Does China's Carbon Trading Policy Improve Regional Energy Efficiency? —An Analysis Based on Quasi Experimental and Policy Spillover Effects

Xue-mei Zhang

Lanzhou University of Technology

Fei-fei Lu (✉ lufeifei2505@163.com)

Lanzhou University of Technology

Dan Xue

Lanzhou University

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Does China's Carbon Trading Policy Improve Regional Energy Efficiency? —An Analysis Based on Quasi Experimental and Policy Spillover Effects

Xue-mei Zhang¹ • Fei-fei Lu¹ • Dan Xue²

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Abstract

Carbon trading policy is important for addressing climate change and reducing carbon emissions. Reducing carbon emissions could further affect energy efficiency (EE). Based on the data of 30 provinces in China from 2006 to 2017, we first calculated the EE by the super-slack-based model (Super-SBM). We then analyzed the theoretical mechanism of the impact of carbon trading policies on EE. We also established a difference-in-difference model and mediation effect model for empirical analysis. Finally, we used the spatial difference-in-difference (SDID) model to test the policy spillover effect of carbon trading policies. The results showed that the high energy efficiency areas gradually shifted to the central and eastern regions with the change of time in space. At the same time, the energy efficiency value in the pilot area of carbon trading policy is obviously higher than that in the non-pilot area. Carbon trading policy had a significant positive effect on improving EE. Among them, green technology innovation and energy structure both had positive mediation effects on carbon trading policies affecting EE. Additionally, the industrial structuring adjustment had no significant mediation effect in its influencing mechanism. Finally, the spatial spillover effect test results show that the carbon trading policy has a positive effect on the energy efficiency of the pilot areas, but has a negative spillover effect on the energy efficiency of the non-pilot areas. That is, the policy may improve the energy efficiency of the pilot areas and reduce the energy efficiency of the non-pilot areas at the same time.

Keywords: Carbon trading policy; EE; Difference-in-difference model; Mediation effect; Spatial difference-in-difference

Introduction

As the Intergovernmental Panel on Climate Change (IPCC) stressed in its fifth assessment, the main source of greenhouse gases is the heavy use of fossil fuels in the process of industrialization. Excessive emissions of greenhouse gases caused by energy consumption, such as carbon dioxide (CO₂), are believed to be the main cause of such a warming (Li et al. 2018, Ma & Kai 2019, Wang & Liu 2017). The international community is actively exploring practicable solutions to achieve low-carbon develop-

ment to reduce greenhouse gas emissions. As a developing country with the largest greenhouse gas emissions, China is obliged to undertake the important responsibility of carbon emissions reduction (Mu et al. 2018). China plans to peak its carbon dioxide emissions by approximately 2030 and will strive to do so as soon as possible (Jiang et al. 2016, Zhang et al. 2019). To be more specific, China will raise the share of nonfossil fuels in primary energy consumption by approximately 20% and, at the same time, achieve voluntary targeted reductions of 60%-65% (in terms of its 2005 level) in carbon dioxide emission intensity (Du et al. 2018, Li et al. 2019). In 2011, China's National Development and Reform Commission approved carrying out trials for trading carbon in seven localities to achieve these goals, including Beijing City, Tianjin City, Shanghai City, Chongqing City, Shenzhen City, Guangdong Province, and Hubei Province (Zheng et al. 2020b). It launched the first carbon trading market in Shenzhen in 2013. In 2017, the policy was introduced to the power industry nationwide. It is also essential to reduce greenhouse gas emissions and fight against pollution from the input end to reduce fossil energy use. Based on this, China's President Xi Jinping proposed improving the dual control of energy consumption and energy efficiency (EE) by reducing the total amount of

Responsible Editor:

Xue-mei Zhang
148439405@qq.com

Fei-fei Lu
lufeifei2505@163.com

Dan Xue
xuedan2748409@163.com

¹ School of Economics and Management, Lanzhou University of Technology, Lanzhou 730000, China

² School of Economics, Lanzhou University, Lanzhou 730000, China

energy consumption and intensity. Will the current carbon trading policy affect China's total energy consumption and intensity, thus changing China's EE? What is the impact mechanism of carbon trading policy on EE? Are there spillovers from policies? These problems deserve our attention and consideration.

The emission right as a commodity to trade in the carbon market is the essence of carbon trading policy (Song et al. 2018). An enterprise is not allowed to exceed the government's initial carbon quotas in the production process. If it does exceed the quota, the enterprise needs to purchase extra amounts on the carbon market. Profits can be acquired by trading remaining quotas in the carbon market if emissions do not reach the quota. Globally, the European Union and other Western countries' carbon trading systems have gone through the exploration stage of gradual improvement, and the industries and trading projects covered by carbon trading have also gradually been enriched. However, as for China, although carbon trading trials have achieved some results, they are still in the exploratory phase. With rapid development in recent years, the international carbon trading market has begun to take shape, and the carbon emissions covered by the operating carbon market account for 8% of the global carbon emissions. It proves self-evident that the establishment of a global carbon trading system is an inevitable trend. Given this condition, studies on carbon trading are increasingly diversified, and the fields involved are more extensive, such as carbon trading social welfare (Cheng et al. 2015), synergy effects (Fujimori et al. 2015), and carbon trading pricing (Shen & Wang 2019). However, most of the existing studies focus on emissions reduction effects and emission reduction mechanisms of the specific country or region's carbon trading policies (due to fixed carbon trading systems serving a certain country or region). On the one hand, most studies on emissions reductions effects of carbon trading policies believe that carbon trading policies can effectively reduce regional carbon emission intensity (Bayer & Aklin 2020, Guo et al. 2020, Zheng et al. 2020a). On the other hand, it is generally believed that carbon trading policy will adjust industrial structures and improve the efficiency of technological innovation through marketization to achieve the target of emission reductions (Jiang & Ye 2020, Tang et al. 2017, Zang et al. 2020).

Studies on EE have mainly focused on the measurement of EE and its influencing factors. In most cases, various total factor EE measurements of inputs and outputs will be considered for replacing the single factor energy measurement; undesirable outputs will also be included in the index system, but the specific

index composition is different (Antonietti & Fontini 2019, Fang et al. 2013, Liu et al. 2020). There are many factors affecting EE, and it is generally considered that industrial restructuring, technological innovation, and energy structure are the important factors that influence EE. The change in industrial structure greatly influences EE, but different scholars have different views. Some scholars believe that the industrial structure's optimization has a prominent promoting effect on EE growth (Yu 2020). Nevertheless, some researchers have argued that regional differences in industrial structure influence EE (Wang et al. 2019). Under the constraint of carbon, the effect of technological innovation on EE is significantly enhanced, while coal consumption has a significant negative impact on EE (Liu et al. 2020, Peng et al. 2019, Wang & Wang 2019). In addition, other influencing factors, such as economic development levels and openness, are also closely related to EE (Jin & Kim 2019, Lin & Abudu 2020, Yu et al. 2020, Zhongshan et al. 2018). However, there is little research on the impact of carbon trading policies on EE. Some scholars have studied the relationship between environmental regulation and EE from an overall perspective, and three different types of relationships between the two have been presented: positive correlation, negative correlation (Bertrand et al. 2004, Bi et al. 2014, Kneller & Manderson 2012), and nonlinear (Guo & Yuan 2020, Wu et al. 2020). This means that different environmental regulation types may have different effects, but the existing studies have not taken environmental regulation's heterogeneity into account. As a market-oriented means of environmental regulation, it is necessary to study further whether carbon trading policy will produce the above three different effects on China's regional EE.

Our research's main purpose is to determine the impact of carbon emission trading policy on China's regional EE and the regulatory role of green technology innovation, industrial structure adjustment, and energy structure. This paper has two contributions. First, this paper enriches the regional research on the assessment of China's carbon emissions trading policy. Second, few existing studies discuss the impact of carbon emissions trading on China's regional EE from a policy research perspective. This paper further investigates whether green technology innovation, industrial restructuring, and energy structure have mediating effects on regional EE in China.

The remaining parts of this paper are as follows. Section 2 establishes the theoretical model of China's regional carbon trading policy's influence mechanism, analyzes the path of carbon trading policy's influence on China's regional EE, and proposes the research

hypothesis. Section 3 describes the methodology, variables, and models. Section 4 introduces data inspection, model analysis results, robustness checks, and mediation tests. Section 5 presents conclusions and policy implications.

Theoretical model and research hypotheses

Theoretical model analysis

Carbon trading policies regulate the behavior of the output end of enterprises' economic activities through carbon constraints. Enterprises carry on production under the premise that guarantees profit maximization, while the government determines the initial carbon quota and conducts market supervision. For low-carbon enterprises with lower carbon emissions in the manufacturing process, the remaining quota can be traded on the carbon market when the quota is not reached. Therefore, trading earnings could be available for research and development or the expansion of production capacity. For high-carbon enterprises whose carbon emissions may exceed the carbon quota, it is necessary to purchase extra quotas on the carbon market. In other words, the carbon trading policy will form an adverse mechanism in terms of enterprises' environmental behaviors, which forces managers to take corresponding measures to cut carbon emissions. Consequently, carbon trading policies may promote green technology innovation and the adjustment of industrial structure and energy structure, all of which are significant factors affecting energy consumption at the input end of enterprise economic activities. We first established the basic model of the carbon trading policy. We then added green technology innovation, industrial restructuring, and energy structure factors to build the theoretical model of the carbon trading policy's impact on EE.

After implementing the carbon trading policy, assuming that the government's carbon quota is Q and the carbon quota used by enterprises for trading is c , then the carbon quota actually consumed is $Q-c$. If $c \leq 0$, the carbon emissions of the enterprise exceed the quota, and they need to purchase emission credits in the carbon market. The trading price is $P = b - ac$, $a > 0, b > 0$, set as a function of the residual amount of the carbon quota, where b is the initial carbon price and a is the marginal cost of the carbon quota. To implement the carbon trading policy, the income brought by unit carbon emissions to enterprises is greater than the initial market price of carbon trading. Suppose the income brought by unit carbon emissions for the enterprise is m ; then, $m > b$. The payoff function of an enterprise can be expressed as:

$$R_i = m(Q - c_i) + Pc_i \quad (1)$$

When considering green technology innovation, relevant parameters should be added on the basis of model (1). Suppose that part of the profit is z_1 , which is regarded as the cost of green technology innovation, the probability of success of green technology innovation is θ_1 , and the carbon quota consumption of the enterprise decreases by λ_1 times after success. In this case, part μ_1 of the carbon quota saved is used for business transactions, and part $1 - \mu_1$ is used for production, among which $z_1, \theta_1, \lambda_1, \mu_1 \in (0, 1)$. Therefore, on the basis of carbon quota marketization, the carbon quota actually consumed is $(1 - \theta_1 \lambda_1)(Q - c_i)$, the carbon quota savings from green technology innovation are $\theta_1 \lambda_1 (Q - c_i)$, the carbon quota used for trading is $c_{i+1} = c_i + \theta_1 \lambda_1 \mu_1 (Q - c_i)$, and the profit function of the enterprise is:

$$R_{i+1} = (1 - \theta)[m(Q - c_{i+1}) + Pc_{i+1}] \quad (2)$$

When considering the impact of industrial structure adjustment, the relevant parameters of industrial structure adjustment should be added on the basis of model (1). Suppose that part of the profit is z_2 , which is regarded as the cost of industrial structure adjustment, and enterprise carbon quota consumption is reduced by λ_2 times after the adjustment. In this case, part μ_2 of the carbon quota saved is used for business transactions, and part $1 - \mu_2$ is used for production, among which $z_2, \lambda_2, \mu_2 \in (0, 1)$. Therefore, the carbon quota actually consumed is $(1 - \lambda_2)(Q - c_i)$. Based on carbon quota marketization, the carbon quota savings from industrial structure adjustment are $\lambda_2(Q - c_i)$, the carbon quota for trading is $c_{i+2} = c_i + \lambda_2 \mu_2 (Q - c_i)$, and the profit function of the enterprise is:

$$R_{i+2} = (1 - z_2)[m(Q - c_{i+2}) + Pc_{i+2}] \quad (3)$$

When considering the influence of the energy structure, the energy structure's relevant parameters should be added based on model (1). The energy structure mainly refers to the ratio between total energy consumption and the use of fossil fuels such as coal. The more fossil fuels are used, the worse the energy structure is. Suppose that the profit part is z_3 . Taken as the cost of energy structure improvement, the carbon quota consumption of enterprises after a rise in the proportion of fossil fuels increases by λ_3 , among which $z_3, \lambda_3 \in (0, 1)$. The actual consumption of the carbon quota is $(1 + \lambda_3)(Q - c_i)$ after a rise in the proportion of fossil fuels in the energy structure increases. As a result, the growth amount of the carbon quota brought by it is $\lambda_3(Q - c_i)$, the carbon quota used for trading is $c_{i+3} = c_i + \lambda_3(Q - c_i)$, and the profit function of the enterprise is:

$$R_{i+3} = (1 - z_3)[m(Q - c_{i+3}) + Pc_{i+3}] \quad (4)$$

Under the constraints of enterprise profit maximization, the simultaneous solution equations (1), (2), (3), and (4) can be obtained as follows:

$c_i = (b-m)/2a$, $c_{i+1} = (b-m)/2a + \theta_1 \lambda_1 \mu_1 [Q - (b-m)/2a]$, $c_{i+2} = (b-m)/2a + \lambda_2 \mu_2 [Q - (b-m)/2a]$, $c_{i+3} = (b-m)/2a - \lambda_3 [Q - (b-m)/2a]$. The results show that $c_i < 0$, indicating that enterprises still need to purchase carbon quotas from the carbon market to support their production after implementing a carbon trading policy. When $Q \leq (b-m)(\theta_1 \lambda_1 \mu_1 - 1)/2a\theta_1 \lambda_1 \mu_1$, $c_{i+1} \leq 0$, it indicates that the amount of carbon quotas owned by the enterprise is insufficient and additional amounts need to be purchased from the carbon trading market. When $Q > (b-m)(\theta_1 \lambda_1 \mu_1 - 1)/2a\theta_1 \lambda_1 \mu_1$, $c_{i+1} > 0$, the amount of the enterprise's carbon quota is sufficient and is traded with other enterprises that need to augment their carbon quotas. However, However, regardless of the value of Q , it is always true that $c_{i+1} \geq c_i$, which means that green technology innovation reduces the carbon demand of enterprises. When $Q \leq (b-m)(\lambda_2 \mu_2 - 1)/2a\lambda_2 \mu_2$, $c_{i+2} \leq 0$, it indicates that the carbon quota of the enterprise is insufficient and more needs to be purchased from the market. When $Q > (b-m)(\lambda_2 \mu_2 - 1)/2a\lambda_2 \mu_2$, $c_{i+2} > 0$, it means that the carbon quota of the enterprise is sufficient and can be traded on the market. Regardless of the value Q , $c_{i+2} \geq c_{i+1}$ indicates that industrial restructuring can reduce the carbon demand of enterprises more than green technology innovation. When $Q > (b-m)(\lambda_3 + 1)/2a\lambda_3$, $c_{i+3} < 0$, it indicates that the carbon quota amount of the enterprise is insufficient and needs to be purchased from the market; when $Q \leq (b-m)(\lambda_3 + 1)/2a\lambda_3$, $c_{i+3} \geq 0$, it indicates that the carbon quota amount of the enterprise is sufficient and it can trade with other enterprises in the market. Regardless of the value Q , it is always true that $c_{i+3} < c_i$ indicates that the worse the energy structure is, the higher the demand for the carbon quota augmentation will be.

According to the theory of economic growth, based on the Cobb-Douglas production function, the demand function of energy is derived in the form of a cost function, and an EE model is built. Assuming that the production function is Hicks neutral, the production function can be expressed as $Y = Af(K, L, E)$, where Y is output, A is the production technology level of the enterprise, and K , L and E are the factor inputs of capital, labor, and energy, respectively. The goal of enterprise operations is to minimize costs. The cost function of Cobb-Douglas is as follows:

$$C(P_K, P_L, P_E, Y) = A^{-1} P_K^{\alpha_K} P_L^{\alpha_L} P_E^{\alpha_E} Y \quad (5)$$

where P represents the price of the factor, α_K , α_L , and α_E represent the output elasticity of each factor, and $\sum \alpha_i = 1$. According to Sheffield's lemma and the assumption that each element has the same marginal productivity under free competition, the induced demand for any input can be calculated by taking the

partial derivative of the production function, so the partial derivative of the energy price in equation (5) can be obtained:

$$E = \frac{\alpha_E A^{-1} P_K^{\alpha_K} P_L^{\alpha_L} P_E^{\alpha_E} Y}{P_E} \quad (6)$$

For simplicity, we suppose that $P = P_K^{\alpha_K} P_L^{\alpha_L} P_E^{\alpha_E}$ and $E = \alpha_E A^{-1} PY / P_E$. The economic connotation of EE refers to obtaining more services or useful outputs with less energy. The production function Y refers to the output factors after considering the interaction of various input factors. Therefore, Y can be regarded as the effective output, and its ratio to energy input can be regarded as the proxy of EE, namely, EE is expressed as:

$$EE = \frac{Y}{E} = \frac{1}{\alpha_E} \frac{P_E}{P} A \quad (7)$$

On the other hand, enterprises need to include carbon emissions in the production function as a constraint when the government restricts carbon emissions, namely:

$$Y = A\phi(Z)(Q-c)^\eta \quad (8)$$

where Z represents the collection of all input elements and $EE = P_E \phi(Y, Z) / [\alpha_E P(Q-c)]$ can be obtained by substituting (8) into (7). It can be seen that EE is inversely proportional to $Q-c$. The above theoretical analysis has proven that green technology innovation, industrial restructuring, and energy structure optimization all increase the carbon quota c of enterprise transactions, reduce $Q-c$, and improve EE .

Research Hypotheses

From the theoretical model analysis, it can be seen that the carbon trading policy enables enterprises to produce under the constraint of carbon emissions and forces enterprises with high carbon emissions and high pollution to reduce carbon emissions through the cost effect. To maximize profits, enterprises promote green technology innovation, carry out industrial restructuring, and improve their energy structure to improve production quality. In the end, enterprises' demand for carbon quotas increase, and actual carbon quota consumption decreases. EE increases with the reduction of actual carbon quota consumption, which is finally reflected in improving EE promoted by carbon trading policy. Therefore, the following research hypotheses are proposed:

H1: China's carbon trading policy has a significantly positive effect on regional EE.

H2: Green technology innovation, industrial restructuring, and energy structure optimization all play an intermediary role in the influence mechanism

of carbon trading policy on EE, and the effects are all significantly positive.

At the same time, the pilot areas of the policy are the regions with relatively developed economy and perfect infrastructure. The carbon trading policy accelerates the adjustment of production scale of enterprises in pilot regions and promotes green technology innovation of enterprises. But to some extent, it increases the production and operation costs of enterprises. There are a large number of underdeveloped areas in the non-pilot areas. Under the environment of advocating coordinated development among regions, some underdeveloped areas undertake industrial transfer from developed areas as well as pollution transfer from developed areas. Therefore, while reducing carbon emissions in pilot areas, carbon trading policy will force pilot areas to transfer businesses with high energy consumption and high carbon emissions to non-pilot areas, so as to reduce emission reduction costs of enterprises in pilot areas. Therefore, the third research hypothesis is proposed:

H3: While improving the local energy efficiency, the implementation of China's carbon trading policy may promote the transfer of high-carbon emission

production activities to non-pilot areas, thus inhibiting the improvement of energy efficiency in non-pilot areas.

Scope and Methods

Research Scope

Beijing, Tianjin, Shanghai, Chongqing, Hunan, Guangdong, and Shenzhen have implemented carbon trading. Shenzhen belongs to Guangdong Province and implemented its carbon trading policy simultaneously, and so we merged Shenzhen into Guangdong Province. This paper will consider Guangdong Province as an overall pilot and will not consider the pilot's impact in Shenzhen alone. We finally identified six pilot areas: Beijing, Shanghai, Tianjin, Chongqing, Hubei, and Guangdong (see Figure 1). Twenty-four other provincial-level regions, excluding Hong Kong, Macao, Taiwan, and Tibet, will serve as control groups. Considering that the global carbon market has achieved initial success since 2005, the investigation period will be set from 2006 to 2017.

Figure 1. Pilot distribution of China's carbon trading policy pilot.

Methods

Super-Slack Based Model (Super-SBM)

We used the data envelopment analysis (DEA) model to measure the EE of 30 provinces in China.

The DEA model uses a linear programming model to construct a nonparametric "effective frontier," which analyzes the nonparametric technical efficiency allocation of multiple inputs and outputs. The basic BCC model and CCR model are the efficiency measurements of the radial angle. However, when

the decision-making unit's efficiency value is 1, neither of the two models can further analyze the results due to the model's limitation. The measurement of efficiency will cause errors due to the relaxation problems in input, output, and radial selection. Therefore, the improved DEA model is used to measure EE. The super slack-based model (Super-SBM) can still be used to further evaluate the efficiency value of the decision-making unit when the efficiency value reaches 1. The model formula is as follows:

where θ is the effective value, m and s are the input and output, respectively, S_i^- and S_i^+ are the relaxation variables of input and output, respectively, and λ is the weight. In the calculation results, the decision-making units (DMUs) are in a relatively invalid state if the efficiency value of the DMUs is less than 1; the DMUs are in a relatively effective state if the efficiency value of the DMUs can be greater than 1.

$$\min \theta = \frac{1 + \frac{1}{m} \sum_{i=1}^m \frac{S_i^-}{X_{i0}}}{1 - \frac{1}{s} \sum_{r=1}^s \frac{S_r^+}{Y_{r0}}} \quad (9)$$

$$s.t. \begin{cases} X_0 \geq \sum_{j=1, \neq 0}^n X_{ij} \lambda_j - S_i^- (j=1, 2, \dots, m) \\ Y_0 \leq \sum_{j=1, \neq 0}^n Y_{ij} \lambda_j + S_i^+ (r=1, 2, \dots, s) \\ \sum_{j=1}^n \lambda_j = 1; \lambda_j \geq 0; S_i^-, S_i^+ \geq 0 \end{cases}$$

The effect assessment model of carbon trading policies on EE

(1) Parallel trend test

Bertrand et al. (Bertrand et al. 2004) argued that one of the preconditions for the effectiveness of the difference-in-difference (DID) model results is to satisfy the parallel trend hypothesis, that is, for the experimental group and the control group, the changing EE trend of implementing relative policy before and after the implementation of the policy should be consistent, and other factors unrelated to the policy have the same influence on individual EE except for the implementation of the carbon trading policy. Therefore, the parallel trend test is carried out before using the DID model. Event research is used to test the dynamic effects of carbon trading policies empirically. The test model is as follows:

$$EE_{it} = \beta_0 + \sum_{t=2006}^{2017} \beta_t \text{treated} \times \text{time} + \beta_4 \sum \text{Controls} + \gamma_t + \lambda_j + \varepsilon \quad (10)$$

where EE_{it} represents the EE of Chinese provinces and treated represents the implementation variable of the policy. Pilot areas with carbon trading policies are assigned a value of 1, while other areas are

assigned a value of 0. The term time represents the implementation variable of the carbon trading policy. The year before the carbon trading policy (2006-2012) is defined as 0, and the year after the carbon trading policy (2013-2017) is defined as 1. The interaction term $\text{treated} \times \text{time}$ indicates whether each province is affected by the carbon trading policy in each period. If a province or city implements the carbon trading policy in the period, its value is 1 in the current year and later years; otherwise, it is 0. In addition, Controls represents the control variable, γ_t represents the year fixed effect, λ_j represents the region fixed effect, and ε represents the random error term. The term β_t is a series of estimated values from 2006 to 2017. If the estimated results contain 0, the coefficient is not significant; otherwise, the coefficient is significant. If the interaction term coefficient was not significant before the policy's implementation, it was significant after implementing the policy, indicating that there was no significant difference between the control group and the experimental group before the implementation of the policy, and the parallel trend test was passed.

(2) Difference-in-difference (DID) model

The DID model is mainly used to evaluate the implementation effect of public policies. In this paper, we also chose the DID model to analyze the impact of carbon trading policies on EE. The DID model divided the research objects into an experimental group and a control group and compared the influence before and after the policy impact by controlling the two groups' systematic differences. The influence is mainly manifested in two aspects: on the one hand, the "time effect" is formed by time changes or economic development, and on the other hand, the "policy treatment effect" is formed after the implementation of policies. Variables that may affect the research objects are further added to the model. Other influencing factors of the experimental and control groups are controlled to make up for the nonrandom defects in sample allocation to obtain the final policy implementation's real effect.

The model was established as follows: first, two dummy variables of the experimental and control groups were determined. Since the carbon trading policy was officially launched in 2013, the experimental group was defined as the provinces and cities where the policy was implemented. The control group was defined as the rest of the provinces and cities. The carbon trading policy then implemented in 2013 was taken as the time point of policy impact to define the year dummy variable. The years after 2013 and 2013 were defined as 1, and the years before 2013 were defined as 0. The basic form of establishing the DID model is as follows:

$$EE_{it} = \beta_0 + \beta_1 \text{treated} \times \text{time} + \beta_2 \text{treated} + \beta_3 \text{time} + \beta_4 \sum \text{Controls} + \gamma_i + \lambda_j + \varepsilon \quad (11)$$

where the variables are defined in the same way as model (10).

Mediating effect model of carbon trading policy and EE

To test the influence mechanism of carbon trading policy on regional EE in China, we established the mediating effect model, which is as follows:

$$EE_{it} = \alpha_1 \text{treated} \times \text{time} + \sum \beta_s \cdot \text{Controls} + \gamma_i + \lambda_j + \varepsilon \quad (12)$$

$$M = \alpha_2 \text{treated} \times \text{time} + \sum \beta_i \cdot \text{Controls} + \gamma_i + \lambda_j + \varepsilon \quad (13)$$

$$EE_{it} = \alpha_3 \text{treated} \times \text{time} + \alpha_4 M + \sum \beta_j \cdot \text{Controls} + \gamma_i + \lambda_j + \varepsilon \quad (14)$$

where M is the intermediary variable, and the checking procedures are as follows. In step one, we test whether the interaction term coefficient α_1 of carbon trading is significant or not. If the coefficient is significantly positive, a carbon trading policy can improve EE. Step two continues to test whether the coefficients α_2 and α_4 are significant. If both of them indicate that carbon trading policy has a visible impact on the intermediary variable, we proceed to step four. However, step three will proceed if at least one of them is not significant. Step three is to directly test $H_0: \alpha_2 \alpha_4 = 0$ with the bootstrap test method. If the indirect effect is significant, we proceed to step four; otherwise, the analysis will be stopped. In step four, we inspect whether the coefficient α_3 is significant or not. If not, the direct effect is not significant and is only a mediation effect. If the direct effect is significant, the comparison needs to be finished between the symbols of $\alpha_2 \times \alpha_4$ and α_3 . It can be recognized as a partial mediation effect when the absolute value of the total effect α_1 is greater than the absolute value of the direct effect α_3 . The proportion of the mediation effect accounting for the total effect can be expressed as $\alpha_2 \times \alpha_4 / \alpha_1$. Conversely, if it represents a contrary sign and the absolute value of α_1 is less than the absolute value of α_3 , it indicates a masking effect.

Spatial difference-in-difference (SDID) model

As mentioned, through implementing carbon trading policies in pilot areas, the government promotes green technology innovation of enterprises in pilot areas and adjusts energy structure to reduce carbon emissions in pilot areas. However, at the same time, policy implementation imposes certain pressure on technological innovation and industrial structure adjustment of enterprises, and enterprises increase production and operation costs in the process of

controlling carbon emission. Does this mean that the implementation of carbon trading policy encourages enterprises to transfer their high-energy and high-carbon businesses to surrounding provinces and cities? In order to verify this hypothesis, we establish SDID model to test the impact of carbon trading pilot policies on surrounding areas.

$$EE_{it} = \alpha_0 + \alpha_1 \text{did} + \alpha_2 W \cdot \text{did} + \alpha_3 \sum \text{Controls} + \gamma_i + \lambda_j + \varepsilon_{it} \quad (15)$$

Where did means the net effect of carbon trading policy implementation, W means spatial weight matrix. Considering that the economic relationship between adjacent regions is not exactly the same, as shown in Equations (16) and (17), the weight matrix $W1$ of geographical distance and the weight matrix $W2$ of economic-geographical distance are set respectively. Where d represents the Euclidean distance between the two regions, and Y_i and Y_j represent the average per capita GDP of regions i and j during the evaluation period.

$$W1 = \begin{cases} 1/d^2, & i \neq j \\ 0, & i = j \end{cases} \quad (16)$$

$$W2 = W1 * W_Y; W_Y = 1/|Y_i - Y_j| \quad (17)$$

Data and Variables

Considering the availability of data and the consistency of statistical caliber, this paper selected China's 30 provinces, autonomous regions, and municipalities directly under the central government (except for Hong Kong, Macao, Taiwan, and Tibet) of the panel data from 2006 to 2017 as the research sample. These data were derived from each province's *statistical yearbook*, *China's energy statistical yearbook*, *China's statistical yearbook*, and *China's environmental statistical yearbook*.

Dependent Variable

We used the Super-SBM model to calculate EE. The input-output indicators for measuring EE are set as follows. According to current studies on EE measurement, most scholars consider labor, capital, and energy as input factors. The output indicators are divided into desirable outputs and undesirable outputs (Wang & Wang 2019, Yang & Wei 2019, Zhou et al. 2019). Among them, the number of employees at the end of the year is a measure of labor input, capital stock is the measurement index of capital input, and fixed asset investments are taken as the proxy variable in the calculation process for capital stock. Fixed asset investments are converted into real prices in 2005 to eliminate the effect of price. Energy input is measured by total energy consumption. Since undesirable pollutants need to be treated, the level of environmental pollution control is incorporated into the input index,

which is expressed as the total amount of investment in environmental pollution control. The GDP of each region expresses the desirable output. Undesirable outputs include major pollutants such as carbon dioxide emissions caused by energy consumption, industrial sulfur dioxide emissions, and industrial wastewater emissions. Carbon dioxide emissions were calculated according to the IPCC's calculation method (Fang et al. 2015). Based on the above indicators, China's regional EE values were calculated and taken as dependent variables

Explanatory variable

The interaction term $treated \times time$ reflects the net effect of carbon trading policy implementations.

Control variables

Control variables were added to the model to eliminate the interference of influencing factors other than carbon trading policies on the EE level.

Table 1. The control variables and their symbol descriptions.

Control variables	Symbol	The description of variables
Level of economic development	Pgdp	Per capita GDP (RMB: Ten trillion yuan)
The energy structure	Ec	The ratio of total energy consumption to coal consumption
Green technology innovation	Green	The ratio of carbon and sulfur emissions to industrial added value
Level of opening-up	Open	The proportion of total imports and exports of goods to GDP
Energy prices	Ep	Energy consumption fuel, power purchasing price index
Human capital	Pec	Per capita local expenditure on education (RMB: One hundred million yuan)
Industrial restructuring	Inr	The output value of the three industries is given weight

These control variables include the economic development level, energy structure, green technology innovation, level of opening-up, energy price, human capital, and industrial structure adjustment. The level of economic development is measured by per capita GDP (Pan et al. 2020). Since coal is the main energy consumption source, the ratio of total energy consumption to coal consumption reflects the energy structure. Green technology innovation affects EE through technology improvement, expressed as the ratio of carbon and sulfur emissions to industrial added value (Wang et al. 2020). The level of opening-up is represented by the proportion of the total import and export volume of commodities in each region. Energy

prices are expressed as fuel and power purchasing price indexes of energy consumption in various regions (Xu & Wang 2018). Human capital is measured by per capita local education expenditures. The adjustment of industrial structure is weighted by the proportion of the three industries (Liu & Xiao 2017). The control variable description is shown in Table 1.

Discussion

Calculation results of China's regional EE

The super efficiency SBM model is used to measure the energy efficiency of each region. We selected four time nodes in 2006, 2010, 2014 and 2017, and used ArcGIS software to divide the national regional energy efficiency into high level efficiency area, medium high level efficiency area, medium efficiency area, medium low level efficiency area and low efficiency area by Jenks natural breakpoint classification method (as shown in Figure 2), then analyzed the changes in its spatial distribution. As is shown in Figure 2, from the perspective of overall space, the areas with higher energy efficiency gradually shift from the western and northeastern regions to the central and eastern regions over time. In 2006, Xinjiang, Inner Mongolia and Heilongjiang were in the high-efficiency zone, but in 2010, 2014 and 2017, their energy efficiency all fell to the lower zone. In the middle and eastern regions, such as Shandong, Jiangsu, Zhejiang and the central provinces, the energy efficiency gradually improved to a higher efficiency area or high efficiency area from 2006 to 2017. Hainan and Guangzhou have consistently been at high or high efficiency levels. This may be due to the rapid economic development since 2006. Based on the requirements of environmental regulations, some developed regions face high costs when setting up enterprises with high energy consumption and high carbon emission. On the other hand, less developed areas in the central and western regions have relatively light environmental regulation and lower emission costs of environmental pollutants. Therefore, some less developed areas accept industrial transfer from more developed areas. As a result, energy efficiency in the western region declined. In the eastern region, while shifting polluting and energy-consuming enterprises, green technology innovation be accelerated to reduce environmental costs and improve energy efficiency.

In order to further analyze the difference of energy efficiency between the experimental group and the control group, the energy efficiency of each region is divided into the experimental group and the control group. The calculated mean value of EE from 2006 to 2017 is shown in Figure 3.

Figure 2. Distribution of energy efficiency in provinces, municipalities and autonomous regions in 2006, 2010, 2014 and 2017

Figure 3 shows that China's average EE changed from stable to declining from 2006 to 2017. The mean value of EE in the control group (untreated) was roughly the same as the national average. However, it was lower than the overall mean value of EE during the

study period. The average EE of the experimental group showed a steady upward trend and declined slightly after 2015. The average EE of the treated experimental group was higher than the national average.

Figure 3. The average energy efficiency of each province, city, and district from 2006 to 2017. Note: EE denotes energy efficiency.

Since the experimental group includes all relatively developed provinces and cities, it has great advantages in the economic development level and production factor allocation. The treatment of undesired output is better than the control group, so the experimental groups' EE is higher than the

national average level. At the same time, it can be seen that the experimental group promoted the overall EE level.

Parallel trend test results

Figure 4 shows the estimated range of the interaction term coefficient of β_t under the 95% confidence interval. If the estimated range contains 0, the coefficient is not significant; otherwise, the coefficient is significant. The interaction term coefficient was not significant from 2006 to 2011,

indicating that there was no significant difference between the experimental group and the control group before the implementation of the carbon trading policy, while the interaction term coefficient was significant after 2013; that is, there was a significant difference between the two groups after the implementation of the carbon trading policy, so it met the parallel trend test.

Figure 4. Analysis of the dynamic effects of the difference-in-difference model.

Analysis of the impact of carbon trading policies on EE

DID model regression was conducted using Stata software to test the impact and degree of carbon trading policy on EE. The test results are shown in Table 2.

Model (1) showed the regression results without adding control variables, and models (2) to (8) showed the regression results that gradually added control variables. According to model (1), the core explanatory variable's coefficient is 0.171 and significantly positive at the 1% level, indicating that the trials' EE value after the implementation of the carbon trading policy is significantly higher than that of the other areas. The carbon trading policy increases the EE of the trials by 0.171 on average. In the process of gradually joining the control variable, the core variable coefficient of the signs and significance level did not change. Although the symbol representing the economic development level changed from negative to positive, its impact was not significant. The rest of the symbols and significance level of the controlled variables were unchanged, which meant that the estimate results were robust.

In model (8), the coefficient of the core explanatory variable $treated \times time$ is 0.156 and significant at the 1% level, which means that the carbon trading policy increased the trials' EE by 15.6% on average in the case of controlling other variables. This indicated that carbon trading policy limits carbon

emissions at the output end of business activities and positively impacts EE at the input end of economic activities. Improving EE relies on energy policy to directly adjust the energy structure and energy market. It requires the end of the corresponding management measures to force the input energy of high quality.

The coefficients of industrial structure adjustment, energy price, and human capital were significantly negative, while green technology innovation's coefficient was significantly positive. The industrial structure had a negative effect on EE, which means that the empirical results differ from the theoretical hypothesis in the influence direction of industrial structure adjustment. The results showed that in the control of carbon trading policy and other variable conditions, industrial structure adjustment in the "crowding effect" and "free-rider effect" suppresses the promotion of the efficiency of energy (Han et al. 2018). Energy prices had a negative impact on EE, indicating that China's energy market system is not perfect. Although the energy price reform has achieved some results, there is still no mechanism for energy prices to be mainly determined by the market. Since the quality of human capital is an important factor in promoting technological innovation and improving EE, the coefficient of human capital is significantly negative, indicating that education investment has a certain time lag effect on the formation of human capital in the short term, which further affects the quality of human capital and hinders

the improvement of EE. The impact of green technology innovation is significantly positive, indicating that the R&D level promotes green technology innovation, thus improving output

efficiency, reducing energy use, and promoting EE. The test results of economic development level, energy structure, and degree of opening to the outside world were not significant.

Table 2. Test of the impact of carbon trading policy on energy efficiency

Variable	(1) EE	(2) EE	(3) EE	(4) EE	(5) EE	(6) EE	(7) EE	(8) EE
treated×time	0.171*** (4.54)	0.192*** (4.93)	0.173*** (4.6)	0.165*** (4.29)	0.159*** (4.16)	0.166*** (4.22)	0.167*** (4.27)	0.156*** (3.94)
treated	0.283*** (2.71)	0.319*** (2.84)	0.465*** (3.56)	0.461*** (3.56)	0.461*** (3.55)	0.390*** (2.25)	0.380*** (2.64)	0.352** (2.52)
time	-0.12*** (-7.24)	-0.086*** (-3.42)	-0.034 (-1.27)	-0.032 (-0.24)	-0.046* (-1.66)	-0.055* (-0.45)	-0.039 (-1.30)	-0.036 (-1.19)
Pgdp		-0.192* (-1.90)	-0.112 (-1.13)	-0.131 (-1.29)	-0.116 (-1.15)	-0.556 (-0.45)	0.377 (0.29)	0.150 (1.08)
Inr			-0.852*** (-4.66)	-0.845*** (-4.61)	-0.865*** (-4.75)	-0.862*** (-4.73)	-0.858*** (-4.73)	-0.879*** (-4.88)
Ec				0.010 (0.85)	0.010 (0.88)	0.014 (1.13)	0.017 (1.36)	0.017 (1.35)
ln Ep					-0.163** (-1.97)	-0.181** (-2.11)	-0.18** (-2.12)	-0.185** (-2.18)
Open						0.069 (0.86)	0.083 (1.06)	0.121 (1.54)
Pec							-0.00004** (-2.08)	-0.00004** (-2.18)
Green								0.0001** (2.02)
Cons	0.716*** (15.29)	0.756*** (14.05)	2.659*** (6.44)	2.635*** (7.17)	3.441*** (5.95)	3.484*** (5.98)	3.488*** (6.02)	3.491*** (6.05)
Wald chi2	66.26	69.77	94.42	95.37	100.46	101.80	107.43	113.03

Note: *, **, and *** indicate significance at the levels of 10%, 5%, and 1%, respectively. EE denotes energy efficiency. Pgdp denotes the level of economic development. Inr denotes industrial restructuring. Ec denotes the energy structure. ln Ep denotes taking the logarithm of energy prices. Open denotes the level of opening-up. Pec denotes human capital. Green denotes green technology Innovation. Cons denotes constant.

In summary, the net effect of carbon trading policy is significantly positive. The regression coefficient changes little, indicating that the

regression results are robust, and the impact of carbon trading on EE is significantly positive, thus, H1 can be verified.

Robustness check

"False" policy implementation area inspection

Since the carbon trading policy experimental group's province selection was not random, a counterfactual test was conducted to exclude the

possible influence of province selection on the results. Six provinces or cities were randomly selected as "fake" carbon trading pilot areas for regression. If the regression results show that "false" trials also have significant effects on EE, the above empirical tests

869 have problems; otherwise, the empirical tests are
870 credible. The three random samplings results are
871 shown in columns (1) to (3) of Table 3.

872 It can be seen from Table 3 that the main
873 explanations of the impact of carbon trading policy on
874 EE are not significant scalar coefficients. Therefore,

875 the carbon trading policy obtained from random
876 sampling has no impact on EE in the area where the
877 "false" carbon trading policy is implemented,
878 excluding the incidental results of nonrandom
879 sampling in the policy implementation area. Therefore,
880 the credibility of the empirical test is high.

881 **Table 3.** Robustness test results

Variable	"False" policy implementation area inspection			DID test with two lags		Placebo test
	(1)	(2)	(3)	(4)	(5)	(6)
	EE	EE	EE	EE	EE	EE
treated $\times$ time	0.026 (0.71)	0.046 (1.46)	0.012 (0.35)	0.140*** (3.33)	0.151*** (3.26)	0.078 (1.18)
treated	0.086 (0.83)	0.029 (0.32)	-0.155 (-1.49)	0.410** (2.87)	0.360** (2.72)	-0.061 (-0.59)
time	-0.049 (-1.57)	-0.055 (-1.75)	-0.043 (-1.35)	-0.004 (-0.16)	- 0.062*** (-2.33)	-0.152*** (-3.83)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Cons	4.191*** (6.97)	4.128*** (6.92)	4.163*** (6.93)	3.596*** (6.09)	3.208*** (5.28)	3.466* (1.82)

882 Note: *, **, and *** indicate significance at the levels of 10%, 5%, and 1%, respectively. Controls denotes control variable.

883 DID model test with two lags

884 Taking 2014 and 2015 as the policy
885 implementation points, the DID model test is
886 performed again to test the impact of carbon emission
887 trading on EE. The test results are shown in columns
888 (4) and (5) of Table 3. According to the results of the
889 two models, the coefficient of the interaction term is
890 significantly positive. If the policy implementation
891 time is 2014 or 2015, the experimental group's EE is
892 significantly different from that of the treatment group.
893 In other words, the impact of carbon trading policy on
894 EE is multiperiod, and policy intensity has been
895 gradually strengthened in recent years. The results
896 show that the empirical process is robust.

897 Placebo test

898 Further placebo tests were performed to
899 demonstrate the robustness of the model (Topalova
900 & Petia 2010). This paper uses the data before the
901 occurrence of the policy node for testing. Assuming
902 that the policy took place in 2011, 1 was assigned to
903 2011 and 2012, and 0 was assigned to each year before
904 2010. The empirical results are shown in Table 3 in the
905 first column (6). In terms of the model result, the
906 regression coefficient of interaction is not significant,
907 which shows that the assumed carbon trading policy in
908 2011 has no effect on EE and that previous empirical
909 results are reliable.

910 Mediating effect model of carbon trading 911 policy and EE

912 Taking green technology innovation, industrial
913 restructuring, and energy structure as intermediary
914 variables, we used the mediating effect model to
915 determine whether carbon trading policy can affect EE
916 through green technology innovation, industrial
917 restructuring, and energy structure.

918 Green technology innovation was tested as a
919 mediator variable, and the results are shown in Table
920 4.

921 Column (1) in Table 4 represents the test results
922 of formula (12). When no mediation variable is added,
923 the interaction term coefficient notably performs at
924 0.167 under the level of 1%, which means that α_1 is
925 positive. Column (2) shows the regression result of the
926 mediation effect formula (13). In this formula, green
927 technology innovation was taken as the explained
928 variable. The interaction term coefficient of the
929 explanatory variable *treated $\times$ time* was significantly
930 positive at the 1% level, indicating that carbon trading
931 policy has a positive impact on green technology
932 innovation, which means that α_2 is positive. Column
933 (3) shows the regression result of formula (14). The
934 interaction term coefficient of the explanatory variable
935 *treated $\times$ time* is significantly positive at the 1% level.
936 The coefficient of green technology innovation is
937 significantly positive at the 1% level, so both α_3 and
938 α_4 are positive. The absolute value of the total effect

α_1 is greater than the absolute value of the direct effect α_3 , indicating that green technology innovation has a partial mediating effect on the impact of carbon trading policy on EE, and it is a positive mediating effect with the proportion of the mediating effect accounting for the total effect being 0.084.

Table 4. Mediation Effect Test -- Green Technology Innovation

Variable	(1) EE	(2) Green	(3) EE
treated×time	0.167*** (4.27)	100.242*** (3.02)	0.156*** (3.94)
Green			0.00013** (2.02)
Controls	Yes	Yes	Yes
Cons	3.488*** (6.02)	-270.266 (-0.56)	3.491*** (6.05)
N	360	360	360
Wald chi2	107.43	208.46	113.03
$\alpha_2 \times \alpha_4 / \alpha_3$		0.084	

Note: *, **, and *** indicate significance at the levels of 10%, 5%, and 1%, respectively.

The mediating effect of industrial structure adjustment was tested, and the test results are shown in Table 5.

Table 5. Mediation effect Test -- Adjustment of industrial structure

Variable	(1) EE	(2) Inr
treated×time	0.176*** (4.28)	-0.021 (-1.80)
Inr		
Controls	Yes	Yes
Cons	1.417*** (3.47)	2.377*** (20.13)
N	360	360
Wald chi2	84.97	410.63
Bootstrap test	coefficient	95% confidence interval
Mediation effect	-0.0013 (-0.07)	(-0.036, 0.034)

Note: *, **, and *** indicate significance at the levels of 10%, 5%, and 1%, respectively.

In Table 5, column (1) is listed as the baseline regression test result, namely, the mediation effect formula (12). When no mediation variable is added, the interaction term coefficient is significantly positive at 1%. That is, the carbon trading policy improved EE and α_1 was positive. Column (2) is listed as the

regression result of the mediating effect formula (13). At this time, industrial structure adjustment is taken as the explained variable. The interaction term coefficient of the explanatory variable is - 0.021 but not significant, so the bootstrap test method is directly used. The test results showed that the 95% confidence interval of indirect effects included 0, and the indirect effects were not significant, so the analysis was stopped. The mediating role of industrial structure adjustment in the impact of carbon trading policy on EE was not significant, and its relationship with EE had certain complexity. Moreover, only emphasizing the quantitative growth in the three industrial outputs cannot enhance EE. We should focus on technological progress and resource allocation efficiency in industrial development and pay attention to industrial structure adjustment quality.

The energy structure was tested as a mediator variable, and the results are shown in Table 6.

Table 6. Mediation effect test -- Energy structure

Variable	(1) EE	(2) EE	(3) EE
treated×time	0.162*** (4.17)	0.587*** (3.28)	0.156*** (3.94)
Ec			0.017 (1.35)
Controls	Yes	Yes	Yes
Cons	3.492*** (6.06)	-2.285 (-0.88)	3.49*** (6.05)
N	360	360	360
Wald chi2	110.36	101.86	113.03
Bootstrap test	coefficient	95% confidence interval	
Mediation effect	0.082** (2.40)	(0.015, 0.149)	
$\alpha_2 \alpha_4 / \alpha_3$		0.523	

Note: *, **, and *** indicate significance at the levels of 10%, 5%, and 1%, respectively.

In Table 6, column (1) is listed as the test result of formula (12). When the mediation variable is not added, the interaction term coefficient is significantly positive at the 1% level, which is positive. Column (2) shows the regression result of the mediation effect formula (13). At this time, the energy structure is taken as the explained variable. The interaction term coefficient of the explanatory variable is significantly positive at 1%, indicating that the carbon trading policy has a positive impact on the energy structure, which is positive. Column (3) shows the regression result of the mediation effect formula (14). The interaction term coefficient of the core explanatory variable was significantly positive at the 1% level, which is 0.156.

998 The energy structure's coefficient was also positive at
 999 the 1% level but not significant, so the bootstrap test
 1000 method was used for testing. The test results show that
 1001 the 95% confidence interval of indirect effects does not
 1002 include 0, so the indirect effects were significant. In
 1003 addition, the coefficient of α_3 was positive and
 1004 significant in column (3), the sign $\alpha_2 \times \alpha_4$ was the
 1005 same as α_3 , and the absolute value of the total effect
 1006 α_1 was greater than the absolute value of the direct
 1007 effect α_3 , indicating that the energy structure has a
 1008 partial mediating effect on the influence of carbon
 1009 trading policy on EE, and it is a positive mediating
 1010 effect. The proportion of the mediating effect
 1011 accounting for the total effect is 0.523.

1012 In summary, carbon trading policy affects EE
 1013 through green technology innovation and energy
 1014 structure, both of which have positive mediating
 1015 effects. However, the mediating role of industrial
 1016 structure adjustment in the impact of carbon trading
 1017 policy on EE is not significant. As a market-based
 1018 means of environmental regulation, carbon trading
 1019 policy, on the one hand, forces enterprises to reduce
 1020 inefficient use of fossil energy consumption and
 1021 promotes the optimal allocation of low-carbon
 1022 resources. On the other hand, we consider carbon
 1023 emissions a constraint to force enterprises to eliminate
 1024 backward capacity through green technology
 1025 innovation and ultimately improve EE. The complexity
 1026 and long-term industrial structure adjustment led to its
 1027 insignificant effect on EE. Thus, the hypothesis H2 is
 1028 not entirely true.

1029 Spatial spillover effect test of carbon trading 1030 policy implementation on energy efficiency

1031 Before the regression of the model, Moran's I test
 1032 was carried out on the residual term, energy efficiency
 1033 and other major variables of the model to judge its
 1034 spatial correlation. The results show that the model has
 1035 significant spatial correlation, which mean the study
 1036 meets the premise of spatial econometric analysis.

1037 Regression analysis was carried out on Equation
 1038 (16) and the empirical results are shown in Table 7.
 1039 Compared with the basic model (1), the net effect of
 1040 carbon trading increases after adding the weight matrix
 1041 of geographical distance and the weight of economic
 1042 geographical distance. Model (2) uses the spatial
 1043 weight of geographical distance, and the policy
 1044 dummy variable is significantly positive at the level of
 1045 1%. Model (3) uses the spatial weight of economic
 1046 geographical distance, and the policy dummy variable
 1047 is significantly positive at the level of 5%. However,
 1048 the regression coefficients of spatial terms of the two
 1049 models are negative at the significance level of 1% and
 1050 5%, respectively. These instructions that carbon
 1051 trading pilot policy implementation of local energy
 1052 efficiency has a positive role in promoting, but the
 1053 implementation of the pilot carbon trading policy in

1054 other areas of energy efficiency exist negative spillover
 1055 effect, namely the energy efficiency of non-pilot areas
 1056 decreases after the implementation of carbon trading
 1057 policy. This indicates that the implementation of
 1058 carbon trading policy may lead the enterprises in pilot
 1059 areas to transfer their high-carbon and high-energy
 1060 businesses to non-pilot areas in order to reduce
 1061 production and operation costs. Therefore, H3 was
 1062 validated.

1063 **Table 7.** Spatial effect test of carbon trading policy

Variable	(1) EE	(2) EE	(3) EE
did	0.156*** (3.94)	0.170*** (3.57)	0.159*** (3.42)
W*did		-0.194*** (-2.58)	-0.426** (-2.53)
Controls	Yes	Yes	Yes
Time fixed effect	Yes	Yes	Yes
Individual fixation effect	Yes	Yes	Yes
Cons	3.491*** (6.05)	1.235*** (2.66)	0.945** (1.99)
Direct effect		0.164*** (3.24)	0.139** (2.52)
The indirect effect		-0.194* (-1.86)	-0.631* (-1.81)
The total effect		-0.029 (-0.22)	-0.493 (0.203)
N	360	360	360

1064 Note: *, **, and *** indicate significance at the levels of
 1065 10%, 5%, and 1%, respectively.

1066 Due to the spatial spillover effect of explanatory
 1067 variables on energy efficiency, the spatial spillover
 1068 effect is further divided into direct effect and indirect
 1069 effect. Table 7 shows that the direct effect of model (2)
 1070 and model (3) is significantly positive at the level of 1%
 1071 and 5%, respectively, while the indirect effect is
 1072 significantly negative at the level of 10% and 5%,
 1073 respectively. Whether measured by geographical
 1074 distance or economic geographical distance, the
 1075 implementation of carbon trading policy has a positive
 1076 impact on the energy efficiency of pilot areas, but a
 1077 negative impact on the energy efficiency of non-pilot
 1078 areas, and the negative impact is greater than the
 1079 positive impact. This means that the influence of
 1080 carbon trading in pilot area policy effect is limited,
 1081 while the carbon trading policy promotes the
 1082 improvement of energy efficiency in pilot areas, the
 1083 lower energy efficiency in non-pilot areas limits the
 1084 improvement of overall energy efficiency. Therefore,
 1085 it is the key to improve the overall energy efficiency to
 1086 further promote the construction of the national carbon
 1087 trading market, especially to raise the threshold for
 1088 non-pilot areas to undertake industrial transfer, and to

1089 formulate reasonable carbon quotas in combination
1090 with the responsibility of carbon emission reduction.

1091 **Conclusions and recommendations**

1092 This paper established a theoretical model of the
1093 relationship between carbon trading policy and EE and
1094 proposed research hypotheses. We also used the DID
1095 model and the mediation effect model to test China's
1096 carbon trading policy's influence mechanism on
1097 regional EE. The combination of these main points
1098 leads to the following conclusions:

1099 First, from the perspective of space, the high
1100 energy efficiency areas gradually shifted to the central
1101 and eastern regions over time, indicating that the
1102 pollution from the eastern region may transfer to the
1103 western region. In terms of time, the EE in those trials
1104 implementing carbon trading policy is significantly
1105 higher than that in other areas in China, indicating that
1106 carbon trading policy can significantly promote
1107 regional EE. This means that carbon trading policy can
1108 effectively reduce the total consumption and intensity
1109 of fossil energy and improve the production efficiency
1110 and quality of industries with high pollution and
1111 emissions. Similarly, the impact of carbon trading
1112 policy on EE is also manifested in multiple periods. As
1113 time goes by, the policy intensity is gradually
1114 strengthened, indicating that EE improvement depends
1115 on the direct regulation effect of energy policies and
1116 forces the input energy to realize high-quality input
1117 through market-based means of terminal governance.

1118 Second, green technology innovation and energy
1119 structure both play a positive mediating effect in the
1120 process of EE affected by carbon trading policy, and
1121 the mediating effect of energy structure is far greater
1122 than that of green technology innovation. However, the
1123 mediating effect of industrial structure adjustment is
1124 not significant. This indicates that carbon trading
1125 policy can reduce pollutant emissions and inefficient
1126 energy input while promoting green technology
1127 innovation and energy structure optimization, thus
1128 improving EE. The adjustment of industrial structure
1129 in the mediating effect test was not significant. The
1130 negative influence of industrial structure on EE still
1131 exists in evaluating the effect of carbon trading policy.
1132 It clearly demonstrates that a long period of complex
1133 adjustment processes is necessary for the industrial
1134 structure, the advantages of structural effects are not
1135 fully exerted in the present adjustment of industrial
1136 structures, and at the same time, there is also no policy
1137 synergy among industrial policy, carbon trading
1138 policy, and energy policy.

1139 Thirdly, the SDID model test shows that the
1140 implementation of carbon trading policy has a positive
1141 effect on the energy efficiency of the pilot areas, but

1142 has a negative spatial spillover effect on the energy
1143 efficiency of the non-pilot areas, which suggest that the
1144 implementation of carbon trading policy reduces the
1145 energy efficiency of the non-pilot areas. At the same
1146 time, the decomposition of spatial spillover effect
1147 shows that the direct effect of carbon trading policy is
1148 positive, while the indirect effect is negative, and the
1149 absolute value of the indirect effect is greater than the
1150 direct effect. This indicates that the EE in non-pilot
1151 areas has pulled down the overall energy efficiency,
1152 indicating that the implementation of carbon trading
1153 policies in pilot areas has a limited impact on energy
1154 efficiency.

1155 This paper's recommendations are as follows:
1156 first, China needs to further expand the implementation
1157 area and coverage of carbon trading policies,
1158 strengthen policy enforcement, and promote EE
1159 improvements in other provinces, cities, and districts.
1160 According to the regional economic and resource
1161 endowment, China must also optimize resource
1162 allocation efficiency, improve its ability to manage
1163 pollution, use resource utilization to manage pollution,
1164 adjust contradictions in regional energy optimization
1165 reform, and utilize carbon interaction trading with
1166 energy policy. Second, it needs to further promote the
1167 industry-wide implementation of carbon trading
1168 policies at the regional industrial level, accelerate
1169 legislation in the carbon trading market, gradually form
1170 a nationwide carbon trading market system, reasonably
1171 set the access conditions for the carbon trading market,
1172 give full play to the role of market mechanisms, and
1173 enhance the effectiveness of carbon trading policies.
1174 Third, China must speed up its optimizing energy
1175 structure, reduce the proportion of fossil energy use,
1176 deepen supply-side structural reform in the energy
1177 sector, guide the transition to clean energy, and
1178 strengthen the connection among overall energy
1179 strategic planning and industrial and regional planning.
1180 Besides, it must establish incentive mechanisms for
1181 innovation by relying on tax relief and financial
1182 subsidies, giving full play to the policy advantages and
1183 economic advantages in trials, encouraging large-scale
1184 enterprises to explore new fields of energy technology
1185 actively, leading the way in establishing low carbon
1186 innovation mechanisms, exerting the demonstration
1187 effect of the innovation industry, and driving other
1188 areas to reduce emissions and improve EE. Fourth, it
1189 must consummate industrial structure adjustment
1190 policy in the center of EE, pay attention to the
1191 technological progress and resource allocation
1192 efficiency in the process of industrial development,
1193 strengthen the supervision over the industrial structure
1194 adjustment of "three high and one capital" (high cost,
1195 high pollution, high energy consumption, resource-
1196 based), and improve the quality of industrial structure

adjustment. Simultaneously, attention should be paid to the interaction between industrial policies and other institutional measures, such as carbon trading policies, and give play to synergies between policies better. Fifth, considering the spatial spillover effect of carbon trading policies on energy efficiency, the construction of the national carbon trading market needs to pay attention to the balanced development and orderly process to avoid the spatial transfer caused by unbalanced development. At the same time, it is necessary to raise the threshold for non-pilot areas to undertake industrial transfer, earnestly adhere to the principle of "common but differentiated responsibilities" for regional carbon emission reduction, share the responsibility for carbon emission reduction between regions, and formulate reasonable carbon quotas in combination with the responsibility for carbon emission reduction

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Figures

Figure 1

Pilot distribution of China's carbon trading policy pilot. Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.

Figure 2

Distribution of energy efficiency in provinces, municipalities and autonomous regions in 2006, 2010, 2014 and 2017. Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.

Figure 3

The average energy efficiency of each province, city, and district from 2006 to 2017. Note: EE denotes energy efficiency.

Figure 4

Analysis of the dynamic effects of the difference-in-difference model.