Impact and Acting Path of Carbon Emission Trading on Carbon Emission Intensity of Construction Land: Evidence from Pilot Areas in China

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Abstract: Recently, the environmental and resource crisis caused by excessive energy consumption has aroused great concern worldwide. China is a major country of energy consumption and carbon emissions, and has attempted to build a carbon emission trading market to reduce carbon emissions. This practice helps to promote the carbon trading projects for both regional carbon emission reduction and sustainable development in the pilot areas, as well as having important theoretical and practical significance for the further improvement of carbon emission trading policies. In this study, we first used the difference-in-difference (DID) model to evaluate the impact of carbon emission trading on the carbon emission intensity of construction land (CEICL). The results showed that the carbon emission trading policy can significantly reduce CEICL in the pilot areas. Furthermore, we adopted the quantile regression model to explore the mechanism and acting path of carbon emission trading on CEICL. The results show that the increase in carbon trading volume (CTV) can effectively reduce the CEICL. However, a high carbon trading price (CTP) tends to reduce the suppressing effect of carbon emission trading on CEICL. Additionally, carbon emission trading also affects CEICL through the indirect acting paths of industrial structure and energy intensity. Finally, we propose to promote regional low-carbon development from the perspective of developing a carbon emission trading market nationwide, rationalizing the carbon quota and trading price mechanism, optimizing the regional industrial structure, and improving the energy consumption structure.

Keywords: carbon emission trading; carbon emission intensity; construction land; difference-in-difference (DID); quantile regression; acting path

1. Introduction

Along with the continuous development of economy, the massive increase in carbon dioxide emissions caused by fossil energy consumption has caused increasingly serious environmental problems such as global warming. Meanwhile, global climate change has also evolved from an issue of single science and technology to a complex environmental, political, and economic issue, arousing particular concern and attention worldwide. According to the International Energy Agency, China surpassed the United States to rank the first in carbon emissions in 2007. Due to rapid urbanization, it is still facing continuous increases in carbon emissions. In this case, the Chinese government has pledged to reduce its carbon emissions generated per unit of GDP (carbon emission intensity) by 40–45% before 2020 relative to those of 2005. Under the multiple pressures of reducing carbon emissions, resource demands, and environmental protection, China has made a series of explorations and efforts, such as controlling energy consumption. Accordingly, the Chinese government launched a pilot project of local carbon
emission trading in 2011, which covered the areas of Beijing, Tianjin, Shanghai, Guangdong, Shenzhen, Hubei, and Chongqing. The project aims to control greenhouse gas emissions and lower the cost of emissions reduction through market mechanisms, as well as provide guidance for the establishment of a carbon emission trading market nationwide.

At present, China’s carbon emission trading market is mainly aimed at high-carbon emission enterprises to assist them to reduce greenhouse gas emissions at lower costs [1]. Construction land is the most important land type for carrying out various social and economic activities such as population, construction, transportation, and industrial production; additionally, it is also characterized by high energy consumption and high carbon emissions [2]. The carbon emission intensity of construction land is dozens or even hundreds of times that of other land types [3]. Therefore, effective control of carbon emission intensity of construction land (CEICL) is extremely important for China to achieve low carbon and sustainable development. However, it remains unknown whether market-based carbon emission trading is possible to effectively alleviate the increase in CEICL and what the possible acting path and mechanism are. Obviously, addressing these issues will help a better understanding of the relationship between the carbon emission trading and CEICL and provide empirical evidence and experience for policy promotion.

With the continuous advancement of China’s carbon emission trading, related pilot projects have gradually become a hotspot of research. Previous research can be summarized by the following aspects. First, some studies are focused on carbon emission trading policies, market construction, system management, operational status, and problems in pilot areas. For example, Weng et al. [4] evaluated the development and current status of China’s carbon emission trading market and further proposed relevant policy suggestions to optimize the carbon emission trading market. Yi et al. [5] constructed a three-dimensional index system, and a total of 34 sub-indices were used to comprehensively evaluate the development of seven pilot areas of carbon trading in China. Deng et al. [6] compared the potential risks of China’s carbon emission trading market, the European Union Emission Trading Scheme, and California’s cap-and-trade system. They found that there are major risks in China’s carbon trading pilot areas. Second, some scholars have studied the carbon quota allocation, carbon tax, and carbon price in the carbon trading market. For instance, Kong et al. [7] combined the data envelopment analysis (DEA) model and entropy method to simulate the carbon quota allocation in 30 provinces of China from the perspectives of equality and efficiency. Ding et al. [8] established a diffusion model to explore the possible impact of different carbon tax conditions on the diffusion of energy technology in China. Wang et al. [9] used the European Union Emissions Trading Scheme as a case to study the bidirectional interactions between trading behaviors and carbon prices. Dutta et al. [10] adopted a bivariate dynamic conditional correlation (DCC-) GARCH model to examine the impact of carbon price risk on the rapeseed oil market, finding that a volatile carbon price would lead to uncertainty in the rapeseed oil price index. Third, some studies have been carried out to evaluate the effectiveness of carbon emission reduction in carbon trading pilot areas and its impact on the economic environment. For example, Li et al. [11] adopted a dynamic computable general equilibrium model embedded in the carbon trading block and designed eight scenarios based on the corresponding industry carbon emission baseline and free quotas ratios, which can simulate the impact of China’s carbon emission trading on the overall economy. Dong et al. [12] used the difference-in-difference (DID) method and improved data envelopment analysis (DEA) model to determine whether the China Emissions Trading Scheme can bring economic and environmental dividends. Zhang et al. [13] evaluated the inhibitory effect of carbon trading intensity on carbon emission trading scheme (ETS) based on six provincial pilots and pilot industries covered by ETS. Xuan et al. [14] adopted a DID model to explore the effect of carbon emission trading on carbon emission reduction.

The existing literature provides an important reference for understanding carbon emission trading policy and lays the foundation for subsequent research. However, first of all, most studies have been focused on the impact of carbon emission trading on carbon emissions reduction [1,14], and few studies have been carried out on the CEICL. Currently, high-carbon emission enterprises on construction land
are the main target of China’s carbon emission trading. Additionally, construction land is also a direct manifestation of industrialization and urbanization, and the level of CEICL is closely related to regional low-carbon sustainable development. Here, we used the regional CEICL instead of that of individual enterprises as the unit to analyze the impact of carbon emission trading on CEICL. The study aims to more fully explore the impact of carbon emission trading on social and economic development and more intuitively evaluate the effectiveness of carbon emission trading market. Secondly, the existing research has been mainly focused on simulating the impact of carbon emission trading and testing the policy effects [11–13], while the indirect acting path of policy has been largely ignored. Further exploration of the internal drive and external assistance of the carbon emission trading mechanism in pilot areas can provide a good demonstration for the implementation of carbon trading policies. Therefore, we took the seven pilot areas in China to test the effect of carbon emission trading on the CEICL by the DID method and explored the impact mechanism and acting path of carbon emission trading on the CEICL using a quantile regression model. The findings are expected to expand the analytical perspective and framework of carbon emission trading policy, as well as provide reference for establishing a carbon trading market nationwide in China.

The rest of this paper is organized as follows. Section 2 presents the research basis; Section 3 describes the methodology and data; Section 4 focuses on the DID testing and results to verify the effect of carbon emission trading on the CEICL; Section 5 explores the impact mechanism and acting path of carbon emission trading policy on the CEICL; and Section 6 summarizes the conclusions and proposes policy implications.

2. Research Basis

2.1. Development and Current Status of China’s Carbon Emission Trading

Carbon emission trading is a market mechanism to reduce CO$_2$ emissions by taking CO$_2$ emission rights as a commodity for trading. The Kyoto Protocol signed in 1997 first proposed an innovative path to take advantage of the market mechanism to solve the problem of greenhouse gas emissions represented by CO$_2$, namely CO$_2$ emission trading [5]. Thereafter, carbon emission trading markets have been gradually developed and flourished in Europe and America under the promotion of Copenhagen, Cancun, and the Durban meeting. Under this background, China launched the pilot project of carbon emission trading in 2011, including Beijing, Tianjin, Shanghai, Guangdong, Shenzhen, Hubei, and Chongqing as the pilot areas. The seven pilot areas are located in the eastern, central, and western regions of China, covering the three administrative levels of provinces, municipalities, and cities. Moreover, these pilot areas also include regions with low energy consumption intensity and the third industry as the pillar industry, as well as economically developed and sub-developed regions driven by high energy consumption. In June 2013, Shenzhen took the lead in seven pilot areas in the establishment of a carbon emission trading market, and finished related work such as system design, data verification, quota allocation, and institution building. Subsequently, carbon emission trading centers were established in other pilot areas.

The carbon emission trading market has been very active in China since its establishment. The carbon trading volume and price of the seven pilot areas have shown a significant upward trend, but the growth rate has gradually slowed down (Figure 1). These results show that with the development of a carbon emission trading market, enterprises gradually adapt to the carbon emission constraint environment and begin to develop low-carbon production modes, and the carbon emission trading market also tends to be relatively stable. In 2017, China’s carbon intensity had dropped by about 46% compared with that in 2005, and the goal of reducing carbon intensity by 40–45% was achieved three years ahead the schedule. The accumulative carbon trading volume in the seven pilot areas was 133.09 million tons, and the accumulative carbon trading price was 2.713 billion yuan. Among them, the accumulative carbon trading volume and price in the Hubei pilot area are both the highest (48.91 million tons and 911.02 million yuan, respectively), accounting for 36.75% and
33.57% of the total. The accumulative carbon trading volume of Guangdong, Shenzhen, and Shanghai accounted for 24.16%, 18.30%, and 7.52% of the total carbon trading volume, while that of Beijing, Tianjin, and Chongqing together accounted for 13.25% of the total trading volume. The total carbon emissions and intensity of industrial enterprises covered by the carbon emission trading market have achieved both carbon reduction and economic development, providing valuable experiences for the construction of China’s carbon emission trading market. In December 2017, China announced the implementation of a national unified carbon emission trading system, which takes the advantage of market mechanisms to reduce carbon emissions and promote green and low-carbon development.

![Image](http://www.tanpaifang.com/)

**Figure 1.** Overview of carbon trade pilot areas in China from 2013 to 2017. Source: [http://www.tanpaifang.com/](http://www.tanpaifang.com/).

2.2. **Mechanism Underlying the Effect of Trading on Carbon Emissions**

As an important market-based regulatory tool [4], carbon emission trading aims to reduce carbon emissions at the lowest cost, actively respond to climate change, and promote regional green and low-carbon development. At present, the carbon emission trading market has shown certain positive effects on the control of greenhouse gas emissions in China’s pilot areas, indicating that it is an effective way to promote low carbon development. Overall, the effects of trading on carbon emissions can be summarized as follows.

(1) Direct effect of trading on carbon emissions. First of all, from the perspective of economics, carbon emission trading follows the Coase Theorem, that is, internalization of external costs through the explicit definition of property rights. Carbon emission trading is the internalization of negative externalities of carbon emissions, which regard carbon emissions as non-public good. Under the control of the existing total carbon emission volume and carbon trading mechanism, the internalization of carbon emissions will lead to increases in production and operation costs. To pursue profit maximization, the enterprises will take full account of the trade-off between the costs and benefits of purchasing carbon emission rights and technological transformations, which may greatly help to promote energy conservation and emission reduction. Secondly, carbon emission trading is mainly operated through the market mechanism. It uses the price of carbon emission rights as the market signal, which is equivalent to setting a green threshold for high-energy and high-emission projects. This threshold can inhibit the expansion of existing high-carbon emission enterprises, eliminate inefficient and backward production, direct the transfer of capital to low-carbon green development, improve the optimal allocation and effective utilization of low-carbon resources, and thus achieve regional carbon emission reduction.
(2) Indirect effect of trading on carbon emissions. The carbon trading mechanism is extremely complex and involves a variety of factors including economics, energy, environment, and trading policies. Ren et al. [15] believes that reducing carbon emission intensity mainly depends on the adjustment of industrial structure, optimization of energy structure, and upgrade of technology. Firstly, carbon emission trading uses market mechanisms to constrain carbon resources, which will eventually guide the flow of carbon resources to enterprises with higher competitiveness and utilization rate. Under this mode of operation, the regional industrial structure will be optimized for carbon emission trading [16], which will then promote the upgrading of industrial structure and reduce carbon emissions. Secondly, the Porter hypothesis believes that reasonable and appropriate environmental regulations will encourage the innovation of enterprises [17]. Faced with the constraints of the carbon emission trading mechanism, enterprises will consider more long-term interests and development, thus generating a series of demands for low-carbon energy. Especially, the technological transformation of high-energy consumption and high-carbon emission enterprises will effectively promote the adjustment and optimization of energy structure, such as reducing the exploitation of traditional fossil energy and promoting the use of clean energy and energy utilization efficiency, which will together reduce carbon emissions effectively. Thirdly, with the improvement of the economy, the level of household consumption has been continuously rising. Under the guidance of a series of low-carbon policies, the concept of low-carbon consumption and life has been gradually strengthened, which can effectively promote the enthusiasm and initiative of regional emission reduction. At the same time, carbon emission trading, as a kind of financial activity, closely links financial activities and the real economy. It uses market means to increase the profits of carbon emission reducers and the necessary economic costs of carbon emission contributors. Thus, it can more effectively stimulate the development of regional energy conservation and emission reduction.

Therefore, we believe that carbon emission trading not only affects carbon emissions in a direct manner, but also indirectly reduces the emissions through some transmission factors such as adjustment of industrial structure, optimization of energy structure, technological progress, and economic development.

3. Methodology and Data

3.1. Methodology

The difference-in-difference (DID) model, which was proposed by Ashenfelter and Card [18] for the first time and has received widespread attention from sociologists, is an effective method to assess the effectiveness of policies. The DID model has also been widely used for evaluation of policies in recent years [12,19–22]. Therefore, we employed the DID model to assess the policy effect of China’s carbon emission trading in reducing CEICL. In addition, we combined the panel quantile regression model to more accurately and comprehensively explore the impact mechanism and acting path of carbon emission trading on CEICL. Additionally, Stochastic Impacts by Regression on Population Affluence and Technology (STIRPAT) was used to support the selection of the impact indicators of CEICL.

3.1.1. Difference-in-Difference Model

In order to determine whether carbon emission trading can effectively reduce the CEICL, we adopted the carbon emission trading pilot policy as a quasi-natural experiment to construct the DID model. The core of the DID is to set up a treatment group that implements the policy and a control group that does not. The effect of the policy is evaluated by observing the difference between the treatment group and control group in a certain indicator before and after the implementation of the policy. Additionally, other control variables can be added into the model to eliminate the interference factors to some extent, which may help to overcome the defect that the natural experiment cannot
be completely random in sample distribution, thus achieving a more objective evaluation of the effectiveness of the pilot policy.

In 2011, China’s National Development and Reform Commission issued the “Notice on Carrying out the Carbon Emissions rights Trading Pilot Work”. According to the plan of pilot work in the carbon emission trading market of China, seven pilot areas of Beijing, Tianjin, Shanghai, Shenzhen, Chongqing, Hubei, and Guangdong were used as study subjects. As the investigation was at the province level, Shenzhen was included into Guangdong Province. Thus, the treatment groups included Beijing, Tianjin, Shanghai, Chongqing, Hubei, and Guangdong, and the non-pilot provinces were taken as the control group (due to the limit of data availability, Tibet, Hong Kong, Macao, and Taiwan were not included). On this basis, we set the assessment model for the impact of carbon emission trading on the CEICL as:

$$Y_{it} = \beta_0 + \beta_1 did_{i,t} + \beta_2 treated + \beta_3 time + ax_{i,t} + \epsilon_{i,t}$$

(1)

where $Y_{it}$ is the CEICL in the $t$ year of $i$ area; $treated$ is used to distinguish the treatment group and the control group ($treated = 1$ and $treated = 0$ indicate that the area is a pilot and non-pilot area of carbon emission trading, respectively); $time$ is the policy time dummy variable (with $time = 1$ and $time = 0$ representing the period after and before the implementation of the trading policy, respectively); according to the carbon emission trading pilot plan, we assigned the time before 2011 as 0, and that after 2011 (including 2011) as 1; $did$ is the core variable that examines whether carbon trading policies can effectively reduce CEICL, and an interaction term of $time$ and $treated$; a significantly positive value of $\beta_1$ indicates that the carbon emission trading does not reduce the CEICL, while a significantly negative $\beta_1$ value represents that it can significantly reduce the CEICL; $x_{i,t}$ represents other control variables, including time and region fixed effects; $\epsilon_{i,t}$ is an error term.

3.1.2. Quantile Regression Model

In order to explore the impact mechanism and acting path of carbon emission trading on CEICL, CEICL was used as the dependent variable, and carbon trading volume (CTV) and the carbon trading price (CTP) were introduced as independent variables to indicate the implementation degree of carbon emission trading policy. Based on the above theoretical analysis, we selected the relevant control variables and constructed a general panel regression model as follows:

$$Y_{it} = \beta_{i,t} + \sum \beta_n x + \sum \beta_m Controls + \epsilon_{i,t}$$

(2)

where $Y_{it}$ represents the CEICL in the $t$ year of $i$ area; $x$ represents the core explanatory variables, including CTV and CTP, for which the data were derived from the China Carbon Emissions Trading Network (http://www.tanpaifang.com/); $ Controls$ indicates other control variables; $\beta_n$ and $\beta_m$ represent the corresponding regression coefficients; $\epsilon_{i,t}$ is an error term.

Quantile regression, which was first proposed by Koenker and Bassett [23], is actually an extension of ordinary least squares (OLS) regression that uses multiple quantile functions to estimate the overall model. In comparison, OLS regression is a simple mean regression, which mainly aims to examine the influence of independent variables on the conditional expectation $E(y|x)$ of the dependent variable. It can only reveal the central tendency of the conditional distribution of an independent variable, but can hardly comprehensively reveal the different influence of an independent variable in different quantiles on the conditional distribution $y|x$. However, quantile regression can provide all the information about the conditional distribution $y|x$. At the same time, the minimum objective function used in quantile regression is based on the weighted average of the absolute values of the residuals, which is not susceptible to extremes or outliers, and the parameter results are more robust. Therefore, we used the panel quantile regression to more accurately examine the impact mechanism and acting path of carbon emission trading on CEICL as follows:

$$Q_{Y_{it}|X_{it}}(\tau) = X_{it}'\beta(\tau) + \alpha_i$$

(3)
where $Y_i$ and $X_i$ represent the explained and explanatory variables, respectively; $\tau$ is the quantile value set at the time of estimation; $\beta(\tau)$ represents the regression coefficient of the model in the $\tau$ quantile; $a_i$ is the individual specific fixed effect parameter. We assign the values of 0.1, 0.25, 0.5, 0.75, and 0.9 to the quantiles of $\tau$.

### 3.1.3. STIRPAT Model

Dietz and Rosa [24] proposed the STIRPAT model based on the IPAT model ($I = PAT$, $I =$ Human Impact, $P =$ Population, $A =$ Affluence, $T =$ Technology), which is widely used to analyze the influencing factors on regional carbon emissions, and the formula is as follows:

$$ I = aP^bA^cT^d $$

where $I$, $P$, $A$, and $T$ represent the environmental pressure, population, affluence, and technological progress, respectively; $a$ is the constant term; $b$, $c$, and $d$ represent the coefficients of $P$, $A$, and $T$, respectively; $e$ is the residual error.

The STIRPAT model is a multivariate nonlinear model. By taking the logarithm to get a linear mode, the equation can be further presented as follows:

$$ \ln I = \ln a + b \ln P + c \ln A + d \ln T + \ln e $$

Based on the existing research results, theoretical analysis, and STIRPAT model [25,26], we selected the impact indicators that affect CEICL. The environmental pressure ($I$) is measured by CEICL; population ($P$) is decomposed into population size (POP) and urbanization rate (UR); affluence ($A$) is decomposed into real GDP per capita (PGDP); and technological progress ($T$) is decomposed into industrial structure (IS) and energy intensity (EI).

### 3.2. Variable Selection and Measurement

CEICL is the carbon emission per unit area of construction land. A high value of CEICL indicates high carbon emissions on the construction land in the region, as well as greater carbon emission reduction pressure and environmental burden [27]. Carbon emissions from construction land are mainly from anthropogenic energy consumption. Therefore, some indirect estimates of energy consumption are usually used to evaluate CEICL during the construction land use process. Considering the availability of data and the existing research results, we selected eight major energy sources: raw coal, coke, crude oil, fuel oil, gasoline, kerosene, diesel, and natural gas [28]. The CEICL was calculated according to the unified standard method recommended by the IPCC Guidelines [2,29]. The calculation formula is as follows:

$$ CEICL = CE/S = \left( \sum E_n \cdot M_n \cdot \phi_n \right) / S $$

where $CEICL$ represents the carbon emission intensity of construction land; $CE$ indicates the carbon emission carried by construction land; $S$ represents the construction land area; $n$ stands for the number of energy types; $E_n$ represents the consumption of energy $n$; $M_n$ is the standard coal coefficient of energy $n$; and $\phi_n$ represents the carbon emission coefficient of energy $n$.

We also controlled other indicators that may affect the CEICL. (1) POP was measured by the total population at the end of the year; UR was measured by the proportion of urban population to total population, which is an indicator to comprehensively reflect the population density and lifestyle of the area. As the urban lifestyle is more energy-consuming, it should have a greater impact on the carbon emission from construction land. (2) PGDP was measured by GDP per capita, which is an indicator to reflect the level of regional economic development. That is, the greater the GDP per capita of a region, the higher the degree of economic development in the region. However, higher economic output requires more energy, which may increase the CEICL. (3) IS was measured by the share of output from secondary industries in GDP. The level of industrialization is an important factor
affecting the carbon emission from construction land. Thus, industrial restructuring will help to alleviate the contradiction between economic development and energy consumption. EI was measured by the energy consumption per unit of GDP, which directly reflects the efficiency of energy use. The optimization of energy structure and improvement of efficiency will effectively reduce CEICL.

3.3. Data Sources

The panel data of 30 provinces and municipalities (excluding Tibet, Hong Kong, Macau, and Taiwan) in China from 2007 to 2017 were taken as the research sample. The data were mainly derived from the China Statistical Yearbook, China Energy Statistical Yearbook, China Urban Construction Statistical Yearbook, and the provincial statistical yearbooks. The economic data of each region were adjusted to the base period of 2007 to eliminate the price impact. In order to more intuitively reflect the changes of the variables in the pilot and non-pilot areas during the non-pilot period (2007–2010) and the pilot period (2011–2017), we examined the changes in the mean values of the main variables and used the ratio method for comparative analysis (Table 1). As shown in Table 1, the mean value of CEICL in pilot areas is lower than that of non-pilot areas before and after the implementation of carbon emission trading policy. After the implementation of carbon emission trading, the mean value of CEICL in pilot areas decreases from 1.437 to 1.368, while that in non-pilot areas increases from 2.070 to 2.119. Additionally, the implementation of carbon emission trading decreases the ratio of the mean CEICL of the treatment group to that of the control group by 0.049. The mean values of other control variables in pilot and non-pilot areas show significant changes before and after the implementation of the trading policy. The significant difference between the treatment group and control group provides an important basis for the follow-up research.

| Variables | Before Pilot (2007–2010) | After Pilot (2011–2017) | Ratio Change |
|-----------|---------------------------|--------------------------|--------------|
| lnCEICL   | 1.437                     | 1.368                    | −0.049       |
| lnPOP     | 8.016                     | 8.118                    | 0.009        |
| lnUR      | 4.200                     | 4.280                    | −0.023       |
| lnIS      | 3.771                     | 3.662                    | −0.013       |
| lnPGDP    | 10.570                    | 10.444                   | −0.012       |
| lnEI      | 0.614                     | 0.661                    | −0.066       |

4. DID Testing and Results

In this section, we first analyzed the empirical results of DID, namely the impact of the carbon emission trading on the CEICL, and further conducted the pre-hypothesis test and robustness test of the empirical results.

4.1. DID Estimation Results

Firstly, the DID model was used to test the impact of the carbon emission trading on CEICL. In order to accurately estimate the regression model, we sequentially estimated the model without control variables, the model with the control variables, and the model with the control variables and time and region fixed effect.

Model (1) is a baseline model without any control variables. Model (2) is a model that controls the time fixed effect based on Model (1). In Model (3), control variables such as POP, UR, PGDP, IS, and EI are added on the basis of Model (1). Model (4) controls time effects again with additive region fixed effects on the basis of Model (3). The estimation results are shown in Table 2. It can be seen that with additive control variables and fixed effects, the value of R-squared increases from 0.945 to 0.970, indicating that the model fitting effect is improved. There is no obvious change in the significance
and coefficient symbols of the core variable “did”, indicating that the estimation results of the model are relatively stable. Therefore, we used the estimated values of Model (4) for interpretation analysis. As a result, the estimated coefficient of carbon emission trading for CEICL is about −0.099. The average CEICL in the pilot areas is 1.296 in 2017, presenting a decrease of approximately 7.638%, which is significantly higher than that calculated by Zhou et al. [30] in 2014 (about 1.9%). These results indicate that the implementation of the carbon emission trading policy can significantly inhibit the increase of CEICL in the pilot areas.

### Table 2. Difference-in-difference (DID) estimation results.

| Variables | Model (1)         | Model (2)         | Model (3)         | Model (4)         |
|-----------|------------------|------------------|------------------|------------------|
| did       | −0.1179 ***      | −0.1179 ***      | −0.1075 ***      | −0.0997 ***      |
|           | (−3.49)          | (−3.79)          | (−3.37)          | (−3.06)          |
| time      | 0.0489 ***       | −0.0290          | 0.1260 ***       | 0.2574 **        |
|           | (2.94)           | (−0.67)          | (6.35)           | (2.19)           |
| treated   | −0.6222 ***      | −0.6222 ***      | −0.4253 ***      | −0.4640 ***      |
|           | (−14.82)         | (−12.89)         | (−3.01)          | (−3.21)          |
| lnPOP     | 0.0188           |                  | −0.2661          |                  |
|           | (0.08)           |                  | (−0.94)          |                  |
| lnUR      | −0.6934 ***      | −0.5803 ***      |                  |                  |
|           | (−3.39)          | (−2.80)          |                  |                  |
| lnIS      | 0.0985           |                  | −0.0301          |                  |
|           | (1.34)           |                  | (−0.35)          |                  |
| lnPGDP    | 0.4906 ***       | 0.3224 ***       |                  |                  |
|           | (5.37)           | (3.16)           |                  |                  |
| lnEI      | 1.6167 ***       | 1.6269 ***       |                  |                  |
|           | (9.47)           | (9.02)           |                  |                  |
| cons      | 1.7053 ***       | 1.6995 ***       | −2.2423          | 1.7566           |
|           | (110.48)         | (58.03)          | (−1.10)          | (0.61)           |
| Year fixed effect | NO | YES | NO | YES |
| Province fixed effect | YES | YES | YES | YES |
| N         | 330              | 330              | 330              | 330              |
| F         | 358.0275         | 355.4447         | 359.3544         | 367.8947         |
| R-squared | 0.9456           | 0.9577           | 0.9672           | 0.9702           |
| p         | 0.0000           | 0.0000           | 0.0000           | 0.0000           |

Note: The figures in parentheses are the robust standard deviation; *** denotes the significant level at 1%; ** denotes the significant level at 5%.

### 4.2. Parallel Trend Test

An important premise for the effectiveness of the DID model is that if the carbon emission trading pilot policy is not implemented, the trend of CEICL in pilot and non-pilot areas should be parallel. We followed the method of Jacobson et al. [31] and used event analysis to perform a parallel trend test. The following test model was built:

\[
Y_{it} = \alpha + \sum_{k=-3}^{3} \beta_k \times D_{i,t0+k} + \eta_t + \gamma_t + \epsilon_{i,t} \tag{7}
\]

where \(Y_{it}\) represents the CEICL in the \(t\) year of \(i\) area; \(D_{i,t0+k}\) is a series of dummy variables that represent the \(k\)-th year in which the pilot policy begins to be implemented; \(t_0\) represents the first year in which the \(i\) area implements carbon emission trading; \(k\) stands for the \(k\)-th year since the implementation of the carbon emission trading policy; \(\beta_k\) indicates the difference in CEICL between the treatment group and the control group in the \(k\)-th year of the implementation of the trading policy. A relatively flat trend of \(\beta_k\) during \(k < 0\) validates the parallel trend hypothesis; conversely, a significantly fluctuating development trend of \(\beta_k\) during the \(k < 0\) period indicates that the treatment group and control
group already had significant differences before the policy was implemented and thus violates the parallel trend hypothesis. Figure 2 shows the results of the $\hat{\beta}_k$ estimation parameters. The trend is relatively flat before the implementation of the policy, and the coefficient of $\hat{\beta}$ drops significantly after the implementation of the policy ($k = 0$). This result indicates that there is a difference between the treatment group and control group, and the carbon emission trading policy significantly reduces the CEICL in pilot areas, which satisfies the preconditions for evaluating the impact of the policy by using the DID.

![Figure 2. Parallel trend test.](image)

### 4.3. Robustness Test

In order to test the robustness of the empirical results, we referred to the study of Zhang et al. [22], and still used 2011 as the initiation time of the policy to conduct the DID estimation by varying the investigation period. Specifically, we performed DID evaluation for the 2 years, 3 years, and 4 years since 2011. Table 3 shows the significance of the coefficients. The regression coefficient of the core variable “did” is negative, and passes the test at a 5% significance level, indicating the robustness of the results. Moreover, in any time period and whether the control variables are included or not, the effectiveness of the carbon emission trading policy shows no obvious changes, suggesting that the implementation of carbon emission trading policy contributes to the decline of CEICL in the pilot areas.

| Variables | 2011–2013 | 2011–2014 | 2011–2015 |
|-----------|-----------|-----------|-----------|
| did       | Model (5) | Model (6) | Model (7) | Model (8) | Model (9) | Model (10) |
|           | $-0.0960^{***}$ | $-0.0682^{**}$ | $-0.1139^{***}$ | $-0.0922^{***}$ | $-0.1137^{***}$ | $-0.0961^{***}$ |
| time      | (2.95)    | (2.02)    | (3.68)    | (2.72)    | (3.94)    | (2.91)    |
| treated   | 0.0942$^{***}$ | 0.0350    | 0.0538$^{*}$  | 0.0025    | 0.0001    | 0.0115    |
|           | (3.46)    | (0.35)    | (1.75)    | (0.02)    | (0.00)    | (0.11)    |
| lnPOP     | $-0.6531^{***}$ | $-0.6292^{***}$ | $-0.6559^{***}$ | $-0.5760^{***}$ | $-0.6592^{***}$ | $-0.5818^{***}$ |
|           | (23.53)   | (3.88)    | (25.14)   | (3.70)    | (25.18)   | (4.02)    |
|           | 0.2525    | 0.2566    | 0.0893    |           |           |           |
|           | (0.72)    | (0.83)    |           |           |           |           |

Table 3. Results of robustness test.
Table 3. Cont.

| Variables          | 2011–2013 | 2011–2014 | 2011–2015 |
|--------------------|-----------|-----------|-----------|
|                    | Model (5) | Model (6) | Model (7) | Model (8) | Model (9) | Model (10) |
| lnUR               | −0.3282   | −0.4265 **| −0.4825 ***|          |          |          |
|                    | (−1.50)   | (−2.14)   | (−2.69)   |          |          |          |
| lnIS               | −0.1071   | −0.0588   | −0.0447   |          |          |          |
|                    | (−0.69)   | (−0.45)   | (−0.42)   |          |          |          |
| lnPGDP             | 0.6073 ***| 0.5902 ***| 0.4954 ***|          |          |          |
|                    | (4.49)    | (4.66)    | (3.95)    |          |          |          |
| lnEI               | 1.6308 ***| 1.5588 ***| 1.3984 ***|          |          |          |
|                    | (6.19)    | (7.82)    | (7.74)    |          |          |          |
| cons               | 1.6697 ***| −6.0309   | 1.6732 ***| −5.6288 *| 1.6815 ***| −3.0135   |
|                    | (86.54)   | (−1.58)   | (77.24)   | (−1.74)  | (71.04)   | (−1.04)   |
| Year fixed effect  | YES       | YES       | YES       | YES       | YES       | YES       |
| Province fixed effect | YES       | YES       | YES       | YES       | YES       | YES       |
| N                  | 210       | 210       | 240       | 240       | 270       | 270       |
| F                  | 881.6003  | 555.3539  | 811.5524  | 563.9221  | 701.6984  | 598.6219  |
| R-squared          | 0.9707    | 0.9774    | 0.9691    | 0.9771    | 0.9684    | 0.9760    |
| p                  | 0.0000    | 0.0000    | 0.0000    | 0.0000    | 0.0000    | 0.0000    |

Note: The figures in parentheses are the robust standard deviation; *** denotes the significant level at 1%; ** denotes the significant level at 5%; and * denotes the significant level at 10%.

5. Impact Mechanism and Acting Path of Carbon Emission Trading on CEICL

The above results suggest that the carbon emission trading policy significantly reduces the CEICL in the pilot areas. On this basis, we further explored the impact mechanism and acting path of carbon emission trading on CEICL.

5.1. Direct Acting Path of Carbon Emission Trading on CEICL

The stata15.0 software was used to perform the regression based on the quantile regression model, and the results are shown in Table 4. From Model (11), it can be seen that the regression coefficient of carbon trading volume (CTV) is significantly negative and passes the significance test, suggesting that the increase in CTV will inhibit the CEICL. Specifically, with increasing quantiles of CTV, the absolute value of the regression coefficient of CTV shows a fluctuating trend: it decreases first, followed by increases and then decreases (−0.023 → −0.021 → −0.012 → −0.021 → −0.019). These results indicate that the CTV in low and high quantiles significantly reduces the CEICL, but that in the middle quantiles has a weaker effect. Therefore, the effect of CTV on reducing the CEICL in low or high areas is significantly greater than that in the middle areas.

Table 4. Estimation results through the quantile regression.

| Variables | 0.1 | 0.25 | 0.5 | 0.75 | 0.9 | 0.1 | 0.25 | 0.5 | 0.75 | 0.9 |
|-----------|-----|------|-----|------|-----|-----|------|-----|------|-----|
| lnCTV     |     |      |     |      |     |     |      |     |      |     |
|           | −0.0231 *** | −0.0206 ** | −0.0120 * | −0.0200 ** | −0.0196 ** | 0.0188 | 0.534 | 0.00764 |     |
|           | (0.00689) | (0.0103) | (0.00649) | (0.0117) | (0.00904) | (0.212) | (0.381) | (0.394) | (0.301) |
| lnCTA     |     |      |     |      |     |     |      |     |      |     |
|           | 0.00911 | 0.00339 | 0.00669 | 0.0230 | 0.0279 * | 0.00970 | 0.0372 | 0.00262 | 0.0193 |
|           | (0.0107) | (0.0181) | (0.0114) | (0.0205) | (0.0159) | (0.0110) | (0.0197) | (0.0118) | (0.0204) |
| lnPOP     | −0.799 | −0.768 | −0.503 | 0.328 | 0.337 | −0.0338 | 0.250 | −0.311 | 0.323 |
|           | (0.474) | (0.801) | (0.506) | (0.910) | (0.705) | (0.509) | (0.916) | (0.548) | (0.948) |
| lnUR      | −1.299 *** | −1.115 ** | −0.826 *** | −0.664 | −0.298 | −1.406 *** | −0.833 | −0.963 ** | −0.877 | −0.662 |
|           | (0.290) | (0.489) | (0.309) | (0.556) | (0.431) | (0.322) | (0.579) | (0.346) | (0.599) |
| lnIS      | −0.0749 | −0.0693 | −0.116 | −0.120 | −0.173 | −0.0625 | −0.0248 | −0.0885 | −0.100 | −0.0187 |
|           | (0.0914) | (0.154) | (0.0975) | (0.175) | (0.136) | (0.0905) | (0.163) | (0.0974) | (0.169) | (0.129) |
| lnPGDP    | 0.341 *** | 0.279 ** | 0.236 | 0.257 | 0.299 ** | 0.191 | 0.298 ** | 0.338 | 0.622 ** |
|           | (0.113) | (0.190) | (0.120) | (0.216) | (0.168) | (0.115) | (0.206) | (0.123) | (0.213) |
| lnEI      | 0.992 *** | 1.121 *** | 1.285 *** | 1.360 *** | 1.755 *** | 0.828 *** | 1.092 *** | 1.322 *** | 1.427 *** | 2.251 *** |
|           | (0.212) | (0.358) | (0.226) | (0.406) | (0.315) | (0.208) | (0.374) | (0.224) | (0.387) | (0.296) |
| lnCTV×lnIS | −0.0110 | −0.0242 | −0.0338 | −0.0356 | −0.0190 | −0.0190 | −0.0342 | −0.0205 | −0.0354 | −0.0207 |
| lnCTV×lnPGDP | −0.00172 | −0.0398 | −0.00776 | 0.00407 | 0.0152 | (0.0170) | (0.0306) | (0.0183) | (0.0317) | (0.0242) |
Table 4. Cont.

| Variables      | Model (11) |          | Model (12) |          |
|----------------|------------|----------|------------|----------|
|                | 0.1  | 0.25 | 0.5  | 0.75 | 0.9  | 0.1  | 0.25 | 0.5  | 0.75 | 0.9  |
| lnCTV×lnEI     | 0.0393 | −0.0688 | 0.137 | 0.269* | 0.310** | 0.0859 | (0.155) | (0.0925) | (0.160) | (0.122) |
| Constant       | 8.603** | 7.831  | 5.286 | −1.009 | −2.926 | 4.124 | 0.193 | 3.646 | −1.716 | 4.287 |
|                | (3.314) | (5.601) | (3.540) | (6.364) | (4.934) | (3.473) | (6.251) | (3.736) | (6.466) | (4.933) |
| N              | 210  | 210  | 210  | 210  | 210  | 210  | 210  | 210  | 210  | 210  |

Note: The figures in parentheses are the robust standard deviation; *** denotes the significant level at 1%; ** denotes the significant level at 5%; * denotes the significant level at 10%.

From the regression coefficient of carbon trading price (CTP), only the 0.9 quantile is positive and passes the significance test, implying that in areas of the middle and low quantiles, CTP has no significant effect on CEICL, but increases the CEICL in high quantiles, which will reduce the effectiveness of carbon emission trading in suppressing CEICL. This result may be due to the fact that excessive CTP will increase the economic pressure in areas, which in turn reduces the activity of the carbon trading market.

5.2. Indirect Acting Path of Carbon Emission Trading on CEICL

The interaction term can represent the internal transmission mechanism and thus can be used to test the effect of the internal interaction of various influencing factors on the CEICL. Therefore, we further considered the interaction of carbon emission trading policies, and used CTV to characterize their implementation, with the addition of multiplicative interaction terms to explore the impact mechanism and indirect acting path of carbon emission trading on CEICL. The quantile regression model was used for analysis, and the results are shown in Table 4.

From Model (12), the regression coefficient of the multiplicative interaction term of CTV and IS (CTV×IS) passes the significance test in the quantiles of 0.50, 0.75, and 0.90, with the values of −0.036, −0.059, and −0.088, respectively. These results indicate that carbon emission trading can effectively reduce the CEICL by the acting path of the industrial structure. Specifically, in areas with low CEICL, the indirect effects of carbon emission trading are not significant, but in areas with high CEICL, carbon emission trading acts on the industrial structure to curb the increase in CEICL. These results may be due to the fact that in high-carbon emissions regions, the industrial structure is still dominated by the secondary industry. At the same time, the internal structure of the secondary industry is also unreasonable, leading to relatively high pressure on carbon emissions reduction. In order to reduce the extra costs caused by excess carbon emission, enterprises use technology and other means to reduce carbon emissions and control carbon emissions within the total carbon quotas. Thus, carbon trading will play a role in promoting regional carbon reduction. The regression coefficient of the multiplicative interaction term of CTV and PGDP (CTV×PGDP) does not pass the significance test in different quantiles, indicating that regional economic development is not a significant acting path for carbon emission trading policy to affect the CEICL. The regression coefficient of the multiplicative interaction term of CTV and EI (CTV×EI) has significantly fluctuating coefficients in different quantiles. The coefficient only passes the significance test in the quantiles of 0.75 and 0.90, with the values of 0.269 and 0.310, respectively. These results indicate that in the low quantile, energy intensity is not a significant acting path by which carbon emission trading policy affects the CEICL. However, in regions with high CEICL, the carbon emission trading policy has a greater impact on CEICL through the acting path of energy intensity. At this stage, most of the areas with higher CEICL are still in the coal-dominated energy structure and extensive industrial development model, which has increased energy consumption and reduced energy efficiency. The use of carbon emission trading as the threshold can inhibit the expansion of high energy-consuming and carbon-emission enterprises as well as eliminate the inefficient and backward production behaviors. These effects will promote regional carbon emission reduction, and may be an effective path for reducing carbon emissions in the future.
The above analysis shows that in areas with low CEICL, carbon emissions can be effectively reduced through the increase in CTV. In other words, it is effective to reduce carbon emissions by promoting the enthusiasm of regional enterprises to participate in carbon emission trading through appropriate incentives. In areas with high CEICL, the carbon emission trading market can also further effectively affect CEICL through the indirect acting paths of IS and EI.

6. Conclusions and Policy Implications

In this study, China’s carbon emission trading pilot areas were used as a case to study the effect of carbon emission trading on the CEICL by the DID model. The results show that carbon emission trading policy can greatly facilitate the reduction of the CEICL in pilot areas, which was further validated by a robustness test. On this basis, we used the quantile regression model to further explore the impact mechanism and acting path of carbon emission trading on the CEICL. The results show that CTV has a negative effect on the CEICL. With increasing quantiles, the absolute value of the regression coefficient of CTV shows a fluctuating trend: it decreases first, followed by increases and then decreases \((-0.023\rightarrow-0.021\rightarrow-0.012\rightarrow-0.021\rightarrow-0.019\)\), indicating that the effects of CTV on reducing CEICL in low or high areas are significantly greater than those in the middle areas. At the same time, excessive CTP will also reduce the effectiveness of carbon emission trading in curbing CEICL.

In addition, it remains unclear whether carbon emission trading reduces CEICL through the acting path of economic development, yet carbon emission trading was found to effectively affect the CEICL through the indirect acting paths of industrial structure and energy intensity. Specifically, in areas with low CEICL, the effect of carbon emission trading on CEICL is not obvious through the indirect acting path of industrial structure and energy intensity. As the quantile increases, the regression coefficient rises continuously. In other words, in areas with high CEICL, carbon emission trading enhances the regulation and control of CEICL by acting on industrial structure and energy intensity paths.

Through the above research and analysis, we propose the following policy implications corresponding to our conclusions. First, the development and completion of the carbon trading market should be continuously promoted nationwide. The empirical results of this paper prove that carbon emission trading can effectively inhibit the increase in CEICL, so as to achieve the goal of regional green development under the framework of carbon emission reduction. The carbon emission trading pilot areas can provide reference and enlightenment for the comprehensive implementation of the carbon trading market nationwide, and standards of carbon emission trading should be established based on the empirical results. Second, the carbon quota and trading price mechanism should be improved. Carbon emission trading is based on clear market price signals. Excessive free carbon quotas will result in low carbon emission trading prices, which will weaken the regulatory effect of carbon emission costs and green thresholds; however, too low free quotas will cause the short supply in the carbon trading market, which will result in high production costs and inactive carbon trading. Hence, we should give full play to the role of market regulation, the overall control of the government, scientific design of carbon quotas and distribution plans, rational setting of carbon emission prices, maintenance of stable market operations, and promotion of the enthusiasm of enterprises, so as to promote the overall low-carbon green development of the region. Third, the regional industrial structure should be optimized. With the addition of the multiplicative interaction term, in areas with high CEICL, carbon emission trading can effectively suppress the increase in CEICL by acting on the industrial structure. Therefore, it is highly necessary to optimize the regional industrial structure and use carbon emission trading to set up a “green threshold” for enterprises to gradually eliminate inefficient and backward production and develop an advanced industrial structure. Fourth, the energy consumption structure should be upgraded. Carbon emission trading can contribute to a significant decline in CEICL by stimulating technological innovation and promoting energy structure adjustment. Therefore, it is essential to rationally control the total energy consumption and carbon emissions and make full use of the regulatory role of the carbon trading mechanism; additionally, the use of clean energy should be encouraged and energy efficiency should be improved. These practices
together may help to achieve the dual goals of low-cost carbon emission reduction and sustainable regional development.

There are some limitations in our research that should be further improved as well. First, only the first seven pilot areas in China were used as the subject of the research, which may not fully reflect the impact of carbon emission trading on the CEICL in China. Therefore, we may further expand the scope of the sample in future research. Second, with the establishment of a carbon trading market nationwide, the relationship between carbon emission trading and CEICL can be examined from a national perspective. Additionally, we selected the indicators that affect the CEICL based on the STIRPAT model and existing research results. However, the carbon emission trading policy may have dynamic changes. Hence, the impact indicators selected in this study may have certain limitations. In future research, we will further improve the selection of indicators in order to more fully explore the impact of carbon emission trading on CEICL.

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