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An empirical analysis on emissions reduction effect and main reduction drivers of China's carbon emissions trading pilot

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ABSTRACT

Empirical evidence substantiates the utilization of market-oriented trading mechanisms as a significant strategic tool for many counties to effectively regulate greenhouse gas (GHG) emissions. This research endeavors to comprehensively evaluate the impact of carbon emission trading scheme on the reduction of carbon emissions in China. To this end, we analyze provincial panel data from China for the period from 2005 to 2019. Our empirical analyses explore the policy effects by employing two-way Fixed Effects model and Propensity Score Matching Difference-in-Differences model. Importantly, we shed a new light on the role of energy intensity on this relationship. The panel analyses find a notable reduction of 27.2% in total carbon emissions in provinces where Emission Trading Pilot has been implemented. Furthermore, we attempt to better understand the underlying mechanism how GHG emissions reduction is achieved, by elucidating the mediating effects of energy intensity in reducing carbon emissions. Our analysis reveals a substantial role of energy efficiency enhancement in reducing carbon emissions: when controlling for the energy intensity level, the policy effect of Emission Trading Pilot shrinks to 9.1%. It implies that 18.1% out of total 27.2% reduction effects are largely attributable to the enhancement of energy intensity. Our findings highlight the importance of efficient use of energy in reducing carbon emissions in a growing economy as well as in enabling sustainable growth.

Key words: Climate Change, Mitigation, Greenhouse Gases, Emissions Reduction, Emissions Trading Pilot, Emissions Trading System, Energy Intensity, Mediating Effect, PSM-DID Model

1. Introduction

Growing evidence from the field of climate and environmental science suggests that human activities have a substantial impact on climate change. The United Nations Intergovernmental Panel on Climate Change (IPCC) has released the 6th Assessment Report in 2023 (IPCC, 2023), indicating that the global average temperature has risen by 1.5 degrees Celsius since the Industrial Revolution, with carbon emissions from human production and living being a significant contributor to the accumulation of greenhouse gases and the resulting climate chang. Reducing carbon emissions has therefore become a crucial issue for countries worldwide.

To figure out ways to address the global warming and climate change, scholars have conducted systematic studies on the various factors influencing carbon emissions from different perspectives, including demographic, economic, technological, energy, and environmental factors. In addition, scholars have proposed various regulatory policies and measures to reduce emissions, such as mandatory carbon target planning, energy efficiency or emission standards, phase-out of fossil fuel subsidies and ban on high emission

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technologies. While these proposals have yielded some positive results, their marginal effects may diminish due to a lack of consideration of mark. In the 1960s, Coase (1960) proposed that environmental problems essentially stem from environmental externalities associated with economic development and that internalizing external costs are necessary to address environmental problems at their root. This concept laid the theoretical foundation for the adoption of market-based mechanisms, leading to an important market-based environmental regulation that provides a price for externalities. According to “Status and Trends in Carbon Pricing” (World Bank, 2022), when the first report was published a decade ago, only 7% of global emissions were covered by either a carbon tax or an ETS. Today, almost a quarter of global greenhouse gas emissions (23%) are now covered by 73 instruments (ETSs and carbon taxes).

In 2005, China discharged an astonishing 6,079.3 Million tons of CO_2 from energy use into the atmosphere, exceeding the emission level of United States and henceforth becoming the largest carbon-emitting nation in the world (BP plc, 2022). Meanwhile, China’s efforts to reduce emissions started relatively late. Since 2013, China has implemented an emissions trading system (ETS) in seven pilot regions, including Beijing, Shanghai, Tianjin, Chongqing, Hubei, Guangdong, and Shenzhen. As one of a few developing countries that have implemented an Emissions Trading System (ETS), China encounters various market and regulatory challenges due to less competitive markets and increased political and economic constraints compared to developed countries (Chiu et al., 2015; Finon, 2019). Therefore, exploring China’s ETS can provide valuable lessons for other developing countries facing similar challenges.

According to the Global Emissions Trading Report published by the International Carbon Action Partnership (ICAP) in 2023 (ICAP, 2023), China has a significant share of the global carbon trading market, highlighting the need to evaluate China’s ETS. Despite that some existing studies explored China’s ETS, they mostly focus on the overall environmental impacts of the policy and ignore underlying mechanisms or pathways through which greenhouse gas (GHG) reduction arise. Thus, this paper employs the Propensity Score Matching (PSM) Difference-in-Differences (DID) model approach to investigate the carbon reduction effects of China’s carbon emission trading pilot. Furthermore, this paper proposes a framework for the policy influence mechanisms and conducts an empirical study elucidating the mediating effects of energy intensity in reducing carbon emissions. Thus, findings of this study enhance our understanding of the reduction mechanism of carbon trading system. Moreover, our analysis is expected to carry theoretical and practical significance in advancing China’s ETS, contributing to the successful achievement of China’s “30.60 dual carbon” goal to reach peak carbon dioxide emissions by 2030 and achieve carbon neutrality by 2060.

2. Literature review

Pigou (1951) espoused the belief that the government ought to intervene to internalize external effects through taxation when negative externalities arise from economic activities. In contrast, Coase (1960) proposed a different approach where economic management should be conducted via property rights. Coase contended that utilizing market and property rights methods can resolve external issues. Dales (1968, pp. 10~12) integrated the notion of property rights, based on Coase’s theory, into environmental pollution control studies. Dales asserted that pollution is a kind of property right conferred upon enterprises by the government. Pollution rights can be transferred through market mechanisms to improve the cost-effectiveness of environmental protection control. This laid a strong theoretical foundation for the analysis of emissions trading scheme. Building on existing theories, many scholars have studied the impact of emissions trading mechanism on emission reduction. Stavins (1998) analyzed sulfur dioxide emissions trading in the United States and observed that this policy had a significant effect in accomplishing the phased goal of the “acid rain plan.” The successful implementation of the sulfur dioxide emissions trading system in the United States served as a basis for the European Union to pioneer a greenhouse gas emissions trading system - the EU Emissions Trading System (EU ETS). In 2005, the EU ETS commenced official operations, encompassing Iceland, Liechtenstein, Norway, and eight EU member states. The EU ETS covers greenhouse gases such as carbon dioxide and sulfur dioxide. Martin et al. (2014) pointed out that the EU ETS has effectively reduced emissions in the EU, and promoted participating nations to reduce their carbon emissions by 10% to 26% from 2008 to 2012.

The carbon emissions trading system in China has introduced by Chinese government as a core policy instrument to address climate change and achieve the "dual carbon goals." Although China's carbon emissions trading system started late, it has developed rapidly and has become an important policy tool for promoting China's green and low-carbon development. China has implemented Emissions Trading System (ETS) pilots in seven provinces and cities, including Beijing, Shanghai, Tianjin, Shenzhen, Chongqing, Guangdong, and Hubei, since 2013. These pilots encompass seven key industries, namely electricity, iron and steel, petrochemicals, building materials, chemicals, papermaking, aviation, and non-ferrous metals.

A range of empirical studies attempt to evaluate the effectiveness of Chinese ETS and its impact on economy using various methods. Liu et al. (2017) employed a multi-regional general equilibrium model to simulate the economic and environmental repercussions of carbon market implementation in Hubei Province. The findings demonstrated that carbon market policies have significantly reduced carbon emissions, while only minimally impacting the economy. In another study, Liu et al. (2016) used a similar methodology to investigate the impact of emission reduction in Tianjin, revealing a noticeable reduction in emissions with a limited negative economic effect. Furthermore, Li et al. (2017) utilized the Stochastic Impacts by Regression on Population, Affluence, and Technology (STIRPAT) model in combination with a dynamic Computable General Equilibrium (CGE) model to evaluate the overall effect of carbon market policies. The results indicate that energy intensity levels in 2020 will decrease by 19.58%~23.71% compared to those in 2015. Wang et al. (2016) examined the potential cost savings of emission reduction or GDP recovery resulting from carbon emissions trading in China. They utilized Data Envelopment Analysis (DEA) optimization model to estimate the potential benefits of carbon trading. The findings suggest that the implementation of the carbon market has a substantial potential for cost savings and emission reduction. Furthermore, various scholars have explored these questions using diverse empirical methodologies. Yi et al. (2020) conducted an empirical study on the emission reduction effects of ETS pilot projects using the Difference-in-Differences (DID) model. The findings reveal that the implementation of carbon markets in Beijing, Shanghai, and Hubei exhibited a significant inhibitory effect on local carbon emissions, while in Guangdong, it had a promoting effect, and no significant effect was found in Tianjin.

Although the literature above has demonstrated that China's carbon emissions trading policy has achieved some degree of success in reducing emissions, it is still subject to certain limitations. Firstly, China's national conditions, such as its large land areas and unbalanced development, necessitate that the Chinese government primarily promotes national growth through regional development strategies, such as revitalizing the northeast, energizing the central region, and developing the western region. However, the existing literature predominantly discusses the environmental impact of China's ETS from the industrial or national level, neglecting to consider the possible heterogeneity that may arise from different regional characteristics within China. This omission diminishes the validity of the policy assessment and the implications. Additionally, the current literature mostly suggests that China's ETS still contributes to positive carbon reduction effects, despite the problems of bounded trading volume, weak market environment, and low market liquidity (Chen et al., 2020; Zhang et al., 2020). This contradictory result underscores the need to better understand the influencing mechanisms of the ETS that account for the policy's emission-curbing impact.

Unfortunately, research in this area remains insufficient. Therefore, in order to fully understand the emission reduction potential of carbon trading scheme, it is necessary to further investigate the main driver of emission reduction under the ETS.

To this end, this paper aims to newly contribute to the existing literature in the following ways: (1) by conducting a comprehensive assessment of the impact of carbon trading scheme in each pilot region of China, based on inter-provincial panel data spanning from 2005 to 2019. We will assess the emission reduction effect of carbon trading policies using the Propensity Score Matching-Difference in Differences (PSM-DID) model; (2) through a mediating effects model, we will investigate whether energy efficiency is a critical pathway for achieving emission reduction through carbon trading policies. Specifically, we will examine both the comprehensive emission reduction effect of carbon trading policy, as well as the mediating reduction effect achieved through improvement in energy intensity.

3. Research design and description of data

3.1. Base regression model: DID

To explore the effectiveness of the carbon emission trading mechanisms in pilot regions, we first employ the Difference-in-Differences (DID) model. This approach involves identifying the impact of the policy by comparing performance differences between the treated group (pilot regions) and the control group (non-pilot regions), while controlling for other factors. DID model is a widely-used methodological framework for examining the impact of policy interventions. Considering the availability of carbon emission and energy data, our study will focus on analyzing data at the regional level in Chin a[1] to evaluate the impact of the emission trading pilot program. Specifically, the six pilot regions (Beijing, Shanghai, Tianjin, Chongqing, Guangdong, and Hubei,) will be treated as experimental group, while all other major regions that were not selected as pilots will serve as control units for comparison purposes. To specify the DID model, we will construct a regression equation as follows:

$$y_{it} = \alpha_0 + \alpha_1 treat_{it} + \lambda \sum_n Controls_{it} + \gamma_t + \mu_i + \varepsilon_{it} \tag{1}$$

In the specified DID model, the carbon emission outcome in region i in year t is denoted by y_{it}. The variable $treat_{it}$ is used to signify whether a province or region i implements a carbon trading pilot in year t. If a pilot is implemented, treat it is assigned a value of 1, otherwise, it is assigned a value of 0. The control variables $Controls_{it}$ accounts for other factors that may affect carbon emissions. Ehrlich and Holdren (1971) suggested that population, affluence, and technological factors are three important aspects affecting environmental outputs and Kaya (1989) suggested that population, per capita GDP, energy intensity, and emission coefficient are the four main factors affecting carbon emissions. Following the previous studies (Luo et al., 2023), we incorporate eight variables into the model as $Controls_{it}$, population aging, population urbanization, the share of the working-age population, economic size, energy intensity, industrial structure, freedom of trade, and technological progress. Additionally, the time and individual fixed effects are represented by γ_t and μ_i, respectively. And the error term is represented by ε_{it}.

Nonetheless, utilizing the proportional growth rate in the Kaya equation enhances effectiveness. Additionally, the power-law formulation of the extended and improved STIRPAT model (Dietz and Rosa, 1997), which builds upon the IPAT equation (Ehrlich and Holdren, 1971), enables the linearization of nonlinear relationships via logarithmic transformation. This adaptation renders it compatible with linear regression models. Hence, our model will subject all variables to logarithmic transformation.

1) Shenzhen has been omitted from this analysis owing to the constraints in data availability at the provincial level.

3.2. Propensity Score Matching DID model

In observational studies, treatment and control groups may exhibit differences even before the intervention. These differences can affect the likelihood of individuals receiving treatment, thereby leading to biased outcomes. The PSM-DID model is a two-step approach that aims to increase the robustness of the results. In the first step, the sample is adjusted for possible systematic differences using the propensity score matching (PSM) model. PSM estimates the probability of the treated group assignment based on observable characteristics, allowing the treated and control groups to be balanced on observable covariates. In the second step, the net effect of the policy is assessed using the DID model, which compares the changes in outcomes between the treated and control groups before and after the policy intervention. The PSM-DID model can increase the internal validity of the study by reducing the bias due to unobservable confounding variables and selection bias.

The PSM model is used to find a comparable province j in the control group for the treated province i based on observable variables. Specifically, a province j in the non-pilot provinces (control group) is selected such that its observable characteristics are sufficiently similar to those of province i, ($x_i \approx x_j$). Based on the assumption of ignorability, when individual characteristics of provinces have no influence on the decision to implement carbon emission trading, we assume that the probability of implementing the policy is similar for province i and province j. Therefore, the systematic differences between the treated and control groups are resolved. However, matching in high-dimensional space may result in data sparsity and difficulty finding suitable matches or may result in a small number of matched pairs that are insufficient for subsequent analysis. Rosenbaum and Rubin (1983) proposed the use of propensity scores to address these issues. The propensity score is the probability of an individual receiving a certain treatment given a set of covariates. Traditional matching methods that use multiple observable variables are difficult to implement in practice. PSM model replaces the multidimensional covariates with a one-dimensional variable - the propensity score P(x)0, which simplifies the matching process by allowing researchers to match based on a single variable.

Before applying the DID model, verifying the “Parallel Trends Assumption” is essential. This assumption suggests that, without the intervention, the trends in the outcome variable for both treatment and control groups would be similar over time. In the absence of treatment, the temporal difference between these groups would remain stable. Once the assumption is confirmed, we align the treatment and control groups using Propensity Score Matching. Subsequently, the DID model is utilized to evaluate the variations in carbon dioxide emissions in provinces affected by the carbon emissions trading system, before and after the policy implementation. And evaluate the average treatment effect on the treated (ATT) for the carbon emissions trading system policy participants.

3.3. Additional analysis: Mediating effect

Carbon trading offers two main pathways for emission reduction. Firstly, the government imposes emission caps aligned with policy goals and distributes initial emission rights to firms. If a company exceeds these limits, it must either reduce production or buy additional emission rights from others. Secondly, carbon trading inherently prompts companies to lessen emissions by enhancing energy efficiency. Companies that improve energy utilization efficiency are more apt to generate excess emission rights, benefiting from the sale of these certificates. Thus, efficiency-focused firms are motivated to continually refine their energy structures and increase efficiency, leading to more certificate sales. Conversely, less efficient companies, facing ongoing costs from buying emission rights and future emission constraints, are pushed towards emission reduction by improving energy utilization. Consequently, under carbon trading policies, boosting energy efficiency emerges as a primary strategy for emission reduction among most firms (Huang et al., 2018; Zhang et al., 2018). This study attempts to investigate how energy efficiency acts as a mediating factor in carbon emission reductions within the framework of carbon trading, examining to what extent improvements in energy utilization efficiency indirectly contribute to emission reduction.

To explore the underlying reduction mechanisms of the ETS, this study employs the mediating effect model based on the influential framework introduced by Baron and Kenny (1986), aiming to illuminate the intricate relationships among the variables. To be more precise, the model consists of three discernible stages. In the initial stage, the model adheres to a base regression framework, similar to Eq.(1), where the treatment effect is solely regressed against the dependent variable (carbon emissions). This stage seeks to establish the extent to which China's pilot ETS effectively contributes to carbon emission mitigation. Advancing to the second stage, the treatment effect is regressed against the mediating factor (energy intensity), enabling a deeper understanding of the policy's influence on these intermediary factors. Specifically, a positive value for ρ_1 in Eq.(3) would suggest a promoting effect, whereas a negative value would indicate a suppressive impact. In the final stage, the treatment effect, mediating factor, and dependent variable are integrated into a unified regression framework. If the coefficient of δ_1 in Eq.(4) loses its significance or diminishes in size compared to β_1 in Eq.(2), while the coefficient of δ_2 maintains statistical significance, the verification of the mediating role of the energy intensity and the underlying mechanism of ETS in reducing carbon emission is established. Furthermore, if the coefficient of δ_2 is greater than zero, it signifies that enhancements in the mediating variable (i.e. lower energy intensity level) lead to a decrease in carbon emissions. The mediating effect model explained above is formulated as follows.

$$\ln y_{it} = \beta_0 + \beta_1 treat_{it} + \lambda \sum_n \ln Controls_{it} + \gamma_t + \mu_i + \varepsilon_{it} \tag{2}$$

$$\ln EI_{it} = \rho_0 + \rho_1 treat_{it} + \lambda \sum_n \ln Controls_{it} + \gamma_t + \mu_i + \varepsilon_{it} \tag{3}$$

$$\ln y_{it} = \delta_0 + \delta_1 treat_{it} + \delta_2 \ln EI_{it} + \lambda \sum_n \ln Controls_{it} + \gamma_t + \mu_i + \varepsilon_{it} \tag{4}$$

Where the variable $\ln EI_{it}$ represents the mediating effect within province or region i at year t. Other symbols employed in these models hold identical interpretations as those presented in Eq.(1).

3.4. Data sources

In order to evaluate the effectiveness of the carbon emission trading mechanisms and elucidate the underlying policy mechanisms, this study analyzes a representative sample comprising 30 provinces and regions across China. The study covers the period from 2005 to 2019. The dependent variable is the aggregate carbon emissions within the province or region i during the year t. The core independent variable in our DID model is whether each region initiated the carbon trading pilot (referred to as "treat") in 2013 or not. The primary objective of this variable is to assess the impact of carbon trading implementation on the regional emissions level . Furthermore, as explained in subsection 3.3, the study incorporates the mediating variable - energy intensity, which represents the regional consumption of fossil energy per unit of GRDP. This variable is included to analyze the mechanism through which the implementation of the carbon trading market influences the dependent variables. Based on the existing literature, this study incorporates several control variables to mitigate potential bias that may arise from omitting other significant explanatory variables. In line with Luo et al. (2023), this study takes into account several pertinent control variables. These variables include population aging, population urbanization, the proportion of the working-age population, per capita GRDP, industrial structure, freedom of trade, investment amount completed in industrial pollution control, and technological progress. By integrating these demographic, social, and economic factors into the analysis, we aim to comprehensively examine and account for their potential influence on the

Table 1. Description and sources of the variables used in the model

Type	Variable	Unit	Definition measuring model	Data source
carbon emissions	CO_2	10,000 tons	total carbon emissions	CSMAR
carbon trading pilot implemented or not	TREAT	/	The implementation of carbon trading in the region is denoted by "1," while the absence of carbon trading in the region is denoted by "0."	CEN
energy intensity	EI	10,000 ton/GRDP	energy use in 10,000 tons of standard coal equivalent relative to GRDP	NBS
technological progress	RND	%	total R&D investment by region as a percentage of GRDP	NBS
industrial structure	IND	/	the ratio of value added in the secondary industry to value added in the tertiary industry	NBS
freedom of trade	FOT	%	total exports and imports as a percentage of GRDP	NBS
population aging	AGING	%	share of the population aged 65 and above in the total population	NBS
working-age population	LAB	%	those aged between 15-64 years as a percentage of the total population	NBS
urbanization	URB	%	share of the urban population in the total population	NBS
economic growth	perGRDP	CNY	per capita real GRDP (¥)	NBS
environmental regulation	ER	100 million CNY	investment amount completed in industrial pollution control	NBS

Table 2. Summary statistics

Variable	Obs	Mean	Std. Dev	Min	Median	Max
$lnCO_2$	450	10.277	0.771	7.377	10.251	11.930
TREAT	450	0.093	0.291	0	0	1
lnEI	450	-0.149	0.545	-1.570	-.171	1.410
lnRND	450	-6.973	1.048	-9.019	-7.228	-3.793
lnIND	450	-0.071	0.384	-1.655	-.028	.640
lnFOT	450	2.885	0.980	.238	2.619	5.149
lnAGING	450	2.261	0.210	1.700	2.260	2.789
lnLAB	450	4.293	0.050	4.150	4.290	4.429
lnURB	450	3.965	0.252	3.291	3.970	4.541
lnperGRDP	450	10.461	0.654	8.528	10.536	12.009
lnER	450	2.595	1.015	-1.022	2.693	4.953

relationship under investigation. Table 1 provides a concise description along with the sources of the major variables.

All the explanatory variables used in this paper are from the National Bureau of Statistics of China (NBS, 2023), while the data on total carbon emissions were obtained from the China Stock Market And Accounting Research (CSMAR; CSMAR Database, 2023) database. The detailed timeline of China's carbon trading pilot program is sourced from the China Energy Network (CEN; China Energy Network, 2023). Table 2 provides the descriptive statistics of the selected variables for all provinces and municipalities between 2005 and 2019. The statistics include the mean, standard deviation, maximum, and minimum values after the logarithmic transformation.

4. Results and discussion

4.1. The impact of emissions trading pilot on carbon emissions

To mitigate potential bias arising from individual differences between the experimental and control groups, this paper employes the PSM-DID model. This approach aims to ensure the accuracy of the policy treatment effects by accounting for confounding factors. The test results demonstrate that the coefficients associated with the effect of the carbon trading policy on total carbon emissions remain statistically significant across multiple matching techniques, including first-neighbor matching, second-neighbor matching, fourth-neighbor matching, and kernel density matching. These findings suggest that the observed reduction in total carbon emissions within the pilot regions cannot be solely attributed to individual differences within those regions. Consequently, these results further validate the robustness of the base regression test findings, supporting the study's conclusions. In this study, we present the results obtained through fourth-neighbor matching techniques. The corresponding findings are summarized in Table 3.

Table 3 presents the estimation results for Eq.(1). In column 1, the PSM-DID model result of a simple regression is presented where no control variables are included. It implies that China's pilot ETS has negative overall impact on carbon emissions. When control variables are incorporated in our main model (column 2), the carbon trading policy exhibit a significant negative effect on carbon emissions. The implementation of the policy results in a substantial decrease of 19.5% in total carbon emissions within the pilot area during the study period. These results indicate that when we account for other related factors, the effect of carbon trading policy becomes even greater. Also, the fixed effects model produces similar results. Carbon trading policy's significant impacts on carbon emissions reduction are consistently found across various model specifications and estimations. These findings suggest that carbon trading policy plays an important role as a driver of carbon emissions reduction in China.

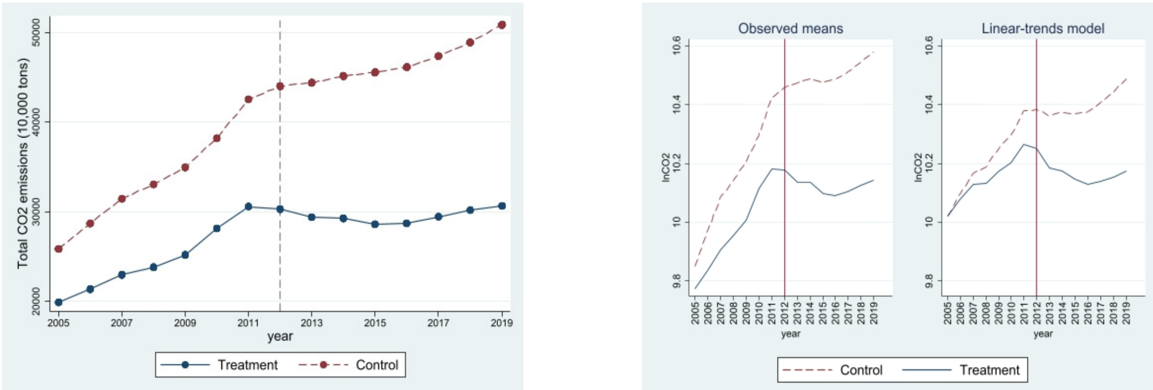
4.2. Robustness test

It is important to acknowledge that the estimations mentioned above are contingent upon certain underlying assumptions, such as the parallel trend assumption of the DID model. Additionally, the empirical results can be susceptible to interference arising from the selection of measurement methods, particularly in the calculation of carbon emissions. Environmental science, especially in the context of calculating carbon emissions, employs diverse measurement methodologies. These include direct methods, like using sensors to monitor emission sources, and indirect methods, which rely on statistical data related to energy consumption or economic activities. The choice of measurement approach can yield different outcomes. Direct measurement is often more precise in reflecting actual emissions, whereas indirect measurement hinges on

Table 3. The total impact of China's pilot ETS on carbon emissions

Variable	Base regression analysis		
	(1) PSM-DID_1	(2) PSM-DID_2	(3) Fixed Effects
TREAT	-0.183*	-0.195**	-0.163**
	(-2.67)	(-3.10)	(-2.77)
_cons	9.797***	-4.331	5.339
	(146.25)	(-0.74)	(0.95)
Control variable	No	Yes	Yes
Province fixed	Yes	Yes	Yes
Year fixed	Yes	Yes	Yes
N	279	279	450
R^2_a	0.771	0.839	0.756
F	20.03	14704.9	58.55

Notes : t statistics in parentheses, $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$



(a) Graphical diagnostics for total carbon emissions

(b) Graphical diagnostics for $lnCO_2$

Fig. 1. Parallel trends of carbon emissions

various assumptions and conversion factors, introducing a higher degree of uncertainty. Considering these sources of uncertainty, this paper undertakes additional measures to reinforce the robustness of the regression results. Specifically, preexisting trend tests and placebo tests are conducted. These tests aim to further scrutinize the validity and reliability of the regression findings, taking into account potential confounding factors and addressing concerns regarding the impact of measurement methods.

4.2.1. Parallel-trends test

Ensuring similar variation tendencies in the treatment group and control group is a critical precondition for the Difference-in-Differences strategy. To verify the parallel trend assumption, this study conducts two tests based on the methodology proposed by Roberts and Whited (2013). Firstly, the annual carbon emissions of the experimental group and control group are plotted before and after applying a logarithmic transformation. As illustrated in Fig. 1 (a) and (b), a parallel trend is observed prior to the implementation of the Emission Trading policy (before 2013). Following the policy's implementation, the experimental group experiences a significant decline in carbon emissions starting from 2013, with a steady decrease in subsequent years. In contrast, the control group continues to exhibit an upward trend in carbon emissions. Secondly, a parallel-trends test is conducted using Stata 17 software to evaluate whether the control and treatment groups followed a parallel path before the policy implementation. The hypothesis of interest is H_0: linear trends are parallel, and F-test indicates that there is insufficient evidence to reject the null hypothesis of parallel trends. The test result, combined with the graphical analysis, supports the parallel-trends assumption.

4.2.2. Placebo test

The DID placebo test revolves around the concept of manipulating the treatment group or policy time for test purpose. By introducing a "pseudo-policy group," researchers can assess the significance of its coefficient and identify potential biases in the original estimation. If the coefficient of the "pseudo-policy group" remains statistically significant, it suggests that the observed changes in the explained variable may be influenced by factors other than the intended policy intervention or random variations. This indicates a potential bias in the original estimation results. To conduct the placebo test, researchers typically re-estimate the regressions using data from years preceding the actual policy implementation. By examining whether the coefficients of the policy dummy variables remain significant in these placebo years, researchers can assess the robustness of the original estimation and determine if the observed effects are indeed driven by the policy intervention.

In this paper, the methodology is based on the study conducted by Shi et al. (2018). It involves employing a random selection process to create a "pseudo-policy dummy group" and conducting 500 iterations to assess the significance of the coefficients associated with this group. The initial regression analysis comprises a treatment group consisting of six regions and a control group consisting of 24 regions. For the placebo test, six regions are randomly selected from the total pool of 30 regions to form the "pseudo-treatment group," while the remaining regions serve as the control group. A "pseudo-policy dummy variable" (interaction term) is then generated for regression analysis, with 2011 designated as the policy dummy time. The regression analysis is repeated 500 times, resulting in 500 sets of regression results that include the estimated coefficients of the "pseudo-policy dummy variables," along with their corresponding standard errors and p-values. Finally, the distribution of the estimated coefficients and their p-values from the 500 "pseudo-policy dummy variables" is plotted, providing a visual representation of the placebo test results. Fig. 2 displays the results obtained from the placebo test.

Fig. 2 displays the distribution of estimated coefficients for the 500 "pseudo-policy dummy variables" and their corresponding p-values. The x-axis represents the magnitude of the estimated coefficients, while the y-axis represents the density values and p-values. The curve represents the kernel density distribution of the estimated coefficients. The blue dots represent the p-values associated with the estimated coefficients. The vertical dashed line corresponds to the true estimate of the DID model (-0.195), and the horizontal dashed line represents the 10% significance level. Upon examination of the figure, it is observed that the estimated coefficients are primarily concentrated around zero. Additionally, a significant majority of the estimated values have p-values greater than 0.1, indicating insignificance at the 10% level. This suggests that our estimates are unlikely to have been obtained by chance nor driven by the influence of other policies or random factors.

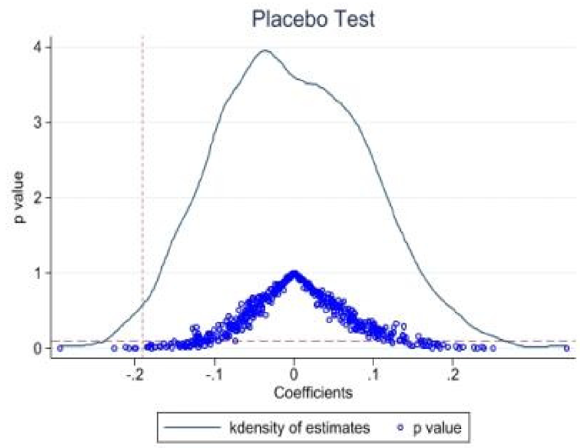


Fig. 2. placebo test of carbon trading pilot

4.3. Underlying mechanism of emission reduction effect

According to our analysis so far, it is evident that the carbon trading policy significantly contributes to the mitigation of carbon emissions. We further investigate the underlying mechanisms that drive this impact and explore the specific paths through which the abatement effect is achieved. As outlined in the theoretical framework and hypothesis presented in the third part of this paper, we hypothesize that the carbon trading policy, as a policy intervention, leads to carbon emission reduction by influencing the energy intensity (mediating variable). To shed light on the influencing mechanism, Table 4 presents the analysis based on Eq.(2) to (4).

The estimation results presented in Table 4 overall suggest the mediating effect between the carbon trading policy and carbon mitigation. The mediating effect in this context is manifested through a decrease in energy intensity, which signifies an increase in the efficiency of comprehensive energy utilization. This finding suggests that the carbon trading policy induces carbon emissions reduction by promoting improvements in energy efficiency. Specifically, the mediating effect is tested in columns 1 to 5 of Table 4. The relationship between the carbon trading policy and energy intensity is examined first. As shown in columns 1-2, the estimated coefficient of carbon trading policy on energy intensity are negative and statistically significant. It indicates that the carbon trading policy has a significant influence on energy intensity and that there is a negative relationship between the two variables. As a result, it can be inferred that the mediating effect exists. Moving on to the columns 3-5, the mediating effect of energy intensity is further demonstrated by observing a decrease in the coefficient of the carbon trading policy and the positive coefficient of energy intensity variable. These results all together suggest that energy intensity plays a mediating role in the relationship between the carbon trading policy and carbon mitigation. Additionally, when control variables are introduced in the analysis (columns 2, 4, and 5), the significance of the coefficients and the overall effect remain consistent, providing consistent supporting evidence for the mediating effect of energy intensity.

Empirical results in Table 4 indicate that the total carbon emissions in the six pilot regions of China's carbon trading policy experiment decreased by 27.2%, with a direct reduction of 9.1% due to the implementation of carbon trading pilot. Furthermore, the result indicate that the market mechanism significantly stimulate a reduction in energy consumption per unit of economic output in these regions, effectively reducing CO_2 emissions. Overall, it is estimated that improved energy efficiency in the ETS pilot region leads to a further reduction of approximately 18.1% (=0.190*0.955) in carbon emissions, significantly contributing to carbon neutrality and climate change mitigation.

5. Conclusions and policy implications

In the context of increasing concern for environment and climate change, and pressure on economic growth, China's commitment to low-carbon development is of paramount societal importance. This paper delves into the impact of China's pilot Emission Trading Scheme (ETS) on carbon emission reduction and its underlying mechanisms. Analyzing panel data from 30 provinces from 2005 to 2019, we employ the Propensity Score Matching-Difference in Differences model and a parallel mediator model for our empirical analysis. Our findings highlight the significant role of the ETS in reducing emissions and cast new light on the mediating effects of energy intensity in this process. We estimate that the enhancement of energy efficiency, spurred by the ETS implementation, accounts for a reduction of 18.1% in carbon emissions. Moreover, even after adjusting for this mediating effect, China's pilot ETS itself has effectively reduced carbon emissions by an average of 9.1% across the nation.

Based on these findings, the study presents the following policy recommendations:

1. Given China's rapid economic growth and high energy consumption, the success of the ETS in reducing emissions is notable. Other regions should adopt and refine this market-based policy, expanding its scope. This

Table 4. Influencing mechanisms of carbon reduction effect

Variable	(1)	(2)	(3)	(4)	(5)
	lnEI	LnEI	$lnCO_2$	$lnCO_2$	$lnCO_2$
TREAT	-0.257^{***}	-0.190^{***}	-0.175^{**}	-0.272^{***}	-0.091^{*}
	(-7.51)	(-5.26)	(-3.12)	(-6.32)	(-2.60)
lnEI					0.955^{***}
					(8.10)
_cons	0.222^{***}	1.616	9.821^{***}	2.710	1.167
	(7.66)	(0.62)	(119.28)	(0.80)	(0.48)
Control variable	No	Yes	No	Yes	Yes
Province fixed	Yes	Yes	Yes	Yes	Yes
Year fixed	Yes	Yes	Yes	Yes	Yes
N	209	209	209	209	209
R^2_a	0.939	0.973	0.771	0.861	0.908

Notes : t statistics in parentheses, $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

involves developing a robust carbon trading platform and diverse regulatory approaches to reduce transaction costs and improve trading efficiency.

2. Improving energy efficiency and altering energy consumption structures are vital for policy effectiveness. China's industrial structure, reliant on coal and fossil fuels, presents environmental challenges. The government should encourage the growth of high-tech industries, modernize traditional sectors, phase out obsolete capacities, and shift towards low-carbon models. Increasing clean energy use, like solar, wind, and hydropower, is crucial. These measures are vital for achieving the "30.60 dual carbon" goal and promoting sustainable, environmentally friendly economic growth, particularly in less developed areas.

While this study provides an in-depth analysis of the ETS's impact, its limited timeframe and scope suggest further research. Future studies should incorporate corporate survey data to understand regional and industry-specific effects and explore additional ways the policy can aid in carbon emission reduction. This would offer a more comprehensive view of the ETS's implications and support more refined policy development.

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