frontiers in Energy Research

ORIGINAL RESEARCH
published: 28 March 2022
doi: 10.3389/fenrg.2022.873324

Improvement Pathway of Energy Transition: From the Perspective of Directed Technical Change

Guisheng Hou* and Hongyu Song

College of Economics and Management, Shandong University of Science and Technology, Qingdao, China

Energy transition can effectively promote the green transformation of economic development. With capital, traditional fossil energy, clean energy generation, thermal power generation, and the GDP of the provinces, we built a stochastic production frontier model based on a translog production function, which measures the bias of directed technical changes and substitution elasticities of 30 provinces in mainland China from 2000 to 2017. The results show that the directed technical change in China is more biased to thermal power generation and deviated from clean energy generation. In addition, except for traditional fossil generation and thermal power generation with a complementary relationship, there is a substitution relationship between other energy factors. At the regional level, the production patterns of 9 provinces (Beijing, Fujian, Hainan, Tianjin, Chongqing, Gansu, Neimenggu, Ningxia, and Xinjiang) are conducive to the external electric transition, and nine provinces (Beijing, Fujian, Guangxi, Hainan, Hubei, Jilin, Jiangsu, Qinghai, and Zhejiang) are beneficial to the internal electric transition. We find that there is a large room for improvement in external and internal electric transitions in most provinces. We propose that the Chinese government should promote the reform of the market-oriented energy pricing mechanism according to different production modes in different regions. Furthermore, the results from the analysis of China show that it is also possible for other countries to treat their energy transition differently due to their characteristic production patterns.

Keywords: energy consumption structure, energy transition, interfule substitution, directed technical change, economic growth

OPEN ACCESS

Edited by:
Diogo Ferraz,
Universidade Federal de Ouro Preto, Brazil

Reviewed by:
Ahmed Samour,
Near East University, Cyprus
Wadim Strielkowski,
Czech University of Life Sciences Prague, Czechia

****Correspondence:***
Guisheng Hou
2434835080@qq.com

Specialty section:
This article was submitted to Sustainable Energy Systems and Policies, a section of the journal Frontiers in Energy Research

Received: *10 February 2022*
Accepted: *28 February 2022*
Published: *28 March 2022*

Citation:
Hou G and Song H (2022) Improvement Pathway of Energy Transition: From the Perspective of Directed Technical Change. Front. Energy Res. 10:873324. doi: 10.3389/fenrg.2022.873324

1 INTRODUCTION

Since the reform and opening up, with the rapid development of China's economic aggregate, energy depletion and environmental deterioration have emerged. Therefore, a green and sustainable development has become the focus of high attention from all sectors of the society (Wu et al., 2020). In 2019, coal, oil, and natural gas consumption accounted for 62.8%, 20.7%, and 8.7%, respectively, while primary power and other energy consumption accounted for only 7.8% (China Statistical Yearbook, 2020). According to the China Energy Statistics Yearbook, fossil energy like coal, oil, and natural gas will play a long-term dominant role in the primary energy consumption structure. Therefore, China is one of the most urgent countries for energy transition in the world (Wang and Feng, 2011; Xu et al., 2014; Jiang et al., 2020). At present, energy transition has been a national strategy. On September 22, 2020, General Secretary Xi Jinping solemnly announced at the

75th UN General Assembly, "China's carbon dioxide emissions strive to peak by 2030 and strive to achieve carbon neutrality by 2060." In addition, according to the Energy Production and Consumption Revolution Strategy (2016–2030), non-fossil energy accounted for about 20% in 2030, and non-fossil energy accounted for more than half in 2050. Therefore, according to the relevant goals of carbon neutrality and carbon peak reaching, the optimization of China's energy transition will continue to advance.

The past 5 decades have witnessed significant progress in the domain of energy transition. Existing studies mainly focus on the inter-fuel transition (Liu et al., 2018; Naeem et al., 2021), such as the substitution among the pairs of natural gas–coal, oil–coal (Hao and Huang, 2018), and renewable–non-renewable (Lin and Ankrah, 2019a; Lin and Ankrah, 2019b). In addition, there are studies on the transition between energy and non-energy, such as the substitution among capital, labor, and energy (Fan and Zheng, 2019; Lin and Abudu, 2019; Zhang and Lin, 2019; Alataş, 2020; Lin and Abudu, 2020; Raza et al., 2020; Alataş et al., 2021). Some studies (Bello et al., 2018) also analyze the transition between hydro power and fossil energy. However, few studies analyze the transition of external and internal electric transition. Therefore, it is hard to obtain the transition pathway of external and internal transition.

The purpose of this article is to promote the internal and external electric transition by classifying the production modes of 30 provinces in China with the substitution elasticities and directed technological changes. The results show that the directed technical change in China is more biased to thermal power generation and deviated from clean energy generation. At the provincial level, the production patterns of 9 provinces (Beijing, Fujian, Hainan, Tianjin, Chongqing, Gansu, Neimenggu, Ningxia, and Xinjiang) are conducive to the external electric transition, and nine provinces (Beijing, Fujian, Guangxi, Hainan, Hubei, Jilin, Jiangsu, Qinghai, and Zhejiang) are beneficial to the internal electric transition. Compared to previous studies, the contribution of this article is mainly the following three points: first, based on the translog production function, we introduce clean energy power generation, thermal power generation, and traditional fossil energy as different input factors into the production function for the first time and further analyze the determinants of production technology efficiency in China. Second, we analyze the directed technical change in internal and external transition, that is, the preference for input factors during production in 30 regions. Third, combining the degree of biased technological change and the substitution elasticity between inputs, the path of promoting the energy transition is analyzed from the perspectives of internal and external transition, respectively.

The rest of the article is organized as follows: **Section 2** covers literature review; **Section 3** provides models, methods, and data; **Section 4** presents the results and discussion of the improvement pathway of energy transition; and **Section 5** summarizes conclusion and policy implications.

2 LITERATURE REVIEW

Optimizing the energy consumption structure will not only need clear development goals and effective policy support but also discuss the alternative relationship between energy inputs on the basis of the development level and resource endowment of different regions. However, directed technological changes determine the preference of input factors in the production process. Research on energy transition has focused mainly on the relationship between fossil and non-fossil energy. Wesseh and Lin (2016) analyzed the alternative relationship between different energy types in Egypt. They found that the average alternative elasticity between renewable and non-renewable energy sources is 1.41. This alternative relationship suggests that inter-energy substitution is possible from a technical perspective. Solarin and Bello (2019) analyzed the possibility of fossil energy and biomass energy substitution in Brazil. Their GDP model showed that using more biomass and less fossil energy can be kept sustainable in the Brazilian economy. Lin and Adubu used ridge regression to analyze alternative elasticity between renewable and non-renewable energy in the Middle Eastern and North African sectors. The results show that the alternative between renewable and non-renewable energy is perfect, with an alternative elasticity value of 0.95. Khalid and Jalil (2019) investigated the inter-fuel substitution by estimating the substitution elasticity among coal, natural gas, petroleum, and hydroelectricity. The findings show that all the factors are subsitutes. Lin and Agyeman (2020) estimated inter-fuel substitution elasticities and bias technical change in Sub-Saharan sectors. From the empirical results, the oil is more likely to be substituted for natural gas than coal. Zhang et al. (2018) surveyed natural gas in various sectors of China. The results show that the demand for natural gas is complementary to coal in industrial and power generation sectors. Wang (2021) measured the substitution between coal, electric power, and fuel in the China's industrial sector. The results show that there is a substitution among coal, electric power, and fuel. However, Malicov et al. (2018) found that the technical substitution between clean and dirty energy inputs may not be strong.

Furthermore, some studies have considered the alternative relationships between energy and non-energy. Yang et al. (2018) analyzed the alternative elasticity between input factors in the Chinese industrial sector and found that the relationship of capital–fossil energy and labor–fossil energy was complementary. These conclusions suggest that a reduced capital input or an increased labor input can lead to a reduction in fossil energy input. Lin and Raza (2021) analyzed the alternative resilience between energy, capital, and labor in Pakistan's agricultural sector and showed that all inputs were alternatives, arguing that labor and capital could reduce carbon dioxide emissions through alternative energy sources. Kim and Heo (2013) studied the substitutions between energy and capital for manufacturing in the Organization for economic cooperation and development (OECD) countries and concluded about substitutability between energy and capital. Zha et al. (2016) analyzed the alternative elasticity between energy and non-energy in the industrial sector based on the translog production function,

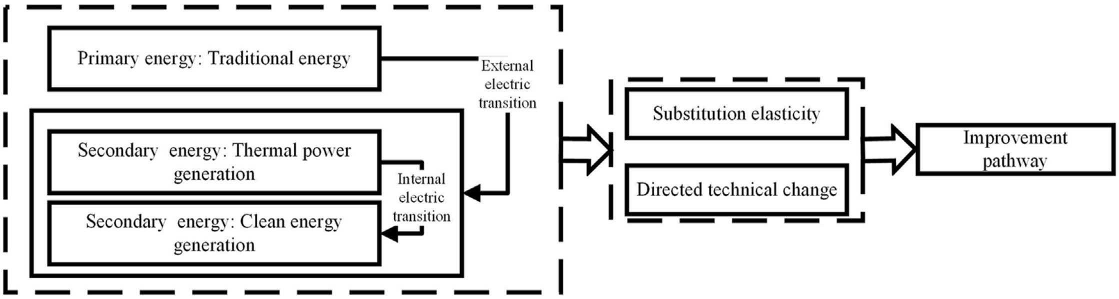

FIGURE 1 | Boundary definition of external and internal electric transition.

which showed that energy and capital have an alternative relationship and the substitution exists between energy and labor, except in 2011. Ouyang et al. (2018) explored the energy substitution effect of the transportation sector in Shanghai and found that the substitution elasticity between labor and energy is around 1.0095. Constantini et al. (2019) computed the substitution elasticity for manufacturing sectors in 21 OECD countries and addressed the capacity of the production system to be adequate for a low-carbon economy. Wei et al. (2019) explored the inter-factor substitution and the influence of technical changes on high-tech industries in China. The results showed that the substitution elasticity between labor and energy was the highest, and the technical progress was biased to saving energy. Lin and Chen (2020) found the exisitence of substitution relation among labor energy and capital in China's non-ferrous metal industries. Raza te al. examined the substitution elasticities of input factors (capital, labor, and energy consumption). The results showed that the elasticities of substitution between capital–energy, capital–labor, and labor–energy consumption are close to 1. The issue of transition from the perspective of fossil energy–non-fossil energy or energy–non-energy has been widely discussed. However, there are relatively few studies on electric transformation.

"Electric transition" requires effective use of electric energy not only to replace loose burning coal, fuel, and other energy consumption methods but also to vigorously develop clean energy power to replace an inefficient thermal power generation production mode. In terms of the "electric transition", it can be divided into "external electric transition" and "internal electric transition" (Liu and Wang, 2019). External electric transition refers to the replacement of traditional fossil energy with clean energy generation and thermal power generation, which is the way to realize the orderly transition from primary energy dependence to secondary energy dependence. Internal electric transition refers to the replacement of thermal power generation with clean energy power generation, which is the way to realize the technical upgradation of clean energy power generation to thermal power generation. The consumption of clean energy has a positive influence on carbon emissions (Abumunshar et al., 2020; Altarhouni et al., 2021; Yazan et al., 2022). Two kinds of electric transition can be seen in **Figure 1**. We refer to it as internal transition and external transition.

In addition, few studies have focused on the key role of directed technical change bias in energy use preferences. Directed technical change bias refers to the change of the factor substitution rate by technological progress. If technological progress leads to a greater increase in the marginal output growth rate of factor j relative to factor k, technological change is biased toward factor j, called technological change biased toward j-using, also known as biased toward k-saving. On the contrary, technological progress is biased to factor k, called technical change biased to k-using, also referred to as biased to j-saving (Hicks, 1932). If technological changes make the marginal output growth rate of both equal, it means that technological changes are Hicks neutral, and technical changes will be combined with a proportional increase of j or k. When considering a pair of input elements for fossil energy and low-carbon energy, technological change that tends to use low-carbon energy and save fossil energy may help in the energy structure optimization. Existing studies have confirmed that the technological change bias can be transformed by adjusting the relative prices between elements. Some studies (Popp, 2002; Acemoglu et al., 2012; Aghion et al., 2016) show that firms tend to innovate relatively more in clean technologies when they face higher tax-inclusive energy prices. Therefore, only through the substitution between factors, there is no scientific judgment that the energy transition is happening. After identifying the bias of technological change between energy inputs, further consideration of the substitution elasticity between factors is the key to analyzing the improvement pathway of the energy consumption structure.

Specifically, in the internal transition, encouraging the development of production technologies biased to clean energy power generation and improving the substitution relationship between clean energy power generation and thermal power generation can effectively help to optimize the energy consumption structure. In the external transition, actively developing the production technology biased to secondary energy and improving the substitution elasticity between secondary energy and primary energy can help realize the transition from primary energy dependence to secondary energy dependence. Wang (Wang and Qi, 2014) measured the factor bias of technological changes from different sources and found that research and development (R&D), import, Foreign Direct Investment (FDI) level spillover, and backward spillover were energy-saving. Zha et al. (2018) used the CES function to measure the technical bias between labor, capital, and energy, finding that technological changes favor energy use between energy and capital or between energy and labor. Xiu et al. (2019) used Ridge regression to measure the energy bias in Chinese technology changes, which show that technological changes favor energy use relative to capital and labor. Zhang et al. (2020) found that green biased technical change varies at both the input side and output side by employing the biased technical change theory and Malmquist index decomposition method in the Yangtze River Economical Belt. As the largest developing country in the world, China's optimized energy structure path such as electric transition has played a referenced role for other developing countries. We try to provide some suggestions for China to improve energy transition by analyzing the elasticity substitution and directed technological change in internal and external transition.

3 METHODOLOGY AND PRODUCTION FUNCTION

3.1 Fixed-Effect Stochastic Frontier Production Function

In this article, we aim to solve two basic problems: first, we analyze whether the production activities in various regions are efficient. If there is inefficiency, then we study the dependent factors of the inefficiency. Second, we estimate the substitution elasticity and directed technological change in 30 regions so as to obtain the improvement pathway of energy transition. The fixed-effect SFA method meets the research purpose of this article, and it can effectively solve the above-mentioned problems and prevent heterogeneity among different provinces, while DEA cannot calculate the substitution elasticity and directed technological change. For the production function, there are many production functions including C-D and CES production functions that can calculate the technological progress bias of substitution elasticity in various regions. However, the translog function becomes our preferred model with an estimable and inclusive advantage. Therefore, according to Diamond (1965), the general form is as follows:

$$y_{it} = \alpha_i + \beta x_{it} + v_{it} - u_{it} \tag{1}$$

where i and t represent the province and the time in years, respectively; y denotes the output; and α_i stands for the individual fixed effect. x means the vector set of input elements, and β is the vector set of the estimated coefficients of the input factors. v is a random error term, which represents the impact of statistical errors and various random factors on frontier output; u indicates a technical inefficiency term, which represents the gap between the actual output and the technological frontier output. The article focuses on analyzing the optimization path of the internal and external electric transition. Therefore, we regard clean energy power generation, thermal power generation, and traditional fossil energy as three independent production factors to identify the biased technological change and the elasticity substitution of the internal and external transition.

In practice, the stochastic frontier production function is widely approximated by a translog production as follows:

$$\begin{aligned}\ln Y_{it} = {} & \alpha_0 + \beta_1 t + \beta_2 \frac{1}{2} t^2 + \beta_3 \ln K_{it} + \beta_4 \ln N_{it} + \beta_5 \ln R_{it} + \beta_6 \ln F_{it} \\ & + \beta_7 t \times \ln K_{it} + \beta_8 t \times \ln N_{it} + \beta_9 t \times \ln R_{it} + \beta_{10} t \times \ln F_{it} \\ & + \frac{1}{2}\beta_{11} \ln K_{it} \times \ln K_{it} + \frac{1}{2}\beta_{12} \ln N_{it} \times \ln N_{it} + \frac{1}{2}\beta_{13} \ln R \times \ln R_{it} \\ & + \frac{1}{2}\beta_{14} \ln F_{it} \times \ln F_{it} + \frac{1}{2}\beta_{15} \ln K_{it} \times \ln N_{it} + \frac{1}{2}\beta_{16} \ln K_{it} \times \ln R_{it} \\ & + \frac{1}{2}\beta_{17} \ln K_{it} \ln F_{it} + \frac{1}{2}\beta_{18} \ln N_{it} \ln R_{it} + \frac{1}{2}\beta_{19} \ln N_{it} \ln F_{it} \\ & + \frac{1}{2}\beta_{20} \ln R_{it} \ln F_{it} + v - u \end{aligned} \tag{2}$$

where Y represents the output of each province; K is the capital; N, R, and F denote the traditional fossil energy, clean energy power generation, and thermal power generation, respectively. Following Liu and Wang (2019), traditional fossil energy, clean energy power generation, and thermal power generation are three independent factors in the translog production function. The variables used in the translog production function are described as follows:

(1) Output (Y): We deflate all current price raw data to the constant 2000 prices and GDP of each province as the output measurement indicator.
(2) Capital (K): Following some existing studies (Shan, 2008), capital stock is used to represent capital investment. We adopt the perpetual inventory method to estimate the capital stock. The formula is as follows: $K_t = (1 - \delta_t)K_{t-1} + I_t$, where k is the amount of capital, δ is the capital depreciation rate, and I_t denotes the annual physical capital investment.
(3) Traditional fossil energy (N): We use terminal fossil energy consumption to represent traditional fossil energy input. The consumption of fossil energy is measured by the sum of consumption of coal, oil, and natural gas.
(4) Clean energy power generation (R): Following Liu and Wang (2019), electricity has the characteristics of "generating and using" and "real-time balance". Since it is hard to count the attribute sources of power products from the user's side, the amount of electricity production can be used to replace electricity consumption approximately. We use the power generation of four kinds of technologies including hydro power, nuclear power, wind power, and solar power to measure clean energy power generation.
(5) Thermal power generation (F): The thermal power data come from the thermal power generation in the China

Electric Power Yearbook. In addition, all the units of energy stock need to be converted into 10^4 tce.

3.2 Technical Inefficiency Equation

Regarding the influential factors of technical inefficiency, we selected the following four factors: R&D intensity (rd), learning by exporting (exp), foreign direct investment (fdi), regional endowment structure (kl), energy consumption structure (str) , and labor productivity (lp)

$$u_{it} = \delta_1 rd_{it} + \delta_2 \exp_{it} + \delta_3 fdi_{it} + \delta_4 L.es_{it} + \delta_5 kl_{it} + \delta_6 lp_{it} \quad (3)$$

(1) R&D intensity (rd): Tu and Leeke (2011) examined the impact of technology on environmental technology efficiency from three aspects: independent research and development, technology introduction, and technological transformation, and confirmed that technology has a significant effect on the environmental technology efficiency. Based on the availability of data, we used the ratio of the internal expenditure of research and experimental development funds in each region to the regional GDP to measure the R&D intensity.

(2) Learning by exporting (exp): The "Learning-by-Exporting" effect refers to exporters who become more efficient by participating in foreign markets (Clerides et al., 1998; Li, 2010). We adopt the share of exports of goods in total output to measure this effect.

(3) Foreign direct investment (fdi): Samour et al. affirm that FDI plays a significant role in clean energy consumption (Samour et al., 2022). Wang (1997) believes that the purpose of foreign capital entering China is to occupy the domestic market rather than to produce internationally advanced products. He believes that FDI will not play a significant role in improving the technical efficiency of enterprises. However, Yao and Zhang (2001) believe that the entry of FDI improves technical efficiency through spillover effects. We use the ratio of FDI inflow and GDP to measure fdi.

(4) Regional structure: We measure the level of regional structure from two dimensions: the organic composition of capital and the proportion of fossil energy, which respectively reflect the regional endowment structure (kl) and regional energy structure (es). The factor endowment structure is one of the main indicators of the technological level in the existing literature. For example, Tu (2008) measured structural factors through regional factor endowments, property rights structure changes, and firm size and confirmed that regional structural factors have a significant impact on the improvement of environmental technology efficiency. Based on the availability of data, we use the ratio of capital stock to labor to measure regional factor endowments. Tu believes that an increase in KL indicates that the economic structure of the region is transforming from labor-intensive to capital-intensive. The energy structure is generally measured by the ratio of fossil energy consumption to total energy consumption.

(5) Labor productivity (lp): On one hand, the improvement of labor productivity reflects the improvement of people's living standards, which is positively related to people's willingness to manage environmental problems, thus improving the "green" technical efficiency (Ye and Zhou, 2011; Shao et al., 2016). On the other hand, the improvement of labor productivity reflects the enhancement of regional economic strength so that the society has more resources to achieve sound and rapid economic development (Tu, 2008). We measure labor productivity by the ratio of regional GDP to labor.

3.3 Factor-Biased Degree of Directed Technical Change

According to Diamond (1965), we can further reveal the biased technical change for each pair of input factors with the following equation:

$$Bias_{nq} = \frac{\partial MP_n/\partial t}{MP_n} - \frac{\partial MP_q/\partial t}{MP_q} \quad (4)$$

where n and q are two different production factors (including K, N, R, F); MP_n and MP_q are the marginal productivities of n and q, respectively. $Bias_{nq}$ represents the relative proportional change over time in pairwise input production elasticities. A positive (negative) sign on $Bias_{nq}$ indicates that the directed technical change is based to use $n(q)$ and save $q(n)$; $Bias_{nq} =$ 0 means the directed technical change in the production process is Hicks neutral. Thus, from **Eq. 2** and **Eq. 4**, we can calculate the biased technical change between any two factors.

For the biased technical change between clean energy power generation and thermal power generation, the following relationship is defined:

$$Bias_{RF} = \frac{\partial MP_R/\partial t}{MP_R} - \frac{\partial MP_F/\partial t}{MP_F} = \frac{\beta_9}{\eta_R} - \frac{\beta_{10}}{\eta_F} \quad (5)$$

In the same vein, the biased technical change between clean energy power generation and traditional fossil energy is calculated by the following specification:

$$Bias_{RN} = \frac{\partial MP_R/\partial t}{MP_R} - \frac{\partial MP_N/\partial t}{MP_N} = \frac{\beta_9}{\eta_R} - \frac{\beta_8}{\eta_N} \quad (6)$$

Similarly, the biased technical change between thermal power generation and traditional fossil energy is specified as follows:

$$Bias_{FN} = \frac{\partial MP_F/\partial t}{MP_F} - \frac{\partial MP_N/\partial t}{MP_N} = \frac{\beta_{10}}{\eta_F} - \frac{\beta_8}{\eta_N} \quad (7)$$

where η_R, η_F, and η_N are the output elasticities of clean energy power generation, thermal power generation, and traditional fossil energy, respectively. The marginal productivity of clean energy power generation (MP_R), thermal power generation

(MP_F), and traditional fossil energy (MP_N) can be obtained as follows:

$$MP_R = \frac{\partial Y}{\partial R} = \frac{Y}{R}\frac{\partial \ln Y}{\partial \ln R} = \frac{Y}{R}\eta_R = \frac{Y}{R}\left(\beta_5 + \beta_9 t + \beta_{13}\ln R_{it} + \frac{1}{2}\beta_{16}\ln K_{it} + \frac{1}{2}\beta_{18}\ln N_{it} + \frac{1}{2}\beta_{20}\ln F_{it}\right) \quad (8)$$

$$MP_F = \frac{\partial Y}{\partial F} = \frac{Y}{F}\frac{\partial \ln Y}{\partial \ln F} = \frac{Y}{F}\eta_R = \frac{Y}{F}\left(\beta_6 + \beta_{10} t + \beta_{14}\ln F_{it} + \frac{1}{2}\beta_{17}\ln K_{it} + \frac{1}{2}\beta_{19}\ln N_{it} + \frac{1}{2}\beta_{20}\ln R_{it}\right) \quad (9)$$

$$MP_N = \frac{\partial Y}{\partial N} = \frac{Y}{N}\frac{\partial \ln Y}{\partial \ln N} = \frac{Y}{N}\eta_N = \frac{Y}{N}\left(\beta_4 + \beta_8 t + \beta_{12}\ln N_{it} + \frac{1}{2}\beta_{15}\ln K_{it} + \frac{1}{2}\beta_{18}\ln R_{it} + \frac{1}{2}\beta_{19}\ln F_{it}\right) \quad (10)$$

3.4 Substitution Elasticity Between Factors

The elasticity substitution of input factor is the core indicator to measure the strength of the substitution relationship between factors. Its initial definition was given by Hicks in "Wage Theory". The factor substitution elasticity (when a given output is constant) is the percentage change in the factor ratio caused by the change in the marginal substitution rate. The elasticity of substitution is as follows:

$$Subs_{RF} = \frac{d\ln(R/F)}{d\ln(MP_R/MP_F)} = \frac{d\ln(F/R)}{d\ln(MP_F/MP_R)} = Subs_{FR} \quad (11)$$

$$\frac{MP_R}{MP_F} = \frac{Y}{R}\frac{\partial \ln Y}{\partial \ln F}\Big/\frac{Y}{F}\frac{\partial \ln Y}{\partial \ln R} = \frac{F}{R}\frac{\eta_R}{\eta_F} \quad (12)$$

$Subs_{RF} > 0$ ($Subs_{RF} < 0$) indicates the relationship between factors is substitution (complementary). The substitution relationship between factors indicates that an increase in the input of one factor will lead to a decrease in the input of another factor. According to **Eq. 11** and **Eq. 12**, we can obtain the elasticity substitution of inputs factors in internal and external transition. The elasticities of substitution between R and F, R and N, and F and N are as follows, respectively,

$$Subs_{RF} = \left[1 + 2\left(\beta_{20} - \frac{\eta_F}{\eta_R}\beta_{13} - \frac{\eta_R}{\eta_F}\beta_{14}\right)(\eta_R + \eta_F)^{-1}\right]^{-1} \quad (13)$$

$$Subs_{RN} = \left[1 + 2\left(\beta_{18} - \frac{\eta_N}{\eta_R}\beta_{13} - \frac{\eta_R}{\eta_N}\beta_{12}\right)(\eta_R + \eta_F)^{-1}\right]^{-1} \quad (14)$$

$$Subs_{FN} = \left[1 + 2\left(\beta_{19} - \frac{\eta_N}{\eta_F}\beta_{14} - \frac{\eta_F}{\eta_N}\beta_{12}\right)(\eta_F + \eta_N)^{-1}\right]^{-1} \quad (15)$$

3.5 Data Description

Based on the available data, we selected panel data from 30 provinces in Mainland China from 2000 to 2017 as the research sample. The Tibet area is not included in the statistics due to incomplete data. In China, the "5-year plan" is an important part of China's national economic plan. The data from 2000 to 2017 cover the end of the "9th Five-Year Plan" period, "10th Five-Year Plan" period, "11th Five-Year Plan" period, "12th Five-Year Plan" period, and the early stage of the "13th Five-Year Plan ". Therefore, the data we select are of wide statistical significance.

We obtain the data of traditional fossil energy including coal, oil, and natural gas from the district energy balance table in the China Energy Statistical Yearbook. The terminal consumption of coal, oil, and natural gas is adopted to prevent the impact of energy processing and conversion. The clean energy generation capacity is selected from hydro power, nuclear, wind, and solar technologies in the China Electric Power Yearbook. Restricted by the unavailability of data, hydro power and nuclear power data are from 2000 to 2017, and wind energy data are selected from 2006 to 2017. Solar energy data range from 2010 to 2017. The thermal power data come from the thermal power generation in the China Electric Power Yearbook. The units of all energy data are uniformly converted into tce according to the energy discount standard coal reference coefficient in the China Energy Statistical Yearbook. In order to eliminate the influence of inflation and other factors, the capital stock and GDP are deflated to the constant 2000 prices according to the price index and GDP index. Data such as capital stock, GDP, GDP index, and price index are from the China Statistical Yearbook. The descriptive statistics of the above-mentioned variables are shown in **Table 1**. The capital stock is calculated using the equation as follows:

$$K_t = K_{t-1}(1 - \delta) + I_t \quad (16)$$

where K is the capital stock, δ indicates the depreciation rate, and I_t means the investment.

4 RESULTS AND DISCUSSION

4.1 Specification Tests of Production Function

In order to test whether the model setting is correct, the following aspects should be tested successively. The results of specification tests of the production function are shown in **Table 2**.

(1) Whether the stochastic frontier model is applicable: H_0: $\gamma = 0$. If the null hypothesis is rejected, it indicates that there are inefficiencies in the model, and the stochastic frontier production model can be used for parameter estimation; otherwise, the stochastic frontier analysis is not needed.
(2) Whether the C–D production function or the translog production function is more appropriate: H_0: $\beta_{tK} = \beta_{tN} = \beta_{tR} = \beta_{tF} = \beta_{KK} = \beta_{NN} = \beta_{RR} = \beta_{FF} = \beta_{KN} = \beta_{KN} = \beta_{KR} = \beta_{KF} = \beta_{NR} = \beta_{NF} = \beta_{RF} = \beta_{tt} = 0$. If the null hypothesis is accepted, the production function is in the C–D form; otherwise, the production function is in the translog form.

TABLE 1 | Descriptive statistics of variables in the production function.

Variable (unit)	Observation	Mean	Standard error	Minimum	Maximum
GDP (109RMB)	540	10,509	10,710	263.7	61,431
K (109RMB)	540	24,246	24,500	848.2	139,859
N (104tce)	540	3,836	2,355	216.9	14,001
F (104tce)	540	1,204	1,138	32.08	6,321
R (104tce)	540	330.9	522.3	0	3,951
RD (%)	540	1.263	1.031	0.091	6.014
EXP (%)	540	15.51	18.22	1.091	92.72
FDI (%)	540	2.551	2.248	0.0386	14.65
LP (10^4RMB/person)	540	4.329	3.128	0.542	16.69
KL (10^4RMB/person)	540	10.65	8.506	1.321	52.14
L.STR (%)	510	73.8	8.11	49.2	90.9

TABLE 2 | Results of specification tests of the production function.

Null hypothesis	LR statistic	$\chi^2_{0.05}$
$\beta_{tt} = \beta_{tK} \cdots = \beta_{RF} = 0$	87.08	15.51
$\beta_t = \beta_{tt} = \beta_{tK} = \beta_{tN} = \beta_{tR} = \beta_{tF} = 0$	43.03	15.51
$\beta_{tK} = \beta_{tN} = \beta_{tR} = \beta_{tF} = 0$	140.16	15.51

(3) Whether there is a technological progress in stochastic frontier production models: H_0: $\beta_t = \beta_{tt} = \beta_{tK} = \beta_{tN} = \beta_{tR} = \beta_{tF}$. If the original hypothesis is accepted, it indicates that there is no technical progress in the model and there is no need to test (4). Conversely, if the counter hypothesis is rejected, the fourth step test is continued.

(4) Whether the technical change is Hicks-neutral: H_0: $\beta_{tK} = \beta_{tN} = \beta_{tR} = \beta_{tF}$. If the null hypothesis is accepted, the model technology progress is Hicks-neutral. On the contrary, it indicates that the technological progress is non-neutral. The generalized likelihood statistic LR is used to test this hypothesis. The original hypothesis of LR is H_0, and the alternative hypothesis is H_1. The formula $LR = -2 \times [\ln L(H_0) - \ln L(H_1)]$ can be used to calculate the statistic LR, which follows the Chi-square distribution $LR \sim \chi^2_{1-\alpha}(k)$, where α is the significance level and the degree of freedom k is the number of constrained variables. If the calculated LR statistic is larger than the critical value, the null hypothesis is rejected; otherwise, the null hypothesis is accepted.

The results in **Table 2** show that the LR statistic of the above test (2) is greater than the critical value of the mixed Chi-square

TABLE 3 | Estimation results of the translog production function and the technical inefficiency equation.

Variables	Coefficient		t-Value	Variables	Coefficient		t-Value
Translog production function							
Constant	−2.5934[a]	(0.9697)	−2.6745	$0.5(\ln N^2)$	1.0877[a]	(0.1864)	5.8364
$\ln K$	4.5195[a]	(0.3470)	13.0254	$0.5(\ln R^2)$	0.0009	(0.0012)	0.6919
$\ln N$	−3.7228[a]	(0.4563)	−8.1592	$0.5(\ln F^2)$	−0.1083	(0.0674)	−1.6058
$\ln R$	−0.0261	(0.0635)	−0.4110	$0.5\ln K\ln N$	−0.4515[b]	(0.2195)	−2.0570
$\ln F$	0.4115[c]	(0.2429)	1.6940	$0.5\ln K\ln R$	−0.0175	(0.0274)	−0.6367
t	−0.3045[a]	(0.0459)	−6.6393	$0.5\ln K\ln F$	0.7641[a]	(0.1127)	6.7802
$t\ln K$	0.0514[a]	(0.0106)	4.8554	$0.5\ln N\ln R$	−0.0019	(0.0284)	−0.0677
$t\ln N$	0.0054	(0.0122)	0.4455	$0.5\ln N\ln F$	−0.7951[a]	(0.1976)	−4.0249
$t\ln R$	−0.0017	(0.0013)	−1.3124	$0.5\ln F\ln R$	0.0434	(0.0303)	1.4318
$t\ln F$	−0.0307[a]	(0.0076)	−4.0419	$0.5tt$	−0.0038[b]	(0.0015)	−2.4553
$0.5(\ln K^2)$	−0.5019[a]	(0.0964)	−5.2080				
Technical inefficiency equation							
δ_0	0.3301[a]	(0.0428)	7.7072	*L.es*	0.0468[a]	(0.0168)	2.7835
rd	−0.0099	(0.0151)	−0.6574	*kl*	0.0253[a]	(0.0022)	11.2723
exp	−0.0083[a]	(0.0020)	−4.0627	*lp*	−0.0468[a]	(0.0039)	−12.1208
fdi	−0.0170[a]	(0.0046)	−3.7135				
Related test							
σ^2	0.0366[a]	(0.0027)	13.6772	γ	0.4118[a]	(0.0590)	6.9798
Log likelihood function					164.63		
LR test					199.37		

Note: Standard errors for coefficients are in parentheses.
[a]*Statistical significance at the 1% level.*
[b]*Statistical significance at the 5% level.*
[c]*Statistical significance at the 10% level.*

distribution, indicating that the null hypothesis should be rejected. Therefore, it is more reasonable to use the translog production function. The results of test (3) and test (4) indicate that there are technical changes in the model, and this change is non-neutral. As shown in **Table 3**, the regression results show that γ significantly passes the t test, which shows that the null hypothesis of the above test (1) is also rejected and the inefficiency term exists. After the above tests, it can be concluded that the stochastic frontier model is applicable, and the production function adopted by the model is the translog production function.

4.2 Estimation Results of the Production Function and Technical Inefficiency Equation

Considering that local governments can determine the share of fossil energy, *es* may have obvious endogenous problems in the inefficiency equation. In this case, the estimation results of the stochastic frontier model may be inaccurate. Therefore, according to Yang et al. (Alataş, 2020), when estimating **Eq. 3**, we use the first-order lag *es* (*L.es*) to control the endogenous problem. The estimation results are shown in **Table 3**. Most of the coefficients in the translog production function (3) are statistically significant. The maximum likelihood function value of the model and the LR test result show that the stochastic frontier model has a strong explanatory power. Therefore, the model we establish can reasonably reflect the changes in the technical efficiency of the 30 provinces.

For the determinants of the inefficient equation, although the coefficient of rd is positive, it is not significant, indicating that the R&D intensity has little effect on promoting the technical efficiency. From the energy production mode of China, it can be found that the current innovation activities of enterprises aim at product upgrading rather than improving energy saving. This result is consistent with some of the existing studies. For example, Xuan and Zhou (Yazan et al., 2022) have no evidence of a significant positive relationship between original innovation activity and energy efficiency. In addition, Yang et al. (2018) believes that the original enterprise innovation is uncertain and cyclical, and an increased cost of innovation may make it difficult to get reports in the short term.

The exp coefficient is negative, meaning that exports can help improve the technical efficiency. This shows that the expected "Learning by Exporting" effect appears in China. It means that enterprises can acquire new knowledge from competitors when exporting so that export behavior improves the technological efficiency.

The fdi coefficient is significantly negative, indicating that fdi can effectively improve the technical efficiency. There are two theories of "pollution paradise" and "pollution halo" on the impact of fdi on technical efficiency. Our empirical results support the latter. It indicates that fdi drives the promotion of more efficient technologies in multinational corporations.

The coefficient of *L.es* is significantly positive, indicating that increased fossil energy consumption is detrimental to improving the technical efficiency. At present, China's energy structure seriously depends on fossil energy, which also shows that China's current energy structure limits the improvement of technical efficiency.

The coefficient of *kl* is significantly positive, indicating that the rising organic composition of capital will lead to a decrease in technical efficiency. This result is consistent with the views of Tu and Leeke (2011) and shao et al. (2016). It also confirms that "capital-intensive" industries tend to be heavy polluting industries, while labor-intensive industries tend to be light polluting industries.

The coefficient of lp is significantly negative, indicating that lp can promote the technical efficiency. On one hand, the improvement of labor productivity is conducive to enterprises to achieve better production with more and other resources. On the other hand, improving living standards can help enhance people's willingness to improve the environment and the "green" technical efficiency.

4.3 Factor-Biased Degree of Directed Technical Change

To discuss the biased technical changes in internal and external transition, we show the mean value of 2000–2017 in **Table 4**. Bias-NR and Bias-NF refer to the biased technical change in the external transition, while Bias-FR means the biased technical change in the internal transition.

In the external transition, for the pair of R and N, only eight provinces prefer to use clean energy, and the remaining 22 regions prefer to use traditional fossil energy. For the pair of F and N, 22 regions prefer thermal power generation, and the other eight provinces prefer traditional power generation. In the internal transition, technological changes are biased toward R in nine of the 30 provinces, while the remaining 21 provinces are biased F. This suggests that the government should continue to encourage producers to value clean production.

In addition, **Table 5** shows the directed technical change bias order of the three input factors. In 20 of the 30 regions, the technical changes are more biased to thermal power generation, which is the first factor of the biased order for the 20 regions. However, only five regions are biased to clean energy generation. The production mode of the above eight provinces is relatively green and sustainable. It can be explained that the larger the production scale of renewable energy, the more advanced the corresponding level of renewable energy production technology is. For example, Hubei ranks the third largest in the renewable energy scale in China, so the renewable energy production technology in Hubei is relatively advanced. Five regions have more preference to traditional fossil energy, which is the first factor of biased order for 14 regions. Therefore, technological changes in these provinces tend to use traditional fossil energy rather than clean power generation or thermal power generation. Therefore, as a whole, the directed technical change in China is more biased to thermal power generation and deviated from clean energy generation.

However, technological changes in 18 regions deviate from clean energy generation, which is the last factor of the biased

TABLE 4 | Biased technical changes in internal and external electric transition.

Province	Bias-NR	Bias-NF	Bias-FR	Province	Bias-NR	Bias-NF	Bias-FR
Anhui	0.116	**−0.208**	0.324	Jiangxi	0.206	0.051	0.155
Beijing	**−0.037**	0.178	**−0.215**	Liaoning	0.124	**−0.795**	0.920
Fujian	**−0.106**	0.873	**−0.980**	Neimenggu	0.134	**−0.033**	0.168
Gansu	0.059	**−0.613**	0.672	Ningxia	0.070	**−0.212**	0.282
Guangdong	0.076	**−0.569**	0.645	Qinghai	0.075	0.642	**−0.567**
Guangxi	0.471	1.462	**−0.990**	Shandong	0.073	**−0.069**	0.143
Guizhou	0.092	**−0.090**	0.182	Shanxi	0.074	**−0.068**	0.142
Hainan	**−0.166**	0.866	**−1.032**	Shanxi2	0.092	**−5.588**	5.681
Hebei	0.077	**−0.166**	0.242	Shanghai	−0.369	**−0.747**	0.378
Henan	0.067	**−0.176**	0.242	Sichuan	0.904	**−0.085**	0.989
Heilongjiang	0.207	**−0.434**	0.641	Tianjin	−0.279	**−0.305**	0.026
Hubei	**−0.263**	**−0.109**	**−0.154**	Xinjiang	0.158	**−2.167**	2.326
Hunan	0.141	**−0.352**	0.494	Yunnan	0.081	**−0.403**	0.483
Jilin	**−1.233**	**−0.268**	**−0.965**	Zhejiang	0.202	0.523	**−0.322**
Jiangsu	0.097	8.106	**−8.008**	Chongqing	−0.866	**−1.174**	0.308

Bold value of Bias-ij indicates the technical change is biased to j factor.

TABLE 5 | Factor-biased order of the technical change in 30 provinces.

Order	Province
F > N > R	Anhui, Gansu, Guangdong, Guizhou, Hebei, Henan, Heilongjiang, Hunan, Liaoning, Neimenggu, Ningxia, Shandong, Shanxi, Shanxi2, Sichuan, Xinjiang, Yunnan
F > R > N	Shanghai, Tianjin, Chongqing
N > R > F	Guangxi, Jiangsu, Qinghai, Zhejiang
N > F > R	Jiangxi
R > F > N	Hubei, Jilin
R > N > F	Beijing, Fujian, Hainan

TABLE 6 | Substitution elasticity in the internal and external electric transition.

Province	Subs-RN	Subs-FN	Subs-RF	Province	Subs-RN	Subs-FN	Subs-RF
Anhui	**−1.098**	**−0.066**	1.855	Jiangxi	**−3.366**	**−0.001**	0.307
Beijing	0.59	**−0.279**	0.546	Liaoning	0.526	**−0.123**	1.455
Fujian	1.419	0.135	0.532	Neimenggu	0.353	0.175	1.467
Gansu	1.233	0.049	2.208	Ningxia	1.005	0.354	2.012
Guangdong	1.35	**−0.109**	0.307	Qinghai	**−5.693**	0.032	0.917
Guangxi	1.599	**−0.251**	0.558	Shandong	0.351	**−0.356**	1.317
Guizhou	1.5	**−0.311**	1.54	Shanxi	0.587	**−0.050**	0.014
Hainan	0.576	0.219	0.679	Shanxi	1.137	**−0.118**	4.42
Hebei	1.469	**−0.306**	1.798	Shanghai	**−1.707**	**−0.064**	1.142
Henan	**−0.776**	**−0.204**	0.922	Sichuan	0.962	**−0.137**	**−42.20**
Heilongjiang	0.402	**−0.046**	**−0.725**	Tianjin	0.489	0.034	2.289
Hubei	**−3.13**	**−0.204**	1.588	Xinjiang	0.596	0.016	6.269
Hunan	1.039	**−0.323**	9.76	Yunnan	1.304	**−0.640**	0.821
Jilin	**−6.371**	**−0.033**	0.967	Zhejiang	**−0.291**	**−0.069**	0.459
Jiangsu	**−0.36**	0.229	0.169	Chongqing	1.494	**−11.81**	0.308

Bold value of Subs-ij means there is a complementary relationship between factor i and j.

order for the 18 provinces in **Table 5**. In addition, technological changes in seven regions are more likely to deviate from thermal power generation, and technological changes in five regions are more likely to deviate from traditional fossil energy, which is the last factor of the bias order for the five regions. The above results show that overall, China's provincial scope prefers to use thermal power over clean energy and traditional fossil energy. They are less inclined to use clean energy rather than thermal power or traditional fossil energy. On one hand, these results confirm the fact that the thermal power generation is popular in China. On the other hand, the results also show that the government departments should encourage the emphasis on clean production.

Based on some studies (Hicks, 1932; Acemoglu et al., 2015; Fredriksson and Sauquet, 2017; Naqvi and Engelbert, 2017; Fried, 2018; Kha, 2019), the degree of factor bias of directed technology

TABLE 7 | Classification results of directed technical change and substitution elasticity between factors (traditional fossil energy vs. clean energy generation).

Estimation result	Province
Bias-NR>0, Subs-NR>0	Gansu, Guangdong, Guangxi, Guizhou, Hebei, Heilongjiang, Hunan, Liaoning, Neimenggu, Ningxia, Shandong, Shanxi, Shanxi, Sichuan, Xinjiang, Yunnan
Bias-NR<0, Subs-NR>0	Beijing, Fujian, Hainan, Tianjin, Chongqing
Bias-NR>0, Subs-NR<0	Anhui, Henan, Jiangsu, Jiangxi, Qinghai, Zhejiang
Bias-NR<0, Subs-NR<0	Hubei, Jilin, Shanghai

TABLE 8 | Classification results of directed technical change and substitution elasticity between factors (traditional fossil energy vs. thermal power generation).

Estimation result	Province
Bias-NF>0, Subs-NF>0	Fujian, Hainan, Jiangsu, Qinghai
Bias-NF<0, Subs-NF>0	Gansu, Neimenggu, Ningxia, Tianjin, Xinjiang
Bias-NF>0, Subs-NF<0	Beijing, Guangxi, Jiangxi, Zhejiang
Bias-NF<0, Subs-NF<0	Anhui, Guangdong, Guizhou, Hebei, Henan, Heilongjiang, Hubei, Hunan, Jilin, Liaoning, Shandong, Shanxi, Shanxi, Shanghai, Sichuan, Yunnan, Chongqing

TABLE 9 | Classification results of directed technical change and substitution elasticity between factors (thermal power generation vs. clean power generation).

Estimation result	Province
Bias-FR>0, Subs-FR>0	Anhui, Gansu, Guangdong, Guizhou, Hebei, Henan, Hunan, Jiangxi, Liaoning, Neimenggu, Ningxia, Shandong, Shanxi, Shanxi, Shanghai, Tianjin, Xinjiang, Yunnan, Chongqing
Bias-FR<0, Subs-FR>0	Beijing, Fujian, Guangxi, Hainan, Hubei, Jilin, Jiangsu, Qinghai, Zhejiang
Bias-FR>0, Subs-FR<0	Heilongjiang, Sichuan

changes is determined by the price and scale effects. Adjusting the relative price will timely adjust the relative demand and actual input between factors in the production process and gradually reduce the difference in the marginal output growth rate of the two energy factors so as to change the degree of factor bias of directed technical changes between factors. Therefore, in the internal transition, the governments can adjust the technical change bias of the provinces by raising the price of thermal power generation or increasing the subsidies for clean energy power generation. In the external transition, the governments can adjust the energy policies of the province by increasing the carbon tax prices or increasing subsidies for clean energy power generation and low-coal thermal power generation. These changes will continue to alter the relative price between factors.

4.4 Substitution Elasticity Between Factors

In **Table 6**, we list the substitution elasticities between factors in the 30 provinces. From the perspective of external transition, for the pair of F and N, there are only nine provinces with substitution relations, and the other 21 other regions have complementary relationships. The complementary relationship between F and N in most provinces can be explained by their need for more energy to meet production demand. In addition, there are complementary relationships between R and N in only nine regions, while the 21 remaining regions have substitution relationships. From the perspective of the internal electric transition, there is a complementary relationship between F and R in only two regions, and the other 28 regions all have substitution relations. It indicates that increased clean energy power generation can currently be used to reduce thermal power generation in these provinces. Although at the provincial level, different regions show an obvious difference in substitution elasticity, there is a substitution relationship between other energy factors except for traditional fossil generation and thermal power generation with a complementary relationship on a whole.

4.5 Improvement Pathway of Energy Transition

In the production process, the internal and external transition can be conducive to the green development and transformation. Therefore, we analyze three transition ways and study the improvement path of energy transition in different regions based on the degree of biased directed technical changes and the substitution elasticity between factors. The classification results of eight external transition pathways and three internal transition pathways are shown in **Tables 7–9**.

First, the classification results between factor N and R are shown in **Table 7**. There are four production patterns according to the factor N and R. Among them, the ideal production mode shows Bias-NR<0 and Subs-NR>0. In this kind of production mode, these regions (Beijing, Fujian, Hainan, Tianjin, and Chongqing) are more inclined to use the clean energy power generation rather than use the traditional fossil energy. Increasing the use of clean energy power generation will reduce the use of fossil energy, which will help to promote the transformation of clean energy to traditional fossil energy.

The mode-like Bias-NR>0 and Subs-NR>0 suggests that the region prefers to use traditional fossil energy over clean energy. In addition, an increase in traditional fossil energy use would lead to a decline in the use of clean energy generation. For these areas, the directed technological change needs to be adjusted; Bias-NR<0 and Subs-NR<0 suggest that the region prefers the use of clean energy generation, and increasing the use of clean energy generation leads to the increased use of traditional fossil energy. These regions need to adjust the alternative relationship between the two energy sources; for areas with Bias-NR>0 and Subs-NR<0, the government needs to encourage technological changes inclined to use clean energy power generation and change the complementary relationship between clean energy power generation and traditional fossil energy.

Second, the classification results with four production patterns between F and N are shown in **Table 8**. The ideal production mode is Bias-NF<0 and Subs-NF>0. Areas that are in line with this production mode (Gansu, Neimenggu, Ningxia, Tianjin, and Xinjiang) are more inclined to use thermal power generation. When expanding the scale of production, they will increase the thermal power generation and reduce traditional fossil energy so as to promote the external transformation of thermal power generation to traditional fossil energy.

Finally, the classification results between F and R are shown in **Table 9**. The mode with Bias-FR>0 and Subs-FR>0 indicates that the province prefers thermal power to clean energy power generation, and there is an alternative relationship in the production process between clean energy power and thermal power. Therefore, the areas with the above mode prefer to use thermal power generation rather than clean energy generation, and the increase of thermal power generation use will lead to the decline of clean energy power generation. For these areas, the technical change needs to be adjusted between the two factors. Areas with Bias-FR>0 and Subs-FR<0 prefer thermal power generation rather than clean energy power generation. For these areas, technological change that is biased to clean energy power generation and use need to be encouraged, and the alternative relationship between thermal and clean energy power generation needs to be adjusted. The ideal production model shows Bias-FR<0 and Subs-FR>0, where the provinces (Beijing, Fujian, Guangxi, Hainan, Hubei, Jilin, Jiangsu, Qinghai, and Zhejiang) prefer the use of clean energy power generation rather than the use of thermal power generation. In addition, increasing the scale of the use of clean energy power generation can reduce the use of thermal power generation in these provinces.

Hence, in order to improve the external and internal electric transition, the Chinese governments should promote the reform of the market-oriented energy pricing mechanism according to characteristic transition modes in different regions. For the provinces with production patterns which can automatically benefit the energy transition, we suggest a moderate policy, while for the other provinces, we suggest a policy of energy price and tax. Moreover, for the enterprises, their production patterns are not easy to change. They usually benefit by minimizing costs under the conditions of homogeneous products and unchanged price. Therefore, the change of the inter-fule price will have an effect on the production costs and the structure of production factors, which improves the energy transition. Finally, the results from the analysis of China show that it is also possible for other countries to treat their energy transition differently due to their characteristic production patterns.

5 CONCLUSION AND POLICY IMPLICATIONS

Promoting the internal and external electric transition is of great significance for China to achieve a green transformation. In this article, with capital, traditional fossil energy, clean energy, thermal power generation, and the GDP of the provinces, we built a stochastic production frontier model based on the translog production function, which measures the bias of directed technical changes and substitution elasticities of 30 provinces in mainland China from 2000 to 2017. Furthermore, we discuss the transition paths with three pairs of energy inputs in 30 provinces.

For all Chinese provinces, export learning, foreign direct investment, and labor productivity can significantly improve the technological efficiency, while increasing fossil energy consumption and capital deepening will have a negative impact on technological efficiency. In addition, there is no evidence that the original R&D activities can significantly improve the technical efficiency.

On the whole, the directed technical change in China is more biased to thermal power generation and deviated from clean energy generation. In addition, except for traditional fossil generation and thermal power generation with a complementary relationship, there is a substitution relationship between other energy factors.

At the provincial level, different regions show an obvious difference in substitution elasticity. It can be found that the technical change is biased to thermal power generation for 21 regions and there is a substitution relationship for 28 regions in internal electric transition. In addition, the technical change is biased to traditional fossil energy instead of clean energy generation for 22 provinces, and 21 regions have complementary relations between them. Moreover, the technical change is biased to thermal power generation instead of traditional fossil energy, and 21 regions have substitution relations between them.

Considering the differentiated production characteristics of different regions, the government should avoid promoting energy transition in accordance with unified policies. According to the directed technical change and substitution elasticity, the government needs to formulate and adopt differentiated improvement measures for energy transition. In the external electric transition, we recommend a relatively moderate adjustment policy for five regions conforming to the (Bias-NR

< 0 mode, Subs-NR > 0) mode and five regions conforming to the (Bias-NF < 0, Subs-NF > 0) mode. In the internal transition, among the 30 provinces, nine regions present the production mode (Bias-FR < 0, Subs-FR > 0). For these provinces, we also recommend a laissez-faire or moderate adjustment policy as their internal transition can be automatically improved. However, for other regions, the biased order of technical change between energies can be changed through the price policy. To sum up, by adjusting the relative price between energies through reasonable fiscal and tax policies, it is expected to achieve the internal and external electric transition. The results of this study can be used for reference by almost all countries in the world. We suggest that the differentiated energy transition should be implemented according to the various production patterns in different regions. Although this research has made contributions, we do not provide specific technical support for China to adjust the technical change bias among different energy sources. This article may contribute to energy transition in various sectors or industries. We also modeled the translog production function under the external and internal electric transition which is significant in carbon emission reduction action.

DATA AVAILABILITY STATEMENT

The raw data supporting the conclusion of this article will be made available by the authors, without undue reservation.

AUTHOR CONTRIBUTIONS

GH: Conceptualization, methodology, software, data curation, writing—original draft. HS: Methodology, software, data curation, writing—original draft.

REFERENCES

Abumunshar, M., Aga, M., and Samour, A. (2020). Oil Price, Energy Consumption, and CO2 Emissions in Turkey. New Evidence from a Bootstrap ARDL Test. *Energies* 13, 5588. doi:10.3390/en13215588

Acemoglu, D., Akcigit, U., Hanley, D., and Kerr, W. R. (2015). Transition to Clean Technology [J]. *Harv. Business Sch. Working Pap.* 124 (1), 52–104. doi:10.1086/684511

Acemoglu, D., Aghion, P., Bursztyn, L., and Hemous, D. (2012). The Environment and Directed Technical Change. *Am. Econ. Rev.* 102 (1), 131–166. doi:10.1257/aer.102.1.131

Aghion, P., Dechezleprêtre, A., Hémous, D., Martin, R., and Van Reenen, J. (2016). Carbon Taxes, Path Dependency, and Directed Technical Change: Evidence from the Auto Industry. *J. Polit. Economy* 124 (1), 1–51. doi:10.1086/684581

Alataş, S. (2020). Towards a Carbon-Neutral Economy: The Dynamics of Factor Substitution in Germany. *Environ. Sci. Pollut. Res. Int.* 27 (8), 26554–26569. doi:10.1007/s11356-020-08955-2

Alataş, S., Karakaya, E., and Hiçyılmaz, B. (2021). What Does Input Substitution Tell Us in Helping Decarbonization and Dematerialization? Industry Level Analysis for South Korea. *Sustainable Prod. Consumption* 27, 411–424. doi:10.1016/j.spc.2020.11.015

Altarhouni, A., Danju, D., and Samour, A. (2021). Insurance Market Development, Energy Consumption, and Turkey's CO2 Emissions. New Perspectives from a Bootstrap ARDL Test. *Energies* 14, 7830. doi:10.3390/en14237830

Bello, M. O., Solarin, S. A., and Yen, Y. Y. (2018). Hydropower and Potential for Interfuel Substitution: The Case of Electricity Sector in Malaysia. *Energy* 151, 966–983. doi:10.1016/j.energy.2018.03.055

China Statistical Yearbook (2020). *China Statistical Yearbook [M]*. Beijing, China: China Statistics Press.

Clerides, S. K., Lach, S., and Tybout, J. R. (1998). Is Learning by Exporting Important? Micro-dynamic Evidence from Colombia, Mexico, and Morocco. *Q. J. Econ.* 113 (3), 903–947. doi:10.1162/003355398555784

Costantini, V., Crespi, F., and Paglialunga, E. (2019). Capital-energy Substitutability in Manufacturing Sectors: Methodological and Policy Implications. *Eurasian Bus Rev.* 9 (2), 157–182. doi:10.1007/s40821-018-0114-z

Diamond, P. A. (1965). Disembodied Technical Change in a Two-Sector Model. *Rev. Econ. Stud.* 32 (2), 161–168. doi:10.2307/2296060

Fan, M., and Zheng, H. (2019). The Impact of Factor price Changes and Technological Progress on the Energy Intensity of China's Industries: Kalman Filter-Based Econometric Method. *Struct. Change Econ. Dyn.* 49, 340–353. doi:10.1016/j.strueco.2018.11.004

Fredriksson, P. G., and Sauquet, A. (2017). Does Legal System Matter for Directed Technical Change? Evidence from the Auto Industry [J]. *Appl. Econ. Lett.* 24, 1–4. doi:10.1080/13504851.2016.1254334

Fried, S. (2018). Climate Policy and Innovation: A Quantitative Macroeconomic Analysis. *Am. Econ. J. Macroeconomics* 10 (1), 90–118. doi:10.1257/mac.20150289

Hao, Y., and Huang, Y.-N. (2018). Exploring the Nexus of Energy Consumption Structure and CO2 Emissions in China: Empirical Evidence Based on the Translog Production Function. *Pol. J. Environ. Stud.* 27 (6), 2541–2551. doi:10.15244/pjoes/81071

Hicks, J. (1932). *The Theory of Wages [M]*. London: Macmillan.

Jiang, Z., Lyu, P., Ye, L., and Zhou, Y. W. (2020). Green Innovation Transformation, Economic Sustainability and Energy Consumption during China's New normal Stage. *J. Clean. Prod.* 273, 123044. doi:10.1016/j.jclepro.2020.123044

Kha, B. (2019). How to Accelerate green Technology Diffusion? Directed Technological Change in the Presence of Coevolving Absorptive Capacity [J]. *Energ. Econ.* 85, 104565. doi:10.1016/j.eneco.2019.104565

Khalid, W., and Jalil, A. (2019). An Econometric Analysis of Inter-fuel Substitution in Energy Sector of Pakistan. *Environ. Sci. Pollut. Res.* 26 (17), 17021–17031. doi:10.1007/s11356-019-05014-3

Kim, J., and Heo, E. (2013). Asymmetric Substitutability between Energy and Capital: Evidence from the Manufacturing Sectors in 10 OECD Countries. *Energ. Econ.* 40 (2), 81–89. doi:10.1016/j.eneco.2013.06.014

Li, C. (2010). Whether There Is a "productivity Paradox" of Chinese export Enterprises: a Test Based on the Data of Chinese Manufacturing Enterprises [J]. *The World Economy* 33 (07), 64–81.

Lin, B., and Abudu, H. (2019). Changes in Energy Intensity during the Development Process:Evidence in Sub-saharan Africa and Policy Implications [J]. *Energy* 183, 15657. doi:10.1016/j.energy.2019.06.174

Lin, B., and Agyeman, S. (2020). Impact of Natural Gas Consumption on Sub-saharan Africa's CO2 Emissions: Evidence and Policy Perspective. *Sci. Total Environ.* 760 (1), 143321. doi:10.1016/j.scitotenv.2020.143321

Lin, B., and Abudu, H. (2020). Can Energy Conservation and Substitution Mitigate CO2 Emissions in Electricity Generation? Evidence from Middle East and North Africa. *J. Environ. Manage.* 275, 111222. doi:10.1016/j.jenvman.2020.111222

Lin, B., and Ankrah, I. (2019b). On Nigeria's Renewable Energy Program: Examining the Effectiveness, Substitution Potential, and the Impact on National Output. *Energy* 167, 1181–1193. doi:10.1016/j.energy.2018.11.031

Lin, B., and Ankrah, I. (2019a). Renewable Energy (Electricity) Development in Ghana: Observations, Concerns, Substitution Possibilities, and Implications for the Economy. *J. Clean. Prod.* 233, 1396–1409. doi:10.1016/j.jclepro.2019.06.163

Lin, B., and Chen, X. (2020). How Technological Progress Affects Input Substitution and Energy Efficiency in China: A Case of the Non-ferrous Metals Industry. *Energy* 206, 118152. doi:10.1016/j.energy.2020.118152

Lin, B., and Raza, M. Y. (2021). Fuels Substitution Possibilities and the Technical Progress in Pakistan's Agriculture Sector. *J. Clean. Prod.* 314, 128021. doi:10.1016/j.jclepro.2021.128021

Liu, K., Bai, H., Yin, S., and Lin, B. (2018). Factor Substitution and Decomposition of Carbon Intensity in China's Heavy Industry. *Energy* 145, 582–591. doi:10.1016/j.energy.2017.12.151

Liu, P., and Wang, Z. (2019). Is China's "energy Transformation" Reasonable? Empirical Study of the Energy Substitution-Complementary Relationship [J]. *China Soft Sci.* 34 (08), 14–30.

Malikov, E., Sun, K., and Kumbhakar, S. C. (2018). Nonparametric Estimates of the Clean and Dirty Energy Substitutability. *Econ. Lett.* 168, 118–122. doi:10.1016/j.econlet.2018.04.017

Naeem, M. K., Anwar, S., and Nasreen, S. (2021). Empirical Analysis of CO2 Emissions and Sustainable Use of Energy Sources in Pakistan. *Environ. Sci. Pollut. Res. Int.* 28, 16420–16433. doi:10.1007/s11356-020-11927-1

Naqvi, S., and Engelbert, S. (2017). Directed Technological Change in a post-Keynesian Ecological Macromodel [J]. *Ecol. Econ. Pap.* 154, 168–188. doi:10.1016/j.ecolecon.2018.07.008

Ouyang, X., Zhuang, W., and Du, G. (2018). Output Elasticities and Inter-factor Substitution: Empirical Evidence from the Transportation Sector of Shanghai. *J. Clean. Prod.* 202 (20), 969–979. doi:10.1016/j.jclepro.2018.08.188

Popp, D. (2002). Induced Innovation and Energy Prices. *Am. Econ. Rev.* 92 (1), 160–180. doi:10.1257/000282802760015658

Raza, M. Y., Liu, X., and Lin, B. (2020). Cleaner Production of Pakistan's Chemical Industry: Perspectives of Energy Conservation and Emissions Reduction [J]. *J. Clean. Prod.* 278 (1), 123888. doi:10.1016/j.jclepro.2020.123888

Samour, A., Baskaya, M. M., and Tursoy, T. (2022). The Impact of Financial Development and FDI on Renewable Energy in the UAE: A Path towards Sustainable Development. *Sustainability* 14, 1208. doi:10.3390/su14031208

Shan, H. (2008). Reestimation of China's Capital Stock K: 1952-2006 [J]. *Quantitative Econ. Tech. Econ. Res.* 25 (10), 17–31. doi:10.13653/j.cnki.jqte.2008.10.003

Shao, S., Luan, R., Yang, Z., and Li, C. (2016). Does Directed Technological Change Get Greener: Empirical Evidence from Shanghai's Industrial green Development Transformation. *Ecol. indicators* 69, 758–770. doi:10.1016/j.ecolind.2016.04.050

Solarin, S. A., and Bello, M. O. (2019). Interfuel Substitution, Biomass Consumption, Economic Growth, and Sustainable Development: Evidence from Brazil. *J. Clean. Prod.* 211, 1357–1366. doi:10.1016/j.jclepro.2018.11.268

Tu, Z., and Leeke, L. (2011). Considering Energy, Environmental Factors for Chinese Industrial Efficiency Evaluation —— Provincial Data Analysis Based on SBM Model [J]. *Econ. Rev.* 32 (2), 55–65. doi:10.19361/j.er.2011.02.007

Tu, Z. (2008). Coordination of Environmental, Resources and Industrial Growth [J]. *Econ. Res.* 54 (02), 93–105.

Wang, B., and Qi, S. (2014). Biased Technological Progress, Factor Substitution and China's Industrial Energy Strength [J]. *Econ. Res.* 49 (02), 115–127.

Wang, F., and Feng, G. (2011). Assessment of the Contribution Potential of Optimizing the Energy Structure to Achieving China's Carbon Intensity Targets [J]. *China's Ind. economy* 29 (04), 127–137. doi:10.19581/j.cnki.ciejournal.2011.04.013

Wang, Y. (1997). *An Empirical Analysis of Foreign Direct Investment and China's Industrial Development, the Internal Discussion Draft of China Economic Research Center*. Beijing, China: Peking University.

Wang, Y. S. (2021). Reseaech on Energy Substitution in Chinses Industrial Sectors Besed on Linear Logit Model [J]. *Fresenius Environ. Bull.* 20 (7), 8777–8785.

Wei, Z., Han, B., Han, L., and Shi, Y. (2019). Factor Substitution, Diversified Sources on Biased Technological Progress and Decomposition of Energy Intensity in China's High-Tech Industry. *J. Clean. Prod.* 231, 87–97. doi:10.1016/j.jclepro.2019.05.223

Wesseh, P. K., and Lin, B. (2016). Output and Substitution Elasticities of Energy and Implications for Renewable Energy Expansion in the ECOWAS Region. *Energy Policy* 89 (2), 125–137. doi:10.1016/j.enpol.2015.11.007

Wu, H., Hao, Y., and Ren, S. (2020). How Do Environmental Regulation and Environmental Decentralization Affect green Total Factor Energy Efficiency: Evidence from China. *Energ. Econ.* 91, 104880. doi:10.1016/j.eneco.2020.104880

Xiu, J., Zhang, G.-x., and Hu, Y. (2019). Which Kind of Directed Technical Change Does China's Economy Have? from the Perspective of Energy-Saving and Low-Carbon. *J. Clean. Prod.* 233, 160–168. doi:10.1016/j.jclepro.2019.05.296

Xu, S.-C., He, Z.-X., and Long, R.-Y. (2014). Factors that Influence Carbon Emissions Due to Energy Consumption in China: Decomposition Analysis Using LMDI. *Appl. Energ.* 127, 182–193. doi:10.1016/j.apenergy.2014.03.093

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. *Energ. Econ.* 72, 166–176. doi:10.1016/j.eneco.2018.04.003

Yao, Y., and Zhang, Q. (2001). Analysis of Technical Efficiency of Chinese Industrial Enterprises [J]. *Econ. Res.* 47 (10), 13–19. + 28-95.

Yazan, Q., Samour, A., and Mohammed, A. (2022). Does the Real Estate Market and Renewable Energy Induce Carbon Dioxide Emissions? Novel Evidence from Turkey [J]. *Energies* 15, 763. doi:10.3390/en15030763

Ye, X., and Zhou, S. (2011). Technological Innovation, Return Effect and Energy Efficiency of China's Industrial Industry [J]. *Finance and trade economy* 32 (01), 116–121. doi:10.19795/j.cnki.cn11-1166/f.2011.01.017

Zha, D., Kavuri, A. S., and Si, S. (2018). Energy-biased Technical Change in the Chinese Industrial Sector with CES Production Functions. *Energy* 148, 896–903. doi:10.1016/j.energy.2017.11.087

Zha, D., Si, J., Zhou, T., and Xue, C. (2016). Energy and Nonenergy Alternative Elasticity Study in Chinese Industrial Sector —— Is Based on Multi-Elastic Measure Method [J]. *Manage. Rev.* 28 (06), 180–191. doi:10.14120/j.cnki.cn11-5057/f.2016.06.018

Zhang, X., Sun, F., Wang, H., and Qu, Y. (2020). Green Biased Technical Change in Terms of Industrial Water Resources in China's Yangtze River Economic Belt. *Int. J. Environ. Res. Public Health.* 17 (8), 2789. doi:10.3390/ijerph17082789

Zhang, Y., Ji, Q., and Fan, Y. (2018). The price and Income Elasticity of China's Natural Gas Demand: A Multi-Sectoral Perspective. *Energy Policy* 113, 332–341. doi:10.1016/j.enpol.2017.11.014

Zhang, Z., and Lin, B. (2019). Energy Conservation and Emission Reduction of Chinese Cement Industry: From a Perspective of Factor Substitutions [J]. *Emerging Markets Finance and Trade* 55 (4-6), 967–979. doi:10.1080/1540496x.2018.1516638

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.

Publisher's Note: All claims expressed in this article are solely those of the authors and do not necessarily represent those of their affiliated organizations or those of the publisher, the editors, and the reviewers. Any product that may be evaluated in this article or claim that may be made by its manufacturer is not guaranteed or endorsed by the publisher.