



China's Energy Transition Policy Expectation and Its CO₂ Emission Reduction Effect Assessment

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Measuring the expected impact of China's energy transition on carbon dioxide (CO₂) mitigation and identifying the key influencing factors in different economic sectors will help to provide better policy recommendations for CO₂ emission reduction. Based on the prediction results of China's CO₂ emissions in 2030 under the baseline scenario and the target scenario, this study constructs the control group and the treatment group of the energy transition policy quasinatural experiment and then uses the difference in difference (DID) model to evaluate the CO₂ emission reduction effect of China's energy transition policy. The results reveal that the energy transition policy has a significant impact on CO₂ emission reduction and helps to achieve China's 2030 carbon emission reduction target. The impact of energy structure transition on CO₂ emission reduction has significant sectoral heterogeneity, which has a positive reduction effect in the industry sector, wholesale and retail sectors, and accommodation and catering sectors, but its reduction effect is not obvious in transportation, storage, and postal sectors. It is suggested that China should implement the sector-differentiated CO₂ mitigation strategy, focus on improving the industrial sector's energy efficiency, and promote the clean, low-carbon transition of energy consumption structure in construction, transportation, storage, and postal industries.

Keywords: China, energy transition, CO₂ emission, policy preassessment, DID model

INTRODUCTION

With the rapid growth of the fossil energy consumption in China, the CO₂ emission reduction has gradually become the focus of global attention (Ouyang and Lin, 2017). Constrained by the structure of energy endowments, China's economic growth is accompanied by the production and consumption of a large amount of coal, which has led to the emission of a large number of greenhouse gases and has a severe impact on the ecological environment. (Wang et al., 2016; Zhang et al., 2017; Li et al., 2019). As the world's second largest economy, China has become the world's largest energy consumer and the largest CO₂ emitter (Hao et al., 2015). In response to international calls for reducing carbon dioxide emissions, China is working hard to reduce carbon dioxide emission intensity (CEI). China promises that CEI in 2030 will be reduced by 60–65% compared to 2005 and strives to reach the peak of carbon dioxide emissions around 2030 as soon as possible. Considering the coal-based energy endowment constraints, the National Development and Reform Commission (NDRC) issued the "Energy Production and Consumption Revolution Strategy

(2016–2030)” at the end of 2016, clearly requiring that the coal consumption structure reaches 48% in 2030 (NDRC, 2016). What impact will this policy orientation have on China’s CO₂ mitigation targets in 2030? What is the expected effect of the policy? To address these issues, this study conducts policy preassessment studies on the energy transition policy.

Scientific prediction of the future trend of CO₂ emissions is the fundamental basis for judging whether China’s CO₂ emissions can peak in 2030 (Zhang et al., 2017). Mi et al. (2017) point out that under the scenario of an average annual GDP growth rate of 5%, China will achieve CO₂ emissions peak of 11.2 billion tons in 2026 and then fall to 1.084 billion tons in 2030. Elzen et al. (2016) indicate that China’s current mitigation policies are challenging to achieve Paris emission reduction commitments in 2030. Zhang et al. (2019) found from past studies that China’s energy consumption structure has improved during the past three FYP periods. It is expected that in the next decades, the energy consumption structure can be optimized further through future policies and become another factor in reducing CO₂ emissions. Under the baseline scenario, China’s total CO₂ emissions in 2030 will reach 14.7–15.4 billion tons, while the policy scenario will be reduced to 13.1–13.7 billion tons. Based on the framework of scenario analysis, Wang et al. (2019a) considered that China will achieve the CEI reduction target in 2030 under the current mitigation policy and difficult to achieve the target of CO₂ emission peak, and it is expected that China’s total CO₂ emissions will reach 11.289 billion tons in 2030. Therefore, whether China can achieve the CEI mitigation goals and the peak emission in 2030 depends on identifying the influencing factors.

Considering social development, economic growth, energy technologies, and other factors, many scholars have analyzed the influencing factors of CO₂ emission reduction based on the framework of the Kaya equation and IPAT model (Zhang et al., 2017; He et al., 2018). According to the consensus view, economic growth and population size are the promotion factors of CO₂ emissions, while energy intensity, energy structure, and industrial structure are the promotion factors of reducing CO₂ (Ang et al., 1998; Wang et al., 2005). Specifically, the regional economic growth and the energy technology progress have a relatively large impact on CO₂ emission reduction, while the total population, the industrial structure, and the energy structure optimization have a relatively small contribution to CO₂ mitigation (Ma et al., 2016; Zhu et al., 2017). As far as the mitigation contribution of each factor, the economic transition development, the energy technology progress, and the energy structure optimization will be the critical paths for China to realize CO₂ emission reduction (Wang et al., 2019a). In fact, many studies have shown that the mitigation effects of economic growth and energy technology progress are very significant. In contrast, the mitigation contribution of energy structure optimization is relatively small. However, considering China’s high-carbon energy structure, the mitigation potential of energy structure optimization still has room for further improvement (Yi et al., 2016). Xu et al. (2020) pointed out that CO₂ emissions will not peak in the business-as-usual scenario, further revealing that adjusting the energy consumption structure is the key to reducing

CO₂ emissions and achieving their peak. Based on the scenario prediction of China’s CO₂ emission by 2030, Wang et al. (2019b) suggest that whether China’s CO₂ emission reduction target in 2030 can be achieved lies in exploiting the mitigation potential of economic growth, energy technology progress, and energy consumption structure optimization, especially in the industrial sector.

The view that energy transition helps to promote CO₂ emission reduction has been widely recognized by scholars at home and abroad (Pan et al., 2017; Gözl and Wedderhoff, 2018). In terms of the existing research, many scholars believe that China’s energy transition mainly involves the clean use of high-carbon energy and the structure optimization of the clean low-carbon energy (Pain, 2017; Chai et al., 2019). At the same time, there is also significant uncertainty in the direction of China’s energy transition, especially in the determination of future clean energy (Ren and Sovacool, 2015; Wang et al., 2017). Besides, the issue of the energy transition has also attracted the attention of many scholars. Many studies have shown that there are many problems in China’s energy transition from coal-based to renewable energy, which involves technological levels, cost constraints, and institutional obstacles (Zhou et al., 2012; Musa et al., 2018). From the perspective of the practice of international energy transition, the developed countries such as Europe and the United States have been leading the energy transition, and the proportion of clean energy in total energy consumption is relatively high. In addition, most of their policy goals of the energy transition are energy security, affordable, and environment friendly (Schmid et al., 2019). However, in a specific practice, the priorities of national energy transition objectives are not the same. For example, the U.S. energy transition’s core motivation is to ensure energy security and reduce dependence on imported energy, and other motivations such as environmental protection are secondary. On the contrary, environmental protection has been the most important motivation for Germany’s energy transition, although energy security motivation is also essential for Germany (Gözl and Wedderhoff, 2018; Karin et al., 2019). In view of this, as the world’s largest energy consumer, China should pay attention to both energy security and acceptable costs as well as the environmental impact of the energy transition, especially its impact on carbon emissions.

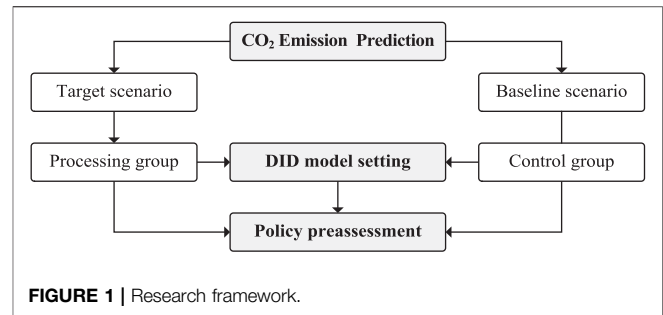
Considering the necessity of reducing carbon dioxide emissions and the urgency of controlling air pollution, China’s energy transition will inevitably require the efficient use of traditional fossil energy. Therefore, the energy consumption structure will eventually tend toward clean and efficient development (BP, 2017; Chai et al., 2019). In “Energy Production and Consumption Revolution Strategy 2016–2030,” China puts forward the strategic orientation of energy transition (NDRC, 2016), which is “security first, conservation first, green, low-carbon, and proactive innovation.” However, in the concrete implementation process, due to the significant sectoral differences in resource allocation and energy technology among China’s economic sectors, the energy consumption structure and its transition process also have sectoral heterogeneity (Wang et al., 2019b). In conclusion, China’s

energy transition is still in the transition period of clean utilization of high-carbon energy and clean energy scale expansion. China's energy transition and sectorial differences will also affect the realization of CO₂ mitigation targets by 2030.

The research on the impact of the energy transition on CO₂ emissions can be divided into two categories. One is based on historical data and measures the CO₂ mitigation effect of energy structure optimization through econometric models, index decomposition, and other methods. For example, Qi and Li (2017) investigated the relationship between renewable energy consumption, carbon emissions, and economic growth in the EU based on the panel vector autoregressive (PVAR) model; Zhang and Da (2015) used the LMDI model to measure the emission reduction effect of energy structure. This kind of method is simple and easy to operate, but limited by data accessibility, the research conclusion can only provide a general direction for policy improvement (Yang et al., 2018). The other is the micropolicy effect evaluation research focusing on energy transition-related policies and using nonexperimental historical data. The policy evaluation methods mainly include the instrumental variable (IV) method, propensity score matching (PSM) method, regression discontinuity (RD) model, and difference in difference (DID) model (Dong et al., 2019; Zhang et al., 2019). Among them, the IV, PSM, and RD methods have certain problems in how to determine the instrumental variables, whether they meet the "one size fits all" threshold, whether there are sufficiently strong assumptions, and whether they have a large number of data samples (Campbell, 1991; Heckman et al., 1997; Angrist and Pischke, 2010; Rosenbaum, 2017).

In contrast, the DID method can solve these problems well and allow the existence of unobservable factors, thereby relaxing the conditions for policy evaluation and making the application of policy evaluation closer to economic reality (Zhang et al., 2019). However, as a major weapon in the policy effect evaluation method, DID has been applied to the effect evaluation of pilot policies that have been implemented for a period of time. Relevant studies on the evaluation of the future implementation effect of a certain policy are relatively rare, which may be limited by the absence of scientific prediction data. Therefore, based on the data obtained from Wang et al. (2019a), this study will use this method to investigate the heterogeneous impact of energy transition policies on CO₂ mitigation in China's different economic sectors. Not only can we make full use of the exogenous nature of explanatory variables but we can also control unobserved individual heterogeneity on the explanatory variables to better achieve unbiased estimates of the effects of policy interventions.

Furthermore, some scholars have conducted scenario prediction studies based on the framework of scenario analysis for the reduction effect of energy structure (Tan et al., 2018). For example, Wang et al. (2019a) predicted the trend of China's CO₂ emission under the baseline scenario and the target scenario based on the extended form of Kaya equation. Furthermore, they measured the CO₂ mitigation potential of China's energy structure optimization with the LMDI model. The scenario



analysis method combines qualitative analysis with quantitative analysis, which can predict different trends in the development of things from a multidimensional perspective, which is helpful to explore the different influences of various factors on future trends of CO₂ emissions under different scenarios (Li et al., 2018; Song et al., 2018). However, this method also has some shortcomings. Although the scenario prediction results is helpful to provide multiple choices for the CO₂ mitigation policy, it is difficult to reveal the CO₂ emission reduction potential of various policy factors. Based on this consideration, this study uses the DID model to analyze the expected mitigation effect of China's energy transition policy on the basis of China's CO₂ emissions forecast results in the baseline scenario and target scenario (Wang et al., 2019a), so as to determine the policy effectiveness of the energy transition.

In summary, this study needs to verify whether the energy transition policy can effectively promote the development of carbon emission reduction in China, and if so, to what extent it will play a role in emission reduction. Furthermore, considering the difference of energy utilization modes in different sectors, whether there is heterogeneity in the impact of energy transition policy on different sectors remains to be evaluated. Therefore, according to the prediction results of China's CO₂ emissions in 2030 under the baseline scenario and the target scenario (Wang et al., 2019a), this study constructs the control group and the treatment group of the energy transition policy quasinatural experiment, uses the DID model to evaluate the expected impact of energy transition on CO₂ emission reduction, and further discusses the sectoral heterogeneity of the emission reduction effect of energy transition, so as to put forward some reasonable policy opinions to meet China's CO₂ mitigation target.

In fact, reasonable policy prediction is more conducive to realizing China's low-carbon development goals and improving the energy transition's policy effect. According to the previous research results, this study designs a quasinatural experiment of the energy transition policy and uses the DID model to evaluate the CO₂ mitigation effect of China's energy transition policy, in order to provide a basis for decision-making to achieve China's CO₂ mitigation target by 2030. Among them, the quasinatural experiment of energy transition policy involves the design of the control group and treatment group, which are based on the forecast results of China's CO₂ emissions under the baseline scenario and target scenario, respectively (Figure 1).

METHODS AND DATA

Model Setting

After implementing the energy structure optimization and transition policy in China, CO₂ emission intensity changes mainly come from three aspects. One is because of the “grouping effect” formed by China under different scenarios, and the other is the “time effect” caused by the inertia of time. The third is the “policy treatment effect” which is part of China’s policy impact under the target situation. The DID method can effectively separate the “policy processing effect” and is widely used to evaluate the effect of policy implementation (Zhang, 2019).

In this study, based on the scenario prediction of China’s CO₂ emissions (Wang et al., 2019a), the DID method is used to construct the binary virtual variable $G = \{0, 1\}$. When the object is China under the target scenario, G takes 1; otherwise, the value is 0; simultaneously, the year of the implementation of the policy is taken as the boundary and divided into before and after the experimental period. The binary dummy variable $T = \{0, 1\}$ is constructed. When entering the experimental period (2017), $T = 1$, and before the experimental period (2017), $T = 0$. Therefore, for China in the target scenario, when $T \geq 2017$, the corresponding dummy variable $G \times T$ is denoted as 1; otherwise, they are all 0. The interaction term $G \times T$ was defined to describe the policy treatment effect of China’s energy structure transition. Based on the above ideas, considering that the reduction of CO₂ intensity is more in line with China’s national conditions than the total CO₂ mitigation, this study selects the CO₂ emission intensity (CEI) to measure the performance of China’s CO₂ emission reduction, so as to construct its basic hypothesis model:

$$\ln CEI_{it} = \lambda_0 + \lambda_1 G_{it} + \lambda_2 T_{it} + \lambda_3 G_{it} T_{it} + \beta \ln X_{it} + \varepsilon_{it}, \quad (1)$$

where subscript $i = 1, 2$, respectively, represents the baseline scenario and target scenario of China’s CO₂ emissions, t represents the time, and X represents other control variables. That is, China’s CEI under the baseline scenario is changing under the current situation and historical development trend of China’s society, economy, resources, and environment, while the target scenario is based on the implementation of certain energy policies. The development trend of the two scenarios before implementing the policy is identical, satisfying the conditions of the parallel trend of the control group and the experimental group used by the DID model. Therefore, the changes in the two groups before and after the experiment are purely caused by the policy treatment effect.

Regarding the selection of control variables, we mainly follow some suggestions and practices put forward by Bernerth and Aguinis (2016). In order to describe and explain the relationship between energy transition policies and carbon emission reduction, we need to control other related variables that may have an unnecessary impact on this relationship. As a systematic, complete, and simple method, the Kaya equation is recognized as an important tool for revealing the links between population, economy, energy, and environment (Kaya, 1989). It is generally

believed that carbon emissions will be affected by demographic, economic, and technological factors. For example, Zhang and Da (2015), Wang et al. (2017), Tan et al. (2018), and Wang et al. (2019a) believe that the total population, economic level, economic structure, energy efficiency, and energy structure are the main factors affecting carbon emissions. Abadie (2005) believes that the addition of the control variable X is helpful to eliminate the interfering factors of the model, so as to make it meet the condition of “common trend.” Without the loss of generality, this study selects total population (P), per capita GDP (A), industrial structure (M), and energy intensity (EI) as control variables. The final DID model was established.

$$\begin{aligned} \ln CEI_{it} = & \lambda_0 + \lambda_1 G_{it} + \lambda_2 T_{it} + \lambda_3 G_{it} T_{it} + \beta_1 \ln A_{it} + \beta_2 \ln P_{it} \\ & + \beta_3 \ln M_{it} + \beta_4 \ln EI_{it} + \varepsilon_{it}. \end{aligned} \quad (2)$$

According to the basic idea of the DID model, the interaction terms and their coefficients are mainly used to investigate the net effect of a certain policy implementation. In the model setting of this study, the coefficient λ_3 is the focus, and it takes into account the change in China’s carbon intensity under the target scenario after the implementation of the energy transition policy. If the target policy does improve China’s CO₂ emission reduction performance in the future, the sign of λ_3 will be significantly negative, otherwise nonsignificant or significantly positive. And as stated in the literature review, the fundamental factor affecting the implementation effect of the energy transition policy is the adjustment of the energy structure, increasing the proportion of low-carbon energy consumption and reducing the consumption of high-carbon energy, especially coal. Many studies have shown that 18 environmental indicators, including CO₂ emissions, are considered to have a certain time lag effect (Kais and Sami, 2016), and environmental impacts show dynamic sustainability. Based on the above research, it is fully considered that the CEI of this period is affected by the previous CEI, and the environmental impact is sustainable. Therefore, the dynamic panel data model is set based on the above model:

$$\begin{aligned} \ln CEI_{it} = & \lambda_0 + \lambda_1 G_{it} + \lambda_2 T_{it} + \lambda_3 G_{it} T_{it} + \beta_1 \ln A_{it} + \beta_2 \ln P_{it} \\ & + \beta_3 \ln M_{it} + \beta_4 \ln EI_{it} + \beta_5 \ln CEI_{it-1} + \varepsilon_{it}. \end{aligned} \quad (3)$$

Data Sources and Processing

In order to investigate the expected impact of energy transition policy, this study empirically examines the expected CO₂ mitigation effect of energy transition policy in the “Strategy of Energy Production and Consumption Revolution (2016–2030)” by using the DID model based on the historical and projected data of CO₂ emissions in China and various sectors from 2000 to 2030. The data in this study include two parts: the historical data and the prediction data.

Historical Data (2000–2016)

The relevant data of China’s total population, economic growth, and energy consumption in various sectors source from the China

TABLE 1 | Basic historical data.

Time	Population	GDP	Energy demand	Energy intensity	CO ₂ emission	CO ₂ intensity
	10 ⁸ person	10 ¹² yuan	10 ⁹ tce	Ton/10 ⁴ yuan	10 ⁹ ton	Ton/10 ⁴ yuan
2000	12.67	10.03	14.70	0.87	32.85	1.95
2005	13.08	18.73	26.14	0.95	58.72	2.13
2010	13.41	41.30	36.06	0.76	78.75	1.67
2011	13.47	48.93	38.70	0.75	85.36	1.65
2012	13.54	54.04	40.21	0.72	87.27	1.57
2013	13.61	59.52	41.69	0.69	89.75	1.49
2014	13.68	64.40	42.58	0.66	90.29	1.40
2015	13.75	68.91	42.99	0.62	90.07	1.31
2016	13.81	73.73	45.07	0.61	95.70	1.30

TABLE 2 | Basic prediction data.

Scenario	Time	Population	GDP	Energy demand	Energy intensity	CO ₂ emission	CO ₂ intensity
		10 ⁹ person	10 ¹² yuan	10 ⁹ tce	Ton/10 ⁴ yuan	10 ⁹ ton	Ton/10 ⁴ yuan
Baseline scenario	2017	13.87	78.89	47.26	0.60	99.83	1.27
	2018	13.93	84.41	49.54	0.59	104.12	1.23
	2019	13.99	90.32	51.94	0.58	108.59	1.20
	2020	14.06	96.64	54.46	0.56	113.24	1.17
	2025	14.34	132.41	67.39	0.51	136.28	1.03
	2030	14.59	177.19	81.45	0.46	159.93	0.90
Target scenario	2017	13.93	77.42	45.26	0.58	93.04	1.20
	2018	14.02	82.07	46.45	0.57	94.49	1.15
	2019	14.11	86.99	47.66	0.55	95.92	1.10
	2020	14.20	92.21	48.90	0.53	97.32	1.06
	2025	14.35	120.52	55.74	0.46	106.33	0.88
	2030	14.50	153.81	62.05	0.40	112.89	0.73

The detailed data can be found in the literature (Wang et al., 2019a).

Statistical Yearbook (National Bureau of Statistics, 2016). Considering the comparability of the data, the relevant economic data are converted at constant prices in 2015. The CO₂ emission (CE) is calculated according to the IPCC model (IPCC, 2006). In addition, this study uses the improved model proposed by Li et al. (2017) to modify the CO₂ emission coefficient, which takes into account the actual calorific value and oxidation rate of fossil fuels in China and calculates the carbon dioxide emissions of each fossil fuel by multiplying the consumption of fossil fuels by its revised CO₂ emission coefficient and oxidation rate. The historical data of relevant indicators from 2000 to 2016 are shown in **Table 1**.

Prediction Data (2017–2030)

The influencing factors of CO₂ emission are relatively complex, and its change trend is often affected by the uncertainty of social, economic, energy, and technology factors, so the prediction results of CO₂ emission should be multidimensional oriented. As an important tool to reveal the relationship among population, economy, energy, and environment, Kaya equation is widely used in scenario prediction of CO₂ emissions (Jung et al., 2012). For example, Wang et al. (2019a) used the Kaya extended model to identify the influencing factors of CO₂ emissions and then to predict the changing trend of China's CO₂

emissions in different scenarios. Based on this study, the control group and the treatment group of the energy transition policy quasinalatural experiment according to the prediction results of China's CO₂ emissions in 2030 under the baseline scenario and the target scenario are constructed and then use the difference in difference (DID) model to evaluate the CO₂ emission reduction effect of China's energy transition policy. This study selects the scenario prediction results of China's CO₂ emission and its related factors from 2017 to 2030 as the basic experimental data, and some relevant data are shown in **Table 2**.

According to the forecast results in **Table 2**, under BS, China's economy will continue to grow at a moderate rate. China's CO₂ emissions will continue to grow at an average annual rate of 3.74% from 9.57 billion tons in 2016 to 15.95 billion tons in 2030. At the same time, the CO₂ emission intensity dropped from 1.29 tons/104 yuan to 0.903 tons/104 yuan, with an average annual decrease rate of 2.56%. In contrast, under TS conditions, China's total CO₂ emission and its growth trend slowed down significantly, from 9.57 billion tons in 2016 to 11.89 billion tons in 2030, with an average annual growth of about 1.51%, which was significantly lower than the baseline scenario. The CO₂ emissions intensity also dropped from 12,298 tons/million in 2016 to 0.73 tons/million in 2030, with an average annual decrease of 3.82%.

TABLE 3 | Descriptive statistics of variables.

Variable	Unit	Mean	Maximum	Minimum	Std. deviation
CEI	Ton/10 ⁴ yuan	1.1667	1.6688	0.7340	0.2683
G	—	0.5000	1.0000	0.0000	0.5060
T	—	0.6667	1.0000	0.0000	0.4771
G × T	—	0.3333	1.0000	0.0000	0.4771
P	10 ⁸ person	14.0455	14.5945	13.4091	0.3600
A	10 ⁴ yuan	6.9794	12.1412	3.5191	2.4045
M	%	41.8690	46.6113	40.0000	2.0378
EI	Tce/10 ⁴ yuan	0.5671	0.7643	0.4034	0.1030

Variable Description

Explained Variable

In the main text of this study, the CEI is chosen as the explained variable, which is calculated in terms of the CO₂ emissions per unit of GDP.

Core Explanatory Variables

This study selects the grouping virtual variable (*G*), the time dummy variable (*T*), and the interaction item (*G* × *T*) for the energy transition policy as explanatory variables. The variable *G* measures the differences of the CEI between the baseline scenario and the target scenario. The variable *T* measures the change of the CEI between the treatment group and the control group and the interactive item (*G* × *T*) measuring the impact of policy implementation on the CEI of the treatment and control groups. It is the core explanatory variable.

Control Variables

Through the analysis of the relevant literature on the factors affecting the intensity of CO₂ emission, the study finally selects the population size, per capita GDP, industrial structure (the proportion of the secondary industry in the regional GDP), and energy intensity as the control indicators. In addition, in order to eliminate possible collinearity and ensure the smoothness of the data, each indicator is logarithmic.

Descriptive Statistics

This study takes China's CO₂ emissions and its related influencing factors from 2000 to 2030 as the research sample. The descriptive statistical results of the relevant indicators are shown in **Table 3**.

PREASSESSMENT OF POLICY EFFECTS

In view of the policy target of 48% coal consumption structure in 2030, this study uses the DID model to investigate the impact of the energy transition policy on the future CEI. Based on the research paradigm of the quasinalatural experiments, this study constructs the “treat group” under the target scenario after the policy intervention and the “control group” under the baseline scenario. Under the premise of controlling other factors that affect CEI, this study isolates the difference in CO₂ emissions performance between the “treatment group” and the “control

group” after the energy transition policy has occurred. Furthermore, this study conducts regression tests for each of China's six major sectors, examining the heterogeneous impact of the energy transition policy on the reduction of CEI across China's economic sectors.

Analysis of Empirical Results

The first two columns in **Table 4** are the full sample estimates for the model (2). The first column only examines the effect of each explanatory variable, and the second column adds the individual control variables to the first column. From the test results of **Eqs 1** and **2**, it is known that there is no substantial change in the sign and significance level of the core explanatory variable's estimated coefficient. The results show that the energy transition policy implementation has an inhibitory effect on China's CEI. In column (1), only the effect of the policy effect' dummy variable *G* × *T* on the CEI intensity is considered, and its *R*² value is relatively low, explaining efforts are weak, contributing 0.131% to the carbon emission intensity. After adding the control variables, the significance level is significantly improved, and the explanation is also significantly strengthened. According to the estimation results in column (2), after controlling the population size, the wealth of residents, the industrial structure, and the energy intensity variables, the estimated value of the energy transition policy impact is significantly negative, and the estimated value increases, indicating some control variables. The suppression of carbon emission intensity does not play a significant role and even has the opposite promotion effect. The implementation of the policy will reduce China's carbon emissions intensity by about 0.0111% each year. In general, the experimental results prove that the energy transition policy will have a more obvious suppression effect on future China's carbon emissions.

TABLE 4 | Descriptive statistics of variables.

Variables	(1)	(2)	(3)	(4)
G	-0.0050 (0.0563)	-0.0024 (0.0034)	-0.0050 (0.0778)	-0.0026 (0.0031)
T	-0.3230*** (0.0484)	0.0128** (0.0050)	-0.1820* (0.0973)	0.0147** (0.0058)
G×T	-0.1310* (0.0763)	-0.0111** (0.0043)	-0.0640 (0.0859)	-0.0150*** (0.0047)
lnA		0.0647*** (0.0173)		0.0403*** (0.0142)
lnP		0.0109 (0.1380)		0.1700* (0.1000)
lnM		-0.2100*** (0.0525)		-0.1580** (0.0639)
lnEI		1.4560*** (0.0225)		1.4040*** (0.0295)
lnCEI ₀₁			0.5430** (0.2090)	0.0145** (0.0065)
_Cons	0.3900*** (0.0384)	-0.0562 (1.4430)	0.1980* (0.1140)	-1.6630 (1.0270)
N	42	42	42	42
R ²	0.7150	1.0000	0.8330	1.0000

Standard errors in parentheses, *p < 0.1, **p < 0.05, ***p < 0.01.

TABLE 5 | The results of the heterogeneity test in China's six sectors.

Variables	1 st	2 nd	3 rd	4 th	5 th	6 th
G	-0.0007 (0.0121)	-0.0023 (0.0038)	0.0012 (0.0096)	0.0042 (0.0187)	-0.0024 (0.0412)	-0.0003 (0.0074)
T	-0.0008 (0.0103)	0.0147*** (0.0050)	-0.0105 (0.0081)	-0.0540** (0.0212)	0.0171 (0.0274)	0.0093 (0.0073)
G×T	-0.0162 (0.0179)	-0.0130** (0.0049)	0.0026 (0.0135)	0.0823* (0.0411)	-0.0406 (0.0498)	-0.0141 (0.0107)
lnA	-0.1370 (0.0865)	0.1970*** (0.0209)	-0.3380*** (0.0641)	-0.0170 (0.2020)	-0.1670 (0.2250)	-0.3380*** (0.0495)
lnP	-0.9150 (0.7290)	0.7510*** (0.1610)	-2.8910*** (0.5760)	-5.4430*** (1.7300)	1.6890 (1.6600)	0.1060 (0.4540)
lnM	-1.7620*** (0.1550)	-1.4480*** (0.0586)	-1.5440*** (0.0920)	-1.2620*** (0.2990)	-0.5120 (0.5810)	1.0370*** (0.0846)
lnEI	1.0960*** (0.1030)	1.9540*** (0.0269)	0.3360*** (0.0758)	0.3740 (0.2440)	0.9310*** (0.2860)	0.1340** (0.0558)
_Cons	9.4110 (7.685)	-10.2400*** (1.6750)	35.3100*** (6.1700)	64.4700*** (18.2800)	-20.2700 (17.1200)	2.0520 (4.8370)
N	42	42	42	42	42	42
R ²	0.9960	1.0000	0.9970	0.9870	0.9440	0.9980

The 1st sector includes agriculture, forestry, animal husbandry, fishing, and water conservancy. The 2nd sector denotes the industry. The 3rd sector denotes the construction industry. The 4th sector includes transportation, warehousing, postal services, and communications. The 5th sector includes wholesale, retail, accommodation, and catering services. The 6th sector includes consumer goods and other industries. The standard errors in parentheses, *p < 0.1, **p < 0.05, ***p < 0.01.

The estimated results of the control variables are shown in column (2) of **Table 4**. First, for China's per capita GDP, the impact of this variable on carbon emission intensity can be divided into positive and negative aspects. On the other hand, the growth of resident income leads to the improvement of living standards, and the needs of the people for the quality of life also increase. People pay more attention to clean energy consumption, which is conducive to reducing carbon emissions caused by energy consumption. The regression results show that the increase in per capita GDP significantly aggravates China's future carbon emissions, indicating that energy demand has increased during the policy implementation period, and there may be a shortage of clean energy supplies. People's daily activities are still mainly dependent on traditional energy.

Second, from the perspective of the population size, a control variable, it is expected that this variable may have two different influences. On the one hand, the population growth increases people's demand for transportation, housing, and various products, resulting in increased demand for energy consumption and aggravating overall carbon emissions. On the other hand, the increase of population enables the full utilization of public facilities and the development of economies of scale, thus improving the efficiency of energy use. The impact of future population growth on future carbon emissions levels is not apparent. Based on the current social status, the population growth rate is set to be small, and there is no massive population increase. Compared to other factors, the impact of normal population expansion on future carbon emissions intensity is negligible.

Third, in terms of the influence of the industrial structure variable on the result, the regression coefficient is significantly negative; it shows that this variable will inhibit carbon emissions in the future. The adjustment of China's industrial structure (reducing the secondary industry's proportion) in the target

scenario will significantly reduce China's future carbon emissions intensity. Finally, for the variable of energy intensity, the regression results show that the continuous increase of energy intensity significantly promotes future carbon emissions, and the massive use of fossil fuels still inhibits low-carbon development.

The latter two columns in **Table 4** are the correlational regression results of **Eq. 3**, which adds a lag term of the CEI to examine the sustainable dynamics of environmental impacts. The results show that the estimated coefficient of the interaction term $G \times T$ is not significant after adding the lag term of the CEI without considering the control variables. This means that the energy transition policy is affected by the development inertia of CEI, and its expected effect of CO₂ emission reduction will decrease. Considering the control variables, the results of column (4) show that the coefficient of the core explanatory variable $G \times T$ is still negative, indicating that the carbon reduction effect of the energy transition policy is more significant. Moreover, the previous CEI's impact on the current CEI has decreased significantly, indicating that CEI's development inertia has been diluted. Meanwhile, the lag coefficient of CEI listed in (3) and (4) is significantly positive, indicating that the CO₂ emission in the previous period has a cumulative and sustainable effect, which will not be conducive to energy transition and CO₂ emission reduction in the future.

Heterogeneity Test

In order to investigate the sectoral heterogeneity of the mitigation effect of the energy transition, this study has conducted a subsample regression on China's six sectors on the premise of controlling other influencing factors (**Table 5**). The results reveal that the impact of energy transition policy on the CO₂ mitigation in China's six sectors are significantly different, which means that

TABLE 6 | Robustness test results.

Variables	(1) lnCE	(2) lnCE	(3) lnCEI	(4) lnCEI
G	-0.0073 (0.1440)	-0.0024 (0.0024)	-1.56e-15 (0.0240)	-4.20e-16 (0.0052)
T	0.3740*** (0.0437)	0.0071* (0.0037)	-0.3650*** (0.0390)	-0.0043 (0.0058)
G×T	-0.2870*** (0.0618)	-0.0099 (0.0069)	-0.1080 (0.0668)	-0.0076 (0.0062)
Control variables	NO	YES	NO	YES
_cons	13.6900*** (0.0357)	-44.2300*** (4.2890)	0.4870*** (0.0170)	-1.6930 (1.6340)
N	42	42	42	42
R ²	0.7650	1.0000	0.4680	1.0000

Standard errors in parentheses, *p < 0.1, **p < 0.05, ***p < 0.01.

the formulation of the mitigation policies in different sectors should be differentiated in the future.

For the 1st sector, the interaction coefficient $G \times T$ is negative and not significant, indicating that the energy transition policy does not have an obvious inhibitory effect on the CEI. The reason may be that the energy demand in this sector is relatively small, and fossil energy consumption does not change much before and after the release of the energy transition policy.

For the 2nd sector, the coefficient of $G \times T$ is significantly negative, indicating that the energy transition policy has played a significant role in curbing the CEI. The root cause is that the industrial sector, as a high energy consumption sector, mainly depends on traditional fossil energy such as oil and coal, and energy transition plays an essential role in the efficient, clean, and sustainable use of energy.

As for the 3rd sector, the coefficient of $G \times T$ is positive and insignificant, indicating that the energy transition is not an effective way to reduce the CEI in the construction industry in the future.

In contrast, the 4th sector is mainly dependent on oil resources, which means that it is difficult to change the energy consumption structure and reduce the CEI in the short term. Therefore, the 4th sector should focus on the progress of new energy technologies in the future and fundamentally reduce its dependence on traditional high-carbon energy.

In terms of the 5th sector, except for the energy efficiency, which has a significant positive impact on the CEI, the impact of other indicators on the CEI is not significant. The root cause is that the proportion of carbon emissions in the 5th sector in the total carbon emissions is small, which leads to the relatively weak impact of energy transition policy on the CEI of the service industry in the future.

For the 6th sector, the impact of the energy transition policy on its CEI is positive, which means that people will focus on green consumption in the future, and the energy required for daily life will gradually shift to clean energy.

In addition, the effects of the control variables on the CEI in different sectors have been examined. The results show that the CO₂ mitigation effects of the economic level and the population size have sectoral heterogeneity, while industrial structure and energy efficiency are expected to have significant mitigation effects.

Robustness Test

The above results show that the implementation of China's energy transition policy has effectively reduced the CEI in the future. In order to illustrate the robustness of the results, the following robustness tests were carried out in this study, and the results are shown in **Table 6**.

Substitution Variable Test

In order to test the robustness of the foregoing conclusions, this study uses the variable substitution method to perform the robustness test. We replace the logarithm of the CO₂ emission intensity (lnCEI) with the logarithm of CO₂ emissions (lnCE) for the explained variables. The columns (1) and (2) of **Table 6** show that, under the influence of control variables, the overall effect of energy transition policy on CO₂ emission is moderate; the baseline regression without control variables is effective, but overall, the effect of energy transition policies on CO₂ emissions remains significant. This shows that the core conclusions of this study are not affected by the measurement method of explained variables, but it is more appropriate to choose the CEI as the control index.

Counterfactual Test

Drawing on the existing research (Wang et al., 2019a), this study conducts a counterfactual test by changing the time of policy implementation. In fact, in addition to the influence of energy transition policy on China's CEI, some other factors may also cause the CEI change, which is not related to the implementation of the energy transition, thus affecting the establishment of the above conclusions. In order to avoid the interference of such factors, this study puts forward the policy implementation time. If the policy treatment effect is still significantly negative at this time, it indicates that the change of China's CEI in the future is influenced by other random factors and not all of which are caused by the energy transition policy. Columns (3) and (4) of **Table 6** show that, with or without the addition of control variables, the assumed policy implementation has no significant impact on future carbon emissions. Therefore, this indicates that the difference in the CEI between the treatment group and the control group is not caused by other factors but comes from the implementation of the energy transition policy.

CONCLUSIONS AND POLICY IMPLICATIONS

Conclusions

The energy transition is one of the important ways to reduce China's CO₂ emission, and evaluating its policy effect is of great significance for the realization of China's CO₂ mitigation target in 2030. Different from previous studies, this study preevaluates the mitigation impact of China's energy structure transition based on the scenario prediction results of China's CO₂ emission (Wang et al., 2019b) and further examines the heterogeneous impact of energy transition policy on CO₂ mitigation in various sectors in China.

The study shows that China's CEI under the target scenario is significantly reduced compared with the baseline scenario, which means that energy transition positively impacts China's expected CEI target in 2030. The study also reveals that the CEI has obvious development inertia during the inspection period, and the previous CEI has a significant impact on its current CEI. The effect of implementing the energy transition policy in the short term may not be obvious. Therefore, the Chinese government needs to pay close attention to it for a long time and strictly implement it to ensure the expected carbon emission reduction effect.

The heterogeneity test reveals that the policy effects of the energy transition on the CEI in China's six sectors are different. Still, on the whole, it has a positive policy impact on the CEI. As an essential way of CO₂ mitigation, the energy transition positively affects the 2nd sector, and its expected mitigation contribution is the most obvious. In contrast, the 4th sector is affected by the high oil and gas energy use patterns, and the mitigation effects of its energy transition are not obvious.

Meanwhile, energy technology has significant heterogeneous impacts on the CEI in different sectors. In terms of their expected mitigation effects, the energy intensity in the industrial sector has the most significant impact on the CEI, indicating that this sector's energy technology can effectively contribute to the decline in the CEI. In contrast, the impact of the 4th sector energy efficiency on the CEI is not significant. The root cause is that the energy consumption of the 4th sector is mostly oil and gas resources, and its energy consumption structure is difficult to change in the short term, which leads to the energy transition policy is difficult to affect the CEI of the sector significantly.

Policy Implications

According to the research results, we can find that the energy transition policy has a significant influence on carbon emission reduction. To some extent, the current carbon emissions will still be affected by the previous period, so the implementation of the energy transition policy will not produce immediate effects. Therefore, the following policy suggestions are proposed in this study. First, China should resolutely implement the energy transition policy, and take into account the development demands and emission reduction potential of various economic sectors, so as to dynamically adjust the carbon reduction policy. Second, the government should strictly control coal-oriented total fossil energy consumption, ensuring a complete substitute of clean

energy for incremental energy demand and gradually begin to replace stock. Third, according to the critical factors of CO₂ emission reduction in different sectors, China should implement a differentiated emission reduction policy in different sectors, focusing on promoting clean energy and improving energy utilization efficiency in the 2nd sector and promoting the clean and low-carbon transition of energy consumption structure in the 4th sector. On this basis, relevant departments should pay attention to the coordinated development of policy objectives of various industries and establish a compatible policies network system to reduce CO₂ emission.

DATA AVAILABILITY STATEMENT

The original contributions presented in the study are included in the article/Supplementary Material, further inquiries can be directed to the corresponding author.

AUTHOR CONTRIBUTIONS

DW, XL and YZ: conceptualization. DW, XL, YZ and XY: methodology. DW, XL, XY and ZZ: writing. XL, XY and ZZ: results. XY, ZZ and XW: validation. XW: artwork. All authors contributed to the article and approved the submitted version.

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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.

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