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Empirical analysis of the impact of China's carbon emissions trading policy using provincial-level data

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Abstract
Investigating the impact of carbon emissions trading policy and elucidating the underlying mechanisms are crucial for enhancing policy effectiveness and refining related systems. This study examines the impact of carbon emissions trading policy by constructing a difference-in-difference model utilizing unbalanced panel data from China's provinces spanning the period from 2005 to 2019. Additionally, a mediating effect model is employed to delve into the underlying mechanisms. The key findings are as follows: Firstly, the implementation of carbon emissions trading policy has a notable inhibitory impact on carbon emissions. Secondly, both the upgrading of industrial structure and the reduction of energy intensity play mediating roles in carbon emissions reduction. However, the development of clean energy industries does not exhibit a significant mediating effect. In conclusion, this study offers policy recommendations aimed at facilitating carbon reduction. These include enhancing the market-based trading mechanism for carbon emissions, optimizing and upgrading industrial structures, fostering innovation in green and low-carbon technologies, and promoting the development and utilization of clean energy.

Keywords Carbon emissions, Market-oriented mechanism, Difference-in-difference, Mediating effect

Introduction

The concept of carbon emissions trading originated from the emissions trading schemes implemented within domestic environmental policy in the United States during the last century. Emissions trading schemes were first widely implemented in the United States and later globally, emerging as a core mechanism for addressing climate change. According to a report published by World Bank, the United States experienced an annual GDP growth rate reduction of 2.59% in the decade following 1973, which was partially attributed to the implementation of stringent environmental protection policy. This observation suggests that traditional approaches to environmental protection might have carried significant economic costs. Consequently, there was a growing need for the

United States to explore more market-oriented and cost-effective strategies to promote sustainable environmental protection. In 1982, various states in the United States implemented cap-and-trade systems for greenhouse gas emissions, allowing companies with differing pollution treatment costs to trade emissions allowances. This policy was highly supported by businesses as both buyers and sellers could potentially benefit from the trading opportunities it offered. However, the level of support and its actual impact on emissions reduction remain topics of further investigation.

Promoting carbon emissions trading is crucial in addressing global climate change, as an increasing number of countries embrace the construction of carbon trading markets. The ultimate objective in China's pursuit of achieving "carbon peak" and "carbon neutrality" is to mitigate carbon emissions. Carbon emissions trading policy represents crucial practice in the mitigation of greenhouse gas emissions, as it utilizes market mechanisms to incentivize emission reductions and promote sustainable development (Cao et al. 2021; Zhang and Wu 2022; Jiang et al. 2022). The utilization of market-oriented mechanisms for mitigating greenhouse gas emissions represents a significant institutional advancement in promoting low-carbon development, which is conducive to overcoming the constraints posed by resources and the environment (Yildiz and Caliskan 2021; Kumar et al. 2022). From the initiation of the pilot carbon emissions trading scheme in 2013 to the establishment of a nationally unified carbon emissions trading market in 2021, carbon emissions trading policy has exhibited positive implications for environmental regulation in China (Qxab et al. 2022).

How is the effectiveness of carbon emissions trading policy, and what is the internal mechanism by which it achieves emissions reduction? Scholars have differing opinions on whether the carbon emissions trading policy can stimulate economic development. However, there is general consensus that the policy is beneficial for improving green total factor productivity. The academic community generally agrees on the role of carbon emissions trading policy in reducing emissions. However, there are differing views regarding the specific way in which the policy achieves emissions reduction, which requires further investigation and clarification. The potential contributions of this paper lie in further clarifying the emissions reduction impact and internal transmission mechanisms of a specific type of carbon emissions trading policy. Additionally, it aims to provide both supplementary and deeper insights into the current research domain of "carbon peak" and "carbon neutrality", particularly focusing on implementation mechanisms.

Method

Research hypothesis

About the effects of carbon emissions trading policy

The transaction cost theory, originated by Ronald H. Coase, suggests that when asset specificity is low, uncertainty regarding the transaction is minimal, and the frequency of transactions is high, and if property rights can be clearly defined and the transaction cost is lower, the market equilibrium will result in an efficient and Pareto-optimal resource allocation (Ke et al. 2021). Carbon emissions levels are high in the industrial sector, therefore, given its significant contribution to overall greenhouse gas emissions, it emerges as a prime target for carbon reduction strategies (Ka et al. 2022). This policy aims to establish a carbon emissions trading market for industrial enterprises. By doing so, it encourages these enterprises to internalize the environmental costs associated with their carbon emissions, thus promoting a more sustainable and environmentally responsible business model (Jl et al. 2022). As a result, the carbon emissions allowance has emerged as an intangible factor of production, effectively requiring industrial enterprises, as consumers, to acquire this factor in order to carry out their production activities. This transformation underscores the increasing importance of carbon management in industrial operations. In the context of industrial enterprises, the primary objective is to optimize economic returns, often in the form of profits. As a result, the implementation of carbon emissions trading schemes is expected to significantly influence the production decisions and behaviors of these enterprises (Wang et al. 2022; Envelope and Mk 2022). This paper employs a profit function, specifying the form and its application in the context of carbon emissions trading, along with graphical representations, to comprehensively analyze the impact of carbon emissions trading policy on the production behavior of enterprises operating within a defined environmental and policy framework.

The enterprise profit function can be expressed as follows:

$$\pi = TR + (kQ - aQ)b - TC \tag{1}$$

By differentiating Formula (1) and subsequently setting the derivative equal to zero, we can derive the conditional formula for profit maximization as follows Formula (2):

$$MR + (k - a)b{=}MC \tag{2}$$

In the above formulas, kQ is the established carbon emissions quota of enterprises stipulated by the government, a is the carbon emissions coefficient of enterprises, b is the market carbon quota trading price, TR is the total revenue, MR is the marginal revenue, and π is the enterprise profit. The following discussion is divided into three cases. For the convenience of analysis, the marginal cost curve is drawn as a straight line inclined to the upper right.

The first case: Enterprises with surplus carbon quota ($k>a$). The marginal income curve moves up $(k\text{-}a)\times b$ units, making the output increase from Q_1 to Q_2 (Fig. 1).

The second case: Enterprises with right carbon quota (k=a). The marginal income curve and marginal cost curve do not move, so the output remains unchanged.

The third case: Enterprises with insufficient carbon quota ($k<a$). The marginal cost curve moves up $(a\text{-}k)\times b$ units, which reduces the output from Q_2 to Q_1 (Fig. 2).

Based on the above analysis, we observe that when the external cost of carbon emissions is internalized, enterprises would change their production behavior. Therefore, enterprises equipped with advanced carbon emission reduction technology would increase their production, while those with limited technology would scale back their output. This paper proposes the following assumption:

H1 The implementation of carbon emissions trading policy has the potential to significantly reduce carbon emissions.

About the intrinsic mechanism

Carbon emissions trading policy aim to associate greenhouse gas emissions with negative externalities, effectively zero-costing them for commodities. This essentially leads to an increase in the prices of those commodities (Djukanovic 2022). Understanding

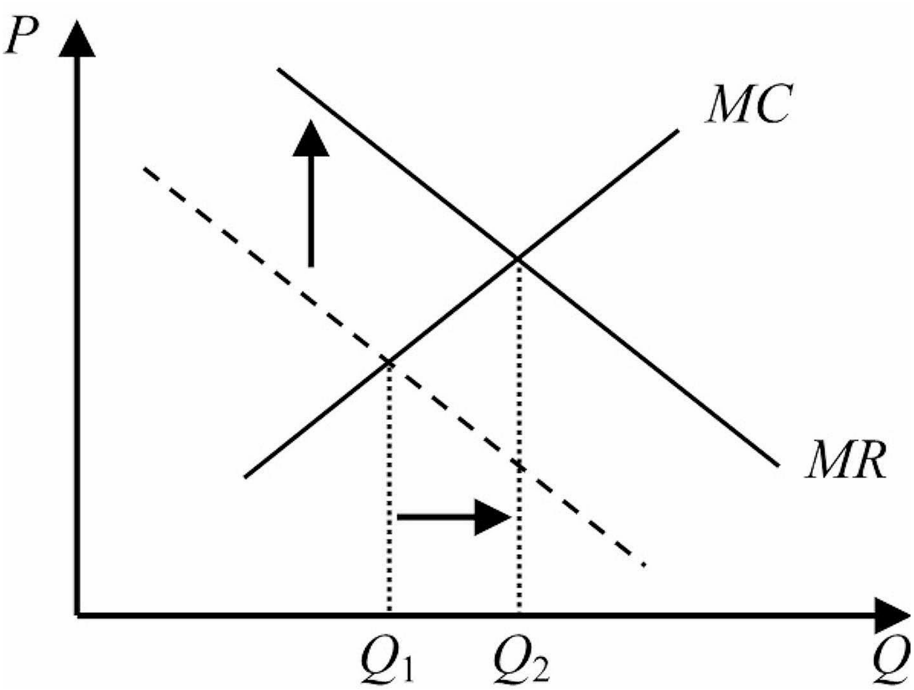

Fig. 1 The output change of enterprises with surplus carbon quota

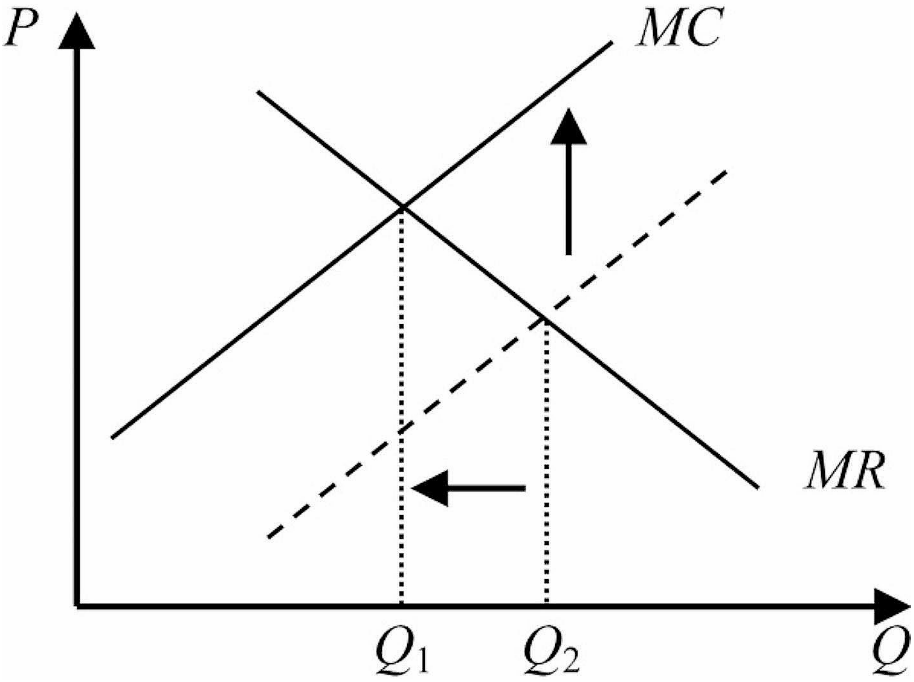

Fig. 2 The output changes of enterprises with insufficient carbon quota

carbon emissions as a normal commodity, the substitution effect and income effect would motivate enterprises, as consumers, to reduce their demand for carbon emissions. This reduction in demand would indirectly manifest in the production process, potentially through technological advancements or cost-effective measures. The substitution effect refers to the phenomenon where enterprises tend to decrease the production of carbon-intensive products and increase the production of those with low or no carbon emissions. Consequently, this leads to a shift in focus from traditional energy-intensive industries towards cleaner energy sectors or even towards the tertiary industry, which primarily encompasses services (Lo et al. 2020; Zhou et al. 2019). The economic incentive from income effect for enterprises is to reduce carbon emissions and lower the energy intensity required for unit production. Enterprises usually achieve this goal by enhancing carbon emission reduction technologies. Drawing upon the preceding discussions in this paper, the intrinsic mechanism underlying the effect of carbon emissions trading policy can be visualized in Fig. 3.

Based on the above theoretical analysis, this paper proposes the following assumptions:

H2a Carbon emissions trading policy promote the upgrading of industrial structures, thus realizing emissions reduction.

H2b Carbon emissions trading policy can facilitate emissions reduction by promoting the development of clean energy industries.

H2c Carbon emissions trading policy can facilitate emissions reduction by reducing energy intensity.

Model building and variable description

We can consider the implementation of carbon emissions trading policy as a quasi-natural experiment, as it naturally occurs in a real-world setting without full manipulation of the research environment. In this quasi-natural experiment, the pilot areas are designated as the experimental group, while the non-pilot areas serve as the control group. We can establish a difference-in-difference (DID) model to compare the differences in carbon emissions between the experimental group and the control group, and hypothesize that the implementation of carbon emissions trading policy will result in a significant reduction in carbon emissions in the pilot areas compared to the non-pilot areas. In addition, we can develop a mediation effect analysis to investigate how this policy operates by selecting certain mediating variables.

Difference-in-difference model

Difference-in-difference model is widely employed in various fields, such as economics, to assess the effectiveness of policy or interventions (Chen et al. 2021; Manley 2013). The

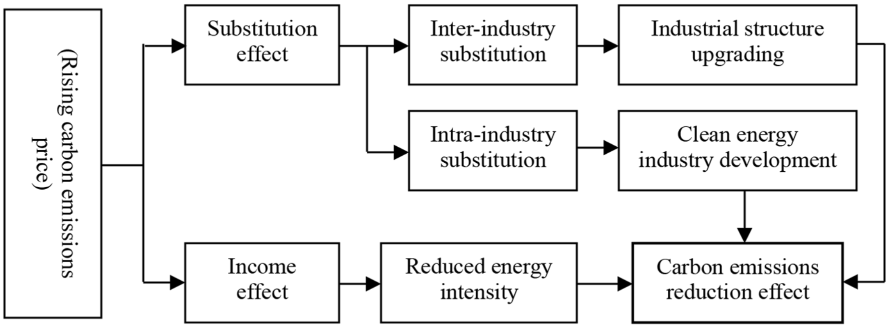

Fig. 3 The intrinsic mechanism of carbon emissions reduction

fundamental principle underlying this analysis is to emulate a quasi-natural experimental setup by introducing two dummy variables: time and region. By intersecting these two variables, we aim to isolate and evaluate the net impact of the policy in question, controlling for both temporal and spatial factors (Kuo et al. 2021). The formula is as follows:

$$Y_{it} = \beta_0 + \beta_1 treat_{it} + \beta_2 period_{it} + \beta_3 did_{it} + \beta_4 X_{it} + \varepsilon_{it} \tag{3}$$

In Formula (3), *treat* is the regional dummy variable, $treat=0$ represents the control group, and $treat=1$ represents the experimental group; *period* is a time dummy variable, $period=0$ represents before the policy implementation, and $period=1$ represents after the policy implementation; $did=treat \times period$, its coefficient β_3 represents the net effect of the policy (Table 1).

This paper takes 2013 as the policy implementation time point, excluding Tibet (due to the unavailability of energy consumption data) and Shanxi (due to the unavailability of crude oil consumption data), and uses the unbalanced panel data of 29 provinces from 2005 to 2019. Among them, the provinces of Beijing, Tianjin, Shanghai, Guangdong, Hubei and Chongqing belong to the experimental group, and the other provinces belong to the control group; 2005–2012 is the years before the policy, and 2014–2019 is the years after the policy. To verify the emissions reduction effect due to carbon emissions trading policy, this paper takes Economic Scale (denoted as *gdp*), Population Size (denoted as *pop*), Environmental Protection (denoted as *ep*) as control variables. The model is constructed as follows:

$$\ln tc_{it} = \rho_0 + \rho_1 did_{it} + \rho_2 \ln gdp_{it} + \rho_3 \ln pop_{it} + \rho_4 \ln ep_{it} + u_i + v_i + \varepsilon_{it} \tag{4}$$

In Formula (4), Total Carbon (denoted as *tc*) is the dependent variable, *did* is the core explanatory variable, economic scale, population size, and environmental protection are the control variables, u_i is the individual fixed effect, and ν_t is the time fixed effect, ε_{it} is a random perturbation term. If the policy can reduce carbon emissions, the coefficient ρ_1 of *did* should be significantly negative.

Mediating effect model

Drawing upon theoretical analysis and research assumptions outlined above, we have constructed a mediating effect model, employing Industrial Structure Upgrading (denoted as *isu*), Clean Energy Industry Development (denoted as *ceid*), and Energy Intensity (denoted as *ei*) as mediating variables. The model is as follows:

$$\ln tc_{it} = \alpha_0 + \alpha_1 did_{it} + \alpha_2 X_{it} + \mu_i + \nu_i + \varepsilon_{it} \tag{5}$$

$$mediation_{it} = \gamma_0 + \gamma_1 did_{it} + \gamma_2 X_{it} + \mu_i + \nu_i + \varepsilon_{it} \tag{6}$$

$$\ln tc_{it} = \lambda_0 + \lambda_1 did_{it} + \lambda_2 mediation_{it} + \lambda_3 X_{it} + \mu_i + \nu_i + \varepsilon_{it} \tag{7}$$

Table 1 The net effect of the policy based on difference-in-difference model

	Before policy implementation	After policy implementation	Difference
Experimental group	$\beta_0+\beta_1$	$\beta_0+\beta_1+\beta_2+\beta_3$	$\beta_2+\beta_3$ (*d*)
Control group	β_0	$\beta_0+\beta_2$	β_2 (*d*)
Difference	β_1 (*d*)	$\beta_1+\beta_3$ (*d*)	β_3 (*did*)

The fundamental principle underlying the verification of mediating effects is as follows. *Step 1*: Conducting a regression analysis using Formula (5) and assessing the significance of the regression coefficient α_1. If found to be significant, it would suggest that the policy has a statistically significant impact on carbon emissions reduction, either positively or negatively. *Step 2*: Regressing on Formula (6) and testing the significance of coefficient γ_1. If it is significant, it indicates that the policy can affect the mediation variable. *Step 3*: Regressing on Formula (7) and testing the statistical significance of coefficients λ_1 and λ_2. If both γ_1 and $\lambda 2$ are statistically significant, then the indirect effect is considered significant. Additionally, if the coefficient λ_1 is statistically significant, the direct effect is deemed significant. *Step 4*: Comparing the signs of $(\gamma_1 \times \lambda_2)$ with those of λ. If the signs of $(\gamma_1 \times \lambda_2)$ and λ are the same, it indicates a mediating effect; if the signs differ, it suggests a masking effect.

Data source and variable description

The dependent variable in this study is Total Carbon (*tc*), which is determined by first converting the total consumption of various energy sources into tons of standard coal equivalent. Subsequently, this converted value is used to calculate the amount of carbon emissions resulting from centralized heating. Then, based on the carbon emissions coefficients of each energy source, the carbon emissions of each energy source are calculated. These emissions are then summed up to obtain the total carbon emissions (= $\sum$ energy consumption × standard coal consumption coefficient × carbon emissions coefficient). The consumption data and standard coal conversion coefficients for various energy sources originate from the China Energy Statistical Yearbook of 2021, whereas the energy carbon emissions coefficients are taken from the IPCC National Greenhouse Gas Inventory Guidelines, Version 2006. Specifically, Table 2 presents the coefficients utilized in converting energy to standard coal equivalents, along with the carbon emissions coefficients.

The control variable of Economic Scale is measured through the gross regional product (GRP). The GRP represents the total market value of all final goods and services produced within a specific region during a given period, and the measurement unit for the GRP is 100 million Chinese yuan. The control variable of Population Size is measured by the permanent population, based on the latest census data available for the region, with a measurement unit of 10,000 people. The control variable for Environmental Protection is specifically measured by the annual amount allocated by the local government for environmental protection purposes, with a measurement unit of 100 million Chinese yuan. The mediating variable of Industrial Structure Upgrading is measured by the ratio of the annual added value (measured in 100 million Chinese yuan) of the

Table 2 The associated coefficients

Energy types	Coefficients of energy conversion to standard coal	Carbon emissions coefficients
Coal	0.714 3 Kg standard coal / kg	0.755 9
Coke	0.971 4 Kg standard coal / kg	0.855 0
Crude oil	1.428 6 Kg standard coal / kg	0.585 7
Gasoline	1.471 4 Kg standard coal / kg	0.553 8
Kerosene	1.457 1 Kg standard coal / kg	0.571 4
Diesel oil	1.471 4 Kg standard coal / kg	0.592 1
Fuel oil	1.428 6 Kg standard coal / kg	0.618 5
Natural gas	1.330 0 Kg standard coal / cubic meter	0.448 3

tertiary industry (which mainly refers to services and knowledge-intensive activities) to that of the secondary industry (which mainly encompasses manufacturing and construction). The mediating variable of Clean Energy Industry Development is measured by the hydropower generation (measured in 100 million kilowatt-hours per year). The mediating variable of Energy Intensity is measured by the ratio of total energy consumption (measured in 10,000 tons of standard coal) to industrial added value (measured in 10 billion Chinese yuan). Since the scale of the data on carbon emissions, regional gross domestic product, year-end resident population, and local fiscal expenditure on environmental protection is considerable, natural logarithms are taken to smooth the data and ensure statistical stability. Due to the presence of both large and small values (including those less than 1) in the hydropower generation dataset, the natural logarithm of the adjusted values [$\ln(x+1)$, where (x) represents the original data] is used to ensure mathematical feasibility and stability in the analysis. The descriptive statistics for the variables are shown in Table 3.

Empirical analysis

The results of difference-in-difference regression

Benchmark regression analysis

Calculations reveal that the growth trend of carbon emissions in the two groups is basically the same before the implementation of carbon emissions trading policy. Building a difference-in-difference model is thus a reasonable and feasible approach to estimating the policy effect. To test Hypothesis H1, regression analysis was conducted on the proposed model in Formula (4). The results, presented in Table 4, indicate a significant relationship between the two variables, supporting our initial hypothesis. In Column (1), we observe that the coefficient of DID is significantly negative when no control variables are included in the model. This indicates that the implementation of the policy could potentially lead to reduced emissions, especially when the influence of other variables affecting carbon emissions is not considered. In column (2), upon including control variables, such as Economic Scale, Population Size, and Environmental Protection, respectively, there was minimal change in the coefficient of DID, which remained significantly negative. This finding indicates a consistent and significant reduction in carbon emissions, despite the presence of various influencing factors. Based on the above analysis, hypothesis H1 is supported.

Based on the above analysis, we have found the following conclusions. Among the three control variables, only the coefficient of Environmental Protection is significantly

Table 3 Descriptive statistics for variables

Variables	Number of samples	Average value	p50	Standard deviation	Minimum	Maximum
treat	450	0.200	0	0.400	0	1
period	450	0.467	0	0.499	0	1
did	450	0.093	0	0.291	0	1
ln*tc*	404	8.984	8.976	0.778	5.835	10.630
ln*gdp*	450	9.378	9.456	1.007	6.213	11.590
ln*pop*	450	8.181	8.251	0.748	6.297	9.433
ln*ep*	390	4.482	4.560	0.781	1.671	6.617
isu	450	1.174	1.029	0.650	0.527	5.234
ln(*ceid* + 1)	429	4.435	4.586	1.813	0.030	8.107
ei	450	3.063	2.622	1.893	0.872	12.560

Table 4 The results of difference-in-difference regression

Variables	**(1)** **ln*tc***	**(2)** **ln*tc***
did	-0.261***	-0.228***
	(-2.81)	(-3.54)
ln*gdp*		0.317
		(1.61)
ln*pop*		0.974
		(1.44)
ln*ep*		-0.128*
		(-1.95)
Constant	8.559***	-1.551
	(178.33)	(-0.31)
Regional fixed effect	Yes	Yes
Time fixed effect	Yes	Yes
Observations	404	350
R-squared	0.667	0.634
Number of idcode	29	29
adj_R^2	0.617	0.617
F	19.26	19.26

Note: ***, ** and * mean respectively significant at the level of 1%, 5% and 10%; The same below

negative. Namely, the negative coefficient indicates that an increase in environmental protection expenditure by local governments is conducive to reducing carbon emissions. The coefficient of Economic Scale is positive but not significant, indicating differences in industrial structures across various provinces. The coefficient of Population Size is positive, albeit not statistically significant, indicating that, despite the fact that an increasing population typically leads to greater demand for energy-intensive products and services, which subsequently drive carbon emissions, the widespread use of new-generation information technology and the continuous advancement of transportation systems have the potential to mitigate these emissions. This, in turn, will foster the growth of trade in low-carbon industrial products.

Placebo tests

To ensure that different change trends are attributable to the policy effect, not confounded by other unobserved factors, a placebo test is required. This paper uses two counterfactual methods to test it by changing the time and fabricating the sample. The results of placebo tests are shown in Table 5. Column (1) is the regression results with the policy implementation time advanced to 2009, and column (2) is the regression results with six randomly selected provinces with the code of 10–15 as the experimental group. The coefficients of DID in the two regression results are not significantly negative, indicating that the treatment effect is not statistically significant. This suggests that advancing the timing of the intervention or replacing the sample from the pilot area does not alter the insignificance of the effect. This proves that the benchmark regression results are robust. Namely, the reduction of carbon emissions can be attributed primarily to the implementation of specific policy functions, rather than to other unobserved factors that may have had a minor impact on the trend.

Table 5 The results of placebo tests

Variables	**(1)** **lntc**	**(2)** **lntc**
did	-0.071	-0.021
	(-1.03)	(-0.30)
ln*gdp*	0.435***	0.455***
	(3.73)	(3.55)
ln*pop*	0.553	0.444
	(0.89)	(0.78)
ln*ep*	-0.122*	-0.133*
	(-1.72)	(-1.79)
Constant	0.888	1.634
	(0.17)	(0.34)
Regional fixed effect	Yes	Yes
Observations	350	350
R-squared	0.511	0.508
Number of idcode	29	29
adj_R^2	0.505	0.503
F	9.783	9.311

Table 6 The results of mediating effect tests

variables *P* value	**Sobel test**	**Boostrap test**
Industrial Structure Upgrading	0.000	0.007
Clean Energy Industry Development	0.985	0.989
Energy Intensity	0.003	0.001

Mediating effect tests

The mediating effect tests are conducted to test H2a, H2b and H2c, and the results are shown in Table 6. The Sobel test and the Bootstrap test for the two variables of Industrial Structure Upgrading and Energy Intensity passed, while the two tests for the variable of Clean Energy Industry Development failed. This shows that the two variables of Industrial Structure Upgrading and Energy Intensity play mediating roles in the process of carbon reduction, while the variable of Clean Energy Industry has not played a mediation role.

The mediating effect of the variable of industrial structure upgrading

The results of the mediating effect of Industrial Structure Upgrading are shown in Table 7. Column (1) is consistent with the conclusion of the benchmark regression. The coefficient of DID is negative and is significant at the 1% level, indicating that the implementation of carbon emissions trading policy has led to a significant reduction in carbon emissions. In column (2), the coefficient of DID is significantly positive, indicating that the policy has promoted industrial structure upgrading. In column (3), when the variable of Industrial Structure Upgrading and policy are included simultaneously, the coefficients of Industrial Structure Upgrading and DID are both significantly negative. The indirect effect is calculated as the product of the path coefficient from the independent variable to the mediator (0.510) and the path coefficient from the mediator to the dependent variable (-0.445), resulting in a negative value of -0.227. This indirect effect has the same negative sign as the direct effect (-0.307), indicating the presence of partial mediation, where the mediator accounts for some but not all of the direct relationship between

Table 7 The mediating effect of the variable of industrial structure upgrading

variables	**(1)** **ln*tc***	**(2)** ***isu***	**(3)** **ln*tc***
did	-0.534***	0.510***	-0.307***
	(-5.43)	(4.78)	(-3.44)
isu			-0.445***
			(-10.23)
ln*gdp*	0.289***	0.352***	0.445***
	(4.49)	(5.04)	(7.62)
ln*pop*	0.339***	-0.732***	0.013
	(5.21)	(-10.36)	(0.21)
ln*ep*	0.137***	0.138**	0.198***
	(2.75)	(2.57)	(4.51)
Constant	2.933***	3.185***	4.350***
	(10.20)	(10.20)	(15.11)
Observations	350	350	350
R-squared	0.605	0.402	0.697
adj_R^2	0.600	0.395	0.693
F	132.07	57.96	158.3

Table 8 The mediating effect of the variable of clean energy industry development

variables	**(1)** **ln*tc***	**(2)** **ln(*ceid* + 1)**	**(3)** **ln*tc***
did	-0.571***	0.007	-0.570***
	(-5.27)	(0.02)	(-5.95)
ln(*ceid* + 1)			-0.129***
			(-9.62)
ln*gdp*	0.260***	-1.302***	0.092
	(3.55)	(-4.89)	(1.37)
ln*pop*	0.363***	1.627***	0.573***
	(5.04)	(6.19)	(8.51)
ln*ep*	0.160***	0.607***	0.238***
	(2.88)	(3.00)	(4.79)
Constant	2.904***	0.728	2.998***
	(9.82)	(0.68)	(11.46)
Observations	333	333	333
R-squared	0.605	0.125	0.692
adj_R^2	0.600	0.115	0.687
F	125.40	11.76	146.9

the independent and dependent variables. Based on the results of the above analysis, hypothesis H2a is supported.

The mediating effect of the variable of clean energy industry development

The results of the mediating effect of Clean Energy Industry Development are shown in Table 8. Column (1) is consistent with the conclusion of the benchmark regression, and the coefficient of DID is negative, indicating that the policy significantly reduced carbon emissions. In column (2), the coefficient of DID is positive but not significant, indicating that the policy does not significantly promote clean energy industry development in the pilot area. In column (3), the coefficients of ln ($ceid+1$) and DID are significantly negative when the variable of Clean Energy Industry Development and policy are included simultaneously, indicating that clean energy industry development and policy can reduce carbon emissions. While the development of the clean energy industry can indeed contribute to reduced carbon emissions, it does not effectively mediate the impact of policy aimed at achieving carbon emissions reduction. The reason is primarily due to one of the main factors limiting the production of clean energy, namely technological bottlenecks. Therefore, hypothesis H2b is not supported.

The mediating effect of the variable of energy intensity

The results of the mediating effect of Energy Intensity are shown in Table 9. Column (1) is consistent with the conclusion of the benchmark regression, and the coefficient of DID is negative and has passed the significance test of 1%, indicating that carbon emissions trading policy significantly reduce carbon emissions. In column (2), the coefficient of DID is significantly negative, indicating that the policy has an active role on reducing the energy intensity of the pilot area. In column (3), the coefficient of the variable of Energy Intensity is significantly positive when Energy Intensity and policy are included simultaneously, and the coefficient of DID is significantly negative. The direction of the indirect effect (-0.538×0.295) is the same as that of the direct effect (-0.375), indicating the presence of a partial mediating effect. Therefore, hypothesis H2c is supported.

Results

Conclusions

This paper applies a DID model to examine the impact of carbon emissions trading policy on carbon emissions and empirically tests the underlying transmission mechanism of policy effect. In summary, the key findings of this study are as follows:

Firstly, the results of the DID regression analysis indicate that the implementation of carbon emissions trading policy has a statistically significant inhibitory effect on carbon emissions, with a regression coefficient of -0.228 (t = -3.45, $p<0.01$). The effects of the variables of Economic Scale and Population Scale are not significant, and the effect of the variable of Environmental Protection is significant.

Secondly, the mediating effects analysis reveals that the carbon emissions trading policy promotes industrial structure upgrading and energy intensity reduction in the pilot

Table 9 The mediating effect of the variable of energy intensity

variables	**(1) lntc**	**(2) *ei***	**(3) lntc**
did	-0.534***	-0.538***	-0.375***
	(-5.43)	(-3.05)	(-4.43)
ei			0.295***
			(11.57)
ln*gdp*	0.289***	-1.759***	0.808***
	(4.49)	(-15.27)	(11.43)
ln*pop*	0.340***	-0.116	0.373***
	(5.21)	(-0.99)	(6.74)
ln*ep*	0.137***	0.821***	-0.106**
	(2.75)	(9.22)	(-2.24)
Constant	2.933***	16.884***	-2.051***
	(10.20)	(32.73)	(-4.14)
Observations	350	350	350
R-squared	0.605	0.723	0.716
adj_R^2	0.600	0.720	0.711
F	132.07	225.23	173.1

areas. In turn, these factors contribute to achieving reductions in carbon emissions. Clean energy industry development does not play an obvious mediation role, and its development itself can reduce carbon emissions.

Suggestions

Based on empirical results and relevant practical issues, this study offers the following policy recommendations for carbon emissions trading and carbon reduction promotion.

Improving the market-oriented mechanism for carbon emissions

We propose that China should bring more high-carbon emissions industries into the scope of carbon emissions trading. Additionally, the launch of carbon financial derivatives in various forms, such as carbon options and carbon futures, would further integrate carbon emissions with the financial market. To ensure the healthy, orderly, and efficient operation of the carbon trading market, it is essential to effectively combine carbon emissions with the financial market and improve the construction of relevant supporting systems, laws, and regulations.

Promoting industrial structure upgrading

China needs to transform and upgrade its traditional energy industry to align with its economic strategy. A key aspect of this strategy involves focusing on the development of the tertiary industry, particularly the service industry. Additionally, it is crucial to cultivate environmental protection industries and high value-added industries to foster sustainable economic growth. To achieve this, the application of high-tech technologies such as 5G, big data, and cloud computing in the energy sector is essential. These technologies not only promote the upgrading of industrial structure but also facilitate the development and expansion of the digital economy.

Accelerating low-carbon technological innovation

Enterprises in China ought to enhance the adoption of cutting-edge technologies, thereby enhancing energy efficiency. The government should prioritize fostering an environment conducive to green and low-carbon technology research, promptly providing tax relief or financial subsidies to enterprises that adopt energy-saving and emissions reduction technologies. Furthermore, the government should facilitate technical collaborations between enterprises and scientific research institutions, accelerating the commercialization of green and low-carbon technological advancements.

Strengthening the utilization of clean energy

On the energy supply side, China should aim to establish a clean energy-centered supply system, gradually transitioning from fossil fuels to renewable energy sources such as hydroelectricity. This approach aims to reduce carbon emissions directly at the source. On the demand side, the country should actively steer market demand towards clean energy and facilitate market-oriented pricing reforms for these energy sources. To ensure effective implementation, local governments must carefully assess the development direction and intensity of clean energy initiatives, taking into account both local natural resource endowments and economic development needs.

Author contributions
X.J. wrote the main manuscript text; W.X. contributed to methodology and analysis; L.D. contributed to funding acquisition and writing reviewing.

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Data availability
No datasets were generated or analysed during the current study.

Declarations

Ethical approval
Not applicable.

Consent to participate
Not applicable.

Consent for publication
Not applicable.

Competing interests
The authors declare no competing interests.

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