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Research on the emission reduction effects of carbon trading mechanism on power industry: plant-level evidence from China

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Abstract

Purpose – Carbon trading mechanism has been adopted to foster the green transformation of the economy on a global scale, but its effectiveness for the power industry remains controversial. Given that energy-related greenhouse gas emissions account for most of all anthropogenic emissions, this paper aims to evaluate the effectiveness of this trading mechanism at the plant level to support relevant decision-making and mechanism design.

Design/methodology/approach – This paper constructs a novel spatiotemporal data set by matching satellite-based high-resolution (1×1 km) CO_2 and $PM_{2.5}$ emission data with accurate geolocation of power plants. It then applies a difference-in-differences model to analyse the impact of carbon trading mechanism on emission reduction for the power industry in China from 2007 to 2016.

Findings – Results suggest that the carbon trading mechanism induces 2.7% of CO_2 emission reduction and 6.7% of $PM_{2.5}$ emission reduction in power plants in pilot areas on average. However, the reduction effect is significant only in coal-fired power plants but not in gas-fired power plants. Besides, the reduction effect is significant for power plants operated with different technologies and is more pronounced for those with outdated production technology, indicating the strong potential for green development of backward power plants. The reduction effect is also more intense for power plants without affiliation relationships than those affiliated with particular manufacturers.

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Originality/value – This paper identifies the causal relationship between the carbon trading mechanism and emission reduction in the power industry by providing an innovative methodology for identifying plant-level emissions based on high-resolution satellite data, which has been practically absent in previous studies. It serves as a reference for stakeholders involved in detailed policy formulation and execution, including policymakers, power plant managers and green investors.

Keywords Emission reduction, Carbon trading mechanism, Green finance, Sustainable energy

Paper type Research paper

1. Introduction

Global climate change has long been a significant threat to sustainable development and thus calls for collective action at the international level to achieve the net-zero emissions target. Although nearly 200 countries have recommitted to Paris Climate Agreement on the COP26, the collective action still finds it easy to fall short of reality due to the classic dilemma of free riding. While neither the cost nor benefit of fulfilling the climate promise is equally distributed across countries, most of them may have incentives to rely on others' emissions reduction efforts without playing their roles (Nordhaus, 2015). Moreover, in the current complex international environment where the staggering COVID-19 pandemic, Russian–Ukraine conflict and slow transformation of energy structure are intertwined, the supply of clean energy still falls behind a rising demand in energy for boosting economic recovery. Given this circumstance, energy-related carbon emissions that plummeted during the early outbreak of COVID-19 have rebounded ever stronger to an annual record-high level of 36.3 billion tonnes with a yearly growth rate of around 6% in 2021, where coal-fired power plants supplied half of the increase in worldwide electricity demand (International Energy Agency, 2022; Ray *et al.*, 2022). As there is no one-size-for-all solution to environmental damages, it requires more immediate and effective domestic efforts to regulate carbon emissions under a renewed international consensus.

Among all policy tools, market-based climate policy is essential for addressing the dilemma between economic growth and carbon emissions control. The market-based climate policies, in contrast to the command-and-control policies that set strict standards and ignore the costs for compliance with emissions control, provide economic incentives for stakeholders to reduce emissions and allocate resources more efficiently. According to the literature, market-based policies in many forms, such as market-based instruments, environmental taxes and emissions trading, are considered more effective and efficient than command-and-control policies in reducing compliance costs and removing information asymmetry (Pan *et al.*, 2022a). Meanwhile, carbon trading-related policies play a leading role among the diverse options in market-based policies. They ensure that the environmental goal is met, and the tradable allowances allow individual emissions sources to set their own compliance path (Goulder, 2013; Gu *et al.*, 2022). Effectively designed carbon trading programmes provide high environmental certainty, lower administrative costs and increase the accountability of reducing, tracking and reporting emissions (Wang and Chen, 2015). According to World Bank, 65 carbon pricing initiatives cover 47 countries worldwide as of April 2021, most of which are developed countries. For instance, Japan introduced a voluntary emissions trading system in 2005 with coverage over various sectors such as electricity production and distribution. Germany launched the German Combustibles Emissions Trading Act in 2021, extending the sector coverage from mainly the large industrial facilities and power plants set by the European emissions trading system to the heating and transport sectors.

However, the developing countries have been cautious in adopting carbon trading-related policies for the cause of low-carbon transition. On the one hand, the developing countries need a high volume of cost-affordable energy supply during the process of industrialisation in case of falling into the energy insecurity trap. On the other hand, domestic pressures are mounting in the developing countries, as the climate policy may lead to a welfare loss (Gavard *et al.*, 2016). Especially in the fossil-fuel-dependent countries such as China, India and Venezuela, the costs of climate policies may result in potential social instability and economic inequality. Doubtlessly, managing domestic climate challenges is crucial, but the question for the developing countries is how. Considering that most of the developing countries are at different levels of economic status, it is vital to make use of the coordination between government intervention and the market power (Zhou and Wang, 2022). In other words, by combining top-to-down and up-to-top approaches, the developing countries may find their respective ideal pathways towards green development. It is thus essential to conduct in-depth analyses of the emission reduction effects of the carbon trading mechanism.

Nevertheless, the extant literature hardly captures the corporate performance under governmental intervention. Existing studies mainly adopted country/province/city-level evidence to investigate the effectiveness of the carbon trading scheme (for example, Wang *et al.*, 2015; Zhao *et al.*, 2017; Chen *et al.*, 2019) or discussed the impact of the carbon trading scheme on decreasing carbon pollution, technology innovation and related aspects (for example, Clarkson *et al.*, 2015; Pan *et al.*, 2022b; Xiao *et al.*, 2021). Even few studies exclusively examine how the carbon trading mechanism impacts certain firms' performance in a given sector and, more importantly, whether the corporates' response brings benefits in alleviating both carbon emissions and air pollution. Hence, it is of great academic and practical importance to identify the effects of the carbon trading mechanism. As one of the largest developing countries and suppliers of Certified Emission Reduction primary market, China has pledged to a goal of reaching the carbon emissions peak by 2030 and carbon neutrality by 2060. To this end, it has made substantial efforts to accelerate decarbonisation represented by implementing the carbon trading pilot mechanism in 2011. It showcases a shift towards market-based policy, emphasising on corporate participation as a supplement to the traditional industrial policy, such as China's Five-year plans. Additionally, given China's solid efforts in combating climate challenges may provide references to its developing counterparts on how to deal with carbon emissions reduction by giving a full play to government-market cooperation, it would be crucial to examine whether these attempts are successful as designed.

To bridge the research gap, this study investigates how the market-based environmental regulation influences the coordinated reduction of CO_2 and $PM_{2.5}$ from 2007 to 2016 based on plant-level emissions, taking China's carbon trading pilot mechanism as a quasi-natural experiment. The empirical results indicate that the carbon trading mechanism induces 2.7% of CO_2 emission reduction and 6.7% of $PM_{2.5}$ emission reduction in power plants in pilot areas on average, implying that the market-based policy encourages the synergy of pollution reduction. However, the reduction effect showcases heterogeneity across corporates. It is statistically significant only in coal-fired power plants but insignificant in their gas-fired counterparts. Furthermore, the reduction effect is significant for power plants operated with different technologies but is more pronounced for those with outdated production technology, indicating the strong potential for green development of power plants with backward technologies. The reduction effect is also more intense for power plants without affiliation relationships than those affiliated with particular manufacturers.

This paper contributes to the existing literature from the following three perspectives. Firstly, we newly constructed a nationwide plant-level emissions panel data set based on high-resolution satellite data from 2007 to 2016, revealing the locations and identities of plant-level emissions in China. Secondly, we apply the difference-in-differences (DID) method to investigate the influence of market-based environmental regulation on dual-track pollution reduction (i.e. CO_2 and $PM_{2.5}$) based on spatially-nuanced plant-level evidence, bridging gaps in earlier research. Finally, we further investigate the heterogeneity of power plant characteristics in terms of fuel, electricity generation technology, ownership structure and affiliation relationship. The heterogeneity analyses provide empirical evidence about enterprise response to and participation in emissions reduction, thus shedding light on the effectiveness of carbon emission trading policy.

The remaining of this paper is arranged as follows. Section 2 briefly reviews the relevant literature. Section 3 presents the research design. Section 4 delves into the empirical results, followed by a further discussion. Section 5 concludes with policy implications.

2. Literature review

The causal relation between carbon trading schemes and carbon emissions reduction has aroused considerable attention in recent years. Extant literature is undertaken mainly from the following two perspectives.

Existing literature delves into the market-based policy for greenhouse gas emissions against the background of climate challenges and further discusses how it accelerates the low-carbon transformation. In fact, the market-oriented mechanism includes diverse forms such as price-based programmes in demand response, cap-and-trade programmes and carbon-trading mechanisms, which would lead to varying environmental outcomes. Wu *et al.* (2020) showed that market-based environmental regulations significantly improved regional eco-efficiency. Zhou and Wang (2022) found that the carbon emissions trading mechanism was beneficial to green technology innovation, which would be enhanced by environmental legislation and development strategy. In turn, it would improve the performance of carbon emission reduction (Rogge *et al.*, 2011). Given that the market-incentive mechanism pays off mainly by encouraging corporates to participate in carbon emission reduction activities, it induces the companies to adjust their business strategy and strengthen the carbon emissions reduction effect (de Groot *et al.*, 2001; Zhao *et al.*, 2018). Besides, Xie *et al.* (2022) discussed the impact of the Chinese carbon trading mechanism in a specific sector. They pointed out that the pilot programme led to a structural upgrading in the power generation technology, which would help overcome carbon emission constraints.

Some scholars are inclined to adopt regional emissions data to measure the environmental costs of the carbon trading scheme. It sheds light on how carbon pricing and related policies impact the green transformation. Yang *et al.* (2021) used Chinese province-year data and found that the environmental outcomes of China's carbon emissions reduction policy varied across provinces. Fleschutz *et al.* (2021) indicated that price-based demand response caused an increase in CO_2 emissions using European country-specific empirical data. Liu *et al.* (2021) found that China's carbon trading programme alleviated the air pollutant emissions level of $PM_{2.5}$ based on city-level monthly data, extending the existing study of climate policy's negative impact on greenhouse gas emissions and air pollution.

Although the existing literature has gone to great lengths about the effectiveness of carbon trading mechanisms in reducing greenhouse gas emissions, certain issues still need to be addressed. Firstly, previous literature has limited choices of indicators to measure carbon emissions reduction with a precise concentration on the country/province/city-specific data. Given that carbon emissions could result from a variety of sources other than the firm that owns power plants, using merely macro-level panel data to analyse the impact of the carbon trading mechanism on corporate performance may be insufficient. Secondly, previous studies mainly focus on a particular aspect of the carbon trading mechanism's environmental consequence or industrial structure optimisation, such as its impact on the carbon emissions reduction, air pollution alleviation and power generation technology structure. Yet most of them fail to consider the co-benefits of reducing both carbon and air pollution emissions, thus neglecting the synergy effect of the carbon trading program. Finally, some scholars are inclined to assess the carbon trading mechanism but pay little attention to a particular sector, especially the power sector, which has long played a significant part in Chinese carbon trading programmes. It thus requires an in-depth study taking the Chinese power sector as a sample.

To bridge these research gaps, this paper provides an innovative and pragmatic methodology for identifying plant-level emissions of CO_2 and $PM_{2.5}$ based on high-resolution (1×1 km) satellite data. We then apply the DID method to examine the carbon trading mechanism's reduction impacts in the power industry and further discuss its heterogeneous effects according to company characteristics.

3. Methodology

3.1 Data and variable definition

3.1.1 Plant-level CO_2 and $PM_{2.5}$ emissions. The main variables of interest include CO_2 and $PM_{2.5}$ emission, which are obtained by matching two satellite-based high-resolution emission databases, the Open-source Data Inventory for Anthropogenic CO_2 (ODIAC) database and the Tracking Air Pollution in China (TAP) database with the geographic location of power plants in China provided by Global Power Plant database developed and maintained by World Resources Institute. The Global Power Plant database collects information about the exact location, power generation capacity, operational status, production technology, fuel and other relevant power plant data from official government data, independent sources and crowdsourced data (World Resources Institute, 2018). This database has proven reliable in the literature, and the detailed information on power plants enables this paper to perform in-depth heterogeneity analyses of power plants' responses to the carbon trading mechanism (Gotzens *et al.*, 2019; Brinkerink *et al.*, 2021).

CO_2 and $PM_{2.5}$ emission data are, respectively, provided by ODIAC and TAP databases. The ODIAC database integrates data collected from satellite-based night-time light sensors with power plant emission profiles to estimate the spatial extent of fossil fuel CO_2 emissions on a global scale (Oda and Maksyutov, 2011; Oda *et al.*, 2018). This fuel-emission-centred estimation strategy also reduces the errors generated by non-anthropogenic emission sources and by emission sources other than fuel consumption, which is out of the scope of this paper (Chen *et al.*, 2020). Meanwhile, the TAP database estimates the $PM_{2.5}$ emission in China based on a two-stage machine learning model coupled with the decision-tree-based gap-filling method and synthetic minority oversampling technique (Geng *et al.*, 2021; Xiao *et al.*, 2021). Both databases cover the whole geographic area of China at least five years earlier and later than the policy experimentation and have high resolutions of 1×1 km. Since all three databases use a unified (World Geodetic System) 84 geographic coordinate system, it is feasible to match the exact geographical locations of power plants with the emission data to obtain plant-level data without significant errors, as shown in Figure 1.

The matching processes are accomplished with QGIS, a free and open-source geographic information system software, and manual data-checking is performed to ensure data accuracy. In all samples, data missing or significant errors occur only in a small portion of the sample ($\approx 2\%$) and should not be problematic after manual data-checking, which verifies the position of locations and cells with ground-level images from the base map provided by Google Earth. Using the best available data from the abovementioned database, we construct a comprehensive CO_2 and $PM_{2.5}$ emission data set that allows for prediction or

Notes: The red cross mark indicates the power plant's location, and the rectangular indicates a cell in the raster data. For these two databases, a cell covers an area of 1×1 km. The colour of the cell is the visualisation of emission data: the brighter the colour, the more intense the respective type of emissions in the cell. The base map is provided by Google Earth, and the map, the raster data, and the locations of power plants are matched by latitude and longitude based on WGS 84 geographic coordinates system

Figure 1. Illustration of matching the geographical location of power plants with high-resolution emission data

causal inference related to the emissions of power plants. With updated fuel statistics and satellite data, it is possible to expand the timeframe of the data set. But it is noteworthy that the facility size of the power plant may change dramatically due to construction, termination of operation or many other reasons. Meanwhile, it is possible that more than one high-pollution facilitates operate in the same cell, which may cause the plant-level emissions to be aggregated in the data of the respective cell. It is thus of great importance to evaluate the endogeneity problem and the omitted variable bias when performing analyses on plant-level emission data.

3.1.2 Carbon trading mechanism. The policy framework of the carbon trading mechanism was first developed in October 2011 according to the "Notice on Carrying out Pilot Carbon Emissions Trading", which was issued by the National Development and Reform Commission. In the pilot areas, which include Guangdong province, Hubei province, Beijing, Shanghai, Tianjin, Chongqing and Shenzhen, carbon emissions allowances/quotas are allocated to firms according to their respective output, and specific benchmarks apply for some industries, such as power and high-technology industries. Based on the relevant literature, the policy-shock dummy variable is defined as zero for time periods before 2012 and is defined as one for time periods equal to or after 2012 (Wang *et al.*, 2019; Qi *et al.*, 2021; Dong *et al.*, 2022). For the treatment-group dummy variable, the value one is given if the power plants are located in the pilot area; otherwise, the value zero is given.

However, some literature suggests an alternative time-setting method of policy shock since the starting times of the carbon trading markets are different for each pilot area (Zhou *et al.*, 2019; Yu and Li, 2021; Zhang *et al.*, 2022). Shenzhen became the first city to initiate the trading market in June 2013, followed by Shanghai and Beijing in November 2013, then Guangdong, Hubei, Tianjin and Chongqing in June 2014. Therefore, the policy-shock dummy variable is defined as zero for time periods before 2014 and is defined as one for time periods equal to or after 2014 in the robustness test.

3.1.3 Control variables. The omitted variable bias and endogeneity problem should not be of great concern in this paper because the scope of research is power plants: the policy-making processes are exogenous to the plant-level decision-making, and few variables correlate with both pilot area selection and plant-level CO_2 and $PM_{2.5}$ emissions. However, we add the following control variables by referring to the literature:

- electricity generation capacity of power plants;
- green finance development level;
- ventilation coefficient [1]; and
- research input of the area (Li *et al.*, 2017; Jiao *et al.*, 2018; Koçak and Ulucak, 2019; Chen *et al.*, 2020; Lee and Lee, 2022).

3.2 Sample and data source

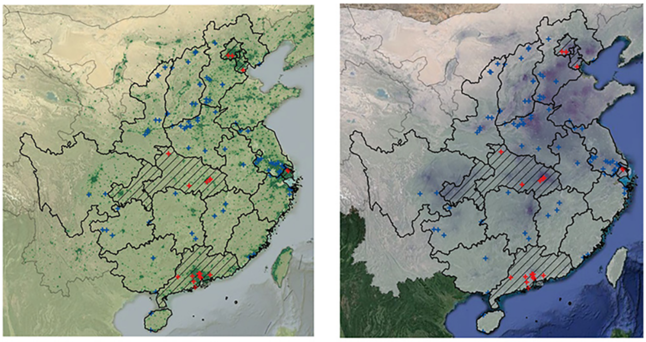
To reduce the bias generated by unobservable factors, the control group consists of the power plants located in provinces that are geographically surrounding the pilot areas, and the treatment group includes those located in the pilot areas [2]. Meanwhile, it is necessary to exclude emission reduction unrelated to the carbon trading mechanism to minimise the estimation bias. Hence, only samples that strictly match all of the following conditions are included in the estimations:

- the power plant is active during the sample time period;
- the facility size of the power plant remains at a constant level during the sample period, i.e. no new unit starts productive operation, and no existing unit retires;
- no remarkable changes in power output; and
- no other high-pollution facilities are located in the same cell, as the plant-level emissions are aggregated in this scenario.

The timeframe of this paper is set as 2007–2016 to increase the number of observations while mitigating the omitted variable bias with strict filtering conditions. After filtering, 110 power plants in 20 provinces/centrally-administered municipalities are included in the sample, in which 21 power plants operate in the pilot area, as shown in Figure 2.

The definitions and data sources are summarised in Table 1, and summary statistics are reported in Table 2. It should be noted that the data set cover power stations with different electricity generation capacity and emission levels. Besides, the research input and green financial development level are much higher in pilot areas than in non-pilot areas, which shows that a selection preference in policy experimentation. In other words, the government tend to choose better-developed areas to conduct the policy experimentation, which may distort the estimation of policy impact if the advantageous market conditions are not controlled. This phenomenon provides the theoretical foundation for the inclusion of control variables in estimations.

The logarithm form is used in estimation for the emissions data of CO_2 and $PM_{2.5}$ as well as the ventilation coefficient since these variables are positively skewed. Table 3 reports the correlations between control variables. The correlation coefficients between some variables are close to 1 and highly statistically significant. To address concerns related to the multicollinearity problem, the variance inflation factor (VIF) test is conducted. The results of VIF are reported in Table 4. Given that the VIF values of all independent variables are less than 5, it can be concluded that the multicollinearity problem is not substantial in this paper.



CO_2 emissions distribution $PM_{2.5}$ emissions distribution

Notes: The shaded areas are pilot areas, and unshaded areas are not pilot areas but are included in the sample. The red cross marks indicate the locations of power plants in the pilot areas, and the blue cross marks indicate the locations of power plants outside the pilot areas but included in the sample. The deeper the colour, the higher the emissions

Figure 2.
Location of sampled power plants and emissions distribution

Category	Definition		Source
Dependent variable	*co2*	Plant-level CO_2 emission data (million tons)	ODIAC database
	pm25	Plant-level $PM_{2.5}$ emission data ($\mu g/m^3$)	TAP database
Dummy variable	*pilot*	1 for the pilot area, 0 for the non-pilot area	–
	policy	1 for time periods equal to or after the year 2012, 0 for before 2012	–
Independent variable	*capacity*	Installed electricity generation capacity of power plants (MW)	Global Power Plant database
	greenfin	Green finance development index (1–10)	China Statistical Yearbook, China Insurance Statistical Yearbook, Statistical Yearbooks of Sample Provinces
	rd_gdp	R&D expense/GDP (%)	
	ven	Ventilation coefficient	Global Environmental Database

Table 1.
Summary of variable definition and data sources

3.3 Model specification

The following standard DID model is constructed to estimate the causal impacts of the carbon trading mechanism on power plants' CO_2 and $PM_{2.5}$ emissions. The DID model is a common method for assessing the causal effects of policies or events, and its applications in environmental economics and energy economics are fruitful (Elrod and Malik, 2017; Ghosal *et al.*, 2019; Najjar and Cherniwchan, 2021). The discrepancy between the different areas before initiating the carbon trading mechanism can be mitigated by analysing the difference between the CO_2 and $PM_{2.5}$ emissions of the non-pilot areas and their pilot counterparts both before and after the policy implementation. The baseline model is specified as follows:

$$co2_{it} = \beta_0 + \beta_1 \times pilot_{it} \times policy_{it} + \alpha \times X_{it} + \mu_i + \varphi_t + \varepsilon_{it} \quad (1)$$

Variable	Obs	Mean	SD	Min	Max
Panel A: Full sample					
co2	1,100	2.702	2.705	0.132	15.590
pm25	1,100	68.492	24.783	13.514	150.742
capacity	1,100	678.785	694.219	50.000	3,970.000
greenfin	1,100	1.668	0.809	0.711	6.921
rd_gdp	1,100	1.610	0.884	0.207	6.014
ven	1,100	1,233.230	283.856	632.295	2,418.158
Panel B: Pilot area sample					
co2	210	2.880	3.271	0.344	15.590
pm25	210	65.875	26.434	21.224	134.451
capacity	210	774.071	930.608	150.000	3,970.000
greenfin	210	2.469	1.091	0.852	6.921
rd_gdp	210	2.406	1.210	1.193	6.014
ven	210	1,126.406	375.880	773.027	2,418.158
Panel C: Non-pilot area sample					
co2_origin	890	2.660	2.553	0.132	13.492
pm25_origin	890	69.109	24.352	13.514	150.742
capacity	890	656.301	624.125	50.000	2,560.000
greenfin	890	1.479	0.585	0.711	2.939
rd_gdp	890	1.422	0.660	0.207	2.619
ven	890	1,258.436	251.117	632.295	1,726.304

Table 2.
Summary statistics

Variable	capacity	greenfin	ven	rd_gdp
capacity	1			
greenfin	−0.042	1		
ven	−0.016	0.135***	1	
rd_gdp	−0.085***	0.849***	0.174***	1

Note: ***Significant at 1%

Table 3.
Correlation coefficients of variables

Variable	VIF		1/VIF
capacity	1.01		0.99
greenfin	3.60		0.28
rd_gdp	3.67		0.27
ven	1.03		0.97
Mean VIF		2.33	

Table 4.
Variance inflation factor test

$$pm25_{it} = \beta_0 + \beta_1 \times pilot_{it} \times policy_{it} + \alpha \times X_{it} + \mu_i + \varphi_t + \varepsilon_{it} \tag{2}$$

where i denotes power plants and t denotes years. The coefficient β_0 of the cross-term *pilot* × *policy* captures the causal effects of interest. X_{it} refers to a set of control variables as defined above. The year fixed effect μ is used to control unexpected impacts over time, and the plant fixed effect φ is added to control unobservable factors that change across power plants but remain constant across time periods. ε_{it} is the error term. The Driscoll–Kray errors are used in estimations to correct heteroskedasticity and autocorrelation. Besides, the logarithm form is used in estimation for the emissions data of CO_2 and $PM_{2.5}$ as well as the ventilation coefficient since these variables are positively skewed.

4. Results and discussions

4.1 Baseline regression results

The baseline results of estimating the impact of the carbon trading mechanism on Chinese power plants' emissions are presented in Table 5. The coefficient of the interactive term *policy* × *pilot* in column (1) is significantly negative at the 1% level, indicating that the CO_2 emissions at the power plant level decreased by 2.2% in the pilot areas after implementing the carbon trading mechanism. This result holds after adding control variables. The coefficient in column (3) is also significantly negative at the 1% statistical level, while the coefficient value changes considerably after adding control variables into the model. The result in column (4) indicates that the $PM_{2.5}$ emissions of power plants in the pilot areas are reduced by 6.7% due to policy effects. These results imply that the carbon trading policy generates substantial co-benefits of carbon emissions reduction and air pollution control in the power industry. Considering the strong emission intensity of the energy industry in China, such plant-level emission reduction effects are highly considerable.

For control variables, the results generally meet our expectations, and some conclusions can be reached. Intuitively, the electricity generation capacity of a power plant is significantly and positively related to its CO_2 and $PM_{2.5}$ emissions. Meanwhile, green finance development also contributes to the control of CO_2 and $PM_{2.5}$ emissions. Nevertheless, *ceteris paribus*, increasing regional research input may only decrease the $PM_{2.5}$ emissions at the power plant level, with little effect on CO_2 emissions. In the meanwhile, the ventilation coefficient is not statistically significant.

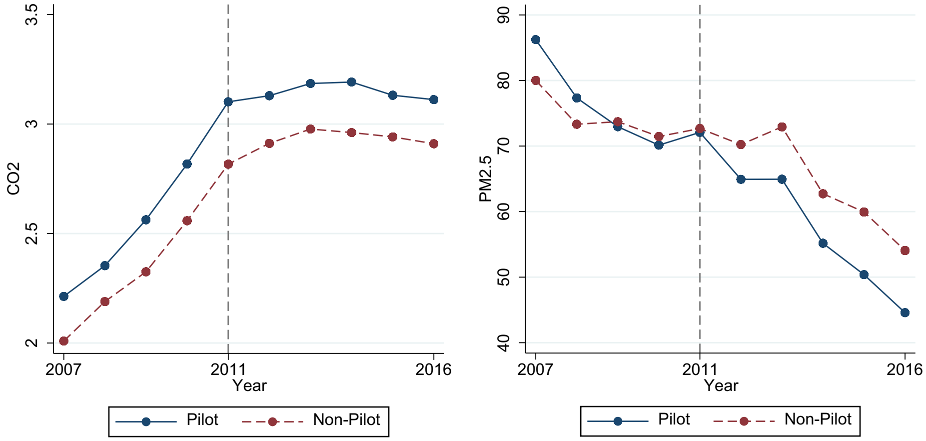
4.2 Robustness analysis

4.2.1 Parallel trend test. The parallel trend test is used to visualise the trend between the pilot and non-pilot areas over time to rule out the possibility of non-policy-related factors influencing CO_2 and PM2.5 emissions trends. Figure 3 illustrates the trends of CO_2 and $PM_{2.5}$ emissions, respectively. It finds that before the policy implementation, the gap in CO_2 emissions between the two areas remains constantly significant, and the gap in $PM_{2.5}$ emissions is constantly small. The pattern of the two trends changed after the carbon

Variable	(1) CO_2	(2) CO_2	(3) $PM_{2.5}$	(4) $PM_{2.5}$
policy × *pilot*	−0.022*** (−5.799)	−0.022*** (−6.458)	−0.171*** (−4.676)	−0.067*** (−8.284)
capacity		0.021*** (52.317)		0.006*** (7.792)
greenfin		−0.004** (−2.368)		−0.034** (−2.559)
ven		−0.042 (−1.097)		0.083 (1.106)
rd_gdp		0.000 (0.169)		−0.271*** (−6.493)
_cons	14.034*** (1.26e + 13)		4.324*** (8.56e + 13)	
Plant FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
N	1,100	1,100	1,100	1,100
r2	0.974	0.974	0.737	0.797

Notes: *t*-values in brackets; models are estimated with Driscoll–Kray errors; **significant at 5%, ***significant at 1%

Table 5. Baseline regression results



CO_2 $PM_{2.5}$

Figure 3.
Parallel trend test

emission programme was implemented in 2011. Thus, it could be concluded that the parallel trend holds for the two variables.

4.2.2 Setting different policy time. Considering the lagged effects of policy implementation, an alternative policy-shock dummy variable *policy2* is used in estimation for additional robustness checks. Table 6 shows that the estimation results with alternative policy time-setting are generally consistent with the baseline results. The coefficients of the DID estimators *policy2* × *pilot* are statistically significant at 1% level, but the value of coefficients decreases on a certain scale, indicating the diminishing marginal utility of the policy effects.

4.2.3 Placebo test. Since it is impossible to incorporate all applicable regulations related to the emissions of power plants in the estimations, a placebo test is conducted based on randomly assigned "false" pilot areas. According to baseline results, the carbon trading mechanism effectively reduces both CO_2 and $PM_{2.5}$ emissions. Thus, the placebo test includes both variables for all areas. If the policy effects do exist, the coefficient of the mimic

Variable	(1) CO_2	(2) CO_2	(3) $PM_{2.5}$	(4) $PM_{2.5}$
policy2 × *pilot*	−0.016** (−3.094)	−0.013* (−2.005)	−0.157*** (−3.656)	−0.066*** (−4.775)
capacity		0.021*** (47.678)		0.006*** (6.315)
greenfin		−0.004** (−2.594)		−0.026* (−1.879)
ven		−0.028 (−0.652)		0.120 (1.384)
rd_gdp		−0.008 (−1.603)		−0.291*** (−8.561)
_cons	14.034*** (1.26e + 13)		4.324*** (8.54e + 13)	
Plant FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
N	1,100	1,100	1,100	1,100
r2	0.974	0.974	0.723	0.797

Notes: *t*-values in brackets; models are estimated with Driscoll–Kray errors; *significant at 10%, **significant at 5%, ***significant at 1%

Table 6.
Robustness check: alternative policy dummy variable

interactive term *policy2* $\times$ *pilot* is expected to be statistically insignificant (Brewer *et al.*, 2018; Wing *et al.*, 2018).

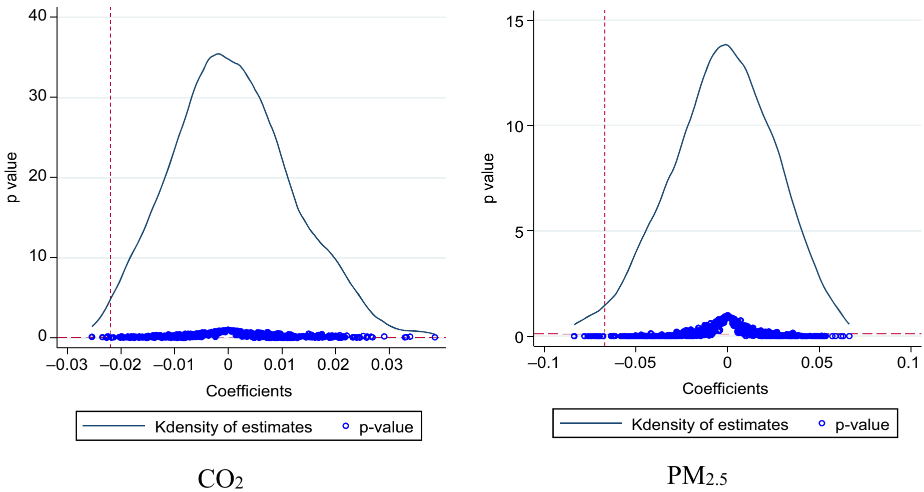
The DID analysis based on equations (1) and (2) is performed 500 times with randomly assigned 10 areas, and the estimated coefficients and their respective *p*-values are plotted in Figure 4. As most of the estimated coefficients generated in the placebo test are centred around zero and deviate significantly from the predicted coefficients in baseline regression (−0.022*** and −0.067***), it indicates that the placebo test provides additional evidence that the baseline DID results and conclusions are robust.

4.2.4 Counterfactual test. To further test the robustness of the results, a counterfactual test is implemented. The periods prior to the introduction of the carbon trading mechanism are selected as the hypothetical year when the mechanism is counterfactually introduced. If under the hypothetical scenarios, the DID estimator is not statistically significant, it can be concluded that no systematic differences between the emissions of the control group and the treatment group exist after removing the impact of the carbon trading mechanism. Therefore, *policy2009* $\times$ *pilot* and *policy2010* $\times$ *pilot* are introduced into the regression, which indicates the policy implementation years are set to 2009 and 2010. The results of the counterfactual test are reported in Table 7.

The results show that the coefficients of *policy2009* $\times$ *pilot* and *policy2010* $\times$ *pilot* are not significant for both CO_2 and $PM_{2.5}$ emissions, indicating that before the introduction of the carbon trading mechanism, there does not exist substantial changes in the CO_2 and $PM_{2.5}$ emissions of the power plants in the pilot areas compared to those in non-pilot areas. It thus rules out the possibility that factors which were in play before the introduction of the carbon trading mechanism triggered the result of this paper and further verifying the robustness of the baseline regression findings.

4.3 Heterogeneity analysis

The emission control behaviours differ in power plants with different fuels, electricity generation technologies, ownership structures and affiliate relationships. Further heterogeneity



Note: The red dotted line represents estimated coefficients and p-values in the baseline regression

Figure 4.
Placebo test

Variable	(1) CO_2	(2) $PM_{2.5}$	(3) CO_2	(4) $PM_{2.5}$
policy2009 × *pilot*	0.004 (0.583)	−0.053 (−0.665)		
policy2010 × *pilot*			−0.007 (−1.184)	−0.036 (−1.573)
capacity	0.021*** (49.191)	0.006*** (6.615)	0.021*** (47.035)	0.006*** (6.347)
greenfin	−0.007*** (−3.544)	−0.044** (−2.618)	−0.007*** (−3.360)	−0.044** (−2.586)
ven	−0.023 (−0.558)	0.119 (1.436)	−0.028 (−0.652)	0.117 (1.340)
rd_gdp	−0.013*** (−3.304)	−0.280*** (−7.069)	−0.007* (−1.881)	−0.284*** (−7.621)
Plant FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
N	1,100	1,100	1,100	1,100
r2	0.974	0.794	0.974	0.793

Notes: *t*-values in brackets; models are estimated with Driscoll–Kray errors; *significant at 10%, **significant at 5%, ***significant at 1%

Table 7.
Counterfactual test results

analyses are thus conducted based on the power plant data that is manually collected or provided by the Global Power Plant database.

4.3.1 Fuel and technology heterogeneity. Intuitively, power plants with different fuels and different electricity generation technologies produce different levels of CO_2 and $PM_{2.5}$ emissions, so as the difficulties in achieving emission reduction. As emission control is gaining acceptance, efficiency improvement, as the prominent practical tool capable of reducing CO_2 and $PM_{2.5}$ emissions from fossil fuel plants in the short-term, has become a key concept for the choice of technology for new plants and upgrades of existing plants.

The sampled power plants can be categorised into two fuel types: coal-powered and gas-powered. As for electricity generation technologies, only the combined cycle technology is available for gas-powered plants, while two different technologies are available for coal-powered plants: subcritical and supercritical. The latter is generally considered the more advanced technology. Subcritical units have power generation efficiencies of between 33% and 37%, whereas efficiency ratings for supercritical coal plants range from 37% to 40%. The increase in efficiency also leads to reductions in emissions given the same level of power output (Gonzalez-Salazar *et al.*, 2018; Rasheed *et al.*, 2021; Whitaker *et al.*, 2012). Empirical evidence shows that the chemical looping combustion-based supercritical and ultra-supercritical units are energetically, exegetically, environmentally and economically advantageous plants for power generation compared to the other variants (Surywanshi *et al.*, 2019). As a result, the impacts of the carbon trading mechanism might be vastly diverse based on the fuel and electricity generation technologies of the power plants. The estimation results of each fuel and electricity generation technology are reported in Table 8.

It finds that the carbon trading mechanism generates significant impacts on coal-power plants, and in particular, coal-power plants with outdated production technology (subcritical). The emission reduction effects are statistically insignificant for coal-powered plants with comparatively more advanced production technology (ultracritical) and for gas-powered plants.

Such a difference can be attributed to two reasons. On the one hand, the less-developed electricity generation technology has more potential for emissions reductions, and thus the policy impact is more significant. On the other hand, the quota calculation model for power plants monolithically applies to all power plants with different production technologies. The quota pressure on technologically disadvantageous power plants is more intense than on

Table 8. Heterogeneity analysis: fuel and electricity generation technology

Variable	Full sample		Coal-powered plants: Subcritical technology		Coal-powered plants: Ultracritical technology		Gas-powered plants	
	(1) CO_2	(2) $PM_{2.5}$	(3) CO_2	(4) $PM_{2.5}$	(5) CO_2	(6) $PM_{2.5}$	(7) CO_2	(8) $PM_{2.5}$
policy × *pilot*	−0.024*** (−6.983)	−0.094*** (−9.840)	−0.022*** (−5.810)	−0.103*** (−7.568)	−0.019 (−1.584)	−0.026 (−0.668)	−0.004 (−0.192)	−0.001 (−0.015)
capacity	0.020*** (50.133)	0.006*** (8.405)	0.021*** (53.581)	0.007*** (9.134)	0.010*** (29.283)	0.004*** (5.815)	0.048*** (56.259)	0.008** (2.632)
greenfin	0.001 (0.582)	−0.102** (−3.164)	−0.005 (−1.351)	−0.105** (−2.988)	0.021 (1.666)	−0.186*** (−4.144)	−0.015 (−1.304)	0.030 (1.220)
ven	−0.047 (−1.152)	0.046 (0.627)	−0.043 (−1.129)	0.023 (0.334)	−0.100 (−1.260)	−0.280 (−1.586)	−0.013 (−0.373)	0.326** (2.876)
rd_gdp	−0.004 (−1.067)	−0.215*** (−5.561)	−0.002 (−0.524)	−0.206*** (−5.094)	0.003 (0.235)	0.088 (0.772)	0.032 (1.606)	−0.206*** (−3.961)
Plant FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
N	1010	1010	810	810	90	90	90	90
r2	0.974	0.976	0.972	0.799	0.992	0.913	0.978	0.869

Notes: *t*-values in brackets; models are estimated with Driscoll–Kray errors; **significant at 5%, ***significant at 1%, power plants with technology marked as "unknown" in database are excluded from technology heterogeneity analysis technologically advantageous power plants, so as the motivations to improve production processes and to reduce emissions. Therefore, this phenomenon also calls for a more detailed and well-developed quota calculation system that motivates the green transformation of all power plants in the power industry.

4.3.2 Ownership structure heterogeneity. According to the current literature, the ownership structure of a company may also influence the effectiveness of environmental regulations and policies. State-owned enterprises (SOE) can defy environmental policy with their advantageous political position, i.e. "central protectionism". The combination of such protectionism and inadequate regulatory capacity in the environmental bureaucracy provides motivations and possibilities for SOEs to violate environmental policies (Eaton and Kostka, 2018; Ran, 2017). Empirical evidence shows that SOEs in the power industry commit over 60% of reported violations (Eaton and Kostka, 2017). It is thus reasonable to further look into the impact of the carbon trading mechanism on power plants owned by SOEs. In China, most power plants are completed owned by SOEs, while a few plants are jointly owned by SOEs and private companies (mixed-ownership) or exclusively owned by private companies (private-ownership). In this paper, both mixed-ownership and private-ownership are considered non-SOE-ownership since their organisational behaviours in emission control are alike (Andersson *et al.*, 2018; Yuan *et al.*, 2021).

As shown in Table 9, the emission reduction effects of the carbon emission trading mechanism are significant for both SOE-owned and non-SOE-owned power plants. While the reductions in CO_2 emissions are of the same scale, the $PM_{2.5}$ emissions reduction is more substantial in SOE-owned power plants than that in non-SOE-owned power plants.

4.3.3 Affiliation relationship heterogeneity. The affiliation relationship of power plants may also influence the emission reduction impacts of the carbon trading mechanism since the quota can be shared with the parent company for power stations with affiliation. Therefore, the incentives for affiliated plants in emission control are expected to be less substantial compared to non-affiliated plants. The estimation results are reported in Table 10, where one may find that the CO_2 and $PM_{2.5}$ emissions of power plants without affiliation were reduced more than those of power plants with affiliation. This disparity also calls for a more detailed quota calculation system for increasing the emission reduction effects of the carbon trading mechanism.

	Non-SOE		SOE	
	(1)	(2)	(3)	(4)
Variable	CO_2	$PM_{2.5}$	CO_2	$PM_{2.5}$
policy × pilot	−0.022*** (−8.106)	−0.045** (−2.846)	−0.022*** (−4.123)	−0.089*** (−9.155)
capacity	0.035*** (83.932)	0.008*** (7.429)	0.018*** (47.770)	0.005*** (8.266)
greenfin	−0.005 (−1.680)	0.028*** (3.803)	0.004* (2.069)	−0.116*** (−3.634)
ven	−0.021 (−0.960)	0.239*** (3.996)	−0.047 (−1.084)	0.064 (0.896)
rd_gdp	−0.002 (−0.266)	−0.301*** (−6.666)	0.001 (0.117)	−0.197*** (−4.966)
Plant FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
N	340	340	760	760
r2	0.987	0.860	0.970	0.778

Notes: *t*-values in brackets; models are estimated with Driscoll–Kray errors; *significant at 10%, **significant at 5%, ***significant at 1%

Table 9.
Heterogeneity analysis: ownership structure

Variable	Non-affiliated plants (1) CO_2	(2) $PM_{2.5}$	Affiliated plants (3) CO_2	(4) $PM_{2.5}$
policy × pilot	−0.024*** (−7.494)	−0.083*** (−6.977)	−0.018* (−2.056)	−0.034** (−2.636)
capacity	0.019*** (67.867)	0.006*** (9.009)	0.050*** (20.907)	0.010*** (3.686)
greenfin	−0.002 (−1.151)	−0.027** (−2.283)	−0.009 (−0.863)	−0.048 (−1.373)
ven	−0.033 (−1.114)	0.027 (0.376)	−0.092 (−0.966)	0.274** (2.513)
rd_gdp	−0.004 (−1.217)	−0.257*** (−6.613)	0.011 (1.203)	−0.310*** (−5.595)
Plant FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
N	890	890	210	210
r2	0.978	0.789	0.966	0.854

Notes: *t*-values in brackets; models are estimated with Driscoll–Kray errors; *significant at 10%, **significant at 5%, ***significant at 1%

Table 10. Heterogeneity analysis: affiliation relationship

5. Conclusion and policy implications

Extant research has expressly emphasised the importance of the carbon emissions reduction against the background of global climate change. Carbon trading mechanism has been developed for curbing carbon emissions by highlighting the corporate viability under the market-based regulation on a global scale. This paper delves into the reduction impacts of the carbon trading mechanism in China and its heterogeneity under different corporate characteristics by using Chinese plant-level evidences from 2007 to 2016 in the power industry. We find consistent evidence that the carbon trading mechanism promotes carbon emission reduction, which is in accordance with previous studies. Furthermore, this paper adds to the body of knowledge in these areas by demonstrating that the lowering impacts of carbon trading mechanisms are accompanied by co-benefits such as reduced carbon emissions and air pollution. The findings are resilient to the heterogeneity of corporate when we take the main characteristics of power plants into consideration. Additionally, we find that the reduction effects are more pronounced in the coal-fired power plants with outdated production technologies or in power plants with no affiliation relations with particular manufacturers. It suggests that the carbon trading mechanism should be highly recommended in the developing countries as it pays off by encouraging corporate viability in reducing pollutant emissions.

Our research also leads to policy implications as follows. First, policymakers should attach more importance to the coordination of government policies and market mechanisms so as to accelerate the upgrading of both energy structure and industrial structure in response to the global climate challenge. Second, they may also consider monitoring the reduction effects of the carbon emission reduction-related policy from a micro perspective, especially at the plant level, which would provide more detailed information regarding the actual environmental outcomes. Finally, design and improve the carbon trading mechanism by borrowing relevant experience from other developing countries so as to attract more investors and experts while expanding the types of trading instruments available to increase the carbon market's efficacy.

Notes

1. Ventilation coefficient refers to the product of mixing depth and the average wind speed. It's an atmospheric state that shows pollution potential or the atmosphere's capacity to dilute and disseminate pollutants throughout an area (Sujatha *et al.*, 2016; Saha *et al.*, 2019).

2. The following provinces/centrally-administered-municipalities are defined as pilot areas according to the policy framework: Beijing, Shanghai, Tianjin, Guangdong and Hubei. No available sample is located in Chongqing, and Shenzhen is a part of Guangdong Province. The following provinces surrounding the pilot areas are included in the data set as non-pilot areas: Anhui, Fujian, Guangxi, Guizhou, Hainan, Hebei, Hunan, Jiangsu, Jiangxi, Shaanxi, Shanxi, Sichuan and Zhejiang.

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