of the impacts of the income on the distribution dynamics of the three energy markets.

The Impacts of Income Levels on Distribution Dynamics

The previous section has provided a comprehensive analysis on the underlying trend and distribution dynamics of the three energy markets, however, in order to provide pertinent policy suggestions for reducing carbon dioxide emissions at a global level, it is necessary to analyze the relationship between income and the energy market.

Given that most of the poor countries are short of investment funds, they usually do not have the required resources to reform their energy structure; while the rich countries have plenty of resources at their disposal, so that they can change their energy structure and develop new types of energy if required. Therefore, a majority of the poor countries can only rely on their existing energy structure; in contrast, rich countries can exercise greater flexibility in selecting their ideal energy structure for the future. It is thus of interest to understand the impacts of income levels on the future development of the three energy markets. The results derived from this analysis not only can provide a guideline for formulating energy polices for countries of different levels of income and economic development, but can also offer crucial information on international aid policy in mitigating carbon dioxide emissions.

The full dataset was divided into four smaller datasets according to the classification of income as proposed by the World Bank. The countries were first categorized into the low, lower-middle, upper-middle, and high-income groups; and then distribution dynamics analyses were conducted on these four groups independently so as to examine this main issue in greater details.

Low-Income Countries

Figure 9 shows the ergodic distributions of the three energy markets and their MPPs for the low-income countries. According to **Figure 9A**, it can be observed that all the three markets would converge at an extremely low level of relative consumption. The highest values of the ergodic distributions of the oil and gas markets are situated below the relative per capita consumption value of 0.5, however, the coal market extends to the relative per capita consumption value of 0.7. It shows that inequality is very high, and the energy consumption levels of the poor countries are far below the global average level. Moreover, it can be observed that the ergodic distribution of the coal market is the most dispersed, followed by the oil market, and then the gas market.

Turning to **Figure 9B** for the MPPs of the three markets, there are two important findings. First, both the MPPs of the oil and gas markets reach−100 around the relative per capita consumption value of 0.5, thereby indicating that the poor countries could not increase their consumption of oil and gas above half of the world average. As the MPP value is −100, it means that whenever the poor countries reach this threshold value, their consumption would be reduced in the future. Second, the MPP value of the coal market has two regions where the MPP value is very high, namely, the region with values from 0.1 to 0.4, and from 1.0 to 1.6. For the region from 1.0 to 1.6, the MPP value is 100, this is a worrisome sign as it means that the poor countries which have an above-average level of coal consumption would have a higher probability in increasing their consumption in the future.

In summary, both figures suggest that many poor countries would strongly rely on coal in the future, and they would increase their consumption even if their consumption levels are much higher than the world average.

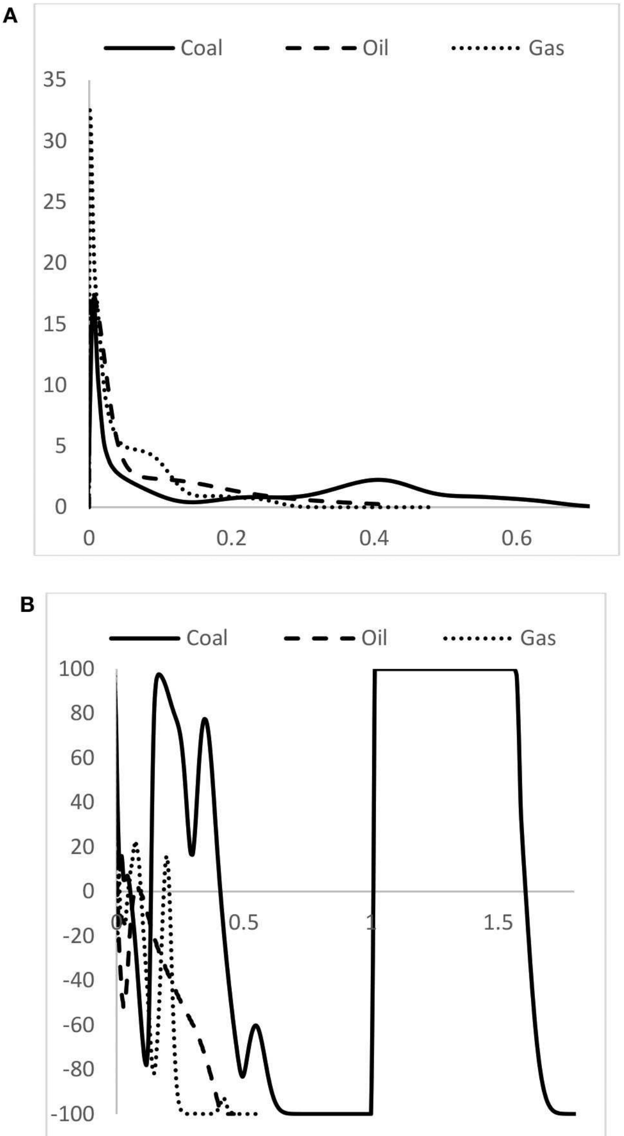

FIGURE 9 | Comparison of the ergodic distributions and MPPs of the coal, oil, and gas markets for the low-income countries. Note: For **(A)**, horizontal axis represents relative per capita consumption, vertical axis represents proportion. For **(B)**, horizontal axis represents relative per capita consumption, vertical axis represents MPP. Source: Authors' calculation.

Lower-Middle-Income Countries

Figure 10A shows that the ergodic distributions of the lower-middle-income countries bear resemblance to those of the low-income countries as the peaks of the three distributions are all situated below the global average. However, it can be observed that the right-hand tail of all the distributions now extend to the relative per capita consumption value of 5 in the figure. By comparing with the ergodic distributions of the low-income countries, it can be concluded that the level of energy consumption increases with the income level of the countries. One more interesting observation is that the ergodic distribution of the gas market is the most dispersed amongst the three, followed by the oil market, and then the coal market. It suggests that the variability of the oil and gas markets is very high amongst the lower-middle-income countries.

The MPPs of the three markets are shown in **Figure 10B**, it is notable that the MPP of the coal market is above the horizontal axis for the relative per capita consumption values from 1.5 to 2.6, thereby suggesting that these countries would have a higher tendency in increasing coal consumption. Similarly, the MPP of the oil market is above the horizontal axis for the relative per

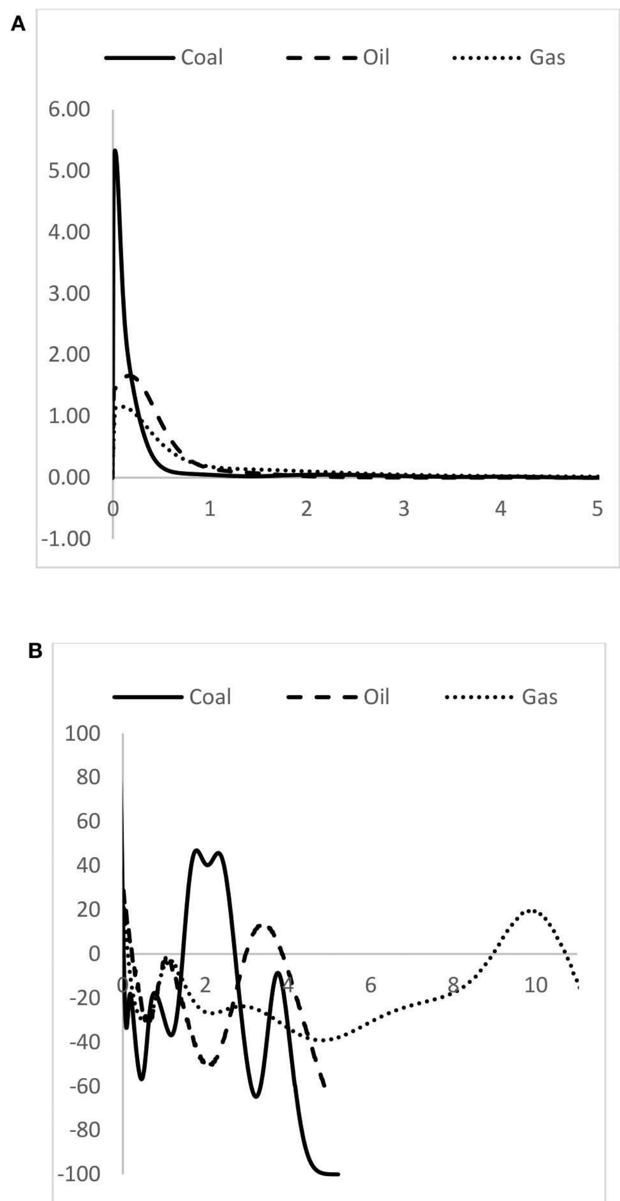

FIGURE 10 | Comparison of the ergodic distributions and MPPs of the coal, oil, and gas markets for the lower-middle-income countries. Note: For **(A)**, horizontal axis represents relative per capita consumption, vertical axis represents proportion. For **(B)**, horizontal axis represents relative per capita consumption, vertical axis represents MPP. Source: Authors' calculation.

capita consumption values from 3.0 to 4.0, and the MPP of the gas market lies above the horizontal axis for the region from 9.0 to 11.0. This is an important finding as it suggests that for the middle-income countries, a few of them would increase their relative consumption even though their consumption levels are much higher than the world average. This phenomenon is the most apparent for gas (with values from 9.0 to 11.0), followed by oil, and then the coal market. The analysis further shows that the distribution dynamics of the three markets are very different.

Upper-Middle-Income Countries

Turning to the ergodic distributions of the upper-middle-income countries which are shown in **Figure 11A**, it can be observed that the right-hand tail of the distributions extends further to the right and reaches the relative per capita consumption value of 10 for the oil and gas markets, while the coal market reaches the relative per capita coal consumption value of 5.5. The shapes of the distributions are very similar to the ones of the lower-middle-income countries, of which the distribution of the gas market is the most dispersed, followed by the distribution of the oil market, and then finally, the coal market. Interestingly, this reveals the finding that the variability of consumption increases with income is still valid for the upper-middle-income countries.

One important finding can also be derived from **Figure 11A**. The peak of the ergodic distribution of the oil market is observed to lie around the relative per capita oil consumption value of one, it means that many of the upper-middle-countries would consume a level of oil similar to the world average, and oil would remain to be a very popular energy source within the upper-middle-income countries.

Figure 11B shows that most of the MPPs lie below the horizontal axis except for the values within the region from 11.0 to 14.5 for the gas market, and for the relative per capita consumption values below one for the three markets. This lends support to the earlier findings that countries which have extremely high levels of gas consumption would have a high likelihood in increasing the consumption further in the future. In contrast, the MPP of the coal market lies under the horizontal axis except for very small relative per capita consumption values, thereby indicating that coal is not a preferred energy source for the upper-middle-income countries.

High-Income Countries

Turning to the high-income countries, **Figure 12A** shows the ergodic distributions of the three energy markets. Similar to the upper-middle-income countries, the shape of the ergodic distribution of the gas market is the most dispersed, followed by the oil market, and the last one is the coal market. Moreover, it can be observed that for the high-income countries, the oil market will converge to a relative per capita oil consumption value of 2.5 which is two and a half times above the world average. It shows that oil is a very important energy source for the high-income countries and the reliance is quite heavy.

Figure 12B shows the MPPs of the three markets for the high-income countries. There are several interesting findings derived from this figure. First, the MPP of the coal market lies under the horizontal axis for nearly all its range save very small values. Second, the MPP of the gas market crosses the axis around a value of relative per capita gas consumption of 2.3. It indicates the consumption of gas for many high-income countries would increase in the future. The MPP of the oil market lies above the horizontal axis for the range from 1.0 to 2.3, and so it means that many above-average users of oil would also increase their consumption in the future. Given that the ergodic distribution is the steady-state distribution in the long run, the shape of the three distributions and the findings derived from the MPP analysis pinpoint the fact that, the consumption of oil and

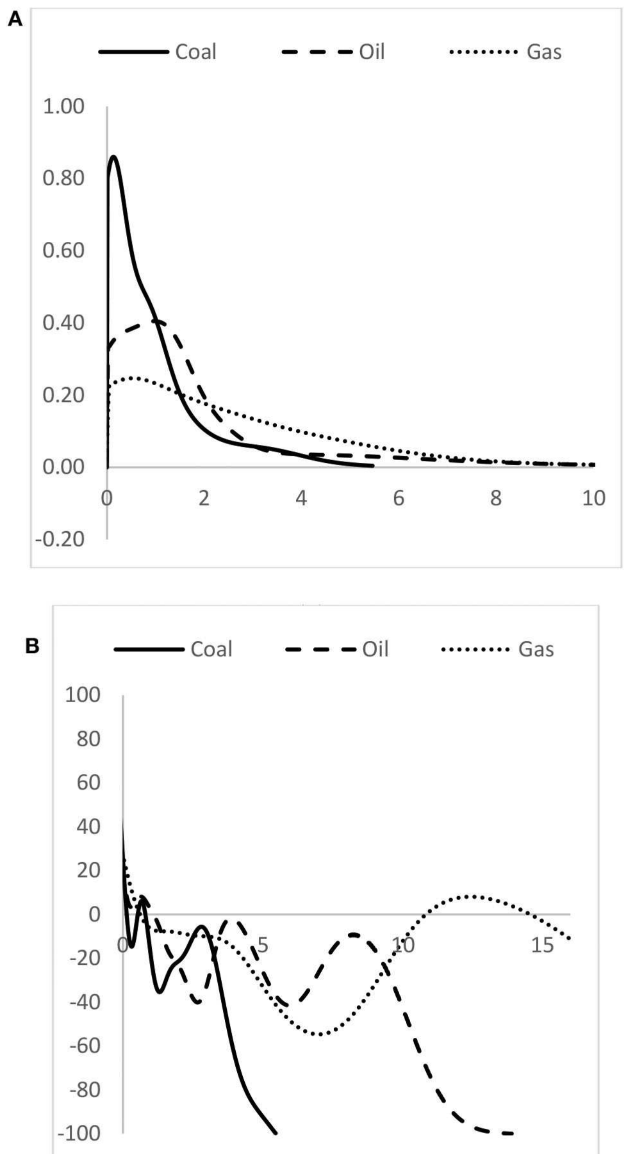

FIGURE 11 | Comparison of the ergodic distributions and MPPs of the coal, oil, and gas markets for the upper-middle-income countries. Note: For **(A)**, horizontal axis represents relative per capita consumption, vertical axis represents proportion. For **(B)**, horizontal axis represents relative per capita consumption, vertical axis represents MPP. Source: Authors' calculation.

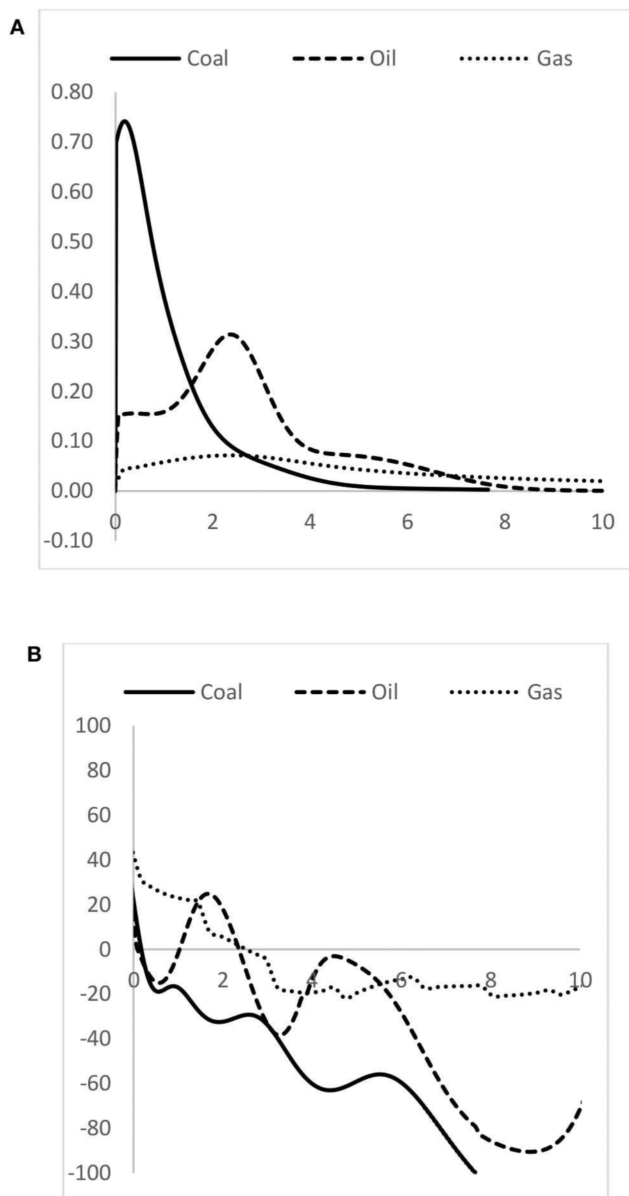

FIGURE 12 | Comparison of the ergodic distributions and MPPs of the coal, oil, and gas markets for the high-income countries. Note: For **(A)**, horizontal axis represents relative per capita consumption, vertical axis represents proportion. For **(B)**, horizontal axis represents relative per capita consumption, vertical axis represents MPP. Source: Authors' calculation.

gas is increasing for the high-income countries, and it may be attributed to their income level which may allow them to adjust their energy structure in the long run.

By comparing the ergodic distributions and MPPs of the three energy sectors in different income groups, one can draw the conclusion that hypothesis 1 is true, thereby implying that the convergence pattern of energy consumption is not the same for the different income groups. Our findings corroborates those reported by Jakob et al. (2012) that convergence of energy use is related to the economic development of a country. Our findings also support another conclusion drawn by them which states that the convergence pattern of the industrialized countries is different from those of the developing countries.

CONCLUSIONS

The improvement in ECS is centrally important for the global society to fulfill the goal of green energy transition and to combat the adverse effects of global climate change. The aim of this study is to investigate the evolutionary trend and future development of the markets of three major energy commodities, namely, coal, oil, and gas. Distribution dynamics analyses were conducted on the Global Trade Analysis Project dataset which is made up of almost all the countries and regions in the world. The first part of the analysis is to provide an overview of the three markets, while the second part is based on a study focusing on the impacts of income on the distribution dynamics of the three markets.

Many important findings have been derived from this study. For an overview of the three markets, our findings show that coal consumption is not high for a lot of the countries and the MPP of the coal market shows that many countries would reduce their coal consumption in the future. In contrast, the oil market is made up of countries from a more diverse background, with many countries having above-average consumption, however, the MPP of the oil market also shows that many countries would reduce their relative consumption of oil in the future.

Finally, our findings reveal that the gas market has the highest variability amongst the three markets. It is an encouraging finding as it implies that it is far easier to implement change in the gas market in adjusting the energy structure for mitigating carbon emissions. From the ergodic distribution of the gas market, it can be observed that convergence clubs may emerge in the long run as the countries would congregate in certain clusters with similar levels of gas consumption.

The second part of the analysis is to evaluate the impacts of income on the distribution dynamics of the energy markets. Our findings demonstrate that the distribution dynamics is very different for the four income groups, and so it is necessary to take income level of a country into consideration in formulating energy policies. There are several pertinent findings. First, the range of the ergodic distribution increases with the income level. It reflects the issue of global inequality amongst the countries as the energy consumption of the poor countries are much lower than the other countries. Besides, since the poor countries are lacking of investment funds, they do not have many choices in their energy structure, and hence it is very difficult for them to change their existing energy structure. In contrast, as the affluent countries have more financial resources at their disposal, so they have higher flexibility in the energy structure which can be demonstrated by the higher variability of the ergodic distributions of the three markets.

One salient finding is that the MPPs of the oil and gas markets of the poor countries reach −100 for the relative per capita consumption value of 0.5, it means that the low-income countries could not increase their oil and gas consumption once it reaches the threshold of one half of the world average; moreover, the MPP of the coal market of the poor countries show that these countries have a higher probability in increasing their coal consumption even if they already have an above-average level of consumption.

Oil is deemed to be the most popular form of energy sources for the upper-middle-income and high-income countries, while coal is not a preferred energy source for the affluent countries. However, gas consumption seems to have a very high variability and the countries can have very different consumption patterns of gas even if they belong to the same income category. Furthermore, it is observed that for the lower-middle-income and upper-middle-income countries, the big consumers of gas tend to increase their gas consumption further. However, it is worth mentioning that the level of income is not the only factor affecting the distribution dynamics, and resource endowments also play a major role. A summary of the findings is provided in **Table 3**.

The findings derived from this study may prove valuable for the policy makers in formulating energy policies for adapting to market changes, and may assist the design of international aid program for mitigating carbon emissions for the poor countries. Several policy implications can be derived. First, as gas is better than oil and coal in terms of greenhouse gas emission, country-specific policies should be formulated for the development of the gas industry. Second, the variability of gas usage is very high, therefore, more resources should be diverted to the gas industry through further research and development activities. Third, the government should

TABLE 3 | Summary of major findings.

	Findings
Coal	1. Coal consumption is not high for a lot of the countries 2. Many countries would reduce their coal consumption in the future
Oil	1. Countries from a more diverse background, with many countries having above-average consumption 2. Many countries would reduce their oil consumption in the future
Gas	1. Has the highest variability amongst the three markets 2. Convergence clubs may emerge in the long run
Income groups	1. Distribution dynamics is very different for the four income groups 2. It is necessary to take income level of a country into consideration in formulating energy policies 3. Huge global inequality in energy consumption can be observed 4. Affluent countries have higher flexibility in the energy structure because of more financial resources at their disposal 5. Low-income countries could not increase their oil and gas consumption 6. Poor countries have a higher probability in increasing their coal consumption 7. Oil is the most popular form of energy sources for the upper-middle-income and high-income countries 8. Coal is not a preferred energy source for the affluent countries 9. Countries can have very different consumption patterns of gas even if they belong to the same income category

also encourage investment in these areas actively so as to mitigate greenhouse gas emission. Fourth, both developing and developed countries should work together, and international aid should be provided to the low-income countries for reducing the use of coal as these poor countries just do not have enough financial resources to change their current energy consumption structure.

This research study offers an innovative perspective for examining three important energy markets in the world. However, given that renewable energy sources have gained importance in recent years, it would be a good idea to conduct an analysis on these new energy sources when the data are available in the future. Another potential way for extending this study is to determine the proper ways for changing the energy consumption structure of the developing countries by employing econometrics analysis so as to mitigate greenhouse gas emission for the world.

DATA AVAILABILITY STATEMENT

Publicly available datasets were analyzed in this study. This data can be found here: https://www.gtap.agecon.purdue.edu/.

AUTHOR CONTRIBUTIONS

The contributions of the authors are the same. They contribute in different areas, but the work load is shared equally among them.

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REFERENCES

Augutis, J., Martišauskas, L., and Krikštolaitis, R. (2015). Energy mix optimization from an energy security perspective. *Energ. Convers. Manage.* 90, 300–314. doi: 10.1016/j.enconman.2014.11.033

BP (2019). 2019-06. *Statistical Review of World Energy*. Available online at: https://www.bp.com/en/global/corporate/energy-economics/statistical-review-of-world-energy.html (accessed August 25, 2019).

Burnett, J. W., and Madariaga, J. (2017). The Convergence of U.S. state-level energy intensity. *Energy Econ.* 62, 357–370. doi: 10.1016/j.eneco.2016.03.029

Çelikbilek, Y., and Tüysüz, F. (2016). An integrated grey based multi-criteria decision making approach for the evaluation of renewable energy sources. *Energy* 115, 1246–1258. doi: 10.1016/j.energy.2016.09.091

Chen, J., Wu, Y., Xu, C., Song, M., and Liu, X. (2019). Global non-fossil fuel consumption: driving factors, disparities, and trends. *Manage. Decis.* 57, 791–810. doi: 10.1108/MD-04-2018-0409

Cheong, T. S., and Wu, Y. (2018). Convergence and transitional dynamics of china's industrial output: a county-level study using a new framework of distribution dynamics analysis. *China Econ. Rev.* 48, 125–138. doi: 10.1016/j.chieco.2015.11.012

Cheong, T. S., Wu, Y., and Wu, J. (2016). Evolution of carbon dioxide emissions in chinese cities: trends and transitional dynamics. *J. Asia Pac. Econ.* 21, 357–377. doi: 10.1080/13547860.2016.1176642

Cheong, T. S., Li, V. J., and Shi, X. (2019). Regional disparity and convergence of electricity consumption in China: a distribution dynamics approach. *China Econ. Rev.* 58:101154. doi: 10.1016/j.chieco.2018.02.003

Dong, K.-Y., Sun, R.-J., Li, H., and Jiang, H.-D. (2017). A review of China's energy consumption structure and outlook based on a long-range energy alternatives modeling tool. *Petrol. Sci.* 14, 214–227. doi: 10.1007/s12182-016-0136-z

Fallahi, F., and Voia, M.-C. (2015). Convergence and persistence in per capita energy use among OECD countries: revisited using confidence intervals. *Energy Econ.* 52, 246–253. doi: 10.1016/j.eneco.2015.10.004

Feng, T., Sun, L., and Zhang, Y. (2009). The relationship between energy consumption structure, economic structure and energy intensity in China. *Energy Policy* 37, 5475–5483. doi: 10.1016/j.enpol.2009.08.008

Herrerias, M. J. (2012). World energy intensity convergence revisited: a weighted distribution dynamics approach. *Energy Policy* 49, 383–399. doi: 10.1016/j.enpol.2012.06.044

Hu, Y., Peng, L., Li, X., Yao, X., Lin, H., and Chi, T. (2018). A novel evolution tree for analyzing the global energy consumption structure. *Energy* 147, 1177–1187. doi: 10.1016/j.energy.2018.01.093

Jakob, M., Haller, M., and Marschinski, R. (2012). Will history repeat itself? Economic convergence and convergence in energy use patterns. *Energy Econ.* 34, 95–104. doi: 10.1016/j.eneco.2011.07.008

Kahia, M., Aïssa, M. S. B., and Charfeddine, L. (2016). Impact of renewable and non-renewable energy consumption on economic growth: new evidence from the MENA Net Oil Exporting Countries (NOECs). *Energy* 116, 102–115. doi: 10.1016/j.energy.2016.07.126

Lawrence, S., Liu, Q., and Yakovenko, V. (2013). Global inequality in energy consumption from 1980 to 2010. *Entropy* 15, 5565–5579. doi: 10.3390/e15125565

Le Pen, Y., and Sévi, B. (2010). On the non-convergence of energy intensities: evidence from a pair-wise econometric approach. *Ecol. Econ.* 69, 641–650. doi: 10.1016/j.ecolecon.2009.10.001

Li, Y., Wei, Y., Shan, S., and Tao, Y. (2018). Pathways to a low-carbon economy: estimations on macroeconomic costs and potential of carbon emission abatement in Beijing. *J. Clean. Prod.* 199, 603–615. doi: 10.1016/j.jclepro.2018.07.093

Liang, J., and Zhang, L. (2009). Analysis on spatial distribution characteristics of urban energy consumption among capital cities in China. *Resour. Sci.* 31, 2086–2092. doi: 10.1007/978-3-642-00205-2_9

Ma, H., and Oxley, L. (2012). The emergence and evolution of regional convergence clusters in China's energy markets. *Energy Econ.* 34, 82–94. doi: 10.1016/j.eneco.2011.02.015

Meng, M., Payne, J. E., and Lee, J. (2013). Convergence in per capita energy use among OECD countries. *Energy Econ.* 36, 536–545. doi: 10.1016/j.eneco.2012.11.002

Mohammadi, H., and Ram, R. (2012). Cross-country convergence in energy and electricity consumption, 1971–2007. *Energy Econ.* 34, 1882–1887. doi: 10.1016/j.eneco.2012.08.001

Ozturk, M., and Yuksel, Y. E. (2016). Energy structure of Turkey for sustainable development. *Renew. Sust. Energy Rev.* 53, 1259–1272. doi: 10.1016/j.rser.2015.09.087

Payne, J. E., Vizek, M., and Lee, J. (2017). Is there convergence in per capita renewable energy consumption across US States? Evidence from LM and RALS-LM unit root tests with breaks. *Renew. Sust. Energy Rev.* 70, 715–728. doi: 10.1016/j.rser.2016.11.252

Quah, D. (1990). Galton's fallacy and tests of the convergence hypothesis. *Scand. J. Econ.* 95, 427–443. doi: 10.2307/3440905

Quah, D. (1993). Empirical cross-section dynamics in economic growth. *Eur. Econ. Rev.* 37, 426–434. doi: 10.1016/0014-2921(93)90031-5

Quah, D. (1997). Empirics for growth and distribution: stratification, polarization, and convergence clubs. *J. Econ. Growth* 2, 27–59. doi: 10.1023/A:1009781613339

Sheng, Y., and Shi, X. (2013). Energy market integration and equitable growth across countries. *Appl. Energy* 104, 319–325. doi: 10.1016/j.apenergy.2012.10.043

Silverman, B. W. (1986). *Density Estimation for Statistics and Data Analysis.* New York, NY: Chapman and Hall.

Thangavelu, S. R., Khambadkone, A. M., and Karimi, I. A. (2015). Long-term optimal energy mix planning towards high energy security and low GHG emission. *Appl. Energy* 154, 959–969. doi: 10.1016/j.apenergy.2015.05.087

Wei, Y., Li, Y., Wu, M., and Li, Y. (2019a). The decomposition of total-factor CO2 emission efficiency of 97 contracting countries in Paris Agreement. *Energy Econ.* 78, 365–378. doi: 10.1016/j.eneco.2018.11.028

Wei, Y., Zhu, X., Li, Y., Yao, T., and Tao, Y. (2019b). Influential factors of national and regional CO_2 emission in China based on combined model of DPSIR and PLS-SEM. *J. Clean. Prod.* 212, 698–712. doi: 10.1016/j.jclepro.2018.11.155

Wu, J., Wu, Y., Cheong, T. S., and Yu, Y. (2018a). Distribution dynamics of energy intensity in Chinese cities. *Appl. Energy* 211, 875–879. doi: 10.1016/j.apenergy.2017.10.097

Wu, J., Wu, Y., Guo, X., and Cheong, T. S. (2016). Convergence of carbon dioxide emissions in Chinese cities: a continuous dynamic distribution approach. *Energy Policy* 91, 207–219. doi: 10.1016/j.enpol.2015.12.028

Wu, Y., Zhu, Q., and Zhu, B. (2018b). Comparisons of decoupling trends of global economic growth and energy consumption between developed and developing countries. *Energy Policy* 116, 30–38. doi: 10.1016/j.enpol.2018.01.047

Yang, Z., Shao, S., Yang, L., and Miao, Z. (2018). Improvement pathway of energy consumption structure in China's industrial sector: from the perspective of directed technical change. *Energy Econ.* 72, 166–176. doi: 10.1016/j.eneco.2018.04.003

Zhang, Z.-H., Chen, Y.-J., and Dai, L.-Y. (2011). Evolution of China's energy consumption structure based on entropy," in *2011 International Conference on Management and Service Science* (Wuhan: IEEE), 1–4.

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Time-Varying Wavelet-Based Applications for Evaluating the Water-Energy Nexus

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This paper quantifies the rising global dynamic, interconnected relationship between energy and water commodities. Over the last decade, increased international concern has emerged about the water-energy nexus. However, recent research still lacks a quantified understanding of the role of water within a financial-economic view of the nexus. The complexity of commodity markets contributes to this lack of understanding. These markets consist of a wide variety of participants having different objectives, resulting in non-stationary time series. Wavelets are mathematical functions that detect common *time-localized* oscillations in non-stationary time series. The novelty of our analysis lies in applying wavelet techniques to better quantify the financial implications and understand opportunities of the dynamic relationship that exists in the water-energy nexus. Using daily water and energy commodity ETF price data from 2007 to 2017 we deconstruct each of the time series into different horizon components and evaluate their respective wavelet transforms. Comparing the wavelet squared coherence (WSC) and the windowed scalogram difference (WSD) allows us to specify nexus similarities and differences. We further analyze the wavelet local multiple correlations (WLMC) by including S&P500 ETF price data to conditionally eliminate market effects. Previous studies heavily focused on the qualitative relationships between water and energy. Whereas, the analysis in this paper, to the best of our knowledge, is the first to confirm the time-varying relationship in a quantitative manner. The most significant financial-economic result from our analysis is that water prices, at certain *time* horizons, lead energy prices during specific *localized* economic events.

Keywords: time-varying analysis, water-energy nexus, complex continuous wavelet transform, wavelet squared coherence, windowed scalogram difference, wavelet local multiple correlation

1. INTRODUCTION

In trying to understand the extremely volatile price dynamics after the 2008 financial crisis, economic researchers introduced the concept of commodity financialization (Cheng and Xiong, 2013), giving rise to energy finance becoming a standalone stream of research. Recently, Zhang (2018) further clarified the concept of energy finance by discussing the fields interdisciplinary nature and emphasizing the need for analyzing linkages between energy commodity markets and other markets to better understand price dynamics. Vacha and Barunik (2012) pointed out that energy commodities affect a wide range of markets and that it is fundamentally important to study the statistical properties and interconnections of these markets. For more recent econometric literature focusing on the dynamic and statistical properties of these markets (see Creti et al., 2013; Abdelradi and Serra, 2015; Ahmadi et al., 2016; Reboredo et al., 2017).

Publications ranging from policy implications to the econometric quantification are supporting the increased need for evaluating the water-energy nexus. Studies that impact policy include the integrated risk analysis of the water-energy nexus with reasonable policy recommendations by Cai et al. (2019), evaluations of water-related impacts due to energy-related decisions by Wang et al. (2019), and a detailed review of existing methods and tools to analyze the water-energy nexus by Dai et al. (2018). Ozturk (2017) goes even further by evaluating the dynamic relationship between food-water-energy and agricultural sustainability in sub-Saharan countries, as well as in earlier work examining countries that make up BRICS (Ozturk, 2015).

For a thorough literature review on the dependency of energy type on water (see Tan and Zhi, 2016). Global studies encouraging the need for evaluating the link between energy and water include the quantitative assessment of the water-energy nexus in the Middle East and North Africa region (Siddiqi and Anadon, 2011), the quantification of the water-energy nexus in Greece (Ziogou and Zachariadis, 2017), studies showing the linkage analysis for the water-energy nexus of Beijing (Fang and Chen, 2017). Additionally, the research of Keulertz and Woertz (2015) looks at the financial challenges of the nexus in the Arab world, Hamiche et al. (2016) comprehensively reviews the links between water and electricity, and Gallegos et al. (2015) studies the potential environmental implications of hydraulic fracturing water use in the United States.

Rising uncertainty in global markets creates fluctuations that lead to increased interdependency between water and energy commodities. For example, a leading global drilling fluids market research report indicates that during the 2014 to 2015 global oil glut, aqueous drilling fluids were most prominent because of low cost and reduced environmental impact. However, this extensive use placed a tremendous amount of stress, globally, on water availability. The need for inclusion of water scarcity within energy planning is more important today than ever before. Costs related to energy and water play a crucial role in decision making at various levels of investing. Smajgl et al. (2016) points out that the integrated and dynamic relationship between these commodities impacts large scale development investments and Wichelns (2017) clearly emphasizes the importance of quantifying investments and integrating research policies needed for future sustainability. To the best of our knowledge our current research is first in quantifying the dynamic financial interaction between water and energy commodities.

Common behaviors or patterns in two jointly stationary time series can be quantified using standard time-domain techniques such as cross-correlation, cross-spectrum, and coherence. However, there are two main reasons for not using traditional financial time series methods in our analysis. First, commodity marketplaces are complex with a wide variety of participants having different objectives. Time series formed by these non-stationary processes consist of combinations of different components functioning at different frequencies making it difficult to analyze with traditional time series methods. Methodologies must address the fact that comovements between commodity markets are time-varying and horizon dependent. For example, Dajcman et al. (2012) provide a discussion on European stock market comovement dynamics comparing the DCC-GARCH and wavelet multiscale analysis, showing that stock market returns are time-varying and scale dependent. Secondly, in financial time series analysis, Fourier analysis is used to identify relationships between frequencies of different time series. The smooth transition of the cosine and sine basis functions in Fourier analysis, however, fails to capture abrupt changes in the stochastic behavior of the commodities time series. We address these issues by breaking individual series into their component pieces or horizons using a continuous wavelet transform and comparing similarity and differences at different scales/horizons and time components together rather than separately. Our analysis provides unique results that are difficult to obtain from only analyzing the aggregate long-run economic impact (Aguiar-Conraria et al., 2014). Davidson et al. (1997) were one of the first papers to introduce the use of wavelets to study commodity price behavior and Connor and Rossiter (2005) estimated price correlations of commodity markets by time series scale/horizon decomposition using discrete wavelets. In recent years, applied research on the comovement of commodities related to the dynamics of energy has increased significantly (Vacha and Barunik, 2012; Mensi et al., 2017). Bilgili et al. (2016) for instance took a wavelet coherence approach to evaluating the impact of biomass on carbon dioxide emissions.

Application of time-varying techniques to augment traditional portfolio management tools by distinguishing across multiple investment horizons or scales is becoming a growing field of interest (Ftiti et al., 2017; Kumar et al., 2017; Wang et al., 2017). Chaudhuri and Lo (2016) who coined the term *spectral portfolio theory* suggests that the flexibility of the wavelet transform could be used to overcome various difficulties of the Fourier transform for spectral portfolio analysis. For an expansive introduction to wavelet theory in finance (see In and Kim, 2012).

Market data such as indices are traditionally used to describe the underlying behavior of a commodity, and ETF's capitalize on these behaviors by tracking commodity indices. To understand the dynamic associations of water and energy commodities, we propose to explore their comovement using time-varying spectral representations. We illustrate the value of these techniques using the wavelet squared coherence (WSC) and the windowed scalogram difference (WSD). Using both the WSC and WSD we can capture, from two different perspectives, the degree of statistically significant similarity in time and scale/horizon for the commodity ETFs representing water and energy. We also introduce the analysis of wavelet local multiple correlations (WLMC), recently published by Fernández-Macho (2018).

Studying the comovement of multiple time series can traditionally be achieved using WSC. The WSD, complementary to the WSC, is a measure designed to compare non-stationary time series in time and scale/horizon for a fixed window (Bolós et al., 2017). Both these techniques evaluate the association between time series, but each of these methods highlights different aspects. The WSD gives greater flexibility in allowing the change of window size depending on which scale/horizon is of interest. The WSC does not have this flexibility. However, the WSC can easily define scale/horizon specific local linear correlations in regions of statistically significant comovement. For example, Pal and Mitra (2017) used WSC to address certain policy concerns of the food-energy nexus. We contribute to this type of analysis by not only looking at the WSC of the water-energy nexus but also the WSD allowing us to identify and confirm scale/horizon specific micro-interactions. Using both these wavelet tools we are able to identify and discuss characteristics not possible with traditional time series tools. Further, by using the recently introduced WLMC method we analyze the time-varying correlations of the S&P500 ETF with the water-energy nexus. We specifically use the WLMC to point out the conditional relationship between the water-energy nexus and the S&P500 by eliminating S&P500 market effects that individually impact the behaviors of the water and energy commodity indices.

The overall goal of this paper was to quantitatively show the time-varying behaviors of the water-energy nexus which could support practitioner in making more fact driven decision. Therefore, the structure of this paper is as follows. Section 2 describes the wavelet-based methods used in the analysis of the water-energy nexus. Section 3 presents a data description, visualization of results, and a discussion on the evaluation of the water-energy nexus after applying the wavelet-based methods from section 2. We conclude the paper with section 4 by examining the dynamic economic behavior between these commodities over the past 10 years and addressing certain policy implications and opportunities for cost reduction in energy production.

2. METHODS

After a mathematical exposition of wavelets in sections 2.1, 2.2, 2.3, and 2.4 introduces statistical methods that extend the capabilities of wavelets to visualize structure in multidimensional data. See the **Appendix** for more details regarding a robustness check on methods.

2.1. Wavelets

Even though promising results in economics and finance have come from implementing wavelet analysis, many of these professionals are still developing their understanding of wavelet-based methods. Consequently, a more expansive and baseline introduction to the wavelet techniques are needed. In support of this development, this section describes in detail the wavelet functions we later implement to analyze the complex time-varying water-energy nexus.

Wavelets are mathematical, wave-like functions that are used to extract information from many different kinds of data. When applied to time series, wavelet transforms synthesize signals into different frequency components, decomposing the original time series into multiple time series. Each of these newly decomposed time series represents specific characteristics unique to a particular investment horizon. For example, an investment horizon of six months corresponds to a scale of 6 months. A better-known label for an investment horizon is a scale. We use the label scales in the mathematical exposition and then later we return to the label investment horizons as it is more appropriate for the application in this paper. We also intentionally refer to the decomposed time series as different frequency components because the relationship between frequency and scale is specifically determined by the center frequency of the wavelet. For the sake of simplicity, the relationship between frequency and scale is defined as, $F_a = F_c/a$, where F_c is the center frequency of the wavelet and F_a the frequency corresponding to scale a. Only when certain specifications related to wavelet frequency are met are scales inversely proportional to frequencies. **Figure 1** demonstrates a simple example of this relationship. If the investment horizon increases (high-scale), the wavelet becomes more spread out, resulting in a lower frequency. An expansion of these relationships and the exact details on these specifications are discussed later in this section.

Given a time series $x(t) \in L^2(\mathbb{R})$ and an analyzing wavelet function $\psi_{a,b}(t) \in L^2(\mathbb{R})$, the decomposition of time series $x(t)$ into time-scale wavelet coefficients can be written as,

$$W_x(a,b) = \langle x, \psi_{a,b} \rangle = \int_{\mathbb{R}} x(t)\psi^*_{a,b}(t)\,dt. \tag{1}$$

The transformation is formally referred to as the continuous wavelet transform (CWT) and * denotes the complex conjugate. The CWT can be seen as a set of continuous band-pass filters applied to a time series.

We define an analyzing wavelet as being derived from the scaling, where $a > 0$ defines the scale, and shifting, where $b \in \mathbb{R}$ defines the shift, of a mother wavelet $\psi(t) \in L^2(\mathbb{R})$ into daughter wavelets $\psi_{a,b}(t) \in L^2(\mathbb{R})$:

$$\psi_{a,b}(t) = \frac{1}{\sqrt{a}}\psi\left(\frac{t-b}{a}\right). \tag{2}$$

The wavelet power, $|W_x(a,b)|^2$, is visualized in the time-scale $\{b,a\}$ half plane with a horizontal linear scale axis in time, b, and a vertical logarithmic scale axis in, a, see **Figure 2** for an example for the power spectrum.

We can ensure reconstruction of a time series from its wavelet transform,

$$x(t) = \frac{1}{C_\psi}\int_0^\infty \left[\int_{\mathbb{R}} W_x(a,b)\psi_{a,b}(t)db\right]\frac{da}{a^2}, \tag{3}$$

if the following conditions are met: (1) $\int_{\mathbb{R}} \psi(t)dt = 0$, (2) $\int_{\mathbb{R}} \psi^2(t)dt = 1$, and (3) the admissibility condition is satisfied. The constant (C_ψ) is called the wavelet admissible constant and a wavelet whose admissible constant satisfies $0 < C_\psi < \infty$ is called an admissible wavelet. Mathematically C_ψ is defined as, $C_\psi = \int_{\mathbf{R}} \frac{\left|\hat{\psi}(\omega)\right|^2}{|\omega|}d\omega$ where $\hat{\psi}(\omega)$ is the Fourier transform of $\psi(t)$ in the CWT.

The Morlet wavelet is the most commonly used mother wavelet in finance and economic research. This choice and the

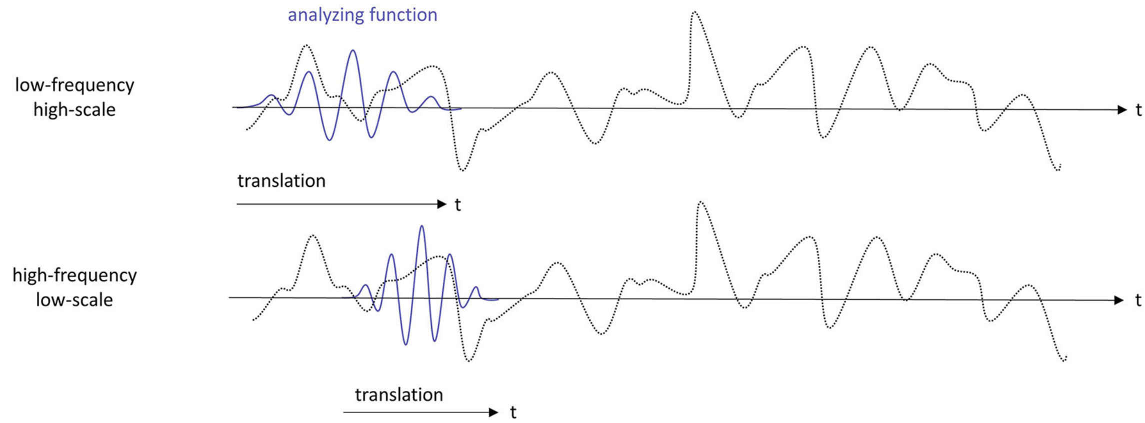

FIGURE 1 | Example of the analyzing wavelet function scaling and shifting across the time series that is being transformed. Equation (1) is the mathematical exposition of what is visualized in this figure.

detailed specifications pointed out in Aguiar-Conraria et al. (2014) proves best when using wavelets to extract investment horizon specific characteristics, because the Morlet wavelet is reasonably localized in both time and scale. The Morlet wavelet is defined as:

$$\Psi^M(t) = \pi^{-\frac{1}{4}} e^{-\frac{1}{2}t^2} e^{i\omega_0 t}, \tag{4}$$

where $\pi^{-\frac{1}{4}}$ normalizes the wavelet, $e^{-\frac{1}{2}t^2}$ is a Gaussian envelope with standard deviation of one, and $e^{i\omega_0 t}$ is the complex sinusoid. For the Morlet wavelet ω_0 is the central frequency. The usual relation of Fourier frequency to scale is $F_a = \frac{\omega_0}{2\pi a}$. As specified in Aguiar-Conraria et al. (2008) and Reboredo et al. (2017) we set $\omega_0 = 6$. We do so because when $\omega_0 = 6$, $F_a \approx \frac{1}{a}$ which provides better interpretability of scale and frequency. Even though the Morlet wavelet is commonly used in finance and economic practice there are various different sources describing different wavelets and their inherent characteristics. One of the more recent sources is Addison (2017).

We are dealing with finite time series in our application of quantifying the water-energy nexus and therefore need to address the issues of edge effects. This problem arises when filters are used for transformation. In dealing with these borders, we follow the methods of Grinsted et al. (2004) and ameliorate these effects by choosing the Morlet mother wavelet, as specified above (Torrence et al., 1998). We limit our interpretations to the areas within the cone of influence.

2.2. Details of the Wavelet Squared Coherence (WSC)

The wavelet squared coherence (WSC) is used in studying the comovement of two time series. Before we can define WSC, we first need to introduce the cross wavelet transform (XWT). Simply put, the wavelet cross spectrum is a measure of the power density and the WSC is a correlation measure between series. In **Figure 2**, we visualize these methods for the water-energy nexus using a time-scale $\{b, a\}$ half plane with logarithmic scale a-axis (vertical) increasing downwards and a linear scale on time b-axis (horizontal).

2.2.1. Cross Wavelet Transform (XWT)

According to Torrence and Webster (1999) the XWT of two time series $x(t)$ and $y(t)$ is

$$W_{x,y}(a,b) = W_x(a,b)W_y^*(a,b), \tag{5}$$

where $W_x(a,b)$ and $W_y(a,b)$ are CWT's of $x(t)$ and $y(t)$ and again * indicates the complex conjugate. We further define $|W_{x,y}(a,b)|$ as the XWT power. While each CWT preserves the energy of an individual time series, the XWT finds regions of high common power between time series across time for all frequencies. The scale or investment horizon in our application is the reciprocal of frequency. For more details on the theoretical distribution of the XWT power of two time series and how confidence levels are calculated (see Torrence et al., 1998).

2.2.2. WSC

By computing WSC we find regions in time-frequency space where the two time series co-vary. The idea is to measure the coherence of the XWT in these regions. The WSC is simple to interpret since it resembles the squared correlation coefficient in regression. The WSC is mathematically defined as

$$WSC(a,b) = \frac{|S(a^{-1}W_{xy}(a,b))|^2}{S(a^{-1}|W_x(a,b)|^2)S(a^{-1}|W_y(a,b)|^2)}. \tag{6}$$

The symbol $S(\cdot)$ is the smoothing operator. Without smoothing, the $WSC(a,b)$ is not in $[0,1]$. See Torrence and Webster (1999) and Grinsted et al. (2004) for how convolution in both scale and time is used to smooth. These details can be adjusted depending on the application.

2.2.3. Wavelet Phase Difference and Interpretation

As defined in Grinsted et al. (2004) and Aguiar-Conraria et al. (2014) the local or instantaneous wavelet phase-angle or

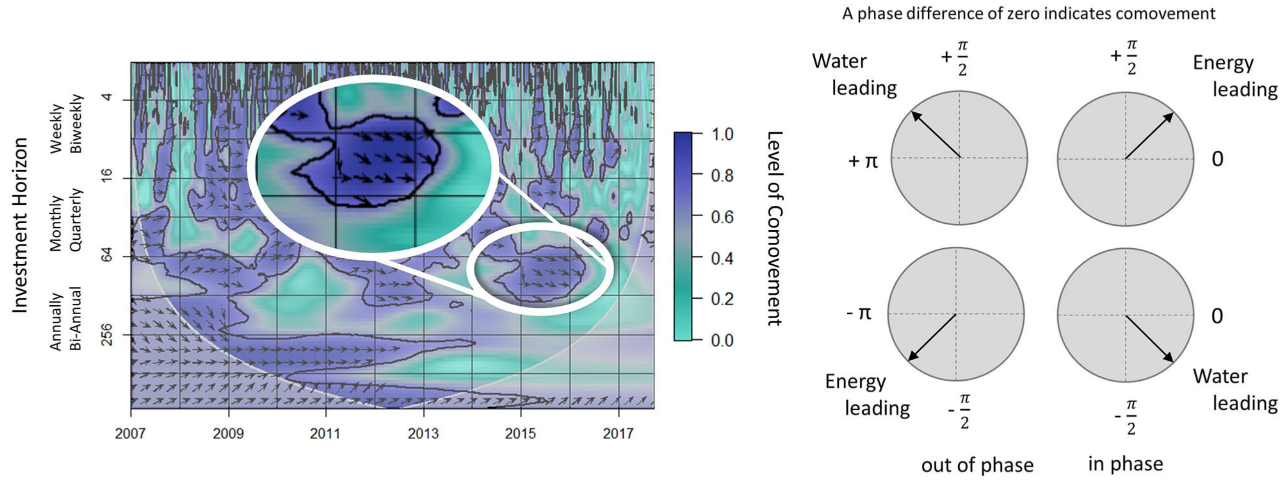

FIGURE 2 | The WSC of prices for water and energy (left) and phase change descriptions (right). The vertical axis shows investment horizons in days and the horizontal axis shows time in years. The darker purple the regions are (areas with arrows), the higher the level of comovement. The regions that are lined with black are regions of statistical significance at the 5% level estimated using multiple Monte Carlo randomizations. The white overlay defines the cone of influence. The arrows are an indication of phase movement (leading-lagging relationship) described in section 2.2.3 and visualized on the right side of this figure. See Gouhier et al. (2016) for more details.

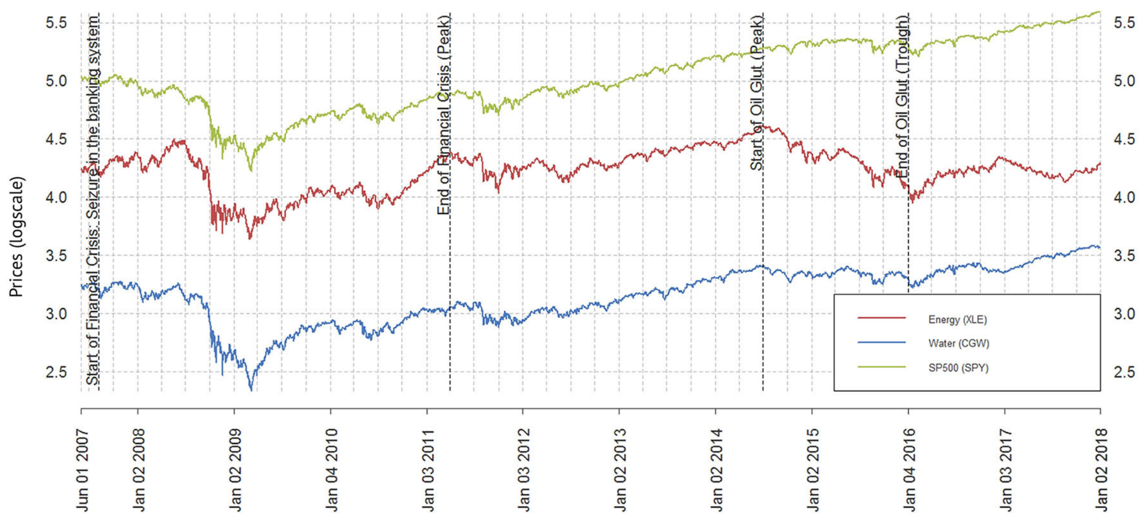

FIGURE 3 | Logscale closing price chart of the ETF's: CGW, XLE, and SPY. Vertical lines are inserted to indicate the approximate (peak to peak) start and end dates of the 2008 financial crisis, two key events during the crisis, and the 2014–2016 global oil glut from peak to trough (Peterson and Carl, 2015).

displacement of periodicity in the interval [$-\pi, \pi$] is,

$$Phase(a, b) = Arg(W_x(a, b)) = tan^{-1}\left(\frac{\Im(W_x(a, b))}{\Re(W_x(a, b))}\right), \quad (7)$$

where $\Re\{W_x(a, b)\}$ is the real part and $\Im\{W_x(a, b)\}$ is the imaginary part of the complex-valued $W_x(a, b)$. For the XWT the phase difference of x over y ($\phi_{x,y}$) localized in time b and scale a is:

$$\phi_{x,y} = tan^{-1}\left(\frac{\Im(S(a^{-1}W_{x,y}(a, b)))}{\Re(S(a^{-1}W_{x,y}(a, b)))}\right). \quad (8)$$

A phase difference of zero indicates comovement. If $\phi_{x,y} \in (0, \frac{\pi}{2})$ the time series are in-phase with y leading x and if $\phi_{x,y} \in (-\frac{\pi}{2}, 0)$ the time series are in-phase with x leading y. If $\phi_{x,y} \in (-\pi, -\frac{\pi}{2})$ the time series are anti-phase with y leading x and if $\phi_{x,y} \in (\frac{\pi}{2}, \pi)$ the time series are anti-phase with x leading y.

See **Figure 2** for visualization of these behaviors using arrows. Arrows pointing right (left) represent time series that are in-phase (anti-phase) and positively (negatively) correlated. Arrows representing $\phi_{x,y} \in (0, \frac{\pi}{2})$ point up and right, $\phi_{x,y} \in (-\frac{\pi}{2}, 0)$ point down and right, $\phi_{x,y} \in$

$(-\pi, -\frac{\pi}{2})$ point up and left, and $\phi_{x,y} \in (\frac{\pi}{2}, \pi)$ point down and left.

2.3. Windowed Scalogram Difference (WSD)

The scalogram was designed to identify scales that are most representative in the time series. As a result time series with similar behavior have similar windowed scalograms (WS), resulting in values close to zero after a $log_2(WSD^{-1})$ transformation. The $log_2(WSD^{-1})$ transformation is primarily implemented to create a scale which is comparable with the WSC. Bolós et al. (2017) designed the WSD to measure the difference between the WS of time series x and y. The WSD of two time series centered at time t and log-scale k where $k \in \mathbb{R}$ for the CWT with log-scale radius r and time radius τ, is defined as

$$WSD_{\tau,r}(t,k) = \left(\int_{k-r}^{k+r} \left(\frac{WS_\tau(t,k) - WS'_\tau(t,k)}{WS_\tau(t,k)} \right)^2 dk \right)^{\frac{1}{2}}, \quad (9)$$

where WS_τ is the WS of time series x and WS'_τ is the WS of time series y. As the name states, the WS has the ability to determine the importance of different scales windowed around a specific time point. The WS is defined as,

$$WS_\tau(t,k) = \left(\int_{t-\tau}^{t+\tau} |W_x(b, 2^k)|^2 db \right)^{\frac{1}{2}}. \quad (10)$$

Bolós et al. (2017) describes in detail the practicality of using base 2 power scales and the process of dealing with boundary conditions. **Figures 7**, **8** are visualizations of the WSD for the water-energy nexus.

2.4. Wavelet Local Multiple Correlation (WLMC)

Fernández-Macho (2018) recently introduced a new method for analyzing the dynamic comovement of various time series simultaneously. The aim of the proposed method is to produce a single set of correlations for each scale along time, instead of the standard pairwise wavelet correlation maps defined in sections 2.2 and 2.3.

Extracting from the details of Fernández-Macho (2018) we let W_{jt} be the scale specific, λ_j, wavelet coefficient for order $j = 1, ..., J$. The maximal overlap discrete wavelet transform (MODWT) of order J is applied to each time series $x_i(t)$ in the multivariate time series X to obtain W_{jt}. The $T \times n$ matrix X is composed of the n real-valued time series, each of length T.

It follows that the wavelet local multiple correlation (WLMC) can be expressed as

$$\varphi_{X,s}(\lambda_j) = \sqrt{1 - \frac{1}{\max \operatorname{diag}(P_{j,s}^{-1})}}, \quad (11)$$

where $P_{j,s}$ is the weighted correlation matrix of $W_{jt} = (w_{1jt}, w_{2jt}, ..., w_{njt})$.

The WLMC can further be simplified by realizing the square of the correlation between the fitted ($\hat{w}_{ijt}$) and observed (w_{ijt}) values is the regression coefficient of determination, where $\hat{w}_{ijt}$ is the local regression of w_{ijt} on the rest of W_{jt} at scale λ_j. Then the WLMC can be simplified to

$$\varphi_{X,s}(\lambda_j) = Corr(\theta(t-s)^{1/2} w_{ijt}, \theta(t-s)^{1/2} \hat{w}_{1jt}). \quad (12)$$

$\theta(\cdot)$ is a given moving average weight function and $s = 1, ..., T$ is the shift we use for the weight function. In our application, we are using the Gaussian window weight function for the best comparison to the Morlet wavelet. In Fernández-Macho (2018), the authors follow with a theorem for the sampling distribution of the WLMC statistic from Equation (12). This allows the construction of confidence intervals for the wavelet multiple correlation coefficient displayed in **Figure 9**.

TABLE 1 | Descriptive statistics of the ETF's: CGW, XLE, and SPY.

	Median	Mean	SD	SE	Range	Skew	Kurtosis
Energy (XLE)	70.29	70.01	12.08	0.23	63.17	−0.06	−0.10
Water (CGW)	24.37	24.05	5.44	0.11	25.79	−0.08	−0.66
S&P500 (SPY)	149.00	161.20	47.30	0.91	209.81	0.30	−0.93

3. RESULTS

3.1. Data Description and Visualization

Figure 3 contains three ETF price series and **Table 1** the descriptive statistics of each series. These ETF's are the Energy Select Sector SPDR Fund ETF (XLE), the Guggenheim S&P Global Water Index ETF (CGW), and the SPDR S&P500 Trust ETF (SPY). The XLE is the largest energy sector ETF and represents the energy sector of the S&P500 which includes companies in energy-related services and drilling as well as companies that produce and develop crude oil and natural gas. The CGW focuses on S&P500 companies important in the global water industry with the U.S. making up more than 50% of its holdings. The reason for choosing CGW compared to other water ETF's was because CGW was designed to expand as the demand for water companies, focusing on the issue of scarcity, increased. These two ETF time series are tracking companies that are representing mostly the U.S. markets from each side of the nexus that we are quantifying. Both the XLE and CGW pull their stocks from the S&P 500 rather than the total market. The addition of SPY is to explore the dynamic interaction of XLE and CGW or more specifically the water-energy nexus with respect to the S&P500 Index. We particularly point out two global economic events and identify behavioral differences between these series during these events. As indicated by **Figure 3** these events are the 2008 financial crisis and the 2014–2016 global oil glut.

The descriptive statistics in **Table 1** indicate non-stationary behavior. To confirm that our series are non-stationary we analyze the behavior of each series using three different tests. The Augmented Dickey-Fuller (ADF) test for the null hypothesis that each series has a unit root, the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test for the null hypothesis that each series is level or trend stationary, and the Phillips-Perron test for the null hypothesis that the series has a unit root against a stationary alternative. All tests confirmed that each of these ETF price series are non-stationary. We also applied the Ljung-Box-Pierce test (Box) concluding there is autocorrelation present in each series.

The rest of this section visually explores and analyzes the statistical properties related to CGW, XLE, and the SPY by implementing all the wavelet techniques we introduced the CWT, WSC, WSD, and WLMC. Throughout the rest of the paper, we refer to XLE as energy, CGW as water, and SPY as S&P500. **Figure 4** summarizes the information provided by each method in section 2.

Note, the graphical summaries also provide inferential information, depicting significance and confidence bands where appropriate. **Figure 5** depicts, the CWT power spectrum of the water and energy price series to identify the optimal investment horizons. **Figure 6** depicts the WSC of the water-energy nexus as well as the WSC of energy and the S&P500 price series. These techniques are used to identify the level of comovement and visualize the dynamics of the leading-lagging relationships between these time series over time. The WSD, presented in **Figure 7**, evaluates the level of similarity within the water-energy nexus as well as the level of similarity between energy and the S&P500, specifically pointing out in **Figure 8**, the level of similarity during a specific time-localized event. The section ends with **Figure 9** evaluation the wavelet local multiple correlations between the water-energy nexus and the S&P500.

We extract data using the R package quantmod (Ryan and Ulrich, 2017). We analyze ten years of daily price data from 2007-06-01 to 2018-01-16 to capture the changing mean behavior in addition to a range of investment horizons. Our data history starts in 2007 to not only study the decade since the 2008 financial crisis but also because CGW was one of the first water ETF's and before its inception in 2007 we were limited to single securities or themed investment trusts having no index that captures all the time-varying behaviors wavelets are best suited to capture.

3.1.1. Continuous Wavelet Transform (CWT)

In **Figure 5**, we decompose the water and energy price series into their respective component pieces each representing an investment horizon. Our evaluation and analysis must be focused on areas with medium to high power intensity (see section 2.1). These regions can be seen as the components that carry most of the behavioral weight. For an example on how to interpret **Figure 5**, consider the wavelet power levels across time for the quarterly investment horizon. This horizon is mostly medium intensity with regions of low intensity. As we point out in section 2.1, wavelet power is visualized in the time-scale half plane. The squared wavelet coefficient values represent the statistical significance of the behavior or better known as the power of a specific feature described at each of the time-scale locations.

Determining and translating scales to relevant time domain periods like investment horizons are useful in seeking future applications. These include finding the optimal investment horizon for each asset in a multi-asset portfolio or identifying the investment horizon that explains most of the behavior in the price series and adjusting risk management accordingly. The high power intensity range of **Figure 5** is of particular interest, but caution should be taken when analyzing this range because it is impacted by the cone of influence and results can be skewed by border effects (discussion in section 2.1 and for further details see Grinsted et al., 2004). As mentioned in section 2.1, we limit our interpretations to the areas within the cone of influence.

3.1.2. Wavelet Squared Coherence (WSC)

The goal of the analysis in **Figure 6** is primarily to study the development of correlation over the past 10 years for the water-energy nexus and to understand more about how these interactions change over time for different investment horizons.

We explore in detail these interactions in section 3.1.4 by pointing out specifically the dates of the two economic events referred to in **Figure 3**. The evaluation on the right analyzes the dynamic interactions of energy and the S&P500 to identify the statistically significant behavioral impact of the market. **Figure 6** also depicts a leading-lagging relationship using the tools mentioned in section 2.2.3. Consider, for example, the quarterly investment horizon in **Figure 6** on the left during the 2014–2016 global oil glut. An arrow pointing down and right (-45° or $-\pi/4$ angle) indicates that water (first series) is leading energy (second series) with statistically significant positive correlation, see the water-energy nexus on the left side of **Figure 6** for magnification of these details. On the right side of **Figure 6** at the annual investment horizon range during the 2008 financial crisis, an arrow pointing up and right (45° or $\pi/4$ angle) indicates that energy (first series) is being led by the S&P500 (second series) with statistically significant positive correlation and an arrow pointing only right indicates that these prices are comoving without any leading or lagging relationship.

3.1.3. Windowed Scalogram Difference (WSD)

The analysis performed using the WSD, as seen in **Figure 7**, is instrumental in distinguishing between behavior impacted by external factors vs. behaviors identified due to dynamic interactions. To further explore the similarity and differences between water and energy we analyze the WSD.

At the quarterly investment horizon in **Figure 7**, the water-energy nexus (left) shows dissimilarity during the 2008 financial crisis. The statistically significant increased similarity during the 2014–2016 global oil glut is identified by the magnified region in **Figure 8**. **Figure 7** (right) demonstrates that there is not a major statistically significant similarity between energy and the S&P500 during the two economic events we are evaluating. This second analysis is useful in trying to eliminate the possibility that the market is significantly impacting the dynamic behavior of the water-energy nexus since we previously identified that the S&P500 is leading the dynamic behavior of energy in **Figure 6**. However, this market leading effect is still not clear and will be addressed in the next section.

3.1.4. Wavelet Local Multiple Correlation (WLMC)

Up to this point, the three different time series have increased levels of comovement and similarity depending on which investment horizon is being considered. However, there seems to be some significance in the water-energy nexus during the 2014–2016 global oil glut. Next, we will analyze the simultaneous

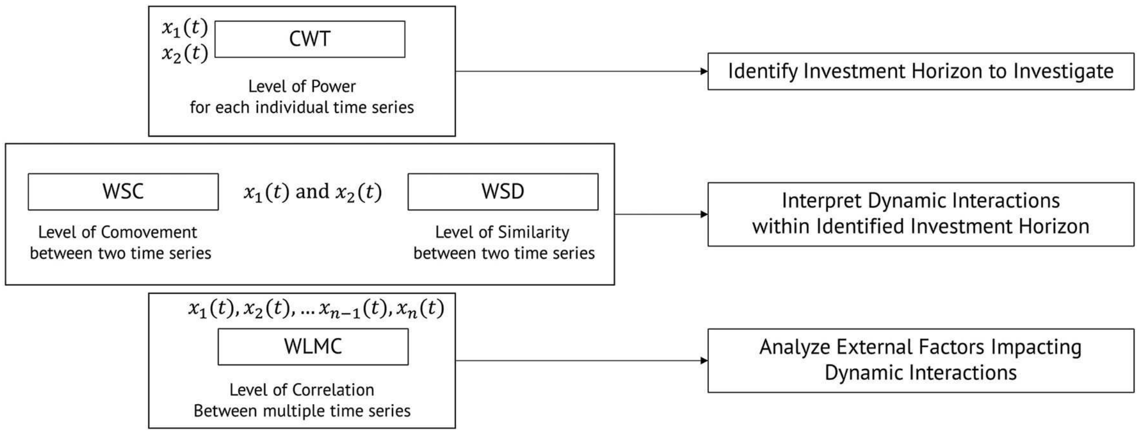

FIGURE 4 | The visualization process of the water-energy nexus has three distinct steps. (1) Identifying the investment horizons to investigate using the CWT. (2) Interpreting the dynamic interactions within the water-energy nexus using the WSC and WSD. And (3) analyzing any external factors impacting the dynamic behavior of the water-energy nexus.

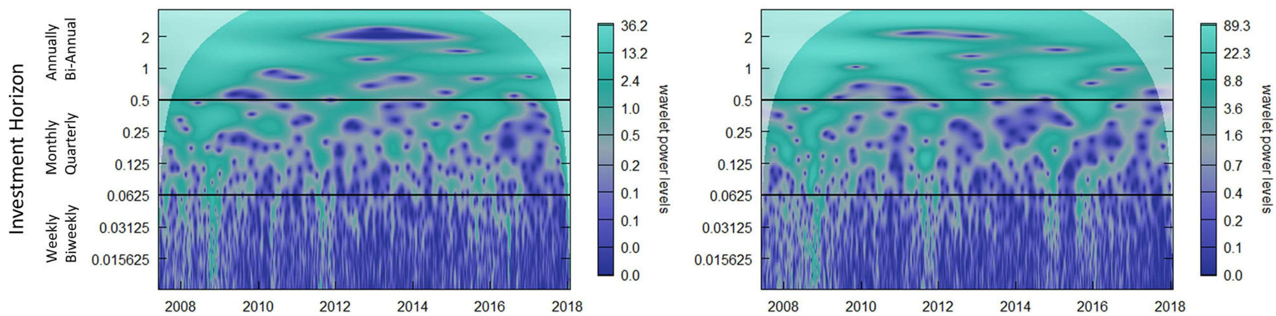

FIGURE 5 | The continuous wavelet transform (CWT) power spectrum of water (CGW left) and energy (XLE right) commodity ETF prices. These two plots are visual representations of the power spectrum of each individual series. The investment horizons (vertical axis) are such that the value one represents 250 days (annual investment horizon) and 0.25 represents 64 days (quarterly investment horizon). The horizontal axis indicates the 10 years of data. These plots are divided into three sections with the goal of separating low (bottom), medium (middle), and high (top) power. These sections are categorized as regions which are representative of short (weekly, biweekly), medium (monthly, quarterly), and long (annually, bi-annual) run behavior, respectively. The white overlay defines the cone of influence. Figures were created by implementing minor modifications to Rösch and Schmidbauer (2014).

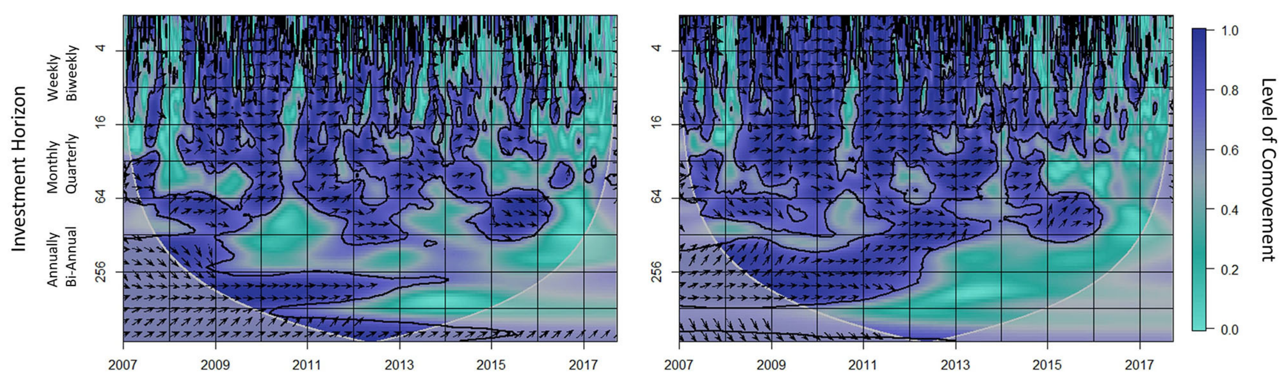

FIGURE 6 | The WSC of the water-energy nexus **(left)** and energy and S&P500 **(right)**. The vertical axis shows investment horizons in days and the horizontal axis shows time in years. The darker purple the regions are the higher the statistical significant level of comovement. The regions that are lined with black are regions of statistical significance at the 5% level estimated using Monte Carlo simulations. The white overlay defines the cone of influence. The arrows are an indication of phase movement (leading-lagging relationship) described in section 2.2.3.

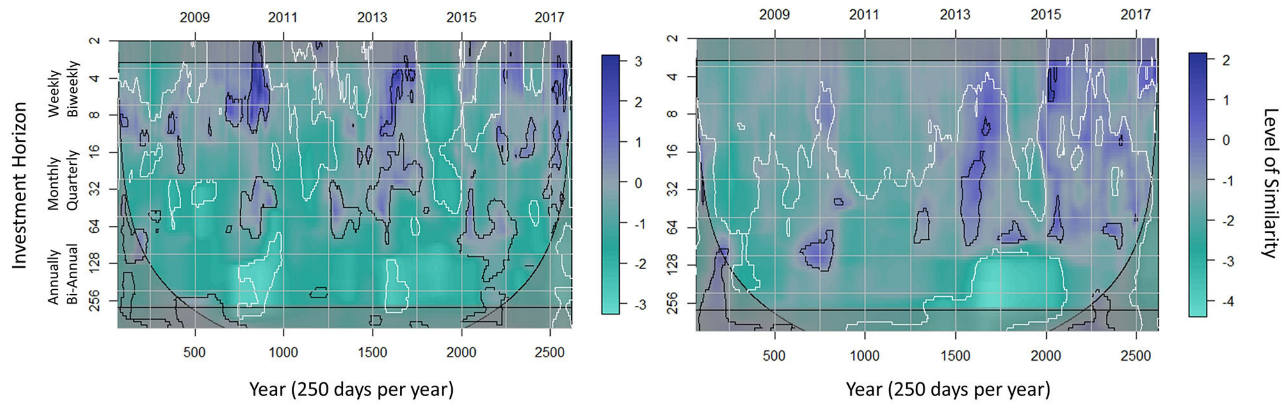

FIGURE 7 | The WSD of the water-energy nexus **(left)** and energy and S&P500 **(right)**. The more purple the color, the higher the similarity is between time series. The black-line regions are regions of statistical significance at the 5% level (high similarity) and the white-line regions are regions of statistical significance at the 95% level (low similarity) estimated using Monte Carlo simulations. The box and thin black region are the border effects and define the cone of influence, respectively. Here we are using a fixed time radius of 64 days and the investment horizon radius (window margins) is determined by the length of the series.

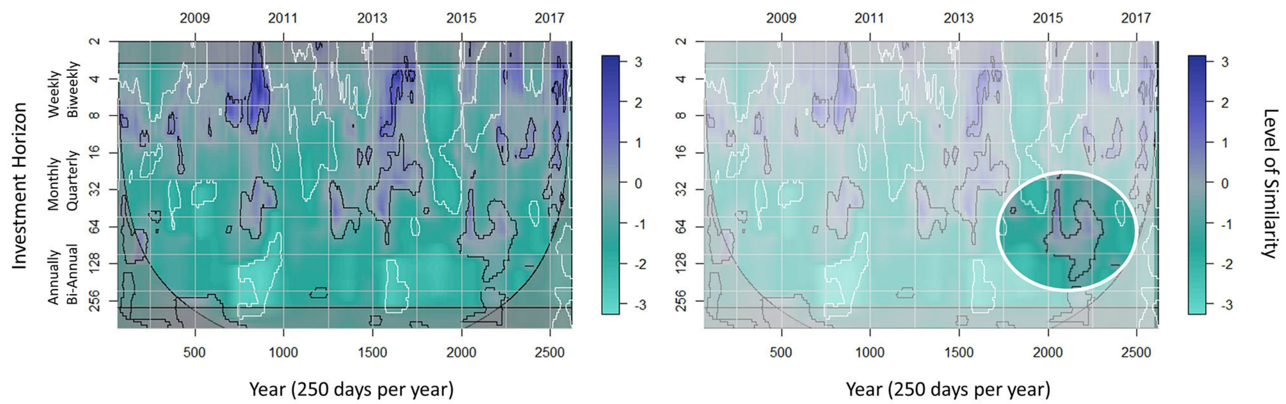

FIGURE 8 | Magnification of the WSD of the water-energy nexus from **Figure 7**. The white circle emphasizes the WSD of the water-energy nexus during the quarterly investment horizon. The black-line regions are regions of statistical significance at the 5% level (high similarity). As we pointed out in section 2.3, the WSD is a difference equation so high similarity means values close to zero.

correlation at a local level to see if we can identify a deviation in the similarity and comovement. The wavelet local multiple correlation (WLMC) (Fernández-Macho, 2018) allows us to extend wavelet methodology to handle comovement dynamics of multivariate time series. This statistical tool allows us to view the joint comovement of the water-energy nexus with the S&P500 (**Figure 9**). The analysis visualized in **Figure 9** (top) shows statistically significant deviations in the high correlation between the water-energy nexus and the S&P500.

The deviations specifically indicative of the 2014–2016 global oil glut are pointed out again in these figures. This is most prominent during the quarterly investment horizon referencing the correlations shown in the (16–128) range. Our evaluation of these figures indicates that during the start of the global oil glut the correlation deviated significantly and by the end, the significant correlation picked back up. These results would be very difficult to obtain using time domain analysis (for example with DCC-GARCH) or even frequency only analysis (Fourier). The dynamics we identified are time-varying requiring simultaneous analysis in both time and at specific horizons to make sense of underlying behaviors or characteristics.

We have now stepped through all three of the visualization processes mentioned in **Figure 4**. In summary, each step was created to optimize the analysis process. The ability to identify the statistically significant dynamic interactions within the water-energy nexus for optimal investment horizons, during certain key economic events, aid in the discussions highlighted in the next section. An interesting result that we identified from our analysis is the potential that market behavior is currently impacted more heavily by energy than energy is impacted by the market behavior. There is very recent literature that supports these findings (Ferreira et al., 2019), however, to clearly recover these results requires expanding our application to include a longer history.

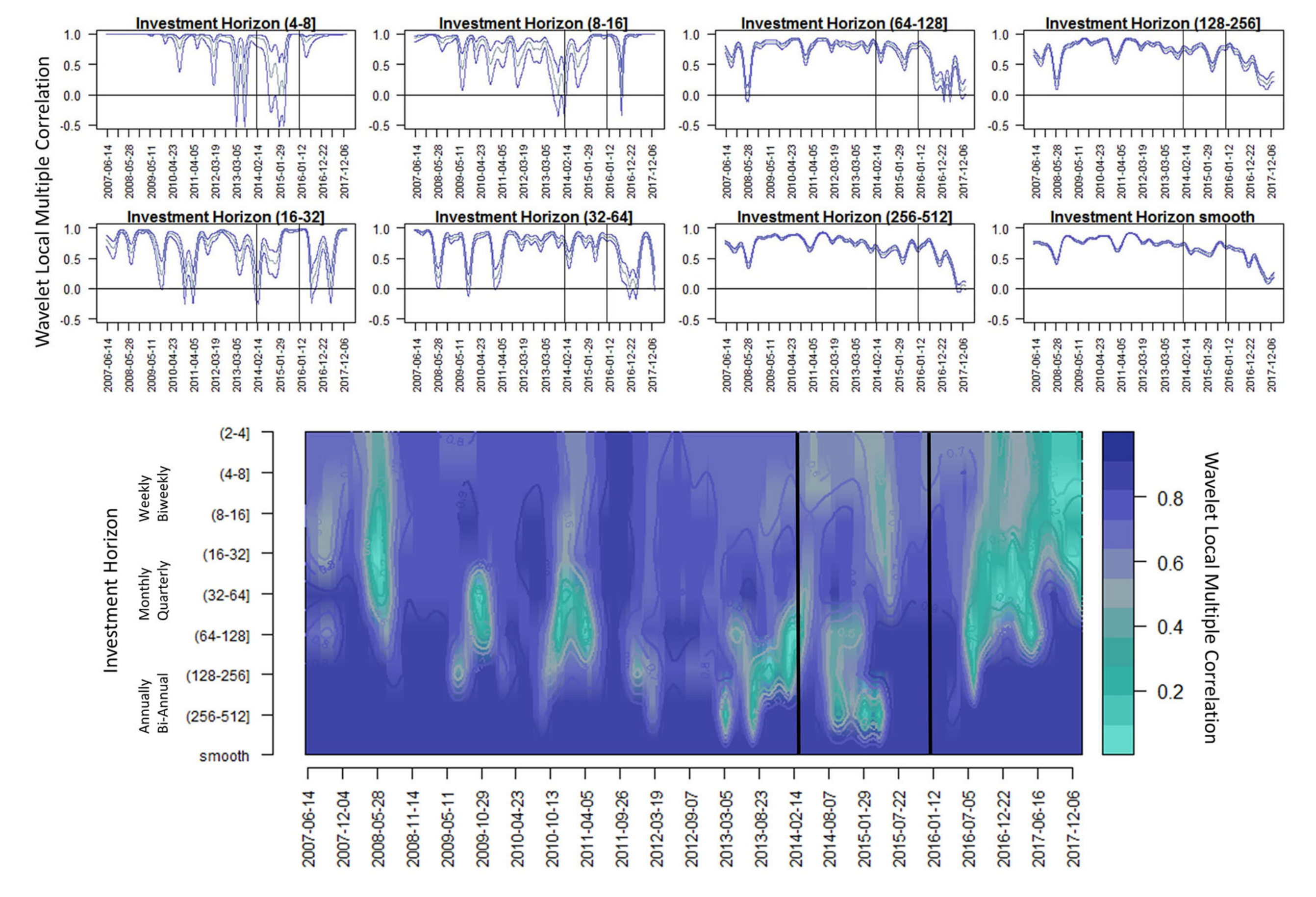

FIGURE 9 | The WLMC of the water-energy nexus and the S&P500. At the top the purple lines correspond to the upper and lower bounds of the 95% confidence interval for the WLMC statistic at four different investment horizons. On the bottom the heat plot corresponds to the single set of correlations for all three time series (XLE, CGW, and SPY) for each scale across time, the contour lines correspond to the confidence intervals depicted for the investment horizons at the top.

3.1.5. Evidence From Time-Varying Spectral Analysis

Understanding the investment horizon and interaction between commodities is important for practitioners to consider in the design of investment models. From the analysis of the CWT, we see a potential investment opportunity for quarterly investment horizons; from **Figure 5** we analyzed that both time series' quarterly contribution to the overall behavior of the series has medium to high power intensity. Further **Figure 6**, clearly indicates a comoving relationship during the quarterly investment horizon, identified by **Figure 5**, as one of the dominant signals in the series. There is an interesting distinctive difference between the interactive behavior during the 2008 financial crisis and the 2014-2016 global oil glut which is also pointed out in **Figure 6** by modeling the comparison between energy and the S&P500.

The WSC from **Figure 6** allows us to examine the water-energy phase behaviors for these two events. During the first event at the quarterly investment horizon energy is leading water, however, for the annual investment horizon, these series are mostly comoving. This relationship can be confirmed by looking at the price series in **Figure 3** and the analysis of **Figure 7**. This comovement is a result of the market impact seen in **Figure 6** (right) where energy and the S&P500 series are mostly in-phase. At the quarterly investment horizon, energy is leading the S&P500, but at the annual investment horizon, the S&P500 is leading. In contrast, during the 2014–2016 global oil glut, there is a clear indication that water and energy are in-phase with water leading energy prices during this quarterly investment horizon.

Our results have the following U.S. policy implications. As fracking expands in the United States and oil prices stay relatively low, the use of aqueous-drilling fluids will increase due to low cost and limited environmental impact as required by the EPA [United States Environmental Protection Agency (EPA), 2000]. Between 2000 and 2014 the average amount of water used to drill a well has increased from 177,000 gallons to 5.1 million gallons per well (Gallegos et al., 2015). As newer technology becomes available to drill deeper into the ground the volume of water needed will place strain on the U.S. water supply. Even though the amount of water needed for fracking is less than that needed for farming and cooling it can still strain water supply in areas where water is limited. As water becomes an increasingly scarce commodity, discussions of the water-energy nexus policy reform need to be addressed alongside the food-energy nexus discussion (Pal and Mitra, 2017). We specifically used the CGW ETF in our analysis because it was initially designed to expand as the demand for water companies, focusing on the issue of scarcity, are added to the portfolio. We believe that the holdings of this ETF are representative of those companies primarily focused on providing water in areas where there exist limited resources. So the result of water leading energy during the 2014–2016 global oil glut indicates that there should be a higher value placed on these water scarcity focused companies.

During the past few years, there have been increased discussions in the Texas Permian Basin suggesting that the future of upstream-energy water management cost reduction is water commoditization or a water price index. The water management market makes up about $20 billion and most of this money is spent on water logistics (Barclays and Columbia Water Center, 2017). The creation of a marketplace for water would allow water services to be accurately priced based on the demand and supply of the market. However, creating this marketplace could potentially lead to various conflicts regarding rights to water resources. If this marketplace should exist or not is a matter of discussion, but as we have shown in this paper there is a quantifiable dynamic relationship between water and energy commodities. Understanding these dynamics and constantly evaluating the time-varying changes of these price behaviors could potentially reduce water management costs in the energy industry. This can be achieved by simply capitalizing on the ongoing leading-lagging relationship and potential investment horizon that is easily identified with the same analysis implemented in this paper.

4. CONCLUSION

We present method and visualization tools that quantify the time-varying relationship between water and energy prices while highlighting key investment-horizon behaviors. Our choice of wavelet-based methods results in strategies for quantified fact-driven decision making about the water-energy nexus. To the best of our knowledge, this paper is the first to confirm the water and energy relationship in a quantitative manner. Our intention, however, is to provide empirical observations and not to suggest an economic mechanism for this observed relationship. The latter perspective is beyond the scope of the paper.

The novelty of our approach lies in the exploration of the water-energy nexus using non-stationary financial instruments in the time-scale domain. We distinguish between the impacts of two economic events on water-energy price movement at different investment horizons. Incorporating the S&P500 into our time-varying study of the price behavior isolates the variation due to general market structure, and that due to the relationship between water and energy. Investment decisions based on the insights presented in this paper can be made under the umbrella of portfolio investment theory to determine the optimal risk-return trade-off between the two commodities. We specifically chose to analyze the water-energy nexus to demonstrate our ability to capture complex time-varying relationships using wavelet based tools.

The water-energy nexus represents complex structures with global impact. For example, the UN forecast for 2035 indicates that energy and water consumption will increase by 35 and 85%, respectively, and the withdrawal of water for energy use would increase by 20%. Correctly identifying the dynamic interactions of water and energy commodities not only creates a vehicle to improve upon current investment strategies within the United States but could also impact decisions and policy processes within countries that have high water stress. Our research speaks directly to this important global challenge of the next two decades by helping investment planners and risk managers, through informing their decisions with quantitative insight, on how to dynamically allocate water to maximize energy returns while preserving potable water sources (Barclays and Columbia Water Center, 2017).

DATA AVAILABILITY STATEMENT

All datasets generated in this study are included in the article/supplementary material.

AUTHOR CONTRIBUTIONS

KR significantly contributed to the conception of the work as well as the analysis and interpretations and was also responsible for drafting the work. KE was responsible for revising it critically for important intellectual content resulting in both authors contributing equally. All authors contributed to the article and approved the submitted version.

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REFERENCES

Abdelradi, F., and Serra, T. (2015). Food-energy nexus in Europe: Price volatility approach. *Energy Econ.* 48, 157–167. doi: 10.1016/j.eneco.2014.11.022

Addison, P. S. (2017). *The Illustrated Wavelet Transform Handbook: Introductory Theory and Applications in Science, Engineering, Medicine and Finance, Second Edition*. Irvine, CA: CRC Press.

Aguiar-Conraria, L., Azevedo, N., and Soares, M. J. (2008). Using wavelets to decompose the time-frequency effects of monetary policy. *Phys. A* 387, 2863–2878. doi: 10.1016/j.physa.2008.01.063

Aguiar-Conraria, L., Soares, M. J., and Aguiar-Conraria, L. (2014). The continuous wavelet transform: moving beyond uni- and bivariate analysis. *J. Econ. Surv.* 28, 344–375. doi: 10.1111/joes.12012

Ahmadi, M., Bashiri Behmiri, N., and Manera, M. (2016). How is volatility in commodity markets linked to oil price shocks? *Energy Econ.* 59, 11–23. doi: 10.1016/j.eneco.2016.07.006

Barclays and Columbia Water Center (2017). *The Water Challenge: Preserving a Global Resource*. Technical report, Barclays.

Bilgili, F., Öztürk, l., Koçak, E., Bulut, M., Pamuk, Y., Muğaloğlu, E., et al. (2016). The influence of biomass energy consumption on CO2 emissions: a wavelet coherence approach. *Environ. Sci. Pollut. Res.* 23, 19043–19061. doi: 10.1007/s11356-016-7094-2

Bolós, V. J., Benítez, R., Ferrer, R., and Jammazi, R. (2017). The windowed scalogram difference: a novel wavelet tool for comparing time series. *Appl. Math. Comput.* 312, 49–65. doi: 10.1016/j.amc.2017.05.046

Cai, Y., Cai, J., Xu, L., Tan, Q., and Xu, Q. (2019). Integrated risk analysis of water-energy nexus systems based on systems dynamics, orthogonal design and copula analysis. *Renew. Sustain. Energy Rev.* 99, 125–137. doi: 10.1016/j.rser.2018.10.001

Chaudhuri, S., and Lo, A. (2016). *Spectral Portfolio Theory*. Technical report, MIT Sloan School of Management.

Cheng, I.-H., and Xiong, W. (2013). The financialization of commodity markets. *SSRN Elecron. J.* 6:419–441. doi: 10.1146/annurev-financial-110613-034432

Connor, J., and Rossiter, R. (2005). Wavelet transforms and commodity prices. *Stud. Nonlin. Dyn. Econ.* 9, 1–22. doi: 10.2202/1558-3708.1170

Creti, A., Joëts, M., and Mignon, V. (2013). On the links between stock and commodity markets' volatility. *Energy Econ.* 37, 16–28. doi: 10.1016/j.eneco.2013.01.005

Dai, J., Wu, S., Han, G., Weinberg, J., Xie, X., Wu, X., et al. (2018). Water-energy nexus: a review of methods and tools for macro-assessment. *Appl. Energy* 210, 393–408. doi: 10.1016/j.apenergy.2017.08.243

Dajcman, S., Festic, M., and Kavkler, A. (2012). European stock market comovement dynamics during some major financial market turmoils in the period 1997 to 2010 - a comparative DCC-GARCH and wavelet correlation analysis. *Appl. Econ. Lett.* 19, 1249–1256. doi: 10.1080/13504851.2011.619481

Davidson, R., Labys, W. C., and Lesourd, J.-B. (1997). Walvelet analysis of commodity price behavior. *Comput. Econ.* 11, 103–128. doi: 10.1023/A:1008666428579

Fang, D., and Chen, B. (2017). Linkage analysis for the water-energy nexus of city. *Appl. Energy* 189, 770–779. doi: 10.1016/j.apenergy.2016.04.020

Fernández-Macho, J. (2018). Time-localized wavelet multiple regression and correlation. *Phys. A* 492, 1226–1238. doi: 10.1016/j.physa.2017.11.050

Ferreira, P., Pereira, E. J. d. A. L., Silva, M. F. d., and Pereira, H. B. (2019). Detrended correlation coefficients between oil and stock markets: The effect of the 2008 crisis. *Phys. A* 517, 86–96. doi: 10.1016/j.physa.2018.11.021

Ftiti, Z., Jawadi, F., and Louhichi, W. (2017). Modelling the relationship between future energy intraday volatility and trading volume with wavelet. *Appl. Econ.* 49, 1981–1993. doi: 10.1080/00036846.2016.1229453

Gallegos, T. J., Varela, B. A., Haines, S. S., and Engle, M. A. (2015). Hyraulic fracturing water use varibility in the United States and potential environmental implications. *Water Resour. Res.* 51, 5839–5845. doi: 10.1002/2015WR017278

Gouhier, T. C., Simko, V., and Grinsted, A. (2016). Biwavelet: Conduct univariate and bivariate wavelet analyses.

Grinsted, A., Moore, J. C., and Jevrejeva, S. (2004). Application of the cross wavelet transform and wavelet coherence to geophysical time series. *Nonlin. Process. Geophys.* 11, 561–566. doi: 10.5194/npg-11-561-2004

Hamiche, A. M., Stambouli, A. B., and Flazi, S. (2016). A review of the water-energy nexus. *Renew. Sustain. Energy Rev.* 65, 319–331. doi: 10.1016/j.rser.2016.07.020

In, F., and Kim, S. (2012). *An Introduction to Wavelet Theory in Finance : a Wavelet Multiscale Approach*. World Scientific.

Keulertz, M., and Woertz, E. (2015). Financial challenges of the nexus: pathways for investment in water, energy and agriculture in the Arab world. *Int. J. Water Resour. Dev.* 31, 312–325. doi: 10.1080/07900627.2015.1019043

Kumar, S., Pathak, R., Tiwari, A. K., and Yoon, S.-M. (2017). Are exchange rates interdependent? Evidence using wavelet analysis. *Appl. Econ.* 49, 3231–3245. doi: 10.1080/00036846.2016.1257108

Mensi, W., Hkiri, B., Al-Yahyaee, K. H., and Kang, S. H. (2017). Analyzing time-frequency co-movements across gold and oil prices with BRICS stock markets: a VaR based on wavelet approach. *Int. Rev. Econ. Fin.* 54, 74–102. doi: 10.1016/j.iref.2017.07.032

Ozturk, I. (2015). Sustainability in the food-energy-water nexus: evidence from BRICS (Brazil, the Russian Federation, India, China, and South Africa) countries. *Energy* 93, 999–1010. doi: 10.1016/j.energy.2015.09.104

Ozturk, I. (2017). The dynamic relationship between agricultural sustainability and food-energy-water poverty in a panel of selected Sub-Saharan African Countries. *Energy Policy* 107, 289–299. doi: 10.1016/j.enpol.2017.04.048

Pal, D., and Mitra, S. K. (2017). Time-frequency contained co-movement of crude oil and world food prices: a wavelet-based analysis. *Energy Econ.* 62, 230–239. doi: 10.1016/j.eneco.2016.12.020

Peterson, B. G., and Carl, P. (2015). PerformanceAnalytics: econometric tools for performance and risk analysis.

Raath, K. C., Ensor, K. B., Scott, D. W., and Crivello, A. (2019). Denoising non-stationary signals by dynamic multivariate complex wavelet thresholding. *SSRN Electron. J.* doi: 10.2139/ssrn.3528714

Reboredo, J. C., Rivera-Castro, M. A., and Ugolini, A. (2017). Wavelet-based test of co-movement and causality between oil and renewable energy stock prices. *Energy Econ.* 61, 241–252. doi: 10.1016/j.eneco.2016.10.015

Rösch, A., and Schmidbauer, H. (2014). WaveletComp: A guided tour through the R-package.

Ryan, J. A., and Ulrich, J. M. (2017). quantmod: Quantitative Financial Modelling Framework.

Siddiqi, A., and Anadon, L. D. (2011). The water-energy nexus in Middle East and North Africa. *Energy Policy* 39, 4529–4540. doi: 10.1016/j.enpol.2011.04.023

Smajgl, A., Ward, J., and Pluschke, L. (2016). The water-food-energy Nexus-Realising a new paradigm. *J. Hydrol.* 533, 533–540. doi: 10.1016/j.jhydrol.2015.12.033

Tan, C., and Zhi, Q. (2016). The energy-water nexus: a literature review of the dependence of energy on water. *Energy Proc.* 88, 277–284. doi: 10.1016/j.egypro.2016.06.154

Torrence, C., Compo, G. P., Torrence, C., and Compo, G. P. (1998). A practical guide to wavelet analysis. *Bull. Am. Meteorol. Soc.* 79, 61–78. doi: 10.1175/1520-0477(1998)079<0061:APGTWA>2.0.CO;2

Torrence, C., and Webster, P. J. (1999). Interdecadal changes in the ENSO-monsoon system. *J. Clim.* 12, 2679–2690. doi: 10.1175/1520-0442(1999)012<2679:ICITEM>2.0.CO;2

United States Environmental Protection Agency (EPA) (2000). *EPA: A Development Document for Final Effluent Limitations Guidelines and Standards for Synthetic-Based Drilling Fluids and other Non-Aqueous Drilling Fluids in the Oil and Gas Extraction Point Source Category*. Technical report, United States Environmental Protection Agency (EPA).

Vacha, L., and Barunik, J. (2012). Co-movement of energy commodities revisited: Evidence from wavelet coherence analysis. *Energy Econ.* 34, 241–247. doi: 10.1016/j.eneco.2011.10.007

Wang, G.-J., Xie, C., and Chen, S. (2017). Multiscale correlation networks analysis of the US stock market: a wavelet analysis. *J. Econ. Interact. Coord.* 12, 561–594. doi: 10.1007/s11403-016-0176-x

Wang, S., Fath, B., and Chen, B. (2019). Energy-water nexus under energy mix scenarios using input-output and ecological network analyses. *Appl. Energy* 233–234, 827–839. doi: 10.1016/j.apenergy.2018.10.056

Wichelns, D. (2017). The water-energy-food nexus: is the increasing attention warranted, from either a research or policy perspective? *Environ. Sci. Policy* 69, 113–123. doi: 10.1016/j.envsci.2016.12.018

Zhang, D. (2018). Energy finance: background, concept, and recent developments. *Emerg. Markets Fin. Trade* 54, 1687–1692. doi: 10.1080/1540496X.2018.1466524

Ziogou, I., and Zachariadis, T. (2017). Quantifying the water-energy nexus in Greece. *Int. J. Sustain. Energy* 36, 972–982. doi: 10.1080/14786451.2016.1138953

Conflict of Interest: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

APPENDIX

A. ROBUSTNESS

We demonstrate through simulation the robustness of the continuous wavelet transform and repeat our analysis on a subset of the data. For additional analysis (see Raath et al., 2019).

A.1. Robustness Check on Methods

All the methods used originally stem from the CWT as seen in **Figure 4**. In **Figure A1**, we test the robustness of the CWT power spectrum to analyze investment-horizon specific behaviors by simulating an additive noise model, with three stationary signals.

A.2. Robustness Check on Data

Evaluating the robustness of the water-energy nexus relationship we eliminate 20% of the data and evaluate the same 64 day leading-lagging relationship analyzed in **Figures 2**, **6**, **9**. The robustness check still validates our conclusion.

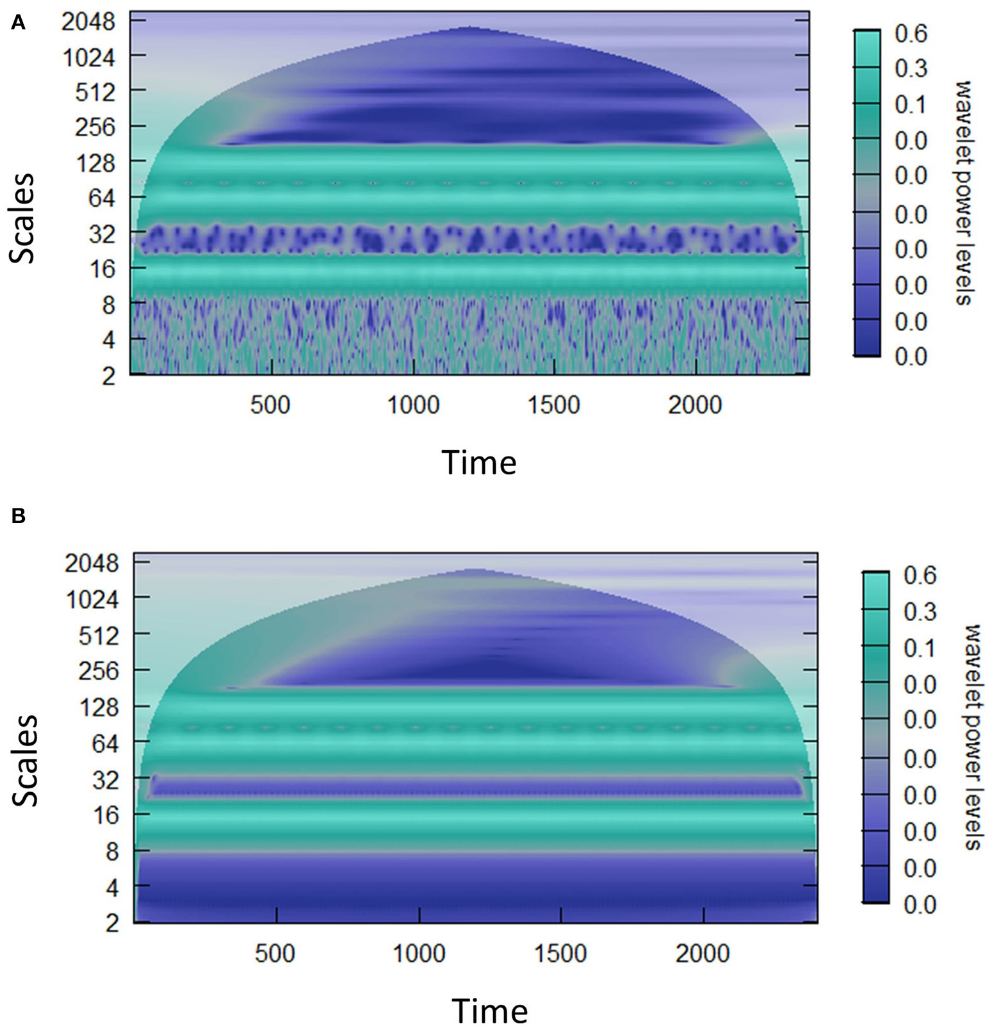

Figure A1 | Additive noise Model. Pure signal. The CWT power spectrum **(A)** of a simple additive noise model with three stationary signals. Biweekly (15 days), quarterly (64 days), and biannually (125 days). Hence we have that $y_t = sin(\frac{2\pi t}{15}) + sin(\frac{2\pi t}{64}) + sin(\frac{2\pi t}{125}) + \epsilon$ where $\epsilon \sim N(0, 0.1)$ and $t = (1, ..., 2400)$. Also in this figure is the CWT power spectrum **(B)** which is the pure signal without noise.

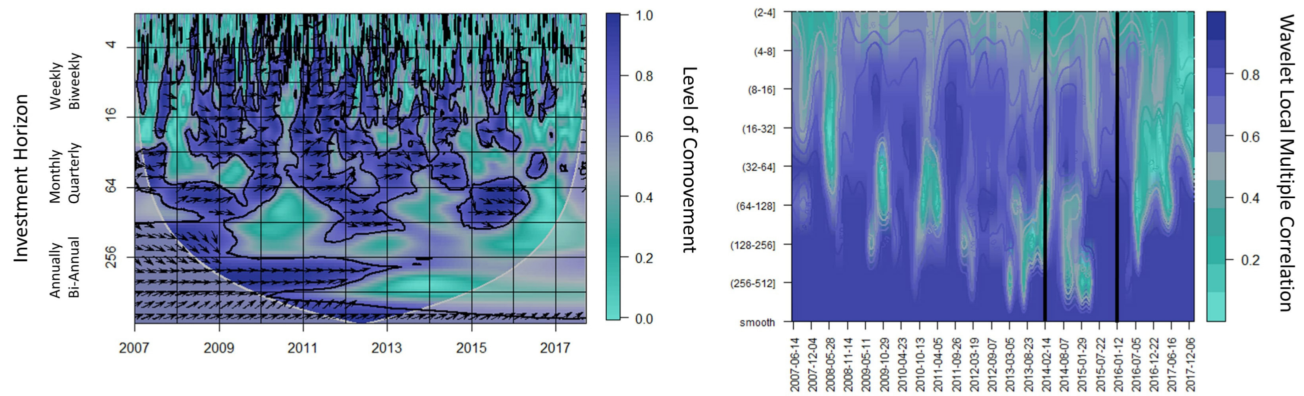

Figure A2 | Eliminating 20% of the data we analyze the results of our analysis using the WSC of the water-energy nexus **(left)** and the WLMC of the water-energy nexus and the S&P500 **(right)**. The vertical axis shows investment horizons in days and the horizontal axis shows time in years. The darker purple the regions are the higher the statistical significance.

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Analyzing Energy Transition Patterns in Asia: Evidence From Countries With Different Income Levels

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Energy transition as the issue of striving to use more environmentally friendly energy sources instead of fossil fuels is a crucial debate for scholars. A key point is how macroeconomic variables can accelerate the energy transition movement in different regions, which may lead to similarities in energy transition patterns among various regions. The main purpose of this study is to determine how energy transition patterns depend on economic variables in Asian economies, classifying based on their income level. To this end, we collected the related variables for 45 economies in Asia over the period 1993–2018 and conducted estimation using the generalized method of moments (GMM) approach. The major results revealed that economic growth has a positive relationship with the energy transition, while CO_2 emissions negatively influence energy transition. Furthermore, in both sub-sample groups (i.e., high and upper-middle-income and low and lower-middle-income groups) an increase in population lows the energy transition process. As an important recommendation, Asian economies with different income levels need different policies to improve and accelerate the energy transition movements. Especially in the developing and emerging economies that have higher economic growth rate and more energy demand, the governments need to implement various supportive policies for easing the access to electricity from green resources in line with the sustainable development goals (SDGs). This is more essential in the current low oil price era.

Keywords: energy transition, fossil fuel consumption, renewable energy consumption, asian regions, GMM estimator

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INTRODUCTION

The issue of striving to use more environmentally friendly energy sources instead of fossil fuels (energy transition) is a crucial debate for scholars. Kaberger (2018) and Rasoulinezhad and Jabalameli (2019) argued that replacing fossil fuels with renewable energy for electricity generation and other economic purposes may be a crucial topic for the future of the world economy. Based on IEA (2019a) report on the importance of clean energy transition, there are not any other alternative scenarios of the energy transition for mankind to combat with the current and future global environmental pollution.

Countries in the form of the global community are trying to reach efficient agreements to transform fossil fuels to cleaner fuels and increase energy efficiency to achieve a carbon zero economy target (Wiseman, 2018), however, this transition is not simple. Shell Energy Transition Report 2019 expresses that demand for fossil fuels would higher in 2030 than today, but the contribution of fossil fuels in the total energy system falls. Moreover, Regarding World Economic Forum (2018), the world needs an "effective energy transition" meaning a timely shift to address global energy-related challenges with creating value for firms and societies. Therefore, reaching an effective energy transformation is not an easy way for countries and needs in-depth studies to clarify different aspects of it.

Due to the complexity of energy transition process, different regions in the world experience different levels of energy transition based on their local energy consumption basket, geographical position, local economic ties with fossil energy, and so on. Singh et al. (2019) showed this fact by conducting the World Economic Forum's Energy Transition Index (ETI). They concluded that based on energy system performance and transition readiness of countries, there are different level of the energy transition in the world. The energy transition movement (renewable energy consumption divide on fossil fuels energy consumption) throughout 1990–2018 is illustrated in **Figure 1**. It can be seen that most regions have not experienced significant energy transformation progress in the last decades. Besides, the South Asian region has a reduction movement to 2010 and then it has experienced a smooth decrease till 2018.

Asia-Pacific is one of the most important regions in the world requiring a faster pace of energy transition. Mohammad (2019) believed that Asia's energy transition can contribute to cleaner earth in the future due to the large share of industrial production and population size in this region. Furthermore, Qiao (2019) expressed that due to the cost reduction of clean energy and improvement of the green energy efficiencies, Asian countries, particularly the South East ones have big opportunity to carry out their energy transition plans. The importance of energy transition in Asia has been also declared by United Nations: Economic and Social Council (2018) due to the increased trend of fossil fuel consumption and their high potential of industrial production. Among Asian countries, China and India drive the global renewable energy generation, which is undergoing a period of energy transition and economic transformation (Mamat et al., 2019). Many studies such as Jairaj and Kumar (2019) and Al-Shamma's et al. (2020) showed the importance of studying energy transition matters in regions and countries of Asia-Pacific. **Figure 2** presents the consumption of various energy resources for different regions over the period 1965–2018.

It can be seen that the Asia-Pacific is a pioneer in having a growth rate of energy consumption among different regions. Furthermore, the Middle East has an increased movement over the last decades. Jia et al. (2011) predict that, as a leader of Asian energy consumers, China will maintain sustained and rapid growth by 2020 and then gradually slow down, reaching 6.6 and 6.2 billion toe in 2050. In line with China, India, South Korea, and Malaysia (Sharvini et al., 2018) have been experiencing high rates of economic growth, leading to increased energy consumption in recent decades. This high level of using non-renewable energy resources has made Asian economies as significant emitters of CO_2. However, Asian economies are geographically located in areas with different climatic conditions such as tropical, humid, and so on, which provides easy access to a variety of renewable energy sources (Shukla et al., 2017).

In terms of increased energy demand, the issue of global warming, and the potential for developing green energy resources in Asia, there is a question of how macroeconomic variables can accelerate or decelerate energy transition movement in different regions in Asia. Despite numerous studies such as Fattouh et al. (2019); Yuan et al. (2018), Sharvini et al. (2018); Aung et al. (2017), Saboori et al. (2017); Taghizadeh-Hesary et al. (2016)Taghizadeh-Hesary et al. (2017); Reddy (2016), and Hess and Mai (2014) focusing on energy consumption and energy transition in Asian countries, we did not find any serious academic research considering energy transition patterns among such countries. Hence, this point covers the major novelty of our research and the gap in the literature our findings may fill.

The rest of our paper is organized as follows. Section 2 represents a brief literature review. The theoretical background is discussed in section 3. Section 4 describes the data and model specifications. Section 5 reports empirical results and Finally, section 6 provides concluding remarks and policy recommendations.

LITERATURE REVIEW

The related literature can be divided into two different strands. First focuses on energy transition issues and the second investigates energy transition in Asia.

The first strand concentrates on energy transition in different countries. Verbong and Geels (2007) analyzed energy transition trends in the Dutch electricity system for the period 1960–2004. The authors revealed that an energy transition, with roots in the 1960s and 1970s, is occurring in the Dutch electricity system but is mainly driven by liberalization and Europeanization. Al-Mulali et al. (2015) studied the relationship between economic growth and renewable energy consumption with the environmental pollution in 23 European countries with the data for the period 1990–2013. The major results proved that there is a positive relationship between economic growth with CO_2 emissions, while renewable electricity generation from solar and wind has not statistically significant effect on CO_2 emissions. Sovacool (2016) discussed the speed of energy transition in different countries. He concluded that such speed is not similar among countries and depends on different factors, policies, geographical location, and energy flows in the region. Al-Mulali et al. (2016) tested the Environmental Kuznets Curve (EKC) (the U-Shape linkage between CO_2 emissions and income level) hypothesis in seven different regions throughout 1980–2010. Dogan and Ozturk (2017) investigated the impacts of fossil fuel energy consumption and non-renewable energy consumption on CO_2 emissions in the United States throughout 1980–2014. They found out the positive and significant impact of fossil fuel energy consumption on environmental pollution in the United States, while there is a negative relationship between green energy consumption and CO_2 emissions there. Leeuwen et al. (2017)

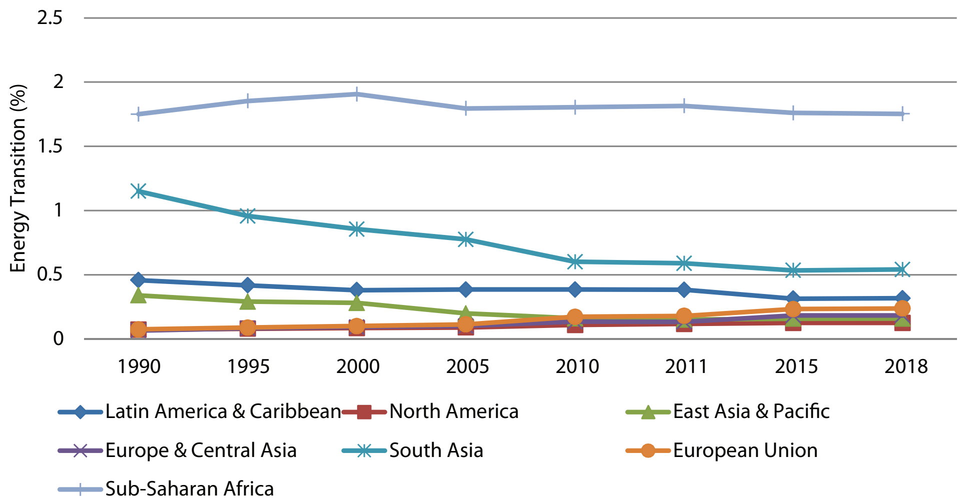

FIGURE 1 | Energy Transition in the different regions, 1990–2018%. Source: Authors' compilation based on data from the World Bank and BP's 2019 statistical report.

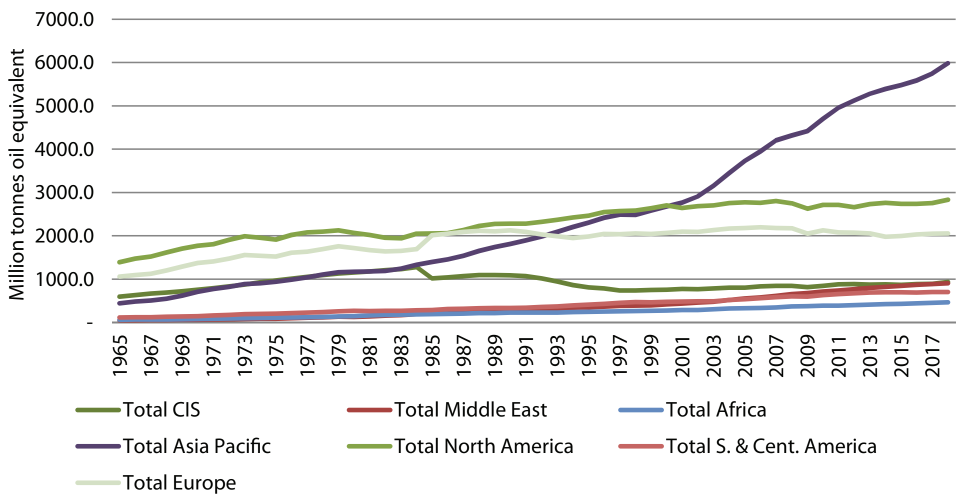

FIGURE 2 | Primary energy consumption in different regions, 1965–2018. CIS stands for Commonwealth of Independent States, Source: Compiled by the authors using BP's 2019 statistical report.

reviewed urban energy transition in the Netherlands with a focus on smart energy management. They concluded that the role of smart energy management as part of the integration of renewable energy into existing infrastructure is vital and can lead to the integration of state policies and the use of cleaner energy sources. Solarin et al. (2017) tried to analyze the existence of the EKC hypothesis in two emerging economies, i.e., India and China. The major results proved that GDP positively impacts on CO_2 emissions in these two countries. Stokes and Breetz (2018) analyzed politics in United States energy transition, particularly in the case of wind, solar, and biofuels. The findings depicted similar patterns across the electricity and transportation sectors. Osti (2018) considered different problems of transition to renewable energy sources on the small island of Sardinia in Italy. He concluded that in this region, three myths of fossil fuels vs. renewables, competition regarding smart grid and storage system technologies, and energy sovereignty vs. energy interdependency should be solved to enhance the energy transition level of Sardinia in the future. Vainio et al. (2019) investigated achieving a sustainable energy transition in Finland with a focus on the importance of citizen's images. The major findings revealed that the sustainable energy transition was strongly supported in Finland, but different socio-economic groups preferred somewhat different images. Szabo et al. (2019) studied types of long-term pathways that exist for electricity sector development in Southeast Europe. They found that to avoid lock-in to carbon-intensive technologies, stranded costs should be carefully considered in decision-making on new fossil fuel generation and gas network investment. Ozcan and Ozturk (2019) focused on the relationship between renewable energy consumption and economic growth in different emerging economies for the period of 1990–2016. The major findings showed evidence of the existence of the neutrality hypothesis due to the non-presence of the relationship between economic growth and renewable energy consumption. Vaillancourt et al. (2019) investigated the role of bioenergy in the low-carbon energy transition in Canada. Their results indicated a larger share of bioenergy in 2030 (up to a threefold increase in the most stringent greenhouse gas reduction scenario), with up to a fourfold increase in the total amount of feedstock used for bioenergy production. Sharif et al. (2019) conducted panel estimations to find out the relationship between fossil fuel and green energy consumption with carbon dioxide emissions for 74 countries from 1990 to 2015. The findings showed the direct and significant impact of fossil fuel energy consumption on CO_2 emissions, while the consumption of non-renewable energy resources can help the countries to lower CO_2 emissions.

The second strand of literature contains earlier studies focused on energy transition issues in different Asian countries. Pachauri and Jiang (2008) attempted to examine the household energy transition patterns in both India and China. They found that trends in energy use and the factors influencing a transition to modern energy are similar in both countries. Ngar-yin Mah et al. (2013) investigated the Japanese model of large smart grids for sustainable energy transitions. They argued that the Japanese model is characterized by a government-led, community-oriented, and business-driven approach with the launch of four large-scale smart-community demonstration projects. The Japanese government has demonstrated its high governing capacity in terms of leadership, and recombinative, institutional, enabling, and inducement capacities. Yildirim et al. (2014) studied the relationship between GDP per capita and energy consumption in the Association of Southeast Asian Nations (ASEAN) member states throughout 1971–2009. The paper concluded that the relationship is dissimilar among ASEAN member states. For instance, the conservation hypothesis is proved for Indonesia, while a bi-directional linkage was found out for the case of Thailand. Apergis and Ozturk (2015) tested the existence of the EKC for 14 Asian nations using the GMM approach. Their results proved the hypothesis for all Asian countries. Reddy (2016) used a bottom-up approach to investigate India's energy system transition. The main results revealed that significant resource savings can be achieved by 2030 through the introduction of energy-efficient and green technologies. In other studies, Ahmed et al. (2017) investigated the factors influencing on long-run CO_2 emissions in South Asia. Analyzing data throughout 1971–2013, the major results revealed that there is a uni-directional linkage from fossil fuel energy consumption and population growth to long-run CO_2 in this region. Gulagi et al. (2017) stimulated a 100% renewable energy transition model for India until 2030. They concluded that technology improvement can be an efficient instrument to reach a 100% energy transition in India. Chapman and Itoaka (2018) attempted to analyze the energy transition in Japan's liberalizing electricity market. They found that future energy transition pathway projections will need to incorporate policy approaches and mechanisms as well as being cognizant of Japan's geographic and cost-competitive renewable energy resource deployment limitations. Kucharski and Unesaki (2018) investigated the role of Japan's energy institutions in the post-Fukushima period. The major results revealed that policy reforms can affect energy sector structure and performance and proved that significant structural and institutional changes are underway in Japan's energy transition.

Considering both strands of literature discussed above, to the best of our knowledge, there has not been any serious academic attempt to investigate energy transition-macroeconomic variables linkages in Asia-Pacific economies and compare them among different groups based on the income levels. Hence, our study aims to fill the literature gap.

THEORETICAL BACKGROUND

Energy sources, that is, renewables and non-renewables are mainly used for electricity generation. For instance, many Asian nations such as Malaysia is highly dependent on fossil fuels as oil, coal and natural gas are major contributors to its power generation (Sharvini et al., 2018). Furthermore, in China and India, the electricity sector is the major consumer of fossil fuels, particularly coal (Zou et al., 2016; Zhang et al., 2019). We can assume that only two economic sectors (industrial and household/residential sectors) consume electricity generated by energy sources. In other words, the demand for renewable and non-renewable energy comes from these two sectors only.

We start with the industry's energy demand. Eq. 1 represents the production function of industry, which is assumed to be in Cobb-Douglas form as in Rasoulinezhad et al. (2020):

$$Y_t^I = F\left(K_t, L_t, ET_t^I\right) = K_t^{\alpha} L_t^{\beta} \left(ET_t^I\right)^{(1-\alpha-\beta)} \quad (1)$$

Here, Y^I is the total output of industry, K is the capital input, L denotes the labor input, ET^1 represents energy inputs of industrial production, which is considered as energy transition (share of renewables to non-renewables) in the industrial sector as written in Eq. 2. By considering constant returns to scale, α is the elasticity of production of capital, β is the elasticity of production of labor, and the elasticity of production of energy resources is equal to $1 - \alpha - \beta$.

$$ET_t^I = \frac{REC_t^I}{NREC_t^I} \quad (2)$$

Where REC^I and $NREC^I$ represent renewable energy consumption and non-renewable energy consumption in the industrial sector, respectively. It should be mentioned that we did not address energy resources as primary (contains original fuels such as oil, coal, natural gas, water, solar and wind) and secondary (like electricity) energies. Because these classifications can not represent an energy transition movement.

According to Hansen et al. (1995), firms are maximizing their profit as follows:

$$Max\ \pi_t = P_t^Y Y_t^I - r_t K_t - w_t L_t - e_t\left(P_t^E + T_t\right) ET_t^I \quad (3)$$

where π is the sector's profit, P^Y is the price of the final products, r denotes the interest rate of capital, w denotes the wage rate, e denotes the exchange rate, P^E denotes energy price and T denotes the transportation cost of energy resources.

By inserting Y^I from Eq. 1 into Eq. 3 and getting the first-order condition of profit (π) with respect to E^I, Eq. 4 will result:

$$\frac{\partial \pi_t}{\partial ET_t^I} = (1-\alpha-\beta)\,\frac{P_t^Y Y_t^I}{ET_t^I} - e_t\left(P_t^E + T_t\right) = 0 \tag{4}$$

The energy transition demand is represented in Eq. 5:

$$ET_t^I = (1-\alpha-\beta)\,\frac{P_t^Y Y_t^I}{e_t\left(P_t^E + T_t\right)} \tag{5}$$

As shown, industry's energy transition demand is a function of the elasticities of production of labor and capital, the real output of industry sector, the price of energy, the exchange rate, and the transportation cost of energy.

Next, we consider household energy demand using the following utility function:

$$U_t = \left(C_t, ET_t^H\right) = \frac{1}{1-\gamma}\left(C_t\right)^{1-\gamma} + \frac{1}{1-\delta}\left(ET_t^H\right)^{1-\delta} \tag{6}$$

As in Taghizadeh-Hesary and Yoshino (2018) C_t donates the consumption of non-energy goods and ET_t^H denotes the consumption of energy goods (representing the energy transition demand of households). Following Cymrot and Seiver (1982), households maximize their utility with respect to their budget, which is the constraint, as shown in Eq. 7:

$$S.T.\ P_t^C C_t + e_t\left(P_t^E + T_t\right) ET_t^H = Y_t^H \tag{7}$$

Where P^C denotes the price of non-energy goods, P^E denotes the energy goods, which depends on energy prices denominated in US dollars, and T denotes the transportation costs, Y^H is the total income of the households.

To maximize the utility of households for defining the factors that determine energy demand, we develop the Lagrange function, as in Eq. 8:

$$\Gamma = U\left(C_t, ET_t^H\right) - \lambda\left\{P_t^C C_t + e_t\left(P_t^E + T_t\right) ET_t^H - Y_t^H\right\} \tag{8}$$

Obtaining the first-order conditions with respect to the ET^H, C, and λ results in Eqs. 9–11:

$$\frac{\partial \Gamma}{\partial ET_t^H} = \left(ET_t^H\right)^{-\delta} - \lambda\left\{e_t\left(P_t^E + T_t\right)\right\} = 0 \tag{9}$$

$$\frac{\partial \Gamma}{\partial C_t} = C_t^{-\gamma} - \lambda\left(P_t^C\right) = 0 \rightarrow \lambda = \frac{C_t^{-\gamma}}{P_t^C} \tag{10}$$

$$\frac{\partial \Gamma}{\partial \lambda} = Y_t^H = P_t^C C_t + e_t\left(P_t^E + T_t\right) ET_t^H \tag{11}$$

Substituting λ from Eq. 10 in Eq. 9 and solving it for ET_t^H, we find that the household's energy transition demand is a function of the exchange rate, electricity tariff, transportation costs of energy, and the income level of the household (in macro-level, the income level of the energy importer), as in Eq. 12:

$$E_t^H = f\left(e_t,\ P_t^E,\ T_t\ Y_t^H\right) \tag{12}$$

The total energy transition demand is equal to the combined energy demand of households and industry (Eq. 13).

$$ET_t = ET_t^I + ET_t^H \tag{13}$$

Therefore, the total energy demand (ET_t) is a function of different factors, as shown in Eq. 14:

$$ET_t = f(P_t^E,\ T_t, e_t,\ Y_t) \tag{14}$$

where P^E is the electricity tariff, and T denotes the transportation costs of energy, e is the exchange rate, and Y_t is the total GDP of the energy importer, which depends on the income level of households (Y_t^H) and the total output of the industry (Y_t^I).

DATA AND MODEL SPECIFICATIONS

The empirical part of this study is based on balanced panel data of variables throughout 1993–2018 (the reason of choosing this period is the availability of data for the variables of the model) for high- and middle- and low-income countries in Asia-Pacific. Our samples are gathered based on the UN regional groups for the Asia-Pacific (un.org) including 55 different nations (see **Appendix 1**). However, due to the lack of data, we had to omit some countries and our finalized samples contained 45 countries. Based on the World Bank Atlas method (worldbank.org), the finalized samples were also divided into two different groups according to income level (to have a sufficient samples size for panel data estimation, we could not consider four income groups of high, upper-middle, lower-middle and low-income groups), that is, a high and upper-middle-income group (24 countries), a and low and lower-middle-income group (21 countries) (see **Appendix 2**).

Furthermore, based on the theoretical model, we employed energy transition (Renewable energy consumption/non-renewable energy consumption) as a dependent variable, and official exchange rate, GDP, population growth (due to the lack of data for energy prices in many countries for our samples, we choose population growth as a proxy for energy price, as the higher population growth rate will increase the energy demand and increase the energy prices), and CO_2 emissions as independent variables. Most of the data were extracted from the BP statistical review of BP, 2019 and the World Bank database. The primary descriptive statistics for 45 Asian countries are presented in **Table 1**.

As shown in **Table 1**, the average annual economic growth of all 45 countries is 4.6% over 1993–2018. Moreover, the maximum is 64.08% (Timor-Leste in 2004) and the minimum is -35.81% (Cambodia in 1993). It is interesting to note that countries with low and lower-middle incomes have the highest average economic growth over 1993–2018 (4.69% compared with 4.65% and 4.67% for countries with high and upper-middle incomes and all samples, respectively). Regarding energy transition, the

TABLE 1 | Descriptive statistics.

Samples	Variables	Unit	Mean	Maximum	Minimum	Std. Dev.
All samples	Economic Growth	%	4.67	64.08	-35.81	5.96
	Exchange rate	LCU per United States$	1185.36	40864.33	0.010	3708.33
	Energy transition	%	1.18	15.25	1.81E-05	2.18
	CO_2 emissions	Metric tons per capita	6.59	70.04	0.03	10.07
	Population growth	%	2.03	17.51	-1.75	1.85
High and upper-middle incomes	Economic Growth	%	4.65	54.15	-33.10	5.59
	Exchange rate	LCU per United States$	852.24	40864.33	0.010	3324.61
	Energy transition	%	0.38	8.72	1.82E-05	1.17
	CO_2 emissions	Metric tons per capita	10.72	70.04	0.28	11.81
	Population growth	%	2.23	17.51	-1.75	2.39
Low and lower-middle incomes	Economic Growth	%	4.69	64.08	-35.81	6.35
	Exchange rate	LCU per United States$	1566.06	22602.05	0.010	4073.03
	Energy transition	%	2.09	15.25	0.00	2.67
	CO_2 emissions	Metric tons per capita	1.88	24.62	0.03	4.03
	Population growth	%	1.82	8.79	-0.35	0.85

Source: Authors' compilation from Eviews 10.

average for countries with low and lower-middle incomes is 2.09%, which is higher than the means of this variable in counties with high and upper-middle incomes (0.38%).

Besides, **Tables 2–4** represent Pearson correlations between variables based on all samples, the high and upper-middle-income group, and the low and lower-middle-income group. According to **Table 2**, for 45 Asian countries, there is a negative relationship between energy transition and exchange rate, and CO_2 emissions and population growth, while economic growth and energy transition have positive linkage over the period.

For the case of the high and upper-middle-income group, it is clear that there is a negative relationship between energy transition and all regressors, while economic growth and population growth are positively linked with energy transition and exchange rate, and CO_2 emissions have a negative relationship with energy transition for the low and lower-middle-income group.

Based on our variables, our econometric equation with a generalized method of moments (GMM) panel approach can be written as in Eq. 15:

$$ET_{it} = \vartheta + \omega ET_{it-1} + \phi X_{it} + \eta_{it} + \varepsilon_{it} \tag{15}$$

where ET indicates energy transition (dependent variable) and X denotes all explanatory variables η_{it} represents the country-specific effects, and ε_{it} is the error term.

For running the regressions, due to the limitations of data we are assuming that the electricity prices and transportations costs are constant. Instead, we are entering two control variables and can also represent these two omitted variables. The entered variables are population growth rate and CO_2 emission. According to Alimi and Mesagan (2018), growth in the population will increase energy consumption (energy demand) leading to an increase in energy prices and vice versa). Besides, longer distances between the origin of fossil fuels (energy exporters) and the importers' countries will result in higher transportation costs and higher CO_2 emissions. Next, some preliminary tests should be conducted to derive reliable empirical estimations. As the first pre-estimation test, the variance inflation factor (VIF) is performed to ascertain whether there is any multicollinearity among the series. The second preliminary test is the Hausman test to check for the existence of heterogeneity, which clarifies the presence of random or fixed effects in our panel. Given that the economies of the Russian Federation and the selected sample have experienced various exogenous and endogenous shocks, the next pre-estimation test checks for cross-sectional dependency among the series. The second-generation unit root test is the last preliminary test and is used to ascertain whether the series are I(1) stationary or I(0) non-stationary. Furthermore, after running the GMM estimations, we conduct two different diagnostic tests. The first is the Arellano-Bond test for zero autocorrelation in the first-differenced errors, and the second is the Sargan test to verify the overidentifying restrictions.

RESULTS

Preliminary Tests

Before presenting empirical findings of GMM estimations, as previously mentioned, some preliminary tests should be conducted. **Table 3** reports the results of the VIF (checking multicollinearity among series) and Hausman (checking the nature of the panel data series) tests.

Based on the results in **Table 3**, we can conclude that there is low multicollinearity between the cross-sections. Besides, the findings of the Hausman test (Chi2) depict the panel data with random effects. Next, we test for the existence of cross-sectional dependence (CSD) in the series; the results are presented in **Table 4**.

The results of the CSD test indicate that cross-sections are present in all series among all samples, the high and upper-middle-income group, and the low and lower-middle-income group. This means that our samples, both in aggregated and

TABLE 2 | Pearson correlation results.

Samples	Dependent variable	Independent variables			
		Economic growth	Exchange rate	CO_2 emissions	Population growth
45 Asian countries	Energy transition	0.008	−0.78	−0.323	−0.111
High and upper-middle incomes group (24 countries)	Energy transition	−0.61	−0.79	−0.260	−0.198
Low and lower-middle incomes group (21 countries)	Energy transition	0.38	−0.153	−0.282	0.005

Source: Compiled by the authors using SPSS 19.

TABLE 3 | Results of VIF and Hausman tests.

Samples	Independent variables	Explanatory variables				
		LET	LGRO	LCO_2	LPOP	LEX
All samples	LET	-	1.28	1.13	1.20	1.31
	LGRO	1.40	-	1.09	1.39	1.28
	LCO_2	1.18	1.55	-	1.11	1.21
	LPOP	1.48	1.19	1.31	-	1.42
	LEX	1.31	1.08	1.42	1.24	-
	Mean VIF	1.34	1.27	1.23	1.23	1.30
	Chi2(5)	12.23				
High and upper-middle incomes group						
	LET	-	1.06	1.18	1.32	1.19
	LGRO	1.04	-	1.02	1.21	1.24
	LCO_2	1.31	1.02	-	1.43	1.29
	LPOP	1.82	1.23	1.02	-	1.31
	LEX	1.45	1.19	1.19	1.42	-
	Mean VIF	1.40	1.12	1.10	1.35	1.26
	Chi2(5)	12.18				
Low and lower-middle incomes group						
	LET	-	1.05	1.24	1.39	1.19
	LGRO	1.42	-	1.39	1.15	1.26
	LCO_2	1.51	1.23	-	1.11	1.36
	LPOP	1.31	1.20	1.38	-	1.02
	LEX	1.28	1.32	1.36	1.41	-
	Mean VIF	1.38	1.20	1.34	1.27	1.21
	Chi2(5)	11.30				

ET = energy transition, GRO = economic growth, EX = exchange rate, CO_2 = CO_2 emissions, POP = population growth. (L) indicates variables in the natural logarithms.
Source: Compiled by the authors.

disaggregated groups, share the same characteristics. Generally, in situations in which there are low multicollinearity and CSD in the series, it is necessary to check the stationarity of variables. Here, we conducted the second-generation panel unit root test (Pesaran's 2007 CIPS test) with the null hypothesis of all series being I(1). The findings are reported in **Table 5**.

The findings of the aforementioned test reveal that all series considering all samples, the high and upper-middle-income group, and the low and lower-middle-income group are I(0).

GMM Findings

After performing all the necessary preliminary tests, the Arellano-Bond dynamic GMM estimation is conducted for the three groups (all samples, high and upper-middle-income group, and low and lower-middle incomes group). The results of the GMM estimation for all 45 Asian countries (all samples) are reported in **Table 6**.

According to the results in **Table 6**, the economic growth of Asia-Pacific economies has a positive effect on the energy transition movement in this region. A 1% increase in economic growth level leads to an approximately 0.79% increase in the energy transition process. This finding is in line with Saidi and Hammam (2015); Adams et al. (2018), Hoon Kang et al. (2019), and Diaz et al. (2019) who found a positive linkage between economic growth and moving from fossil fuels to renewables. Our result is in contrast to Maji (2015) and Chen et al. (2019), who proved a mixture of negative and positive relationships between green energy usage and economic growth. Regarding CO_2 emissions, the estimation proves that this variable negatively affects the energy transition process. A 1% increase

TABLE 4 | Cross-sectional dependence test results.

Samples	Variables	CSD test	Corr.	Abs. (corr.)	Significant at 1% level
All samples	LET	6.17	0.313	0.313	Yes
	LGRO	9.73	0.491	0.491	Yes
	LCO_2	8.55	0.482	0.482	Yes
	LPOP	9.11	0.329	0.329	Yes
	LEX	8.72	0.319	0.319	Yes
High and upper-middle incomes group	LET	6.81	0.366	0.366	Yes
	LGRO	10.05	0.592	0.592	Yes
	LCO_2	7.90	0.429	0.429	Yes
	LPOP	10.32	0.628	0.628	Yes
	LEX	8.23	0.429	0.429	Yes
Low and lower-middle incomes group	LET	6.30	0.383	0.383	Yes
	LGRO	9.15	0.539	0.539	Yes
	LCO_2	8.64	0.428	0.428	Yes
	LPOP	9.28	0.613	0.613	Yes
	LEX	9.53	0.662	0.662	Yes

ET = energy transition, GRO = economic growth, EX = exchange rate, CO_2 = CO_2 emissions, POP = population growth. (L) indicates variables in the natural logarithms. Source: compiled by the authors.

in CO_2 emissions may decrease the energy transition process in Asia by nearly 1.7%. Our finding is in line with Ito (2015) and Bilgili et al. (2016), who found a negative linkage between these two variables. Besides, the effect of the exchange rate was found to be statistically insignificant, while population growth has a positive sign, meaning it has a positive effect on energy transition in Asia.

Table 7 reports the estimated coefficients of variables for the high and upper-middle-income group. The results prove the positive effect of economic growth on the energy transition process for this group. A 1% increase in the economic growth of these 24 nations leads to an almost 0.8% increase in renewable energy consumption. This finding is in line with Teulon (2014) who argued that due to the developed economic structure in these kinds of countries, a higher economic

TABLE 5 | Pesaran (2007) panel unit root test results.

Samples	Variables	Without trend	With trend
All samples	LET	0.301	1.529
	LGRO	0.319	−0.729
	LCO_2	0.288	−−0.818
	LPOP	−0.472	−0.929
	LEX	0.298	1.832
High and upper-middle incomes group	LET	0.392	1.616
	LGRO	0.361	−0.782
	LCO_2	0.291	−0.618
	LPOP	−0.515	−0.872
	LEX	0.310	−1.482
Low and lower-middle incomes group	LET	0.362	1.482
	LGRO	0.417	−0.832
	LCO_2	0.318	−0.792
	LPOP	−0.391	−0.892
	LEX	0.328	−1.449

ET = energy transition, GRO = economic growth, EX = exchange rate, CO_2 = CO_2 emissions, POP = population growth. (L) indicates variables in the natural logarithms. Source: Compiled by the authors.

TABLE 6 | Estimation results for 45 Asian countries.

Explanatory variables	Coefficients	Significant at 1% levels
Constant	0.53	No
LGRO	0.79	Yes
LCO_2	-1.73	Yes
LEX	0.008	No
LPOP	0.882	Yes
No. of observations	1170	
Range	1993–2018	
Cross-sections included	45	
Wald Chi2 (5)	723.14	Yes

ET = energy transition, GRO = economic growth, EX = exchange rate, CO_2 = CO_2 emissions, POP = population growth. (L) indicates variables in the natural logarithms. Source: Compiled by the authors.

TABLE 7 | Estimation results for the high and upper-middle income group.

Explanatory variables	Coefficients	Significant at 1% levels
Constant	0.04	Yes
LGRO	0.89	Yes
LCO_2	−2.17	Yes
LEX	−0.03	Yes
LPOP	−1.98	Yes
No. of observations	624	
Range	1993–2018	
Cross-sections included	24	
Wald Chi2 (5)	551.83	Yes

ET = energy transition, GRO = economic growth, EX = exchange rate, CO_2 = CO_2 emissions, POP = population growth. (L) indicates variables in the natural logarithms. Source: Compiled by the authors.

growth accelerates financing green projects leading to more consumption of renewable energy sources. Furthermore, the rest of the variables were found to harm the energy transition. The estimation reveals that a 1% increase in CO_2 emissions, exchange rate, and population growth, may reduce the energy transition process in this group by approximately 2.1%, 0.03%, and 1.9%, respectively.

The GMM estimation for the low and lower-middle incomes group proves the positive effect of economic growth and exchange rate, while population growth and CO_2 emissions are found to have a negative effect on the energy transition process of this group. According to the results in **Table 8**, a 1% increase in economic growth and exchange rate leads to an increase of the energy transition of this group by approximately 0.9% and 0.07%, respectively, whereas a 1% increase in CO_2 emissions and population growth led energy transition to decelerate by nearly 1.5% and 2.8%, respectively. The magnitudes of impacts from CO_2 emissions and population growth are stronger than the impacts of economic growth and exchange rate. This finding is in line with Spencer and Mathur (2019) who expressed that emerging and developing nations with a lower income level need to link decarbonization policies (manage and lower CO_2 emissions) with their energy transition process.

As the final stage in the empirical estimations, we conducted diagnostic tests to verify the characteristics of the model. As shown in **Table 9**, the Arellano and Bond diagnostic test and Sargan test yield the following results.

TABLE 8 | Estimation results for the low and lower-middle income group.

Explanatory variables	Coefficients	Significant at 1% levels
Constant	0.11	Yes
LGRO	0.96	Yes
LCO_2	−1.57	Yes
LEX	0.07	Yes
LPOP	−2.88	Yes
No. of observations	546	
Range	1993–2018	
Cross-sections included	21	
Wald Chi2 (5)	616.38	Yes

ET = energy transition, GRO = economic growth, EX = exchange rate, CO_2 = CO_2 emissions, POP = population growth. (L) indicates variables in the natural logarithms. Source: Compiled by the authors.

TABLE 9 | Diagnostic test results for GMM estimation.

Samples	Statistics	AR(2)z	Chi2
All samples	Arellano-Bond test	−2.42**	–
	Sargan test	–	2781.11***
High and upper-middle incomes group	Arellano-Bond test	−2.18**	–
	Sargan test	–	3287.32***
Low and lower-middle incomes group	Arellano-Bond test	−2.01**	–
	Sargan test	–	3121.19***

*** and *** indicate statistical significance at 1% and 5% levels, respectively. Source: Compiled by the authors.*

TABLE 10 | Robustness check using FMOLS.

Samples	Independent variables			
	LGRO	LCO_2	LEX	LPOP
Full sample	0.07**	−0.13***	0.03	0.11**
High and upper-middle incomes group	0.12***	−0.10**	−0.17***	−0.29***
Low and lower-middle incomes group	0.06***	−0.25***	0.19***	−0.34***

*ET = energy transition, GRO = economic growth, EX = exchange rate, CO_2 = CO_2 emissions, POP = population growth. (L) indicates variables in the natural logarithms. ** and *** indicate statistically significant at 1% and 5% levels, respectively. Source: Compiled by the authors.*

The findings strongly reject non-autocorrelation, and the Arellano-Bond model assumptions are therefore satisfied. Besides, the Sargan test results prove that there are not any overidentifying restrictions, meaning that we can conclude that our three models are suitable.

Robustness Analysis

To check the GMM estimation results, reported in **Tables 6–8**, we used alternative panel data techniques, namely fully modified ordinary least squares (FMOLS), to check the robustness of our major findings. As shown in **Table 10**, estimation results do not significantly differ, which suggests our results are robust.

CONCLUDING REMARKS AND POLICY RECOMMENDATIONS

Based on annual data over the period 1993–2018, this study attempts to model energy transition in Asia-Pacific economies. To this end, we selected a sample of 45 countries and divided the sample based on the level of income to achieve better results. The high and upper-middle-income group included 24 countries and the low and lower-middle-income group included 21 countries.

Based on the empirical analysis using a GMM model, we determined similarities and dissimilarities in energy transition models among the sample groups. As for the similarities, economic growth has a positive relationship with the energy transition, while CO_2 emissions negatively influence energy transition in all sample groups. The results, regarding the economic growth-energy transition linkage, is in line with Saidi and Hammam (2015); Saad and Taleb (2017), Adams et al. (2018); Hoon Kang et al. (2019), Diaz et al. (2019) and Kouton (2020), who found a positive correlation between economic growth and moving from fossil fuels to renewables (energy transition). Our result is in contrast to Maji (2015) and Chen et al. (2019), who proved a mixture of negative and positive relationships between green energy usage and economic growth. Regarding the negative linkage between CO_2 emissions and energy transition, our finding is in line with Ito (2015), Bilgili et al. (2016) and Bilan et al. (2019), who found a negative linkage between these two variables and that the negative impact of air pollution in terms of CO_2 emissions on green sources consumption does not depend on country income level. Reduction in air pollution can be an indicator of a reduction in fossil fuel consumption and an increase in using renewable energy sources. Moreover, a major motivation for transitioning to renewable energy is to reduce CO_2 emissions. Although the energy transition is not the only way for reducing CO_2 emissions. According to the United States Environmental Protection Agency (EPA), agricultural, forestry, and land use including crops, livestock and deforestation are responsible for 24% of the global carbon emissions (EPA, 2018). Regenerative agriculture sequesters carbon in the soil (the best indicator of healthy soil is its carbon content). This means in addition to shifting to renewable energy, for reducing CO_2 emissions transitioning from industrial agriculture to regenerative agriculture and preventing the deforestation are required.

The existence of differences among energy transition patterns of countries is in line with Chen et al. (2019) and Chen et al. (2020) who found out the dissimilar relationship between carbon dioxide emissions and renewable energy consumption across different regions.

Furthermore, in both sub-sample groups (i.e., high and upper-middle-income and low and lower-middle-income groups), increase the population leads to a decrease in the energy transition process. This result is in contrast with Salim and Shafiei (2014), who found a negative effect of population density on non-renewable energy consumption. The main reason for the negative effect is that the main energy source in Asia-Pacific is still fossil fuels. As dissimilarities, the results revealed that depreciation of the national currency in the high and upper-middle-income group may lead to an increase in renewable energy consumption in these countries, while this decreases energy transition movement in the low and lower-middle-income group. This happened because in the former group there are several exporters of renewable energy technologies such as China, Japan, Malaysia and while most countries in the latter group are the importer of green technologies and depreciation of the local currency makes the price of the imported renewable technology more expensive in the local currency as a result making the energy transition costlier and more difficult.

Based on IEA (2019b), the energy transition is a complexed process which needs interactions and cooperation among countries with different levels of development. Therefore, solving the complexity of energy transition requires global or regional cooperation and integration. According to Elshurafa et al. (2019), energy transition may take longer and has a heavy cost, so countries should make global or regional cooperation to facilitate these challenges in the way of energy transformation. This policy is in line with Kern and Smith (2008) who argued the necessity of energy transition management model to make integration in policies and plans to go to reach a higher level of energy transition which is a sign of economic development (Zahid et al., 2020). Another current challenge for energy transition development in Asia-Pacific is the Coronavirus (Covid-19) pandemic that hits demand for all fossil fuel resources and reduced the oil prices dramatically. According to the International Energy Agency (IEA, 2020) as a consequence of global lockdown measures due to the Covid-19 crisis, 57% of global oil demand declined at an unprecedented scale in early 2020. Renewable energy projects will lose their competitiveness in low fossil fuel prices that will endanger the Paris agreement on climate change and the climate and clean energy-related SDGs.

Therefore in the post-Covid era proactive and efficient support and plans of government can keep the renewable energy sector and the energy transitions alive. Supportive plans such as the green credit guarantee scheme (Taghizadeh-Hesary and Yoshino, 2019) and policy and financial de-risking (Taghizadeh-Hesary and Yoshino, 2020) are necessary as renewable energy projects in the current timing find more difficulties in accessing to finance and investments.

Overall, we suggest that countries with different income levels have quite dissimilar energy transition patterns. Hence, they need different policies to improve energy transition movement. However, the inter-connected approach among countries in the field of energy transformation is a vital factor in success. Moreover, we recommend that Asia-Pacific countries need to alter their present energy policies [in line with Gulagi et al. (2020)] to enhance various policies for easing the access to electricity from green resources.

Notwithstanding its limitations, we believe that this study contributes to the existing literature on energy transition patterns. We recommend future research employs different control variables such as trade openness, interest rate, and inflation rate in econometric models, considering direct and indirect effects (following Taghizadeh-Hesary et al., 2013, 2019) and conducts causality tests to distinguish short- and long-run linkages between energy transition and independent variables.

DATA AVAILABILITY STATEMENT

The datasets analyzed in this manuscript are not publicly available. Requests to access the datasets should be directed to ER, e.rasoulinezhad@ut.ac.ir.

AUTHOR CONTRIBUTIONS

Both authors contributed equally to the manuscript and reviewed the final manuscript.

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REFERENCES

Adams, S., Klobodu, E., and Apio, A. (2018). Renewable and non-renewable energy, regime type and economic growth. *Renew. Energy* 125, 755–767. doi: 10.1016/j.renene.2018.02.135

Ahmed, K., Rehman, M. U., and Ozturk, I. (2017). What drives carbon dioxide emissions in the long-run? Evidence from selected South Asian Countries. *Renew. Sustain. Energy Rev.* 70, 1142–1153. doi: 10.1016/j.rser.2016.12.018

Alimi, O. Y., and Mesagan, E. (2018). Population growth, energy use, crude oil price, and the nigerian economy. *Ikonomicheski Izsledvania* 27, 115–133.

Al-Mulali, U., Ozturk, I., and Lean, H. H. (2015). The influence of economic growth, urbanization, trade openness, financial development, and renewable energy on pollution in Europe. *Nat. Hazards* 79, 621–644. doi: 10.1007/s11069-015-1865-9

Al-Mulali, U., Ozturk, I., and Solarin, S. A. (2016). Investigating the environmental Kuznets curve hypothesis in seven regions: the role of renewable energy. *Ecol. Indic.* 67, 267–282. doi: 10.1016/j.ecolind.2016.02.059

Al-Shamma's, A., Alturki, F., and Farh, H. (2020). Techno-economic assessment for energy transition from diesel-based to hybrid energy system-based off-grids in Saudi Arabia. *Energy Trans.* 4, 31–43. doi: 10.1007/s41825-020-00021-2

Apergis, N., and Ozturk, I. (2015). Testing environmental Kuznets curve hypothesis in Asian countries. *Ecol. Indic.* 52, 16–22. doi: 10.1016/j.ecolind.2014.11.026

Aung, T. S., Saboori, B., and Rasoulinezhad, E. (2017). Economic growth and environmental pollution in Myanmar: an analysis of environmental Kuznets curve. *Environ. Sci. Pollut. Res.* 24, 20487–20501. doi: 10.1007/s11356-017-9567-3

Bilan, Y., Streimkiene, D., Vasylieva, T., Lyulyov, O., Pimonenko, T., and Pavlyk, A. (2019). Linking between renewable energy, CO2 emissions, and economic growth: challenges for candidates and potential candidates for the EU membership. *Sustainability* 11:1528. doi: 10.3390/su11061528

Bilgili, F., Kocak, E., and Bulut, U. (2016). The dynamic impact of renewable energy consumption on CO2 emissions: a revisited Environmental Kuznets Curve approach. *Renew. Sustain. Energy Rev.* 54, 838–845. doi: 10.1016/j.rser.2015.10.080

BP, (2019). *BP Statistical Reivew of World Energy 2019*. Available online at: https://www.bp.com/en/global/corporate/news-and-insights/press-releases/bp-statistical-review-of-world-energy-2019.html (accessed September 7, 2019).

Chapman, A. J., and Itoaka, K. (2018). Energy transition to a future low-carbon energy society in Japan's liberalizing electricity market: precedents, policies and factors of successful transition. *Renew. Sustain. Energy Rev.* 81, 2019–2027. doi: 10.1016/j.rser.2017.06.011

Chen, C., Pinar, M., and Stengos, T. (2020). Renewable energy consumption and economic growth nexus: evidence from a threshold model. *Energy Policy* 139:111295. doi: 10.1016/j.enpol.2020.111295

Chen, Y., Zhao, J., Lai, Z. H., Wang, Z. H., and Xia, H. (2019). Exploring the effects of economic growth, and renewable and non-renewable energy consumption on China's CO2 emissions: evidence from a regional panel analysis. *Renew. Energy* 140, 341–353. doi: 10.1016/j.renene.2019.03.058

Cymrot, D., and Seiver, D. (1982). A note on individual utility maximization in a household context. *Eastern Econ. J.* 8, 211–214.

Diaz, A., Marrero, G. A., Puch, L. A., and Rodriguez, J. (2019). Economic growth, energy intensity and the energy mix. *Energy Econ.* 81, 1056–1077. doi: 10.1016/j.eneco.2019.05.022

Dogan, E., and Ozturk, I. (2017). The influence of renewable and non-renewable energy consumption and real income on CO2 emissions in the USA: evidence from structural break tests. *Environ. Sci. Pollut. Res.* 24, 10846–10854. doi: 10.1007/s11356-017-8786-y

Elshurafa, A., Farag, H. M., and Hobbs, D. A. (2019). Blind spots in energy transition policy: case studies from Germany and USA. *Energy Rep.* 5, 20–28. doi: 10.1016/j.egyr.2018.11.001

EPA (2018). Available online at: https://www.epa.gov/ghgemissions/global-greenhouse-gas-emissions-data (accessed June 14, 2020).

Fattouh, B., Poudineh, R., and West, R. (2019). The rise of renewables and energy transition: what adaptation strategy exists for oil companies and oil-exporting countries?. *Energy Trans.* 3, 45–58. doi: 10.1007/s41825-019-00013-x

Gulagi, A., Bogdanov, D., and Breyer, C. H. (2017). The demand for storage technologies in energy transition pathways towards 100% renewable energy For India. *Energy Proc.* 135, 37–50. doi: 10.1016/j.egypro.2017.09.485

Gulagi, A., Ram, M., Solomon, A., Khan, M., and Breyer, C. H. (2020). Current energy policies and possible transition scenarios adopting renewable energy: a case study for Bangladesh. *Renew. Energy* 155, 899–920. doi: 10.1016/j.renene.2020.03.119

Hansen, P., Peeters, D., and Thisse, J. (1995). The profit-maximizing weber problem. *Location Sci.* 3, 67–85. doi: 10.1016/0966-8349(95)00011-6

Hess, D. J., and Mai, Q. D. (2014). Renewable electricity policy in Asia: a qualitative comparative analysis of factors affecting sustainability transitions. *Environ. Innovat. Soc. Trans.* 12, 31–46. doi: 10.1016/j.eist.2014.04.001

Hoon Kang, S., Islam, F., and Kumar Tiwari, A. (2019). The dynamic relationships among CO2 emissions, renewable and non-renewable energy sources, and economic growth in India: evidence from time-varying Bayesian VAR model. *Struct. Change Econ. Dyn.* 50, 90–101. doi: 10.1016/j.strueco.2019.05.006

IEA (2019a). *Energy Transitions Indicators*. Paris: IEA.

IEA (2019b). *The Critical Role of Buildings: Perspectives for the Clean Energy Transition*. Available online at: https://www.iea.org/reports/the-critical-role-of-buildings (accessed June 13, 2020).

IEA (2020). *COVID-19*. Available online at: https://www.iea.org/topics/covid-19 (accessed June 13, 2020).

Ito, S. (2015). Printable solar cells. *WIREs Energy and Environment* 4, 51–73. doi: 10.1002/wene.112

Jairaj, B., and Kumar, P. (2019). An assessment of India's energy transition: Paris and beyond. *Jindal Glob. Law Rev.* 10, 35–47. doi: 10.1007/s41020-019-00085-2

Jia, L., Wenying, C. H., and Deshun, L. (2011). Scenario analysis of China's future energy demand based on TIMES model system. *Energy Proc.* 5, 1803–1808. doi: 10.1016/j.egypro.2011.03.307

Kaberger, T. (2018). Progress of renewable electricity replacing fossil fuels. *Glob. Energy Interconnect.* 1, 48–52.

Kern, F., and Smith, A. (2008). Restructuring energy systems for sustainability? Energy transition policy in the Netherlands. *Energy Policy* 36, 4093–4104.

Kouton, J. (2020). The impact of renewable energy consumption on inclusive growth: panel data analysis in 44 African countries. *Econ. Change Restruct.* doi: 10.1007/s10644-020-09270-z

Kucharski, J., and Unesaki, H. (2018). An institutional analysis of the Japanese energy transition. *Environ. Innovat. Soc. Trans.* 29, 126–143. doi: 10.1016/j.eist.2018.07.004

Leeuwen, R., Wit, J., and Smit, G. (2017). Review of urban energy transition in the Netherlands and the role of smart energy management. *Energy Convers. Manag.* 150, 941–948. doi: 10.1016/j.enconman.2017.05.081

Maji, I. K. (2015). Does clean energy contribute to economic growth? Evidence from Nigeria. *Energy Rep.* 1, 145–150. doi: 10.1016/j.egyr.2015.06.001

Mamat, E. R., Sani, M. S., and Sudhakar, K. (2019). Renewable energy in Southeast Asia: policies and recommendations. *Sci. Total Environ.* 670, 1095–1102. doi: 10.1016/j.scitotenv.2019.03.273

Mohammad, A. (2019). *Asian's Energy Transition. McKinsey & Company*. Available online at: https://www.mckinsey.com/featured-insights/asia-pacific/asias-energy-transition# (accessed June 10, 2020).

Ngar-yin Mah, D., Wu, Y., Jasper, I. P., and Hills, P. (2013). The role of the state in sustainable energy transitions: a case study of large smart grid demonstration projects in Japan. *Energy Policy* 63, 726–737. doi: 10.1016/j.enpol.2013.07.106

Osti, G. (2018). The uncertain games of energy transition in the island of Sardinia (Italy). *J. Clean. Prod.* 205, 681–689. doi: 10.1016/j.jclepro.2018.08.346

Ozcan, B., and Ozturk, I. (2019). Renewable energy consumption-economic growth nexus in emerging countries: a bootstrap panel causality test. *Renew. Sustain. Energy Rev.* 104, 30–37. doi: 10.1016/j.rser.2019.01.020

Pachauri, S. H., and Jiang, L. (2008). The household energy transition in India and China. *Energy Policy* 36, 4022–4035. doi: 10.1016/j.enpol.2008.06.016

Pesaran, H. (2007). A simple panel unit root test in the presence of cross-section dependence. *J. Appl. Econ.* 22, 265–312. doi: 10.1002/jae.951

Qiao, L. (2019). *Why the Ti,e is Now for an Energy Transition in South East Asia. GWEC*. Available online at: https://gwec.net/why-the-time-is-now-for-an-energy-transition-in-south-east-asia/ (accessed June 10, 2020).

Rasoulinezhad, E., and Jabalameli, F. (2019). Russia-EU gas game analysis: evidence from a new proposed trade model. *Environ. Sci. Pollut. Res.* 6, 24482–24488. doi: 10.1007/s11356-019-05681-2

Rasoulinezhad, E., Taghizadeh-Hesary, F., Sung, J., and Panthamit, N. (2020). Geopolitical risk and energy transition in russia: evidence from ARDL bounds testing method. *Sustainability.* 12:2689. doi: 10.3390/su12072689

Reddy, B. S. (2016). India's energy system transition—Survival of the greenest. *Renew. Energy* 92, 293–302. doi: 10.1016/j.renene.2016.02.027

Saad, W., and Taleb, A. (2017). The causal relationship between renewable energy consumption and economic growth: evidence from Europe. *Clean Technol. Environ. Policy* 20, 127–136. doi: 10.1007/s10098-017-1463-5

Saboori, B., Rasoulinezhad, E., and Sung, J. (2017). The nexus of oil consumption, CO2 emissions and economic growth in China, Japan and South Korea. *Environ. Sci. Pollut. Res.* 24, 7436–7455. doi: 10.1007/s11356-017-8428-4

Saidi, K., and Hammam, S. (2015). The impact of CO2 emissions and economic growth on energy consumption in 58 countries. *Energy Rep.* 1, 62–70. doi: 10.1016/j.egyr.2015.01.003

Salim, R. A., and Shafiei, S. (2014). Urbanization and renewable and non-renewable energy consumption in OECD countries: an empirical analysis. *Econ. Model.* 38, 581–591. doi: 10.1016/j.econmod.2014.02.008

Sharif, A., Raza, S. A., Ozturk, I., and Afshan, S. (2019). The dynamic relationship of renewable and nonrenewable energy consumption with carbon emission: a global study with the application of heterogeneous panel estimations. *Renew. Energy* 133, 685–691. doi: 10.1016/j.renene.2018.10.052

Sharvini, S. R., Noor, Z., Chong, C. H., Stringer, L., and Yusuf, R. (2018). Energy consumption trends and their linkages with renewable energy policies in East and Southeast Asian countries: challenges and opportunities. *Sustain. Environ. Res.* 28, 257–266. doi: 10.1016/j.serj.2018.08.006

Shell Energy Transition Report, (2019). *Shell Energy Transition Report*. Available online at: https://www.shell.com/energy-and-innovation/the-energy-future/shell-energy-transition-report/_jcr_content/par/toptasks.stream/1524757699226/3f2ad7f01e2181c302cdc453c5642c77acb48ca3/web-shell-energy-transition-report.pdf (accessed June 10, 2020).

Shukla, A., Sudhakar, K., and Baredar, P. (2017). Renewable energy resources in South Asian countries: challenges, policy and recommendations. *Resour. Efficient Technol.* 3, 342–346. doi: 10.1016/j.reffit.2016.12.003

Singh, H. V., Bocca, R., Gomez, P., Dahlke, S., and Bazilian, M. (2019). The energy transitions index: an analytic framework for understanding the evolving global energy system. *Energy Strategy Rev.* 26:100382. doi: 10.1016/j.esr.2019.100382

Solarin, S. A., Al-Mulali, U., and Ozturk, I. (2017). Validating the environmental Kuznets curve hypothesis in India and China: the role of hydroelectricity consumption. *Renew. Sustain. Energy Rev.* 80, 1578–1587. doi: 10.1016/j.rser.2017.07.028

Sovacool, B. K. (2016). How long will it take? Conceptualizing the temporal dynamics of energy transitions. *Energy Res. Soc. Sci.* 13, 202–215. doi: 10.1016/j.erss.2015.12.020

Spencer, T., and Mathur, A. (2019). *Energy Transition in Emerging and Developing Countries: Promoting the New Paradigm. G20 2019 Japan*. Available online at: https://www.g20-insights.org/wp-content/uploads/2019/05/t20-japan-tf3-6-energy-transition-emerging-developing-countries-1.pdf (accessed June 11, 2020).

Stokes, L., and Breetz, H. (2018). Politics in the U.S. energy transition: case studies of solar, wind, biofuels and electric vehicles policy. *Energy Policy* 113, 76–86. doi: 10.1016/j.enpol.2017.10.057

Szabo, L., Kelemen, A., Mezosi, A., Pato, Z., Kacsor, E., Resch, G., et al. (2019). South East Europe electricity roadmap – modelling energy transition in the electricity sectors. *Clim. Policy* 19, 495–510. doi: 10.1080/14693062.2018.1532390

Taghizadeh-Hesary, F., Rasoulinezhad, E., and Kobayashi, Y. (2017). Oil price fluctuations and oil consuming sectors: an empirical analysis of Japan. *Econ. Policy Energy Environ.* 2, 33–51. doi: 10.3280/efe2016-002003

Taghizadeh-Hesary, F., and Yoshino, N. (2018). Assessment of the channels of transmission of oil price fluctuations to the economy. *Argumenta Oeconomica* 41, 5–34. doi: 10.15611/aoe.2018.2.01

Taghizadeh-Hesary, F., and Yoshino, N. (2019). The way to induce private participation in green finance and investment. *Finance Res. Lett.* 31, 98–103. doi: 10.1016/j.frl.2019.04.016

Taghizadeh-Hesary, F., and Yoshino, N. (2020). Sustainable solutions for green financing and investment in renewable energy projects. *Energies* 13:788. doi: 10.3390/en13040788

Taghizadeh-Hesary, F., Yoshino, N., Abadi, M. M. H., and Farboudmanesh, R. (2016). The response of macro variables of emerging and developed oil importers to oil price movements. *J. Asia Pac. Econ.* 21, 91–102. doi: 10.1080/13547860.2015.1057955

Taghizadeh-Hesary, F., Yoshino, N., Abdoli, G., and Farzinvash, A. (2013). An estimation of the impact of oil shocks on crude oil exporting economies and their trade partners. *Front. Econ. China* 8, 571–591. doi: 10.3868/s060-002-013-0029-3

Taghizadeh-Hesary, F., Yoshino, N., Rasoulinezhad, E., and Chang, Y. (2019). Trade linkages and transmission of oil price fluctuations. *Energy Policy* 133:110872. doi: 10.1016/j.enpol.2019.07.008

Teulon, F. (2014). Economic growth and energy transition: overview and review of the literature. *J. Energy Dev.* 40, 247–262.

United Nations Economic and Social Council, (2018). *Energy Transition in Asia and the Pacific: Pathways to Ensure Access to Affordable, Reliable, Sustainable and Modern Energy for All*. Available online at: https://www.unescap.org/sites/default/files/APEF2018_2.PDF (accessed June 10, 2020).

Vaillancourt, K., Bahn, O., and Levasseur, A. (2019). The role of bioenergy in low-carbon energy transition scenarios: a case study for Quebec (Canada). *Renew. Sustain. Energy Rev.* 102, 24–34. doi: 10.1016/j.rser.2018.11.025

Vainio, A., Varho, V., Tapio, P., Pulkka, A., and Paloniemi, R. (2019). Citizen's images of a sustainable energy transition. *Energy* 183, 606–616. doi: 10.1016/j.energy.2019.06.134

Verbong, G., and Geels, F. (2007). The ongoing energy transition: lessons from a socio-technical, multi-level analysis of the Dutch electricity system (1960–2004). *Energy Policy* 35, 1025–1037. doi: 10.1016/j.enpol.2006.02.010

Wiseman, J. (2018). The great energy transition of the 21st century: the 2050 Zero-Carbon World Oration. *Energy Res. Soc. Sci.* 35, 227–232. doi: 10.1016/j.erss.2017.10.011

World Economic Forum, (2018). *Fostering Effective Energy Transition*. Available online at: https://www.mckinsey.com/~{}/media/mckinsey/industries/oil%20and%20gas/our%20insights/a%20framework%20for%20fostering%20effective%20energy%20transitions/fostering-effective-energy-transition.ashx (accessed June 10, 2020).

Yildirim, E., Aslan, A., and Ozturk, I. (2014). Energy consumption and GDP in ASEAN countries: bootstrap-corrected panel and time-series causality tests. *Singapore Econ. Rev.* 59:1450010. doi: 10.1142/s0217590814500106

Yuan, X., Lyu, Y., Wang, B., Liu, Q., and Wu, Q. (2018). China's energy transition strategy at the city level: the role of renewable energy. *J. Clean. Prod.* 205, 980–986. doi: 10.1016/j.jclepro.2018.09.162

Zahid, T., Arshed, N., Munir, M., and Hameed, K. (2020). Role of energy consumption preferences on human development: a study of SAARC region. *Econ. Change Restruct.* doi: 10.1007/s10644-020-09279-4

Zhang, X., Zhang, H., Zhao, C. H., and Yuan, J. (2019). Carbon emission intensity of electricity generation in Belt and Road Initiative countries: a benchmarking analysis. *Environ. Sci. Pollut. Res.* 26, 15057–15068. doi: 10.1007/s11356-019-04860-5

Zou, C., Zhao, Q., Zhang, G., and Xiong, B. (2016). Energy revolution: from a fossil energy era to a new energy era. *Nat. Gas Ind. B* 3, 1–11. doi: 10.1016/j.ngib.2016.02.001

Conflict of Interest: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

APPENDIX 1

TABLE A1 | Asia-Pacific group of the UN regional groups.

Afghanistan
Bahrain
Bangladesh
Bhutan
Brunei Darussalam
Cambodia
China
Cyprus
Democratic People's Republic of Korea
Fiji
India
Indonesia
Iran (Islamic Republic of)
Iraq
Japan
Jordan
Kazakhstan
Kiribati
Kuwait
Kyrgyzstan
Lao People's Republic
Lebanon
Malaysia
Maldives
Marshall
Micronesia (Federated States of)
Mongolia
Myanmar
Nauru
Nepal
Oman
Pakistan
Palau
Papua New Guinea
Philippines
Qatar
Republic of Korea
Samoa
Saudi Arabia
Singapore
Solomon Islands
Sri Lanka
Syrian Arab Republic
Tajikistan
Thailand
Timor-Leste
Tonga
Turkey*
Turkmenistan
Tuvalu
United Arab Emirates
Uzbekistan
Vanuatu
Vietnam
Yemen

Source: https://www.un.org/Depts/DGACM/RegionalGroups.shtml.

APPENDIX 2

TABLE A2 | Classification of samples based on income.

Low and lower-middle incomes	High and upper-middle incomes
Afghanistan	Bahrain
Bangladesh	China
Bhutan	Cyprus
Brunei Darussalam	Fiji
Cambodia	Iran (Islamic Republic of)
India	Iraq
Indonesia	Japan
Kiribati	Jordan
Kyrgyzstan	Kazakhstan
Mongolia	Kuwait
Myanmar	Lebanon
Nepal	Malaysia
Pakistan	Maldives
Papua New Guinea	Oman
Philippines	Qatar
Tajikistan	Republic of Korea
Timor-Leste	Samoa
Uzbekistan	Saudi Arabia
Vanuatu	Singapore
Vietnam	Sri Lanka
Yemen	Thailand
	Turkey
	Turkmenistan
	United Arab Emirates

Source: Authors' compilation from the World Bank.

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Promoting Economic Recovery From the Perspective of Energy-Economic Resilience: Model Construction and Case Study

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Energy is both a basic resource needed for economic growth and an essential tool for economic recovery. The topic of resilience is becoming increasingly prominent in the energy-economic domain and has also entered policy discourse. Yet the measuring method of resilience based on post-disruption events and the relationship between energy consumption and economic recovery are far from settled. This paper develops the idea of resilience and proposes a model to evaluate the economic recovery ability of an economy from the perspective of energy consumption. It also proposes a decoupling model to address the impact of energy-related elements on economic recovery. These ideas are then used for a preliminary empirical analysis of 14 countries against the context of the 2007–2008 financial crisis. The analysis showed that developing countries generally performed better than developed countries, that energy consumption is not a necessity for promoting economic recovery, and that energy-economic decoupling has a positive effect on economic recovery.

Keywords: energy resilience, economic recovery, post-disruption, inter-resilience, decoupling model

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INTRODUCTION

Energy is a basic resource needed for economic growth and is an essential tool for economic recovery. Numerous studies have demonstrated the important relationship between energy consumption and economic recovery (Mahadevan and Asafu-Adjaye, 2007; Tang et al., 2016; Destek and Aslan, 2017). Currently, researchers have extended the idea of resilience into the energy-economic domain in order to measure how quickly local and regional economies could recover from shocks and emergencies. The application of resilience into energy-economic study is also in line with the International Energy Agency's (IEA's) definition of national energy security: "short-term energy security focuses on the ability of the energy system to react promptly to sudden changes in the supply–demand balance" (IEA, 2020).

According to the dissipative structure theory, an energy system is an open complicated system, with non-linear interactions among the inner elements. Prior experience showed that the linear management method usually leads to lower social value. In recent decades, widespread and persistent disruptions (e.g., energy shortages, energy price fluctuations, climate change, and environmental pollution, etc.) have consistently demonstrated the failure of single-target optimization of energy systems. With the increase of such failures, we need to seek new solutions to the growing energy security problems beyond traditional approaches. Under this circumstance, researchers have begun to focus on the idea of resilience, an approach related to philosophy and pragmatism. It is supposed that resilience will be used to seek solutions for addressing these problems.

Prior research on energy resilience originates from both ecology resilience and engineering resilience, spanning across general energy systems and some specific systems (O'Brien and Hope, 2010), such as hydropower systems (Afgan and Veziroglu, 2012), electricity systems (Molyneaux et al., 2012; Kharrazi et al., 2015; Ibrahim et al., 2016), and energy infrastructure systems (Ouyang et al., 2012; Alderson et al., 2015). The definitions of energy resilience vary according to different research goals, and these definitions can be generally classified into two categories; the first highlights resilience as the capability to resist disturbances coming from outside and which helps the target system to recover as fast as possible (O'Brien, 2009; Korhonen and Snäkin, 2015; Arghandeh et al., 2016), and the second one emphasizes the core ability of resilience as adaption, including adaption to strikes and the involution of the system itself (O'Brien and Hope, 2010; Skea, 2010).

In terms of research method, a majority of prior research employed a qualitative research method to explore the specific resilience value of target energy systems (DiMase et al., 2015; Hosseini et al., 2016), the key elements that can affect the level of an energy system's resilience (McLellan et al., 2012), and conceptual frameworks that can help to normalize resilience management (Sharifi and Yamagata, 2015; Xie et al., 2018). Little research has investigated energy resilience from the perspective of economic recovery (Rose, 2007; Briguglio et al., 2009). Given that energy security is not only important for economic growth, but also the foundation of national security, it is vital to quantify the relationship between energy resilience and economic recovery. Therefore, to fill the above research gaps, this paper aims to propose a set of models to evaluate energy-economic resilience based on post-disruption events. Further, data from 14 countries will be used to demonstrate the usefulness of our model.

The rest of this paper is organized as follows. The next section reviews the literature on measuring models that have been used to investigate economic recovery and energy resilience. Section Methodology introduces our proposed model to compute resilience and losses to the economy and energy, as well as their inner relationship. Section Case Study presents a case study of 14 countries to illustrate the model's applicability in future. Finally, Section Discussion and Conclusion concludes the paper and makes suggestions for future research.

LITERATURE REVIEW

Over the past few years, the impact of economic resilience on disasters has drawn more and more attention from both researchers and policymakers. At the early stage, the qualitative method was widely used to investigate the necessity to embed resilience into energy systems, the elements that affect energy resilience, and the framework that guides resilience assessment (Sharifi and Yamagata, 2016; Child et al., 2018). However, compared to the qualitative method, it is still too early to use a quantitative method to examine the above topic. Nevertheless, several quantitative methods have been used in prior research and will be introduced below.

One of the quantitative methods is setting up indicators or employing a proxy for resilience; Molyneaux et al. applied resilience to an electricity system by setting up a composite resilience index which consists of seven indicators (Molyneaux et al., 2016). Korhonen et al. used diversity as a proxy of energy system resilience (Korhonen and Snäkin, 2015). Hosseini et al. (2016) identified four domains of resilience: organizational, social, economic, and engineering. Blum et al. set up a resilience index from the angle of economic operation capacity to handle energy-related effects (Blum and Legey, 2012).

The second method is to define resilience through comparisons with historical data; Afgan and Cvetinovic (2013) defined the resilience index R as the integral value of the sustainability index between the time point of a sudden change in respective indicators and the time point when it resumes a stable state value, as follows:

$$\mathrm{R} = \sum_{i=1}^{i=k} w_i \int_{t-t_0}^{t-t_1} \left[100 - q_i\right] dt \tag{1}$$

where W_i is the weighting coefficient and q_i is an indicator. A similar method is also used in research on natural gas supply resilience, network resilience (Dassisti and Carnimeo, 2013; Rabbani et al., 2015), and some other deterministic models related to energy resilience (Mulyono, 2015; Ibrahim et al., 2016).

Another representative quantitative method used for resilience evaluation is based on the input-output (IO) model. Usually an IO model is combined with integrating linear programming; He et al. developed a resilience model which helps to estimate the maximum level of energy import reduction that an economy can endure (He et al., 2017). Sato evaluated energy resilience by measuring diversity from the perspective of both direct and embodied energy supplies (Sato et al., 2015). Based on the multi-regional IO model, they attempted to use the Shannon-Weaver index and a cosine similarity as a complementary index to evaluate the supply diversity of 134 countries. With the same method, Kharrazi et al. evaluated the electricity diversity in production-based and consumption-based trade networks (Kharrazi et al., 2015).

To sum up, the above three quantitative analysis methods have been widely adopted by researchers. However, the issues of energy consumption and economic recovery from a resilience point of view have not been clarified enough. Models involve economic-energy characteristics only consider economic characteristics, such as economic impacts on disruptions (Rose et al., 2018) and investment optimization (Fang and Sansavini, 2017; Nezamoddini et al., 2017). In this work, we propose the enhancement of energy economic resilience post a disaster event. Particularly, we employ resilience loss to develop a model to address economy recovery with consideration of energy consumption.

METHODOLOGY

Resilience and Recovery Assessment

Measuring the resilience loss of a target system after a disruptive event is fundamental to assess the relationship between economic recovery and energy consumption. As is shown in **Figure 1**, the resilience loss is calculated by Equation (2), in which *RL* is a two-dimension vector represented by the shadow area.

$$RL = \frac{1}{T * Q_{t_0}} \int_{t_0}^{t_1} [E_t - Q_t] d_t \quad (2)$$

where, *RL*: Average resilience loss during period T (from t_0 to t_1)

t_0: Start time of disruption
t_1: End time of disruption
T: The whole period from time t_0 to t_1
E_t: The expected value based on historical data
Q_t: The actual value
Q_{t_0}: The actual value from time t_0 to t_1
Δ: Performance attenuation
λ: Level of recovery.

RL is the average integral value of the difference between *Et* and *Qt*. δ represents performance attenuation which indicates the largest deviation of a target system when experiencing disruption during time T. λ describes the recovery level of the system after the disruption, which is relative to its basic performance.

Inter-resilience Analysis of Energy-Economic Decoupling

Although the calculation of resilience loss can provide a way to measure the basic resilience state caused by a disruption, it cannot reflect the interrelationship between economic recovery and energy consumption. Given this, we modify the model from Blum and Legey (2012) to measure the resilience loss of energy consumption and electricity consumption. Also, a number of studies have shown that economic growth relies heavily on electricity consumption (Shahbaz et al., 2017; Zhang et al., 2017), so the relative impact of economic recovery on the change of energy as well as electricity consumption during a certain period will be established. From the perspective of energy consumption and economic growth, we define the changing ratios as follows:

$$\varepsilon_{en} = \frac{\frac{\Delta GDP}{GDP}}{\frac{\Delta Energy}{Energy}} = \frac{RL_{GDP}}{RL_{en}} \quad (3)$$

$$\varepsilon_{el} = \frac{\frac{\Delta GDP}{GDP}}{\frac{\Delta Electricity}{Electricity}} = \frac{RL_{GDP}}{RL_{el}} \quad (4)$$

(1) If the energy-related factors have no impact on economic recovery, then $\varepsilon = 0$
(2) If the energy-related factors have an impact on economic recovery, then $0 < |\varepsilon| < 1$.

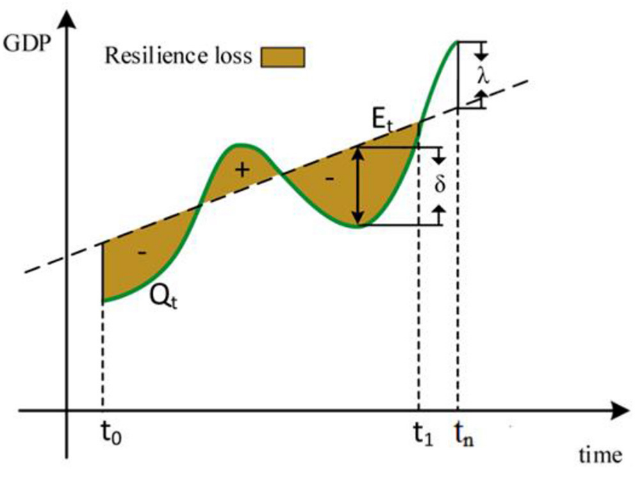

FIGURE 1 | Resilience assessment of post-disruption event.

(3) If the energy-related factors affect economic recovery in the same proportion, then $|\varepsilon| = 1$.
(4) If the effects are amplified, then $|\varepsilon| > 1$.

Furthermore, taking different energy efficiencies of different countries/regions into account, we take the method of resilience coupling/decoupling to evaluate recovery performance. Decoupling is originated from environmental kuznets curve (EKC), which is applied in economic growth and environmental problems research. In this paper, the term decoupling is applied to economic growth and energy resilience during a post-disruption period. By improving Vehmas' model (Vehmas et al., 2007), six possible scenarios are established in this paper and each scenario is placed in the coordinate axis according to its resilience performance. These scenarios, shown in **Figure 2**, are: absolute decoupling, relative decoupling, expensive coupling, recessive decoupling, recessive coupling, and strong coupling.

As shown in **Figure 2**, from the best-case category (I) to the worst-case category (VI), each category is determined by three parameters: ΔRL_{GDP}, RL_{en}, and $\Delta(RL_{en}/RL_{GDP})$. When $\Delta(RL_{en}/RL_{GDP})$ is <0, it is decoupling in the lower area of the diagonal line including "I," "II," and "IV;" in these areas the energy efficiency can be improved. When $\Delta(RL_{en}/RL_{GDP})$ is more than 0, it is coupling in the up area of the diagonal line including "III," "V," and "VI." Each area can be further divided into three categories according to the value of ΔRL_{GDP} and RL_{en}. Taking area "I" as an example, the ΔRL_{GDP} increases with a decrease of RL_{en} and $\Delta(RL_{en}/RL_{GDP})$, which is the most ideal state of all six states with the best performance of output and efficiency. The explanation of the six categories are listed in **Table 1**.

CASE STUDY

Fourteen countries whose total GDP exceeds 70% of the world's GDP in 2018 were examined, and their final energy consumption

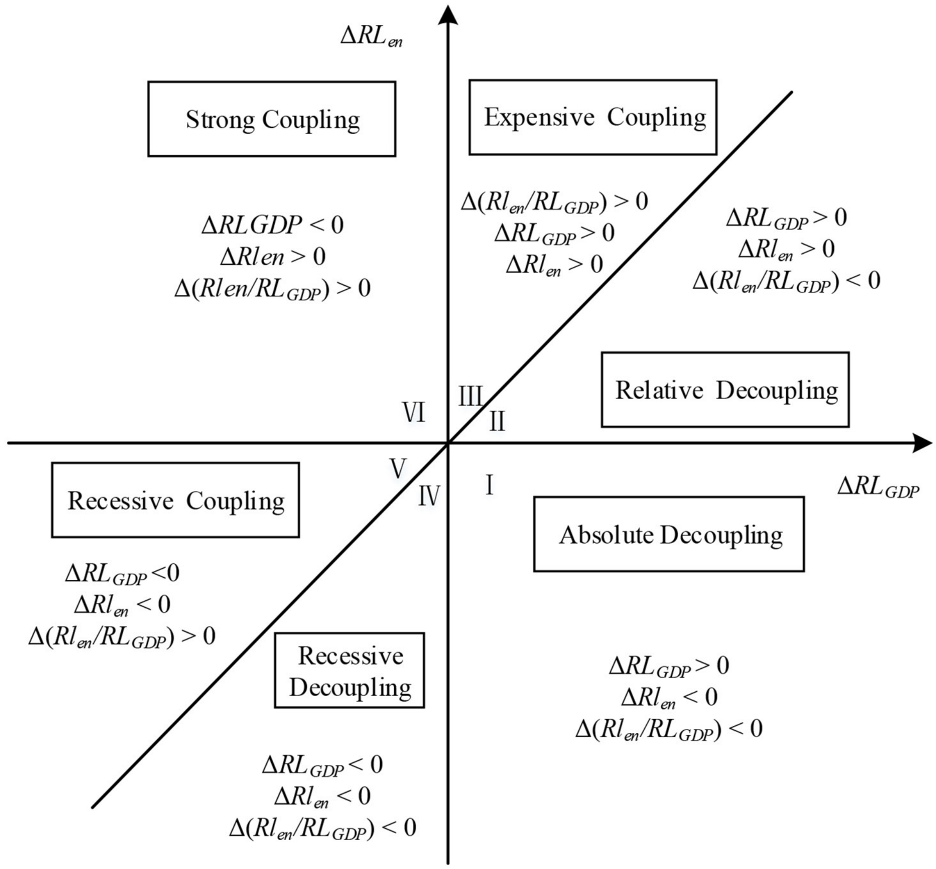

FIGURE 2 | The degrees of coupling and decoupling of energy resilience.

TABLE 1 | Meanings of each coupling/decoupling category.

Coupling/decoupling type	Description
Absolute decoupling I	The most ideal state is that RL_{GDP} increases with the decrease of RL_{en} and $\Delta(RL_{en}/RL_{GDP})$.
Relative decoupling II	Ideally, both RL_{GDP} and RL_{en} increase, and $\Delta(RL_{en}/RL_{GDP})$ improves as well.
Expensive coupling III	Less ideally, the three parameters all decrease.
Recessive decoupling VI	The less negative state is that when RL_{GDP} and RL_{en} decrease, $\Delta(RL_{en}/RL_{GDP})$ will improve.
Recessive coupling V	The negative state is that RL_{GDP}, RL_{en}, and $\Delta(RL_{en}/RL_{GDP})$ all decrease.
Strong coupling VI	The most negative state is that when RL_{GDP} decreases, both RL_{en} and $\Delta(RL_{en}/RL_{GDP})$ will increase.

and final electricity consumption account for over 65 and 70% of world's total, respectively, in 2018. The Middle East is excluded because of its current situation of unrest. In addition, South Africa and Singapore are included as South Africa is supposed to be a promising economy, and Singapore, as a resource-poor country, represents developed countries that performed well during the 2007–2008 financial crisis. The expected value Et is based on historical data using the method of regression, and fitting degree is supposed to be more than 95%. All the data is from the (IEA) and World Bank.

Resilience Loss

Fourteen countries whose total GDP exceeded 70% of the world's GDP in 2018 were examined; their final energy consumption and final electricity consumption account for over 65 and 70% of world's total consumption, respectively, in 2018. According to the aforementioned model, the resilience loss for GDP, total final energy consumption, and total final electricity consumption of the 14 countries are shown in **Figure 3**.

From the results, we can see that the countries were grouped into three categories: almost unaffected (China, India, and Indonesia), almost recovered (South Africa, Korea, Singapore, Brazil, and Germany), and unrecovered (France, the United States, Canada, Japan, the United Kingdom, and Russia). Aligned with the RL_{en} and RL_{el}, it is assumed that the GDP growth rate of China was affected a little bit during the 2007–2008 financial crisis, which exceeded the historical

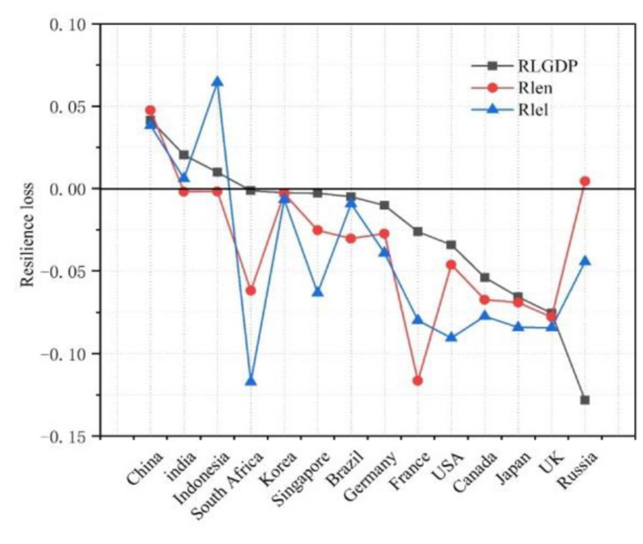

FIGURE 3 | Resilience loss for GDP, final energy consumption, and final electricity consumption.

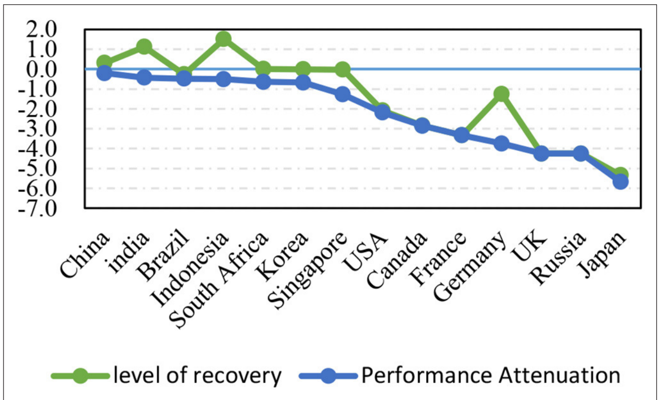

FIGURE 4 | Performance attenuation and recovery level.

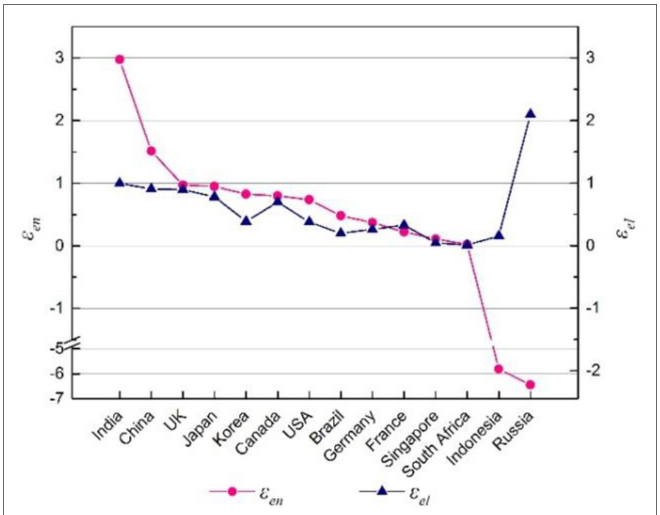

FIGURE 5 | Change rate of economic resilience to energy/electricity resilience.

expectation by an average rate of 4% per year. Accordingly, the total energy consumption and total electricity consumption increased by 2.7 and 4.5%, respectively. This means that during the year 2007–2018, China's electricity consumption exceeded the expected value significantly. As to India and Indonesia, their GDP were barely affected. India's total final energy consumption increased slightly, and Indonesia decreased slightly. Both countries had significant increases in total final electricity consumption. Obviously, apart from Russia, the developing countries performed better than the developed countries.

Performance Attenuation and Level of Recovery

Performance attenuation and recovery level are used to indicate the scale of impacts from the financial crisis. As is shown in **Figure 4**, the following points were concluded: (1) Countries that suffered more have a relatively poor recovery performance, except for Germany. Although Germany was hard-hit by this financial crisis, it performed much better than other countries at the end of 2018; (2) Developing countries (except Russia) generally performed better than developed countries in terms of both performance attenuation and recovery level.

Germany's astonishing recovery was due to increased trade with developing countries, especially China, which offset its trade reduction with other countries. Further, Germany took a powerful economic stimulus plan focusing on infrastructure investment and tax relief to help small- and medium-sized enterprises. As for Russia, the oil price fluctuation affected RL_{GDP} a lot, which is a reflection of "Dutch disease" and the result of its irrational industry infrastructure.

Inter-resilience and Decoupling

Results of inter-resilience of economic recovery to energy/electricity consumption are shown in **Figure 5**. It can be seen that in terms of ε_{en}, there are four countries whose figures are not in the reasonable scope (from −1 to 1): China, India, Indonesia, and Russia. For the first three countries, they had a much faster GDP growth than the total final energy consumption. Russia's GDP has sharply reduced by nearly 9% per year while having only about a 1% increase per year in energy consumption. Considering both ε_{en} and ε_{el}, Russia's capability of handling energy-related problems is clearly insufficient.

According to the results, 14 countries were sorted into the six areas as shown in **Figure 6**; these 14 countries are spread out over five areas. Strong coupling and recessive coupling are occupied by Russia and Brazil, respectively; Russia shows the worst resilience performance during this period, with an increasingly decaying economic recovery performance yet without a decline in total energy consumption. Considering the fixed assets investment and the sharp decrease of RL_{el}, Russia's overdependence on resources

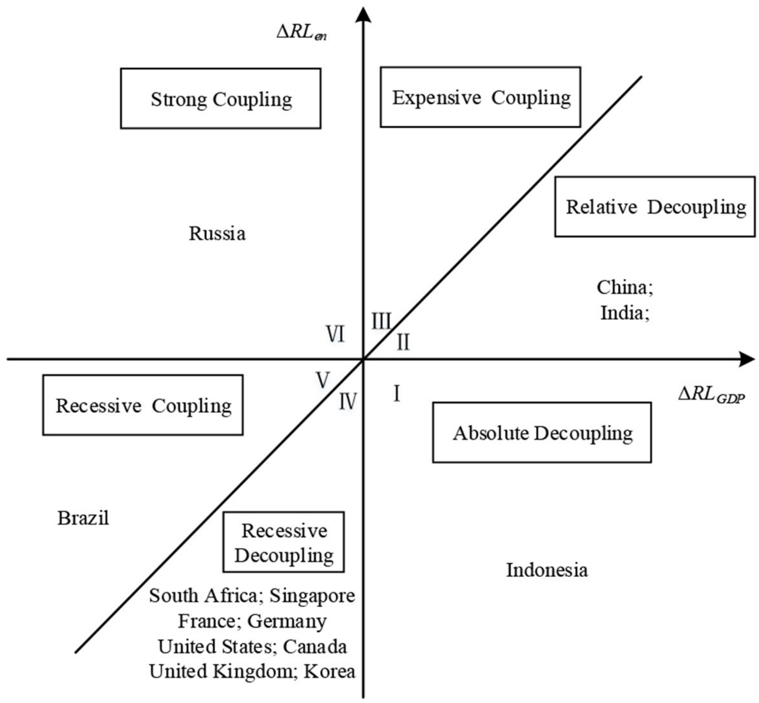

FIGURE 6 | Countries distribution based on resilience decoupling model.

export suffered a lot during this period because of the energy price fluctuation and the shrinking energy demand.

Indonesia lies in the most desirable condition-absolute decoupling. This is mainly because the Indonesian government paid more attention to domestic demand rather than export. They also paid more attention to high-tech industry rather than labor-intensive industry, meaning quality and efficiency of GDP growth were stable. China and India are in the relative decoupling area; the two prominent fast-growing economies benefit from both expanding domestic demand and their multilateral trade strategies. South Africa and all developed countries are in the recessive decoupling state, although South Africa is not the same as other countries because it is a developing country with a relatively low fixed assets investment percentage (around 20% in 2018). But for long-term economic development, a low fixed assets investment may lead to a lack of development motivation.

One of the main findings in our study is that developing countries' economic resilience is better than developed countries when faced with a national crisis, excluding the ones who overly rely on resource extraction. In particular, overreliance on energy/electricity consumption is shown to considerably weaken the ability of the economy to mitigate crisis. Hence, continually decreasing energy reliance will be a promising way to enhance economic resilience.

Another important insight from our study in section Case Study is that boosting domestic demand and strengthening multilateral trading can yield improvements to economic resilience. The governments may be able to exploit this to enhance their economic resilience and energy security, by expanding domestic demand and re-designing the cross-border trade interdependencies.

DISCUSSION AND CONCLUSION

In this work, we have proposed a novel approach to evaluate the impact of energy consumption on economic recovery from a perspective of resilience. The proposed models are shown to yield problems in the format of decoupling status. The proposed framework can provide valuable decision-support for policy-makers to study the impact of energy consumption on economic recovery, and also guide decision-makers on how to improve the resilience of an economy.

One of the main findings in our case study is that, during the 2007–2008 financial crisis, developing countries were less affected and had better recovery performance than developed countries, except for Russia. Russia is overly dependent on energy export, and its energy efficiency is much lower than most other countries. Furthermore, in terms of developed countries, Korea and Singapore, located in Asia, have better recovery performance than other countries. Germany had experienced an astonishing recovery compared to all the other countries because of its successful trade strategy shift to Asian countries and its efficient tax policy.

For future studies, an alternative multiregional resilience framework can be explored, which classifies the driving factors behind promoting economic recovery based on production-consumption patterns in the energy supply chain. Renewable energy consumption is also playing an increasingly significant role in economic productivity; researchers can quantitatively investigate the role of renewable energy in improving economic recovery, and ultimately improving the resilience of an economy.

DATA AVAILABILITY STATEMENT

Publicly available datasets were analyzed in this study. This data can be found here: https://www.worldbank.org.

AUTHOR CONTRIBUTIONS

ZG takes charge the conceptualization, formal analysis, and the original draft writing of this paper. YW is responsible of data curation, methodology construction, and funding acquisition of this paper. WP is in charge of data calculation, analyzing the results, writing-review and editing, and the validation of this paper. All authors contributed to the article and approved the submitted version.

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REFERENCES

Afgan, N., and Veziroglu, A. (2012). Sustainable resilience of hydrogen energy system. *Int. J. Hydrogen Energy* 37, 5461–5467. doi: 10.1016/j.ijhydene.2011.04.201

Afgan, N. H., and Cvetinovic, D. B. (2013). Resilience evaluation of the South East European natural gas routes system catastrophe. *Int. J. Eng. Innovative Technol.* 2013, 175–180.

Alderson, D. L., Brown, G. G., and Carlyle, W. M. (2015). Operational models of infrastructure resilience. *Risk Anal.* 35, 562–586. doi: 10.1111/risa.12333

Arghandeh, R., Von Meier, A., Mehrmanesh, L., and Mili, L. (2016). On the definition of cyber-physical resilience in power systems. *Renew. Sustain. Energy Rev.* 58, 1060–1069. doi: 10.1016/j.rser.2015.12.193

Blum, H., and Legey, L. F. L. (2012). The challenging economics of energy security: ensuring energy benefits in support to sustainable development. *Energy Econ.* 34, 1982–1989. doi: 10.1016/j.eneco.2012.08.013

Briguglio, L., Cordina, G., Farrugia, N., and Vella, S. (2009). Economic vulnerability and resilience: concepts and measurements. *Oxford Dev. Stud.* 37, 229–247. doi: 10.1080/13600810903089893

Child, M., Koskinen, O., Linnanen, L., and Breyer, C. (2018). Sustainability guardrails for energy scenarios of the global energy transition. *Renew. Sustain. Energy Rev.* 91, 321–334. doi: 10.1016/j.rser.2018.03.079

Dassisti, M., and Carnimeo, L. (2013). A small-world methodology of analysis of interchange energy-networks: the European behaviour in the economical crisis. *Energy Policy* 63, 887–899. doi: 10.1016/j.enpol.2013.09.015

Destek, M. A., and Aslan, A. (2017). Renewable and non-renewable energy consumption and economic growth in emerging economies: evidence from bootstrap panel causality. *Renew. Energy* 111, 757–763. doi: 10.1016/j.renene.2017.05.008

DiMase, D., Collier, Z. A., Heffner, K., and Linkov, I. (2015). Systems engineering framework for cyber physical security and resilience. *Environ. Syst. Decisions* 35, 291–300. doi: 10.1007/s10669-015-9540-y

Fang, Y., and Sansavini, G. (2017). Optimizing power system investments and resilience against attacks. *Reliab. Eng. Syst. Saf.* 159, 161–173. doi: 10.1016/j.ress.2016.10.028

He, P., Ng, T. S., and Su, B. (2017). Energy-economic recovery resilience with input-output linear programming models. *Energy Econ.* 68, 177–191. doi: 10.1016/j.eneco.2017.10.005

Hosseini, S., Barker, K., and Ramirez-Marquez, J. E. (2016). A review of definitions and measures of system resilience. *Reliabil. Eng. Syst. Saf.* 145, 47–61. doi: 10.1016/j.ress.2015.08.006

Ibrahim, M., Chen, J., and Kumar, R. (2016). "A resiliency measure for electrical power systems," in *13th International Workshop on Discrete Event Systems (WODES)* (Xi'an: IEEE), 385–390. doi: 10.1109/WODES.2016.749787

IEA (2020). *Energy Ealances: Energy Projections for IEA Countries[EB/OL].* Available online at: https://doi.org/10.1787/data-00473-en (accessed october 15, 2018). doi: 10.1787/data-00473-en

Kharrazi, A., Sato, M., Yarime, M., Nakayama, H., Yu, Y., and Kraines, S. (2015). Examining the resilience of national energy systems: measurements of diversity in production-based and consumption-based electricity in the globalization of trade networks. *Energy Policy* 87, 455–464. doi: 10.1016/j.enpol.2015.09.019

Korhonen, J., and Snäkin, J. (2015). Quantifying the relationship of resilience and eco-efficiency in complex adaptive energy systems. *Ecol. Econ.* 120, 83–92. doi: 10.1016/j.ecolecon.2015.09.006

Mahadevan, R., and Asafu-Adjaye, J. (2007). Energy consumption, economic growth and prices: a reassessment using panel VECM for developed and developing countries. *Energy Policy* 35, 2481–2490. doi: 10.1016/j.enpol.2006.08.019

McLellan, B., Zhang, Q., Farzaneh, H., Utama, N. A., and Ishihara, K. N. (2012). Resilience, sustainability and risk management: a focus on energy. *Challenges* 3, 153–182. doi: 10.3390/challe3020153

Molyneaux, L., Brown, C., Wagner, L., and Foster, J. (2016). Measuring resilience in energy systems: Insights from a range of disciplines. *Renew. Sustain. Energy Rev.* 59, 1068–1079. doi: 10.1016/j.rser.2016.01.063

Molyneaux, L., Wagner, L., Froome, C., and Foster, J. (2012). Resilience and electricity systems: a comparative analysis. *Energy Policy* 47, 188–201. doi: 10.1016/j.enpol.2012.04.057

Mulyono, N. B. (2015). Mutual support in energy sector: toward energy resilience. *Procedia Comput. Sci.* 60, 1041–1050. doi: 10.1016/j.procs.2015.08.149

Nezamoddini, N., Mousavian, S., and Erol-Kantarci, M. (2017). A risk optimization model for enhanced power grid resilience against physical attacks. *Electric Power Syst. Res.* 143, 329–338. doi: 10.1016/j.epsr.2016.08.046

O'Brien, G. (2009). Vulnerability and resilience in the European energy system. *Energy Environ.* 20, 399–410. doi: 10.1260/095830509788066457

O'Brien, G., and Hope, A. (2010).Localism and energy: negotiating approaches to embedding resilience in energy systems. *Energy Policy* 38, 7550–7558. doi: 10.1016/j.enpol.2010.03.033

Ouyang, M., Dueñas-Osorio, L., and Min, X. (2012). A three-stage resilience analysis framework for urban infrastructure systems. *Struct. Saf.* 36–37, 23–31. doi: 10.1016/j.strusafe.2011.12.004

Rabbani, M., Bahadornia, S. M., and Torabi, S. A. (2015). Designing a resilient oil supply network with an intelligent solution algorithm. *Uncertain Supply Chain Manage.* 3, 289–310. doi: 10.5267/j.uscm.2015.3.001

Rose, A. (2007). Economic resilience to natural and man-made disasters: multidisciplinary origins and contextual dimensions. *Environ. Hazards* 7, 383–398. doi: 10.1016/j.envhaz.2007.10.001

Rose, A., Wei, D., and Paul, D. (2018). Economic consequences of and resilience to a disruption of petroleum trade: the role of seaports in US energy security. *Energy Policy* 115, 584–615. doi: 10.1016/j.enpol.2017.12.052

Sato, M., Kharrazi, A., Nakayama, H., Kraines, S., and Yarime, M. (2015). The resilience of embodied energy networks: a critical dimension for sustainable development goals (SDGs). *Glob. Environ. Res.* 19, 187–198.

Shahbaz, M., Sarwar, S., Chen, W., and Malik, M. N. (2017). Dynamics of electricity consumption, oil price and economic growth: global perspective. *Energy Policy* 108, 256–270. doi: 10.1016/j.enpol.2017.06.006

Sharifi, A., and Yamagata, Y. (2015). A conceptual framework for assessment of urban energy resilience. *Energy Procedia* 75, 2904–2909. doi: 10.1016/j.egypro.2015.07.586

Sharifi, A., and Yamagata, Y. (2016). Principles and criteria for assessing urban energy resilience: a literature review. *Renew. Sustain. Energy Rev.* 60, 1654–1677. doi: 10.1016/j.rser.2016.03.028

Skea, J. (2010). Valuing diversity in energy supply. *Energy Policy* 38, 3608–3621. doi: 10.1016/j.enpol.2010.02.038

Tang, C. F., Tan, B. W., and Ozturk, I. (2016). Energy consumption and economic growth in Vietnam. *Renew. Sustain. Energy Rev.* 54, 1506–1514. doi: 10.1016/j.rser.2015.10.083

Vehmas, J., Luukkanen, J., and Kaivo-oja, J. (2007). Linking analyses and environmental Kuznets curves for aggregated material flows in the EU. *J. Clean. Prod.* 15, 1662–1673. doi: 10.1016/j.jclepro.2006.08.010

Xie, W., Rose, A., Li, S., He, J., Li, N., and Ali, T. (2018). Dynamic economic resilience and economic recovery from disasters: a quantitative assessment. *Risk Anal.* 38, 1306–1318. doi: 10.1111/risa.12948

Zhang, C., Zhou, K., Yang, S., and Shao, Z. (2017). On electricity consumption and economic growth in China. *Renew. Sustain. Energy Rev.* 76, 353–368. doi: 10.1016/j.rser.2017.03.071

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