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*Research Article*

# Evaluating the Effect of China's Carbon Emission Trading Policy on Energy Efficiency of the Construction Industry Based on a Difference-in-Differences Method

**Shasha Xie and Jinjing Wang**

*School of Civil Engineering and Architecture, Wuhan Institute of Technology, Wuhan 43000, China*

Correspondence should be addressed to Jinjing Wang; wjin1994@163.com

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China's construction industry makes important contributions to energy consumption and pollution emissions. It is significant to improve energy efficiency in the construction industry. Since 2011, the introduction of China's carbon emission trading policy has had a great impact on energy conservation and emission reduction. The implementation of the carbon emission trading policy provides us with an opportunity to find solutions to improve the energy efficiency of the construction industry (EECI) in China. In this article, the implementation of carbon emission trading is regarded as a quasi-natural experiment, and the impact of the carbon emission trading policy on the energy efficiency of the construction industry is evaluated by analyzing the panel data related to the energy of the construction industry in 30 provincial regions from 2008 to 2016 through a difference-in-differences method. The main conclusions are as follows. First, the carbon emission trading policy can improve EECI. Second, the carbon emission trading policy can achieve the policy effect of improving EECI by optimizing the allocation of construction machinery resources and enhancing regional technical innovation. At the same time, strengthening government environmental regulation can strengthen the policy effect as well. Finally, some policy implications based on the study are proposed.

## 1. Introduction

Since the twentieth century, the coordination between economic development and environmental protection has gradually attracted the attention of most of the world. To realize sustainable development, some consensus on environmental protection has been reached among many countries [1]. Climate change is one of the most important issues, and some international clauses have been signed. For example, the Paris Agreement reached in 2015 is a measure for mankind to jointly deal with climate change after the United Nations Framework Convention on Climate Change in 1992 and the Kyoto Protocol in 1997, which committed to reducing greenhouse gas emissions. Representatives of China signed the Paris Agreement in 2016, which was followed by the approval of the National People's Congress Standing Committee [2]. In 2020, the President Xi of the People's Republic of China announced at the 75th UN General Assembly that China is striving to peak its carbon dioxide emissions by 2030 and to achieve the carbon-neutral target by 2060.

As a matter of fact, the Chinese government has implemented several policies trying to achieve energy conservation and emission reduction in the past two decades, and the carbon emissions trading policy is one of them. Carbon emission trading policy is considered as a market-oriented environmental regulation [3], which has been effectively carried out in Europe and other regions; and has recently proved to be an effective energy conservation and emission reduction policy implemented in China by empirical research [1]. In 2011, China's National Development and Reform Commission (NDRC) declared a pilot carbon emissions trading scheme, approving Beijing, Shanghai, Tianjin, Chongqing, Hubei, Guangdong, and Shenzhen to start carbon emissions trading. In June 2013, the pilot project gradually started carbon emission trading.

At the end of 2016, Fujian launched carbon emissions trading. In 2017, the national power industry issued the policy. In 2021, the national carbon emissions trading market opened. The implementation of the carbon emission trading policy in different regions in China covers different industries. The specific industries covered include power, heat, cement, chemical, metal, petrochemical, automobile, public construction, etc. [4]. It can be seen that the power, steel, and cement industries are the key regulated industries. Looking back at the policy implementation of the first six pilots, as of December 31, 2016, the seven carbon market pilots (including Fujian) had a transaction volume of 160 million tons, valued at nearly 2.5 billion yuan [2]. Undoubtedly, the implementation of the policy has had a significant impact on energy consumption in pilots [5].

China's construction industry is a national pillar industry, which not only contributes to the world economy; but also makes important contributions to energy consumption and pollution emissions [6]. Based on life cycle assessment, the energy consumption of the construction industry in China has increased rapidly. In 2016, its total energy consumption was 410 million tons of standard coal, accounting for about 9% of the whole society, and it quadrupled from 2000 to 2016 [7]. Actually, the implementation of the carbon emission trading policy provides us with an opportunity to find solutions to the energy consumption problem in China. In addition, compared with developed countries, China's energy technology and management level are relatively low and underdeveloped, and energy efficiency is not high [8]. For the construction industry, energy efficiency is a key indicator for evaluating the sustainable development of the construction industry [6]. Therefore, the study uses energy efficiency to measure and evaluate the impact of the carbon emissions trading policy on the energy efficiency of the construction industry in China.

This article takes the implementation of the carbon emission trading policy as a quasi-natural experiment. Difference-in-differences (DID) approach is used to evaluate the policy effect of the carbon emission trading policy on EECI, while Propensity Score Matching (PSM)-DID approach is used to further test the benchmark results and simulated repeated random sampling is used for the placebo test. The robustness of the benchmark results is further examined by other methods. The article explores three ways to strengthen the policy effect through mechanism analysis. At the same time, several influencing factors of EECI are presented. According to the research results, policy implications for the implementation of the carbon emission trading policy to enhance EECI are proposed.

The rest of this study is organized as follows. Section 2 is the literature review. Section 3 describes methods and data. Section 4 presents the empirical analysis. Robustness tests are provided in Section 5. Section 6 explores the mechanism analysis. In the end, Section 7 is the conclusion and policy implications.

## 2. Literature Review

The implementation of carbon emission trading policies mainly depends on the carbon emission trading system. The carbon emissions trading system refers to a market trading system for the control of greenhouse gas emissions and targets greenhouse gas emission allowances or greenhouse gas emission credits [9]. The party that produces more emissions gets the right to emit coal from the other party, and the other party produces lower levels of carbon emissions. Buyers can use emissions reductions to mitigate greenhouse effects and meet emissions reduction goals [10].

The carbon emissions trading market has been effectively implemented in Europe, the USA, and other places after years of development. The EU has an earlier and more mature organization of carbon trading in the world [11]. There are many studies to evaluate the policy effect of carbon emissions trading policy. Lise et al. analyzed the impact of the EU Emissions Trading Scheme on electricity prices by studying 20 countries [12]. Martin et al. studied the EU's carbon emission system and found that carbon trading could reduce the pollutants emitted by these companies [13]. Murray and Maniloff demonstrated that a regional emissions trading program of the Regional Greenhouse Gas Initiative lead to substantial reductions in carbon dioxide emissions in the northeastern USA [14]. Simulation results of Choi et al. suggested that South Korea's emissions trading scheme had significant abatement effects [15]. As these studies have shown, carbon emissions trading policies can reduce carbon dioxide emissions.

In China, recent studies related to carbon emission trading policy are increasing and varying. Such as the impact on carbon emission reduction [16], carbon trading prices [17], carbon market maturity [18], and carbon trading efficiency [19]. The evaluation of the impact of carbon emission trading policy on the economy and the environment is one of the main research topics, which is highly relevant to this study. Dong et al. proved that the carbon emission trading policy had a significant impact on the joint benefits of total carbon reduction and air quality improvement [20]. The empirical work of Chen and Lin identified the role of carbon emission trading policy in promoting energy conservation and emission reduction as an effective policy tool to promote carbon neutrality [21]. Wu et al. confirmed that the carbon emission trading policy had a significant impact on agricultural ecological efficiency [22]. Chai et al. called carbon emission trading policy an effective market-driven environmental regulation policy and demonstrated it from the perspective of carbon emission efficiency [11]. The fact that China's coal emissions trading policy improves regional energy efficiency was demonstrated in the article of Zhang et al. [5]. More interestingly, the research results of Yu et al. show that carbon emission trading policy may significantly reduce urban-rural income inequality [3], and there are more studies on the evaluation of carbon emission trading policy.

As mentioned above, the economic and environmental impact of carbon emission trading policy involves various aspects. However, there is a gap in the assessment of carbon emission trading policies involving the construction industry. As suggested by Zhang et al. [23], future research can be carried out in sectors and industries most responsive to carbon emission trading. This article focuses on the impact of the carbon emission trading policy on EECI, which fills this research gap. Furthermore, recent articles on the evaluation of carbon emission trading policy make extensive use of DID approach [1, 3, 4, 11, 20, 22]. These articles provide a practical research method for this article. DID removes the effects of individual heterogeneity and time-varying factors [24]. Using the DID approach, the net impact of policy implementation is estimated by comparing the intervention and control groups before and after the event [24]. PSM-DID has been also adopted by many researchers [3, 4, 11, 23], and it can select more suitable samples to reduce the deviation caused by sample selection [25]. In this article, DID is used for benchmark estimation, and PSM-DID is used to further test the estimation results.

In addition, evaluating energy efficiency is of great significance to energy conservation and improving the level of energy utilization. Research on EECI focuses on the measurement of energy efficiency and its influencing factors. EECI is measured mainly in terms of two methods, Single Factor Energy Efficiency (SFEE) and Total Factor Energy Efficiency (TFEE). SFEE measurement indicators include the thermodynamic index, physical-thermal index, economic-thermal index, and economic index [26, 27]. The most popular SFEE indicator is the economic-thermal index [27], which is the ratio of economic output to energy consumption and the reciprocal of energy intensity. Hu is the first to propose TFEE [28, 29]. TFEE considers a variety of inputs and outputs and uses stochastic frontier analysis (SFA) and data envelope analysis (DEA) methods to comprehensively evaluate energy efficiency. For example, Gao et al. [30] evaluated embodied energy efficiency and direct energy efficiency of the construction industry in China by DEA–SBM. The inputs are energy, capital, and technology, the outputs are the value added to the construction industry and the completed area of construction. Wang et al. [31] estimated the energy efficiency of the Chinese building industry based on the game cross-efficiency DEA model. Unlike the study by Gao et al., in their study, energy, capital, labor, and mechanical equipment are inputs, and gross output, completed area, and $CO_2$ emission are the outputs. Even if the same object is being analyzed, the input and output elements used by different scholars are different. That is to say, the research of TFEE without a unified standard is still in the exploratory stage. Compared with the TFEE method, the SFEE method is simple, straightforward, easy to understand, and has a high degree of consensus. Thus, this article adopts the economic-thermal index calculated by SFEE method to measure EECI in China.

After the measurement of EECI, influencing factors analysis is usually carried out, which is relevant to this article. Liang et al. [6] took urbanization, the per capita GRP, technical equipment ratio, energy consumption structure, innovation support, environmental supervision, industry contribution rate, and industry concentration as marketization as exogenous environmental variables, which can affect EECI in China. Zhu et al. [32] assessed the effects of technological progress on EECI. Chen et al. [27] listed a table of the factors influencing energy efficiency from previous literature, considering energy consumption structure, industrial development level, industrial open degree, industrial scale structure, market ownership structure, market industry structure, market specialization-division structure, and technological innovation as environmental variables influencing EECI. Li et al.'s article show that labor productivity is considered as an important influencing factor for the assessment of the carbon emissions peak in China's construction industry [33]. Du et al. [34] and Zhou et al. [35] take the total power of mechanical equipment as an input variable of carbon emission efficiency similar to TFEE in the construction industry. Gao et al. adopt technical equipment rate as an input of TFEE in the construction industry [30]. According to Gong and Song [36] and Liang et al. [6], urbanization is an important factor of EECI. Chen et al. [27], Liang et al. [6], and Gong et al. [36] regarded electric consumption as a percentage of total energy consumption as the energy consumption structure. In accordance with Chen et al. [27] and Liang et al. [6], regional R&D expenditure intensity which stands for technological level is positive to EECI. Some variables are commonly considered to be related to EECI. The following research in this article draws on these studies to select variables in the model.

Compared with the existing literature, the main research innovations of this article are as follows: (1) there have been many evaluations of the impact of carbon emission trading policy on the economy and the environment in recent years, but there are few studies on the impact of carbon emission trading policy on sectors and industries, especially the impact of carbon emission trading policy on EECI. The widely accepted DID approach taken by these studies provides the research methodology used in this article. Therefore, this article adopts DID to evaluate the impact of carbon emission trading policy on EECI and tries to fill this research gap; (2) the positive policy effect of implementing carbon emission trading policy on EECI is confirmed by DID and some ways to strengthen the effect of carbon emission trading policy on EECI are explored by regression and mechanism analysis. Practical policy implications of carbon emission trading policy for improving EECI are proposed, which is a contribution that provides a reference for policymakers.

## 3. Methods and Data

*3.1. DID Model.* The difference-in-difference method is a common method for evaluating policy effects. This article uses the DID method to estimate the impact of the carbon emission trading policy on EECI in China. First, the implementation of the carbon emission trading policy is viewed as a quasi-natural experiment in which subjects are divided into an intervention group and a control group. The intervention group is defined as the group intervened by the policy, that is, the carbon emission trading policy pilot regions. The control group is defined as the group that is not intervened by the policy, that is, the non-pilot regions. By observing the changes in the intervention group and the control group before and after the implementation of the policy, the influence of the time effect can be eliminated, and the net effect of the policy is estimated. In this study, the first batch of carbon emission trading policy pilots approved by NDRC in 2011 is selected as the intervention group. The intervention group included six pilot regions in Beijing, Tianjin, Shanghai, Chongqing, Hubei, and Guangdong (including Shenzhen). These six pilots actually launched the carbon emissions trading market at the end of 2013 and early 2014, so 2014 is considered to be the time for policy implementation [3, 16]; due to the launch of the carbon emissions trading market in Fujian at the end of December 2016 and the introduction of carbon emission trading policy into the national power sector in 2017, the data used are as of 2016 to avoid their interference with the experiment. Referring to previous researches [3, 4, 16], the DID model is constructed as follows:

$$\ln ee_{it} = \alpha_0 + \alpha_1 \text{treat}_i\text{post}_t + \sum \alpha_j X_{it} + \mu_i + \gamma_t + \varepsilon_{it}, \tag{1}$$

where $\ln ee_{it}$ denotes the natural logarithm of EECI at provincial region $i$ in year $t$. $\alpha_0$ denotes the constant. $\alpha_1$ and $\alpha_j$ refer to the coefficient of the corresponding term. $\text{treat}_i$ is the carbon emission trading policy dummy variable, if the region is the pilot of carbon emission trading, $\text{treat}_i$ is equal to 1, otherwise it is equal to 0. $\text{post}_t$ is the time dummy variable, which equals 1 when $t$ is greater than or equal to 2014, otherwise it equals 0. $\text{treat}_i\text{post}_t$ is the interaction term, which indicates whether region $i$ has implemented the carbon emission trading policy in year $t$. $X_{it}$ indicates control variables and may affect $\ln ee_{it}$. $\mu_i$ denotes the individual fixed effect for provincial region. $\gamma_t$ represents the time fixed effect for the year. $\varepsilon_{it}$ means the random error term. The coefficient $\alpha_1$ is the core coefficient to study whether carbon emission trading policy can promote $\ln ee$, indicating the net effect of carbon emission trading policy on $\ln ee$.

*3.2. Mechanism Analysis Model.* The article takes two methods to explore the mechanism. Referring to Xuan et al. [16], the first group of models is constructed as follows:

$$\begin{aligned}
\ln ee_{it} &= \beta_0 + \beta_1 \text{treat}_i\text{period}_t + \sum \beta_j X_{it} + \mu_i + \gamma_t + \varepsilon_{it},\\
M_{it} &= \beta_0 + \beta_2 \text{treat}_i\text{period}_t + \sum \beta_j X_{it} + \mu_i + \gamma_t + \varepsilon_{it},\\
\ln ee_{it} &= \beta_0 + \beta_3 \text{treat}_i\text{period}_t + \beta_4 M_{it} + \sum \beta_j X_{it} + \mu_i + \gamma_t + \varepsilon_{it},
\end{aligned} \tag{2}$$

where $M_{it}$ is the intermediary variable and the other symbols are consistent with those in model **(1)**, and $M_{it}$ should be checked as follows. In the first step, if $\beta_1$ is significant, it means that the carbon emission trading policy has a significant effect on $\ln ee_{it}$, then the second step of verification will be performed, otherwise, the procedure will terminate; the second step is to verify whether carbon emission trading policy has an effect on $M_{it}$ according to whether $\beta_2$ is significant; if $\beta_2$ is significant, then go to the third step, otherwise terminate; the third step is to judge whether $M_{it}$ is an intermediary variable according to whether $\beta_4$ is significant or not.

Referring to Qiu et al. [37], the second group of models is constructed as follows:

$$\begin{aligned}
\ln ee_{it} = {} & \lambda_0 + \lambda_1 \text{treat}_i\text{period}_t N_{it} + \lambda_3 \text{treat}_i\text{period}_t \times N_{it}\\
& + \sum \lambda_j X_{it} + \mu_i + \gamma_t + \varepsilon_{it},
\end{aligned} \tag{3}$$

where $N_{it}$ is the moderator variable, $\text{treat}_i\text{period}_t \times N_{it}$ represents the interaction term between the moderator variable $N_{it}$ and the implementation of carbon emission trading policy $\text{treat}_i\text{post}_t$. The other symbols are defined as the same as those in model **(1)**. The article mainly focuses on the sign and significance of $\lambda_1$ and $\lambda_3$. If both of them are significant, it means that $N_{it}$ has a moderating effect on the impact of $\text{treat}_i\text{post}_t$ on $\ln ee_{it}$. These analysis results can provide valuable policy implications.

### 3.3. Variables and Data

*3.3.1. Explained Variable.* The explained variable is the natural logarithm of EECI at provincial region (ln *ee*) [1], calculated by the natural logarithm of the ratio of the gross output value to the energy consumption in the construction industry. The gross output value of the construction industry in regions is from the China Statistics Yearbook of Construction (CSYC). The energy consumption of the construction industry in various regions is from the row for construction of Energy Balance Sheet by Region in China Energy Statistics Yearbook (CESY). Energy consumption refers to energy consumption in the construction stage and demolition stage [32, 36, 38]. The article uses the method of conversion of various energy sources in the sheet into a standard coal equivalent. Coefficients of conversion of various energy sources into standard coal are from the General Rules for Calculation of the Comprehensive Energy Consumption (GRCCEC, GB/T 2589–2020).

*3.3.2. Core Explanatory Variable.* The core explanatory variable is $\text{treat}_i\text{period}_t$. $\text{treat}_i\text{period}_t = 1$ means carbon emission trading policy is implemented in provincial region $i$ in year $t$. $\text{treat}_i\text{period}_t = 0$ indicates that region $i$ is not a carbon emission trading policy pilot or year $t$ is not after the implementation of the policy, or neither. If the coefficient of $\text{treat}_i\text{period}_t$ is positive and significant, it indicates that carbon emission trading policy can promote EECI.

*3.3.3. Control Variables and Others.* The principle of variable selection is to consider the previous research and its correlation with dependent variables. Labor productivity, mechanical power equipment, urbanization, energy structure, and regional R&D expenditure intensity are the control variables. Labor productivity (proctivity) of construction enterprises in this article refers to the labor productivity calculated by gross output value from raw data of CSYC [33]. The mechanical power equipment rate (machinery) of construction enterprises from raw data of CSYC is designed to measure the mechanical equipment in the article [30, 34, 35]. It means mechanical resource allocation. The urban population as a percentage of total population (urbanratio) which is raw data that comes from the China Statistical Yearbook (CSY) is the measurement of urbanization [6, 36]. The article defines the natural logarithm of electric consumption as a percentage of total energy consumption in the construction industry as an energy consumption structure (lnesratio) [6, 27, 36]. It is calculated by converting them into standard coal equivalent with data from Energy Balance Sheet by Region in CESY. Regional R&D expenditure intensity (rdratio) is derived from raw data of the China Statistical Yearbook of Science and Technology (CSYST) [6, 27]. It is the ratio of R&D expenditure to GDP in a region and represents regional technological innovation. The R&D expenditure is invested by the whole society in a region.

In addition, mechanical power equipment (machinery), regional R&D expenditure intensity (rdratio), and environmental regulation level (lneninratio) are used for mechanism analysis. Environmental regulation level of the government (lneninratio) which is the natural logarithm of the ratio of environmental protection expenditure to total government expenditure is adopted as a moderator variable for mechanism analysis, calculated by data from CSY. Per capita GDP ($pgdp$) raw data that comes from CSY is a covariate of PSM-DID estimation. Both of them are relevant to EECI [6]. Table 1 shows a description of the variables.

The research data of this article are panel data of 30 provincial regions (excluding Tibet, Taiwan, Hong Kong, and Macau, which have incomplete data) in China with a time span of 9 years from 2008 to 2016. The 30 provincial regions are divided into an intervention group with 6 regions and a control group with 24 regions. The year of carbon emission trading policy implementation is defined as 2014. Table 2 shows descriptive statistics of the variables.

## 4. Empirical Analysis

*4.1. Benchmark Regression Results.* The policy effect of carbon emission trading policy on EECI is estimated by model **(1)**. Table 3 shows the estimation result, in which the province and year are fixed, that is, two-way fixed effect, and standard errors are clustered at the provincial level. The rest of the regressions below follow this standard. According to column **(1)** to column **(5),** the coefficient of $\text{treat}_i\text{period}_t$ is always positive and passes the significance test all the time. It demonstrates that the carbon emission trading policy pilot policy has significantly improved EECI and the result is robust. Compared with column **(1)** without control variables, the coefficient of column **(5)** with control variables increased from 0.210 of significance at 10% to 0.226 of significance at 1%. The estimated coefficient of 0.226 indicates a 22.6% increase in ln *ee* in the carbon emission trading policy regions relative to the non-pilot regions. Consistent with the conclusion proved by Gu et al. that the energy consumption per unit of GDP in the carbon emission trading policy pilot regions is significantly reduced [1], the conclusions of this study are highly similar to those of Zhang et al. [5]. Taking the natural logarithm of regional energy efficiency as the explanatory variable, the coefficients estimated by Zhang et al. range from 0.149 to 0.262 above 5% significance [5].

In addition to the carbon emission trading policy, we also find some other factors that may affect EECI. The coefficients of labor productivity (productivity), urbanization (urbanratio), energy consumption structure (lnesratio), and regional R&D expenditure intensity (ratio) are positive and pass the significance test. This indicates that they are positively correlated with EECI. In contrast, the mechanical power equipment rate (rdratio) of which coefficient is negative and passes the significance test is negatively correlated with EECI.

China's construction industry is shifting from extensive development to intensive development. Labor productivity under uneven technical levels of the labor force and irregular labor management are obstacles to intensive development. Labor productivity has a depressing effect on China's construction industry's carbon emissions [33]. As for EECI, this article shows that labor productivity promotes it. EECI can benefit from labor productivity, which is caused by the improvement of labor quality and the improvement of labor technology support.

The SFA regression results of Liang et al. represent that urbanization is negative to energy input in the analysis of EECI [30]. Urbanization is now shown to be positively correlated with EECI. With reference to Liang et al. [30], the increasing urbanization may promote the inflow of high-quality educational resources and talents, thus increasing the labor value, accelerating the development of energy-saving technologies, and improving energy efficiency.

The SFA regression results of Chen et al. indicate that energy consumption structure is negative to energy consumption in the construction industry [27]. The SFA regression results of Liang et al. represent that energy consumption structure is negative to energy input in the analysis of EECI [30]. The carbon emission trading policy has an impact on reducing total energy consumption and adjusting energy consumption structure, thus carbon emissions intensity is decreased [4, 16]. Similar to these results, the energy consumption structure of the construction industry in this article is positively correlated with EECI. The emergence of this situation may be caused by the gradual replacement of traditional coal energy with renewable energy, and this replacement also accelerates the development of energy technology.

Regional R&D expenditure intensity is positively related to technological innovation, and technological innovation can improve the utilization efficiency of social energy. The carbon emission trading policy can strengthen R&D investment [23]. Regional R&D expenditure intensity is positively correlated with EECI in this article, which is consistent with Chen et al. [27].

Unlike other variables, the mechanical power equipment rate is negatively correlated with EECI. It indicates that mechanical resource allocation is worth optimizing. The result is similar to Hydes et al.'s views [39]. They point out that reducing the use of equipment or facilities should be seen as one of the most effective ways to improve EECI [39].

*4.2. Parallel Trend Test.* One of the most important assumptions in the empirical analysis is that the intervention group and the control group obey a common trend prior to

Table 1: Description of the variables.

| Variables | Definition | Description | Source |
|---|---|---|---|
| Lnee | Energy efficiency of the construction industry | The natural logarithm of the ratio of gross output value to energy consumption in the construction industry | CSYC CESY |
| Productivity | Labor productivity | The per capita labor productivity of construction enterprises from raw data | CSYC |
| Machinery | Mechanical power equipment | The per capita mechanical power equipment of construction enterprises from raw data | CSYC |
| Urbanratio | Urbanization | The urban population as a percentage of the total population from raw data | CSY |
| Lnesratio | Energy structure | The natural logarithm of electric consumption as a percentage of total energy consumption in the construction industry | CESY |
| Rdratio | Technological innovation | The ratio of R&D expenditure to GDP from raw data | CSY |
| Lneninratio | Environmental regulation level of the government | The natural logarithm of the ratio of environmental protection expenditure to total government expenditure | CSY |
| Pgdp | Per capita GDP | The per capita GDP from raw data | CSY |

Table 2: Descriptive statistics of the variables.

| Variables | Count | Mean | Std. Dev | Min | Median | Max |
|---|---|---|---|---|---|---|
| Lnee | 270 | 3.169 | 0.724 | 1.280 | 3.114 | 4.884 |
| Productivity | 270 | 27.170 | 10.345 | 10.378 | 26.763 | 90.304 |
| Machinery | 270 | 6.360 | 3.060 | 2.100 | 5.800 | 27.400 |
| Urbanratio | 270 | 0.547 | 0.131 | 0.291 | 0.526 | 0.896 |
| Lnesratio | 270 | −1.754 | 0.624 | −3.604 | −1.676 | 1.000 |
| Rdratio | 270 | 0.015 | 0.011 | 0.002 | 0.012 | 0.061 |
| Lneninratio | 270 | −3.561 | 0.338 | −4.639 | −3.571 | −2.821 |
| Pgdp | 270 | 4.270 | 2.259 | 0.882 | 3.731 | 11.820 |

the intervention of the carbon emission trading policy. Figure 1 shows that the average $\ln ee$ of the intervention group and the control group kept almost the same increasing trend excluding 2012 before the policy implementation in 2014, with no obvious deviations. However, after 2014, the mean $\ln ee$ of the intervention group continued to increase, and that of the control group almost stopped increasing in 2014 and began to decline since 2015, showing a significant deviation. The intervention group and the control group are preliminarily judged to satisfy the parallel trend test.

Referring to Liu [40], a regression model based on model **(1)** is built for further parallel trend tests. Model **(1)** is extended to the following:

$$\ln ee_{it} = \delta_0 + \delta_t \sum_{2008, t \neq 2013}^{2016} treat_i period_t + \sum \delta_j X_{it} + \mu_i + \gamma_t + \varepsilon_{it} \quad (4)$$

where $\text{period}_t$ is the dummy variable of time year, if the year is at $t$, the value is 1; otherwise, the value is 0. The series of coefficients ($\delta_t$) for the interaction term ($\text{treat}_i\text{period}_t$) is the primary interest of this test. To satisfy the parallel trends, the coefficients of the interaction terms before 2014 are expected to be statistically insignificant and fluctuate within a certain range, indicating that the trends in the control and intervention groups are not statistically significantly biased. However, the coefficients of those after the carbon emission trading policy are expected to be significant, indicating a statistically significant deviation from the trends in the control and intervention groups. $\text{period}_{2013}$ is dropped and it is the base period. In addition, the model can examine the dynamics of policy effects.

Table 3: Impact of the carbon emission trading policy on energy efficiency of the construction industry.

| | (1) lnee | (2) lnee | (3) lnee | (4) lnee | (5) lnee |
|---|---|---|---|---|---|
| $\text{treat}_i\text{post}_t$ | $0.210^{*}$ | $0.334^{***}$ | $0.301^{**}$ | $0.294^{***}$ | $0.226^{***}$ |
| | (1.84) | (2.76) | (2.70) | (3.39) | (2.92) |
| Productivity | | $0.008^{**}$ | $0.008^{***}$ | $0.008^{***}$ | $0.007^{***}$ |
| | | (2.75) | (2.79) | (3.40) | (3.11) |
| Urbanratio | | $5.798^{**}$ | $5.892^{***}$ | $3.307^{**}$ | $3.659^{**}$ |
| | | (2.66) | (2.79) | (2.13) | (2.28) |
| Machinery | | | $-0.027^{***}$ | $-0.014^{*}$ | $-0.017^{**}$ |
| | | | (−3.03) | (−1.87) | (−2.31) |
| Lnesratio | | | | $0.472^{***}$ | $0.467^{***}$ |
| | | | | (6.01) | (5.50) |
| Rdratio | | | | | $29.223^{**}$ |
| | | | | | (2.16) |
| _Cons | $3.155^{***}$ | −0.247 | −0.134 | $2.033^{**}$ | 1.455 |
| | (413.69) | (−0.20) | (−0.11) | (2.33) | (1.45) |
| Province FE | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes |
| Adj. $R^2$ | 0.891 | 0.901 | 0.906 | 0.938 | 0.941 |
| $N$ | 270 | 270 | 270 | 270 | 270 |

Standard errors are clustered at the provincial level. $t$ statistics in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

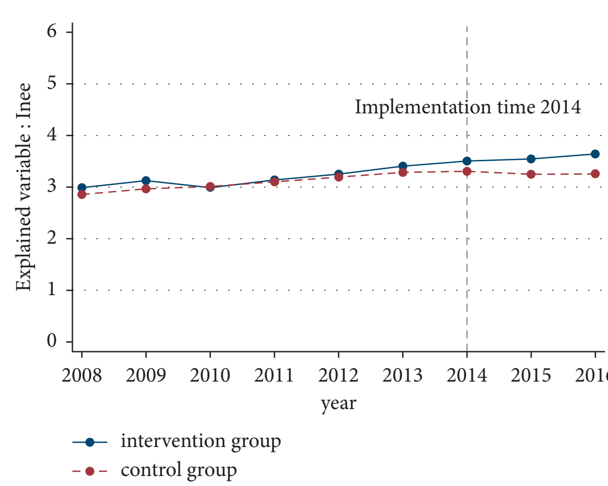


Figure 1: Average trend of the natural logarithm of energy efficiency of the construction industry in 2008–2016.

Figure 2 shows the evaluation results of model (6). It can be seen from Figure 2 that the coefficients from 2008 to 2012 are all statistically insignificant and fluctuate around 0, while the coefficients from 2014 to 2016 are significantly at the 10% significance level with the coefficients' significance and value increasing over time. Two important results are drawn from the regression. First, the intervention group and the control group before 2014 meet the parallel trend test; second, the significance and value of the coefficients after 2014 continue to increase, indicating that the implementation effect of the policy has become more and more prominent and carbon emission trading policy had an increasing effect on the EECI of the intervention group. This may be related to the expanding implementation scope of the carbon emission trading policy. The more industries carbon emission trading policy covers, the more relevant it is to the construction industry, and the greater the impact of the policy on EECI.

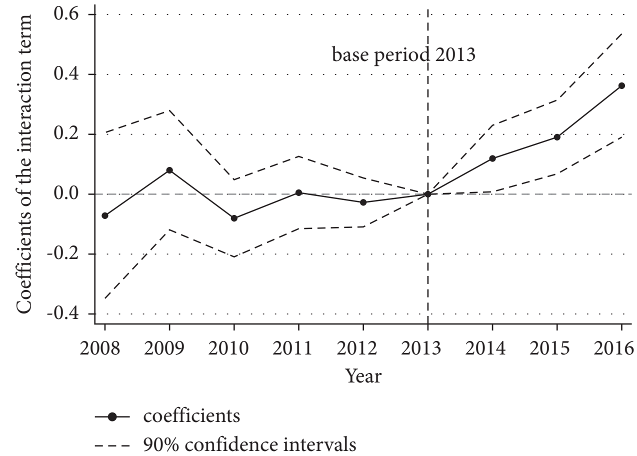


FIGURE 2: Coefficients of the interaction term and confidence intervals in the parallel trend test.

## 5. Robustness Tests

*5.1. Placebo Test.* Referring to Yu et al. [41], the placebo test is to eliminate the intervention of other unobserved missing variables on the EECI evaluated in this study. The basic idea is that 6 regions are first randomly selected from 30 regions as fake carbon emission trading policy pilots and the DID model **(1)** is used to estimate the coefficient of this core explanatory variable, and then the experiment is repeated 500 times. According to the distribution and significance of the coefficient values, if most of the coefficients are clustered around 0, the deviation from the estimated coefficient of the real quasi-natural experiment is large and not statistically significant, then it means that the carbon emission trading policy actually improves the EECI.

Figure 3 presents the results of the placebo test. The vertical red dashed line represents the true coefficient of 0.226, the horizontal red dashed line represents the 10% level of significance, the blue dashed line is the estimated *P* value, and the curve is the density distribution of the coefficients. Most of the coefficients deviate from the true coefficients and are not statistically significant, concentrated around 0 in Figure 3. Only a few are larger than the true coefficient and statistically significant. The policy effects of the carbon emission trading policy are not obtained by chance. Therefore, the placebo test shows that it is indeed a carbon emission trading policy that increases the EECI.

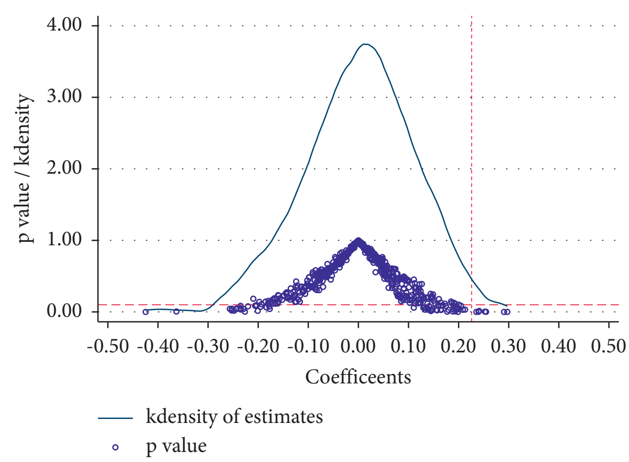


FIGURE 3: The distribution of coefficients of the core explanatory variable after random 500 simulations.

*5.2. Excluding Outliers and the Counterfactual Time.* According to the researches of Liu et al. [40] and Song et al. [42], the outliers are excluded or the policy implementation time is changed to test the robustness of the results. The dataset in this article may contain outliers that substantially affect the estimated results, and columns (1) and (2) in Table 4 show the regression results with the outliers excluded. The winsor2 algorithm for excluding outliers is to replace the values less than the 1% percentile and greater than the 99% percentile with the 1% and 99th percentile values, respectively. The results show that whether the control variable is added to the regression or not, the coefficient of the core explanatory variable is around 0.2 and is statistically significant. It indicates the benchmark results are robust.

Another test is to change the "policy implementation time," known as the counterfactual test. This test is conducted by changing the policy implementation time from 2014 to 2010, 2011, 2012, and 2013, respectively, and the other settings of the test are consistent with the benchmark regression [42]. The coefficients for the core explanatory variables from 2010 to 2012 shown in columns (3) to (8) in Table 4 are all statistically insignificant with and without the control variable, consistent with the parallel trend test. Column (9) and (10) shows that the coefficient of the core explanatory variable without the control variable in 2013 is not significant, while the coefficient of the core explanatory variable with the control variable is 0.168 at 5% significance, its value and significance are lower than the benchmark results. This result in column (10) may be due to the pre-policy effect of the carbon emission trading policy launch and the policy effect of some policy pilots

Table 4: Excluding outliers and changes of time.

| | (1) lnee Winsor | (2) lnee Winsor | (3) lnee 2010 | (4) lnee 2010 | (5) lnee 2011 | (6) lnee 2011 | (7) lnee 2012 | (8) lnee 2012 | (9) lnee 2013 | (10) lnee 2013 |
|---|---|---|---|---|---|---|---|---|---|---|
| $Trea_{ti}pos_{tt}$ | $0.210^{*}$ | $0.189^{**}$ | 0.010 | 0.031 | 0.094 | 0.102 | 0.135 | 0.124 | 0.175 | $0.168^{**}$ |
| | (1.85) | (2.69) | (0.05) | (0.24) | (0.59) | (1.11) | (0.99) | (1.45) | (1.40) | (2.14) |
| Productivity | | $0.012^{*}$ | | $0.007^{**}$ | | $0.006^{**}$ | | $0.005^{*}$ | | $0.006^{**}$ |
| | | (2.03) | | (2.57) | | (2.25) | | (1.82) | | (2.34) |
| Machinery | | $-0.018^{*}$ | | $-0.019^{**}$ | | $-0.019^{**}$ | | $-0.019^{**}$ | | $-0.018^{**}$ |
| | | (−1.97) | | (−2.49) | | (−2.45) | | (−2.45) | | (−2.39) |
| Urbanratio | | $3.582^{**}$ | | 2.529 | | 2.730 | | 2.961 | | $3.294^{*}$ |
| | | (2.14) | | (1.31) | | (1.50) | | (1.68) | | (1.97) |
| Lnesratio | | $0.525^{***}$ | | $0.470^{***}$ | | $0.476^{***}$ | | $0.472^{***}$ | | $0.470^{***}$ |
| | | (6.74) | | (6.01) | | (5.83) | | (5.74) | | (5.59) |
| Rdratio | | $33.329^{**}$ | | $36.771^{**}$ | | $32.578^{**}$ | | $31.589^{**}$ | | $29.904^{**}$ |
| | | (2.36) | | (2.52) | | (2.29) | | (2.26) | | (2.14) |
| _Cons | $3.155^{***}$ | 1.416 | $3.168^{***}$ | 1.998 | $3.157^{***}$ | $1.968^{*}$ | $3.154^{***}$ | 1.871 | $3.154^{***}$ | 1.689 |
| | (415.36) | (1.44) | (94.12) | (1.65) | (147.88) | (1.70) | (208.44) | (1.68) | (284.18) | (1.60) |
| Province FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Adj. $R^2$ | 0.892 | 0.944 | 0.888 | 0.938 | 0.888 | 0.939 | 0.889 | 0.939 | 0.890 | 0.940 |
| N | 270 | 270 | 270 | 270 | 270 | 270 | 270 | 270 | 270 | 270 |

Standard errors are clustered at the provincial level.$t$ statistics in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

launched at the end of 2013, but it is not robust to the result in column (9) and the benchmark result. The counterfactual time test indicates that the benchmark results are robust.

*5.3. PSM-DID.* Considering that the differences between samples are obvious, to further select comparable samples, this section adopts the PSM-DID for robustness testing. Referring to Liu et al. [24], the variables highly related to $\ln ee$(such as pro du ctivity, machinery, urbanratio, lnesratio, ratio, and $pg\,dp$) are selected as the covariates to conduct the nearest neighbor 1:4 matching, which is statistically significant in logit regression. There should be no difference between the matched intervention (treated) group and the matched control group in terms of the selected covariates. A balance test is conducted and Table 5 lists the results of the balance test. After PSM matching, the biases of the variables in the intervention group and the control group are greatly reduced, and the biases are almost all within 10%. $P$-values are mostly statistically significant before matching and mostly statistically insignificant after matching which means that the PSM obtains a smaller deviation between the variables in the intervention group and the control group to obtain a better estimation.

After matching, the PSM-DID regression is performed. The estimation results in Table 6 show that the coefficients of the core explanatory variables are positive and statistically significant at 5% whether there are control variables or not, which indicates that the carbon emission trading policy does improve $\ln ee$. Additionally, the signs of control variables in column **(2)** are consistent with those in the benchmark results. The PSM-DID proves the robustness of the benchmark results in this article.

## 6. Mechanism Analysis

The benchmark regression and robustness tests aim to study the policy effect of carbon emission trading policy on EECI and the robustness of the results. Then, what is the transmission mechanism of the policy's impact on EECI? Two methods are adopted to answer this question [16, 37]. Based on model **(2)**, model **(3),** and model **(4)**, the mechanical power equipment rate (machinery) and regional R&D expenditure intensity (rdratio) are tested as mediator variables. This article examines the environmental regulation level (lneninratio) as a moderator variable by model **(5).**

Table 7 shows the estimation results of the mechanism analysis. The coefficient of the core explanatory variable in column **(1)** is negative and significant at the 1% level, indicating that the carbon emission trading policy can reduce the rate of mechanical power equipment. The coefficient of machinery in column **(2)** is negative and significant at the 5% level, indicating that machinery is negatively correlated with $\ln ee$. Combining columns **(1)** and **(2)**, it shows that the carbon emission trading policy can improve EECI by reducing the mechanical power equipment rate. In the construction industry, construction machinery is common at the construction site. Due to extensive construction management, many mechanical equipment resources are idle and the operation efficiency is low, which leads to low EECI. Updating equipment, eliminating high-power machinery, using energy-saving and efficient machinery, and optimizing resource allocation in construction organization can reduce the rate of mechanical power equipment and improve EECI. This finding is similar to that of Qiu et al. [37] who proved that the low-carbon city pilot policy can make resource allocation more efficient, thus improving efficiency. A carbon emission trading policy can also make the allocation of mechanical equipment resources more effective, thus improving EECI.

Table 5: Balance test for PSM.

| Variable | Unmatched Matched | Mean | | %Reduct | | t-test | |
|---|---|---|---|---|---|---|---|
| | | Treated | Control | %Bias | \|bias\| | $t$ | $p > t$ |
| Productivity | U | 36.775 | 24.769 | 105.7 | | 8.6 | 0 |
| | M | 28.553 | 27.423 | 9.9 | 90.6 | 0.36 | 0.72 |
| Machinery | U | 6.5019 | 6.325 | 5.8 | | 0.38 | 0.705 |
| | M | 5.805 | 5.6612 | 4.7 | 18.7 | 0.16 | 0.877 |
| Urbanratio | U | 0.72339 | 0.5033 | 188.9 | | 14.84 | 0 |
| | M | 0.58937 | 0.59442 | −4.3 | 97.7 | −0.19 | 0.848 |
| Lnesratio | U | −1.8552 | −1.7292 | −20.3 | | −1.33 | 0.185 |
| | M | −1.8887 | −1.8012 | −14.1 | 30.6 | −0.54 | 0.594 |
| Rdratio | U | 0.02823 | 0.01152 | 146.8 | | 13.13 | 0 |
| | M | 0.0165 | 0.01601 | 4.3 | 97.1 | 0.3 | 0.762 |
| Pgdp | U | 6.6224 | 3.6821 | 128.3 | | 10.01 | 0 |
| | M | 4.3698 | 4.3081 | 2.7 | 97.9 | 0.1 | 0.92 |

Table 6: The estimation results of PSM-DID.

| | (1) lnee | (2) lnee |
|---|---|---|
| $treat_i post_t$ | 0.957** | 0.371** |
| | (2.95) | (2.58) |
| Productivity | | 0.005 |
| | | (0.42) |
| Machinery | | −0.061 |
| | | (−1.37) |
| Urbanratio | | 5.814** |
| | | (2.36) |
| Lnesratio | | 0.691*** |
| | | (3.45) |
| Rdratio | | 35.738 |
| | | (1.60) |
| _Cons | 3.212*** | 0.889 |
| | (132.68) | (0.57) |
| Province FE | Yes | Yes |
| Year FE | Yes | Yes |
| Adj. $R^2$ | 0.843 | 0.945 |
| N | 45 | 45 |

Standard errors are clustered at the provincial level. $t$ statistics in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

The coefficient of the core explanatory variable in column **(3)** is negative and significant at the 1% level, indicating that the carbon emission trading policy is positive to regional R&D expenditure intensity (rdratio). The coefficient of $r\,dr\,atio$ in column **(4)** is positive and significant at the 5% level, indicating that $r\,dr\,atio$ is positively correlated with $\ln ee$. Combining columns **(3)** and **(4)**, it shows that carbon emission trading policy can improve EECI by increasing regional R&D expenditure intensity. Regional technological innovation is positively correlated with regional R&D expenditure intensity, improving technological innovation can accelerate the development of energy-saving technologies, thereby elevating EECI. This finding is consistent with that of Zhang et al. [5] who proved that green technological innovation plays a positive intermediary role in carbon emission trading policies that affect energy efficiency.

Columns **(5)** and **(6)** in Table 7 show that the coefficients for the core explanatory variable and the interaction term ($treat_i period_t \times$ lneninratio) are both positive and both pass the significance test. Combined with the benchmark results, this shows that the environmental regulation level has a positive moderating effect on the policy effect of the carbon emission trading policy on EECI, which indicates that strengthening environmental regulation in the carbon emission trading policy pilot can improve the promotion of carbon emission trading policy on EECI. This result is consistent with the well-known Poynter hypothesis that appropriate environmental regulation by the government can motivate firms to innovate more, while technological innovation can improve energy efficiency. Similarly, Boyd et al. [43] confirmed that environmental regulation is positive to “emission reduction” and “growth.” With the

Table 7: The estimation results of mechanism analysis.

| Explained variable | (1) Machinery | (2).Lnee | (3).Rdratio | (4).Lnee | (5).Lnee | (6).Lnee |
|---|---|---|---|---|---|---|
| $treat_i post_t$ | $-1.628^{***}$ (−2.91) | $0.226^{***}$ (2.92) | $0.002^{***}$ (3.22) | $0.226^{***}$ (2.92) | $1.386^{***}$ (3.55) | $1.542^{**}$ (2.74) |
| Productivity | 0.001 (0.03) | $0.007^{***}$ (3.11) | $0.000^{*}$ (1.86) | $0.007^{***}$ (3.11) | | $0.007^{***}$ (2.96) |
| Urbanratio | $13.857^{*}$ (1.72) | $3.659^{**}$ (2.28) | −0.012 (−0.72) | $3.659^{**}$ (2.28) | | $3.676^{**}$ (2.45) |
| Lnesratio | $-1.488^{*}$ (−1.99) | $0.467^{***}$ (5.50) | 0.000 (0.21) | $0.467^{***}$ (5.50) | | $0.469^{***}$ (5.69) |
| Rdratio | 215.803 (1.35) | $29.223^{**}$ (2.16) | | $29.223^{**}$ (2.16) | | $31.863^{**}$ (2.48) |
| Machinery | | $-0.017^{**}$ (−2.31) | $0.000^{**}$ (2.29) | $-0.017^{**}$ (−2.31) | | $-0.017^{**}$ (−2.24) |
| Lneninratio | | | | | −0.065 (−0.36) | 0.021 (0.17) |
| $treat_i post_t \times lneninratio$ | | | | | $0.320^{***}$ (2.95) | $0.366^{**}$ (2.34) |
| _Cons | −6.950 (−1.04) | 1.455 (1.45) | $0.020^{*}$ (1.99) | 1.455 (1.45) | $2.922^{***}$ (4.48) | $1.493^{*}$ (1.72) |
| Province FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Adj. $R^2$ | 0.571 | 0.941 | 0.984 | 0.941 | 0.892 | 0.943 |
| N | 270 | 270 | 270 | 270 | 270 | 270 |

Standard errors are clustered at the provincial level. $t$ statistics in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

increase in environmental regulation, Qiu et al. [37] pointed out that the rising environmental costs force enterprises to innovate and reduce their dependence on energy.

## 7. Conclusions and Policy Implications

This article aims to evaluate the performance of China's carbon emissions trading policy in terms of EECI. DID, the parallel trend test, robust tests, and mechanism analysis are used to explore the effect of carbon emission trading policy on EECI. Based on the above research, the following conclusions are drawn: (1) carbon emission trading policy can improve the EECI in pilot regions relative to non-pilot regions, and its policy effect gets better over time. The robustness of the benchmark results is demonstrated by several methods; (2) results of mechanism analysis show that carbon emission trading policy can improve EECI by reducing the mechanical power equipment rate or increasing regional R&D expenditure intensity. Increasing the environmental protection expenditure ratio in the carbon emission trading policy pilot can improve the promotion of carbon emission trading policy on EECI; (3) labor productivity, urbanization, energy consumption structure, and regional R&D expenditure intensity are positive to EECI, while the mechanical power equipment rate is negative to EECI.

The main policy implications are as follows: (1) for EECI, as the carbon emission trading policy is implemented longer and more widely, the greater the relationship between the policy effects and EECI. More specifically, the government should increase the time, intensity, and scope of implementing the carbon emissions trading policy; (2) the government can improve EECI by stimulating regional technological innovation and appropriately strengthening environmental regulations in the regions where the carbon emission trading policy is implemented. In terms of mechanical resource allocation, the government can use the carbon emission trading policy market effect to promote construction enterprises to strengthen resource allocation management and construction organization, eliminate high-power and inefficient equipment, and use new energy-saving equipment with the goal of increasing EECI. Construction enterprises can also take the initiative to adopt the above measures to reduce the rate of mechanical power equipment for increasing EECI; (3) the government can take measures to reduce the use of traditional energy such as coal to adjust the energy structure for improving the EECI. Construction enterprises can increase labor productivity by improving the professional ability and technical level of workers, thus increasing the EECI.

The conclusions and policy implications are summarized above, but this article has some defects. Short-term policy effects are estimated while long-term policy effects are omitted due to the selection of periods. Besides, policy effects and mechanisms analysis cannot be fully explored. Further research is expected to address these issues.

## Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

## Conflicts of Interest

The authors declare no conflicts of interest.

## Authors' Contributions

S.X. conceptualized and supervised the study, administrated the project, and carried out funding acquisition; J.W. developed methodology, helped with software, validated the study, carried out formal analysis, and wrote and prepared the original draft. All authors have read and agreed to the published version of the manuscript.

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