Environmental Impact Assessment Review 103 (2023) 107286

Contents lists available at ScienceDirect

Environmental Impact Assessment Review

journal homepage: www.elsevier.com/locate/eiar

Can low carbon policies achieve collaborative governance of air pollution? Evidence from China's carbon emissions trading scheme pilot policy

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ARTICLE INFO

Keywords:
Carbon emissions trading pilot
Spatial spillover effect
Sulfur dioxide
Haze pollution
Collaborative governance
Spatial difference-in-differences model

ABSTRACT

In the context of environmental and climate governance, the efficiency with which low-carbon policies reduce air pollution is vital for enhancing the effectiveness of environmental policy implementation. Using the emissions trading scheme (ETS), the most representative low-carbon policy in China, as an example, this study employs a panel data set of 250 Chinese cities for the period 2003–2016. Additionally, a spatial difference-in-differences (SDID) model is utilized to explore the ETS pilot policy's impact on sulfur dioxide (SO_2) emissions and haze pollution ($PM_{2.5}$ concentrations) and identify the mechanism underlying these effects. Our results show that the policy helps to reduce both types of air pollution, thereby having a significant collaborative-governance effect. Moreover, while the ETS pilot policy improves $PM_{2.5}$ concentrations in neighboring cities significantly, it fails to curb SO_2 emissions in these areas. The mechanism identification results point to a collaborative-governance effect of the policy via industrial structure upgrading, energy structure optimization, and green technology innovation. According to heterogeneity analysis, while the policy has a more evident impact on air pollution in central and western China, it does not exert a collaborative-governance effect on SO_2 emissions in non-key environmental protection and energy-oriented cities.

1. Introduction

The rapid urbanization and industrialization of China has made it imperative to reduce carbon emissions, which impede high-quality economic development and pose a significant obstacle to achieving the goals of carbon peaking and carbon neutrality. To effectively address this issue, the Chinese government has implemented the Emission Trading Scheme (ETS) pilot policy in seven regions since 2013. Several studies have demonstrated the policy's effectiveness in reducing carbon emissions in these areas (Hu et al., 2020; Huang and Yi, 2023). In 2017, the ETS pilot policy was extended to the national level, making it the earliest and most representative low-carbon policy implemented in China to date.

Since China's reform and opening up 40 years ago, ecological and environmental issues have worsened progressively alongside economic development. Among these issues, air pollution, particularly in the form of haze pollution, has become increasingly prominent. Environmental governance has been prioritized as a key element of China's ecological civilization strategy. Given the close relationship between climate governance and environmental governance (Chen et al., 2023; Guan et al., 2023), the Chinese government and academia have gradually recognized the potential for realizing a "win-win" situation by achieving positive interactions and multiplier effects between efforts to control air pollution and reduce carbon emissions. This recognition has been reflected in the policy goals of the ETS pilot implemented in Beijing in 2014.[1] Furthermore, the "Management Measures for Carbon Emission Trading (Trial Implementation)," issued by China's Ministry of Ecology and Environment in 2020, clearly emphasizes the crucial role played by the collaborative air pollution governance in the calculation and allocation of carbon quotas.[2] Therefore, it is imperative that low-carbon policies be implemented effectively to tackle both carbon emissions and air pollution in China. Achieving collaborative emission reduction is essential for reducing the cost associated with implementing environmental policies and enhancing the efficiency of environmental governance.

Has the ETS pilot policy effectively facilitated collaborative emission

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[1] See http://www.beijing.gov.cn/zhengce/zfwj/zfwj/szfwj/201905/t20190523_72655.html.
[2] See https://www.gov.cn/gongbao/content/2021/content_5591410.htm.

https://doi.org/10.1016/j.eiar.2023.107286
Received 1 July 2023; Received in revised form 1 September 2023; Accepted 13 September 2023
Available online 21 September 2023

reduction efforts to mitigate air pollution? Prior research has mainly evaluated the ETS policy's implementation in terms of its impact on economic factors and carbon emission reduction. Several research have explored the anticipated impact of the policy on reducing total carbon emissions (Anderson and Maria, 2011; Hu et al., 2020) and carbon intensity (Dai et al., 2022). For example, Anderson and Maria (2011) discovered that the manufacturing sector's carbon emissions were significantly decreased under the EU ETS. Other research has concentrated on how this low-carbon policy affects economic factors such as employment rate (Yu and Li, 2021), firm value (Bode, 2006; Yu et al., 2020), and labor productivity (Marin et al., 2018).

While prior researches have examined the economic and carbon-reduction effects of the ETS policy extensively, insufficient attention has been dedicated to investigating its potential for facilitating collaborative air pollution governance. Liu et al. (2021) and Yan et al. (2020) explored this topic. In particular, Liu et al. (2021) explored how the ETS pilot policy influence $PM_{2.5}$ concentrations in Chinese cities. Yan et al. (2020) conducted empirical testing to evaluate whether the ETS pilot policy achieved collaborative governance of air pollution. Additionally, Yan et al. (2020) investigated how design elements within carbon markets, such as penalty mechanisms, participant scope, and market access numbers, impact the effectiveness of the collaborative governance of air pollution control. While these studies provide initial empirical support for the collaborative-governance effect of the policy, they overlooked the spatial spillover effect of pollutants. Unlike existing studies, this research utilizes a spatial difference-in-differences (SDID) model to take into consideration the impacts of spatial spillover.

Although the impact of environmental policies on air pollution has been richly discussed in the existing literature (Jefferson et al., 2013; Zhang et al., 2019; Zhang et al., 2023), the majority of these policies, e.g., the "two control zones" policy for SO_2 control and the "Air Pollution Prevention and Control Action Plan" for haze, specifically target the reduction of air pollution. However, the ETS pilot policy chosen in this study aims to reduce carbon emissions rather than direct air pollution reduction. Examining the collaborative-governance effects of environmental policies targeting carbon emissions reduction on air pollution is crucial, as it can enhance policy efficiency and reduce implementation costs. In order to evaluate the collaborative-governance effects of the ETS pilot policy on air pollution control, this study focuses on $PM_{2.5}$ and sulfur dioxide (SO_2) as representative air pollutants and conducts a coherent derivation, empirical analysis, and mechanism identification. This study contributes to existing literature in three aspects. First, this paper identifies the collaborative effects of the ETS pilot policy on air pollution control empirically from the perspective of spatial spillover effects, for the first time. Due to a variety of natural factors and economic mechanisms, air pollution often causes considerable spatial spillover effects (Maddison, 2007; Poon et al., 2006; Shao et al., 2016). This makes it possible that while the policy can achieve collaborative governance in pilot areas, they may also worsen the environmental quality of surrounding areas through pollution "leakage" effects (Cao et al., 2021). However, most prior research has disregarded these effects when examining the ecological implications of the ETS pilot policy, which may have resulted in partial empirical findings. Especially, China is now gradually incorporating environmental quality into the performance appraisal system of local government officials (Wu and Cao, 2021). In such a context, failure to scientifically evaluate the spatial spillover effects of the ETS pilot policy could hinder the policy's extension to the national level. Therefore, this study covers not only how the policy affects air pollution within the region but also how it affects neighboring regions spatially, offering a more comprehensive evaluation of its implementation.

Second, in this paper, the SDID model is constructed by embedding the spatial Durbin model (SDM) into the DID model, which not only allows us to explore the policy's spatial spillover effects, but also makes our model satisfy the stable unit treatment value assumption (SUTVA), thus allowing us to obtain more accurate empirical results than related studies. As mentioned above, the existing literature mainly utilized the traditional DID model to identify the collaborative effects of the ETS pilot policy, thereby violating the SUTVA required by the DID model due to the neglect of spatial spillover effects, diminishing the credibility of their findings. Hence, this study adopts the empirical strategy developed by Jia et al. (2021b) to utilize an SDID model, thereby providing more convincing empirical evidence under the more robust condition of controlling for spatial spillover effects.

Third, this paper specifically investigates the differential impact mechanisms of the ETS pilot policy on $PM_{2.5}$ concentrations and SO_2 emissions, so that we can provide a more targeted empirical decision basis for the implementation of the ETS pilot policy in China. As typical representatives of air pollution, SO_2 and haze pollution have certain similarities in their causes. When examining the collaborative-governance effects of the policy, some of the literature has selected only one of the pollutants to characterize air pollution (Liu et al., 2021). Meanwhile, another part of the literature, while giving simultaneous attention to the two air pollutants, does not distinguish the potential differences in the impact mechanisms between them (Yan et al., 2020). It should be noted that although SO_2 and haze pollution have the same origin, their outbreaks in China did not coincide. Haze pollution only appearing frequently after 2011, while SO_2 was already effectively controlled during the period. Therefore, it is necessary to specifically investigate the mechanisms of the heterogeneous impact of the ETS pilot policy on the two air pollutants.

Section 2 of the study presents a theoretical analysis of the ETS pilot policy's impacts on $PM_{2.5}$ concentrations and SO_2 emissions. Section 3 introduces the empirical strategy and data employed in this study. Section 4 discusses the baseline regression and robustness tests results, while Section 5 analyzes the mechanisms and heterogeneity. Finally, Section 6 concludes this paper.

2. Mechanisms and hypotheses

2.1. Industrial structure upgrading

According to existing studies, the high share of highly polluting heavy industries in China is the main causal factor of air pollution (Cheng and Kong, 2022; Shao et al., 2019a). By shifting the focus of industrial development from relying heavily on the manufacturing-based secondary industry to service-based tertiary industry (Liu et al., 2021), the ETS pilot policy can alleviate air pollution. The policy can mitigate air pollution in the pilot regions by restricting the development of the heavily-polluting industrial sector. This is achieved by imposing limits on carbon quotas and mandating reductions in carbon emissions. Consequently, backward productivity can be eliminated, resulting in a less polluted environment. Additionally, the ETS pilot policy plays a pivotal role in establishing a robust carbon financial system (Zhou and Li, 2019). As the carbon finance system continues to evolve, the allocation of various resource across industries will be optimized. Capital, technology, and policies are continuously tilted to green, low-carbon, and highly productive industries (Lin and Xie, 2023), thus promoting the development of clean industries. This transformation tackles air pollution while promoting the growth of advanced and environmentally friendly industries.

2.2. Energy structure optimization

China's reliance on coal-based energy is a significant contributor to its high SO_2 emissions and haze pollution levels (Wang and Feng, 2003). The ETS pilot policy is expected to facilitate the use of cleaner energy sources (Palmer et al., 2011), thereby improving air quality. Specifically, the introduction of a carbon price within ETS pilot areas means that companies that use coal and other fossil energy sources will face additional costs (Tang et al., 2021), thereby putting significant pressure on them to adopt cleaner energy sources to control air pollution.

Furthermore, carbon emission rights, as a novel form of underlying asset, play a crucial role in advancing the development of the green financial system in the pilot regions. The enhancement of the green financial system facilitates access to cost-effective financing channels for the development of green and clean energy industries (Lin and Xie, 2023), thereby encouraging the use of clean energy and reducing reliance on traditional fossil fuels in the pilot regions.

2.3. Green technology innovation

The importance of technology upgrading as a means of addressing air pollution cannot be overstated. Appropriate environmental regulations can incentivize companies to invest more heavily in technological upgrading (Porter and Linde, 1995). Within the framework of Porter's hypothesis, most prior literature has argued for a theoretical mechanism by which ETS policy can achieve environmental governance through incentivizing firms to engage in green technological innovation (Jeroen and Ivan, 2021; Yang et al., 2020). Specifically, if firms maintain their current technological level, they must comply with carbon quota restrictions by either purchasing additional carbon quotas or reducing their production levels (Hübler, 2011), both of which can increase production costs or decrease operating profits. Consequently, companies focused on profit maximization will be driven to engage in green technology innovation, thereby having a positive impact on air pollution control.

Therefore, we propose the following two hypotheses:

Hypothesis 1. The introduction of the ETS pilot policy reduces both $PM_{2.5}$ concentrations and SO_2 emissions, resulting in significant collaborative-governance effects.

Hypothesis 2. The ETS pilot policy's implementation achieves the collaborative governance of air pollution primarily through upgrading the industrial structure, optimizing energy structure, and promoting green technology innovation.

3. Empirical strategy

3.1. Model

To mitigate potential endogeneity problems, we choose the ETS pilot policy and employ a DID model to analyze the collaborative-governance effects of low-carbon policy on air pollution. As discussed previously, air pollution often has spatial spillover effects, which may cause the traditional DID model to violate the SUTVA (Jia et al., 2021b), resulting in less credible estimation results. Therefore, it is essential to apply spatial econometric modeling concepts to create an SDID model that can effectively control for spatial spillover effects.

In spatial econometric models, independent variables, dependent variables, and random disturbance terms typically display spatial correlation. However, SDM is uniquely able to take into account the spatial correlation among all three aspects (Elhorst, 2014). Moreover, in contrast to other spatial econometric models, SDM allows for any potential spatial spillover effects without imposing restrictions on their size (Elhorst, 2010). Thus, following the idea of Jia et al. (2021b), we create an SDID model that integrates SDM into the traditional DID model:

$$\begin{aligned} AP_{it} = \alpha + \rho \sum_j w_{ij} AP_{jt} + \beta ETS_{it} + \theta \sum_j w_{ij} ETS_{jt} \\ + \boldsymbol{\gamma} \mathbf{X}_{it} + \boldsymbol{\psi} \sum_j w_{ij} \mathbf{X}_{jt} + \mu_i + v_t + \varepsilon_{it} \end{aligned} \tag{1}$$

where AP_{it} denotes $PM_{2.5}$ concentrations ($PM_{2.5}$) or SO_2 emissions (SO_2) of city i in year t; $ETS_{it} = 1$ denotes that city i is an ETS pilot city in year t, while $ETS_{it} = 0$ indicates that city i does not belong to the pilot regions in year t; w_{ij} represents spatial weights that reflect the proximity between cities; control variables are denoted by $\mathbf{X}_{it}$; μ_i and v_t represent city fixed effect and year fixed effect, respectively; and ε_{it} denotes the random disturbance term. It is important to note that, Eq. (1) includes a spatial lag term in the independent variables, so the use of ordinary least squares (OLS) for estimation results in biased and inconsistent findings. Thus, we apply the quasi-maximum likelihood estimation (QMLE) method to estimate Eq. (1).

3.2. Variables and data

In 2017, China officially initiated the establishment of a national carbon market, expanding carbon emissions trading to the nationwide level. This policy would impact all cities in the sample of the study, making the DID model no longer applicable after 2017. Furthermore, on July 12, 2017, the National Bureau of Statistics of China introduced a new accounting system for China's national economy. The most significant alteration in this new system, in contrast to the previous one, is the capitalization of R&D expenditures and their inclusion in fixed capital formation, thereby expanding the scope of GDP accounting. To mitigate the influence of the initiation of the national carbon market construction and the alteration in GDP accounting standards on the findings of the study, we adopt the data spanning the period of 2003–2016. In addition, due to the unavailability of $PM_{2.5}$ concentrations and energy consumption data in certain cities, 250 sample cities are selected for the study. The selection criteria for each variable utilized in this study are described below.

3.2.1. The dependent variables and the independent variables

We choose SO_2 emissions and $PM_{2.5}$ concentrations as the dependent variables. Data on $PM_{2.5}$ concentrations are extracted from the global annual average $PM_{2.5}$ concentrations raster data publicly available through Columbia University's Socioeconomic Data and Applications Center (SEDAC). Based on this extraction, $PM_{2.5}$ values are calculated at the city level using ArcGIS software (Shao et al., 2019a). We obtain SO_2 emissions data by measuring industrial SO_2 emissions. Both the annual SO_2 emissions and $PM_{2.5}$ concentrations are presented in logarithmic form in this study (SO_2, $PM_{2.5}$). The independent variable is the ETS pilot policy. Considering that the policy has been implemented since 2013, we assign a value of 1 to pilot cities after 2013 and 0 otherwise.

3.2.2. Mechanism variables

(1) Industrial structure (*IS*). According to the mechanism analysis conducted in the study, the ETS pilot policy encourages the upgrading of the industrial structure, which results in a transition from the secondary industry to the more environmentally friendly tertiary industry. To assess the impact of the ETS pilot policy in this regard, we choose the ratio of the value added of tertiary and secondary industries to represent industrial structure (Yu et al., 2020).

(2) Energy structure (*ES*). In provincial-level research, the energy structure is frequently quantified by the fraction of coal usage in the total energy consumption. However, due to the scarcity of city-level data on coal usage, alternative indicators are necessary to characterize energy structure. Since electricity is a clean energy source, its percentage in total energy consumption can provide indications of energy cleanliness to a certain extent. Therefore, following Xu et al. (2021), we calculate the energy structure using the proportion of electricity usage in total energy consumption. Notably, since city-level energy consumption data is rarely obtainable from public sources, we initially obtain energy intensity data from statistical yearbooks and social development statistical communiqué. Subsequently, we calculate city-level energy consumption by multiplying the obtained data with the gross domestic product (GDP).

(3) Green innovation (*GT*). Based on the International Patent Classification (IPC) codes in the Green Patent List published by the World Intellectual Property Organization (WIPO), we conduct a patent database search at the State Intellectual Property Office (SIPO) to determine

the quantity of green patents. This enables us to collect data on the annual number of green invention patents, green utility model patents, and green design patents applied for and authorized in each prefecture-level city. According to the definition of the three types of patents in the General Principles of China's Patent Law, invention patents and utility model patents contain a higher level of technical content compared to design patents.[3] Furthermore, compared to the number of patent applications, the number of authorizations can more accurately reflect a region's substantive innovation capacity and innovation performance (Hsu et al., 2014). Thus, to assess the extent of green innovation in a region, we utilize the total number of authorized green invention patents and green utility model patents as indicators.

3.2.3. Control variables

The concentrations of air pollutants are closely related to the economic patterns, residential characteristics, and energy use of the area (Combes et al., 2012; Jia et al., 2021a; Zhang and Da, 2015). Hence, we choose the following control variables. (1) Living standard (*LS*): The level of living standard of residents is estimated by the logarithmic measure of the GDP per capita. (2) Population density (*PD*): This variable is typically represented by the logarithm of the number of individuals per unit area. (3) Human capital (*HC*): This variable is typically represented by calculating the logarithm of the number of students enrolled in higher education. (4) Government intervention (*GI*): This variable is quantified by calculating the share of fiscal expenditure in GDP, after excluding expenditure on education and scientific undertakings (Jia et al., 2021a). (5) Information Development (*ID*): To measure information development, we utilize the logarithmic measure of the workforce engaged in information transmission computer services and the software industry. (6) Energy efficiency (*EE*): We use the GDP per unit of energy consumed to measure *EE*.

In mechanism tests, we select appropriate control variables for each mechanism variable. Specifically, the control variables for *IS* include *LS*, *HC*, *ID*, *PD*, and environmental regulation (*ER*), those for *GT* include *LS*, *HC*, *PD*, *GI*, *EE*, and science and technology (*ST*), and those for *ES* include *LS*, *HC*, *PD*, *GI*, *EE*, *ST*, and energy conservation policy (*EP*). To take into account the impact of energy conservation policies on the energy structure of cities during the sample period, we incorporate the 2006 "Decision of the State Council on Strengthening Energy Conservation Work" as a representative policy, and introduce a continuous DID term (*EP*). This term is constructed by cross-multiplying the dummy variable for policy implementation time and energy efficiency (i.e., the reciprocal of energy intensity). The dummy variable for this policy is set to 1 for the post-2006 period, and 0 for the pre-2006 period. We set *EP* in this way due to variations in the implementation intensity of energy efficiency policies across cities. Specifically, cities with lower energy efficiency are assumed to face more stringent policy constraints (Shao et al., 2019b). In this study, we measure *ER* in a region by the comprehensive utilization rate of general industrial solid waste. Additionally, *ST* in a region is measured using the natural logarithm of the number of employees in scientific research and integrated technical services.

All the data used in our study, except for the energy consumption, the number of patents, and the $PM_{2.5}$ concentrations, are sourced from the China Statistical Yearbook, the China Urban Statistical Yearbook, and previous statistical yearbooks of provinces and cities. Furthermore, the benchmark year is set as 2003. Table 1 presents the descriptive statistics for the aforementioned variables.

Table 1
Summary descriptive statistics.

Variables	Unit	Mean	Sd	Min	Max
SO_2	ton	10.610	1.180	0.693	14.238
$PM_{2.5}$	micrograms/m^3	3.706	0.518	1.147	4.702
ETS	–	0.042	0.201	0.000	1.000
LS	yuan/person	9.911	0.751	7.752	12.030
PD	person/km^2	5.812	0.828	3.663	6.953
HC	person	10.296	1.726	−7.116	13.871
GI	–	−2.242	0.463	−3.573	0.375
ID	ten thousand person	−1.037	0.992	−3.912	4.237
EE	ten thousand yuan/ton of standard coal	0.832	0.432	0.062	3.187
ER	–	−0.304	0.462	−5.319	2.298
ST	ten thousand person	−0.853	1.160	−4.605	4.234
IS	–	0.827	0.412	0.094	4.166
GT	–	0.200	0.328	0.000	2.693
ES	–	−2.228	0.517	−4.705	−0.766
EP	ten thousand yuan/ton of standard coal	0.687	0.535	0.000	3.187

3.3. Spatial weight matrices

In order to investigate the spatial correlation of air pollution, we utilize a widely used spatial weight matrix based on geographical distance, denoted as $\mathbf{W}_1$. The mathematical expression for each element w_{ij} in $\mathbf{W}_1$ is presented in Eq. (2):

$$w_{ij} = \begin{cases} \dfrac{1}{d_{ij}}, i \neq j \\ 0, i = j \end{cases} \tag{2}$$

where d_{ij} is the geographical distance between cities i and j calculated by their respective latitude and longitude coordinates.

Since air pollution can exhibit spatial correlation due to economic mechanisms, such as industrial transfers, relying solely on a geographical distance-based spatial weight matrix may face limitations in capturing economic correlation effects. Thus, to ensure the credibility of our empirical findings, we construct a nested matrix that considers both geographic and economic factors ($\mathbf{W}_2$) following the methodology proposed by Shao et al. (2016): $\mathbf{W}_2 = \omega\mathbf{W}_1 + (1-\omega)\mathbf{W}_3$. Specifically, $\mathbf{W}_3$ represents the matrix of economic distance, with each element being the inverse of the absolute difference of the annual average value of GDP per capita between different regions. ω is assigned a value of 0.5 without any loss of generality.

4. Baseline regression results and robustness tests

4.1. Spatial correlation test and parallel trend test

In this study, the SDID model combines the features of both the spatial econometric model and the DID model. Therefore, satisfying the spatial correlation and parallel trend assumption is critical for the model's efficacy.

4.1.1. Moran's index

In the examination of environmental-economic issues, the interactive influences at the spatial level need to be fully considered (Anselin, 2001). In terms of natural factors, with the atmospheric circulation, air pollution can realize transboundary transfer in the global domain (Ramanathan and Feng, 2008), thus generating spatial spillover effects. In terms of economic mechanisms, air pollution usually exhibits significant spatial spillover effects due to industrial transfer and transportation flow. Specifically, according to the pollution haven effect, pollution-intensive industries will move from areas with stronger environmental regulations to areas with weaker regulations. In addition, through transportation modes, such as automobile and high-speed rail, the spatial correlation of atmospheric pollution is not only reflected in the fact that high-emission primary pollutants are transported between cities in close proximity to each other, and the formation of haze pollutants can even be transported over long distances across regions (Shao

[3] See http://www.npc.gov.cn/zgrdw/huiyi/lfzt/zlfxzaca/2009-02/05/content_1517163.htm.

Table 2
Global Moran's I (SO_2).

	W_1			W_2		
	I	Z	P	I	Z	P
2003	0.053	7.231	0.000	0.092	6.409	0.000
2004	0.046	6.400	0.000	0.088	6.149	0.000
2005	0.053	7.337	0.000	0.091	6.385	0.000
2006	0.057	7.734	0.000	0.101	7.045	0.000
2007	0.040	5.633	0.000	0.090	6.350	0.000
2008	0.044	6.145	0.000	0.087	6.166	0.000
2009	0.038	5.461	0.000	0.085	6.000	0.000
2010	0.037	5.286	0.000	0.068	4.946	0.000
2011	0.041	5.784	0.000	0.069	4.971	0.000
2012	0.051	7.215	0.000	0.063	4.650	0.000
2013	0.072	9.841	0.000	0.062	4.470	0.000
2014	0.051	7.391	0.000	0.047	3.608	0.000
2015	0.058	7.909	0.000	0.063	4.497	0.000
2016	0.051	7.006	0.000	0.039	2.844	0.004

Table 3
Global Moran's I ($PM_{2.5}$).

	W_1			W_2		
	I	Z	P	I	Z	P
2003	0.196	25.365	0.000	0.099	6.860	0.000
2004	0.182	23.680	0.000	0.134	9.210	0.000
2005	0.189	24.503	0.000	0.142	9.782	0.000
2006	0.180	23.429	0.000	0.129	8.888	0.000
2007	0.201	26.106	0.000	0.131	9.016	0.000
2008	0.184	23.869	0.000	0.116	8.004	0.000
2009	0.193	25.028	0.000	0.131	9.020	0.000
2010	0.196	25.385	0.000	0.130	8.978	0.000
2011	0.200	25.859	0.000	0.120	8.284	0.000
2012	0.191	24.787	0.000	0.138	9.500	0.000
2013	0.216	27.899	0.000	0.116	7.983	0.000
2014	0.215	27.797	0.000	0.105	7.221	0.000
2015	0.235	30.248	0.000	0.113	7.754	0.000
2016	0.222	28.602	0.000	0.118	8.094	0.000

et al., 2019a).

At both the global and local levels, we assess the spatial correlation of both SO_2 and $PM_{2.5}$. The global Moran's index (Moran's I) provides insights into the overall spatial correlation of the variables. A positive value implies a positive spatial correlation, while the opposite suggests negative spatial correlation. The formula for calculating this index is presented below:

$$I=\frac{n\sum_{i=1}^{n}\sum_{j=1}^{n}w_{ij}(x_i-\overline{x})\left(x_j-\overline{x}\right)}{\sum_{i=1}^{n}\sum_{j=1}^{n}w_{ij}\sum_{i=1}^{n}(x_i-\overline{x})^2} \tag{3}$$

where n represents the count of sampled cities, w_{ij} is the element of the spatial weight matrix, x_i and x_j denote the annual $PM_{2.5}$ concentrations or SO_2 emissions in city i and city j, respectively, and $\overline{x}$ is the corresponding mean value.

Tables 2 and 3 present the global Moran's I values computed for the two air pollutants for the period 2003–2016. The results demonstrate that the global Moran's I values are significantly positive for both the $\mathbf{W}_1$ and $\mathbf{W}_2$ spatial weight matrices. This suggests that both SO_2 emissions and $PM_{2.5}$ concentrations have substantial positive spatial correlations across cities.

Using 2007 and 2016 as examples, we generate local Moran's I scatterplots for the standardized annual SO_2 emissions and $PM_{2.5}$ concentrations. The horizontal axis represents these variables, while the vertical axis displays their correlated spatially lagged values. As shown in Figs. 1–4, numerous cities' scatter points are situated in the first and third quadrants under either the $\mathbf{W}_1$ or $\mathbf{W}_2$ weight matrix, denoting a significant positive spatial correlation of either high-high or low-low clustering in the spatial distribution of both two air pollutants. This finding underscores that the management of spillover effects plays a crucial role in the traditional DID model.

4.1.2. Lagrange multiplier statistic

The previous results of the global and local Moran's I indicate a clear spatial correlation across cities regarding air pollutants. To determine the suitable spatial econometric model, we compute the corresponding Lagrange multiplier (LM) statistic. Table 4 displays the results of LM tests for the selection of the spatial lag model (SLM) and the spatial error model (SEM). One can see that both SEM and SLM pass the LM test for both SO_2 and $PM_{2.5}$, irrespective of the use of matrices $\mathbf{W}_1$ or $\mathbf{W}_2$. Therefore, it can be preliminarily concluded that the SDM is the most suitable.

4.1.3. Parallel trend test

To test the parallel trend assumption, we construct the following event analysis model:

$$AP_{it}=\alpha^{'}+\rho^{'}\sum_j w_{ij}AP_{jt}+\sum_{-4}^{3}\beta_k D_{it}^k+\boldsymbol{\gamma}^{'}\mathbf{X}_{it}+\boldsymbol{\psi}^{'}\sum_j w_{ij}\mathbf{X}_{jt}+\mu'_i+v'_t+\varepsilon'_{it} \tag{4}$$

where D_{it}^k is a dummy variable, and the other variables are defined as in the previous section. Our sample includes data for the period 2003–2016, so we only consider the three-year period after the policy's initiation in 2013. Therefore, we use 2003 as the benchmark year and set the boundary for D_{it}^k between the first 4 and the last 3 periods of policy implementation. Specifically, D_{it}^{-4} is assigned one if $t-2013\leq-4$, otherwise, it is zero; D_{it}^k is defined one if $t-2013=k$, $k\in(-3,3)$, and it is zero otherwise.

The non-spatial econometric model considers $\beta_k(k<0)$ as valid when there is no significant difference from zero, implying that the parallel trend hypothesis holds. However, the SDID model varies from the DID model by causing a chain of circular feedback effects in space due to changes in the indenpendent variables, thereby leading to direct, indirect, and total effects. The direct effect in our study represents the comprehensive impact of independent variables on local air pollutants (SO_2 and $PM_{2.5}$), while the indirect effect indicates the cumulative impact of these factors on air pollutants in the neighboring regions. Consequently, the direct effect of $D_{it}^k(k<0)$ must be statistically insignificant for the parallel trend hypothesis to be valid. We present the direct effects and their corresponding 95% confidence intervals for the two air pollutants in Figs. 5 and 6, under the $\mathbf{W}_2$ spatial weight matrix setting.

The Figs. 5 and 6 demonstrate that no direct effects of D_{it}^k are significantly different from zero prior to the ETS pilot policy's implementation, indicating that the trends of both air pollutants in pilot and non-pilot cities share similarities, thereby satisfying the assumption. In addition, following the implementation of the ETS pilot policy, the collaborative-governance effects on both SO_2 emissions and $PM_{2.5}$ concentrations show an increasing trend year by year. However, the impact on SO_2 emissions is relatively limited, which can be attributed to the superimposed influence of SO_2 emissions governance resulting from the launch of SO_2 emissions trading scheme in China in 2007. Specifically, there is a partial overlap in the implementation timeline and pilot areas between SO_2 emissions trading policy and the ETS pilot policy, significantly diminishing the effectiveness of the latter because the former plays a significant role in reducing SO_2 emissions (Hou et al.,

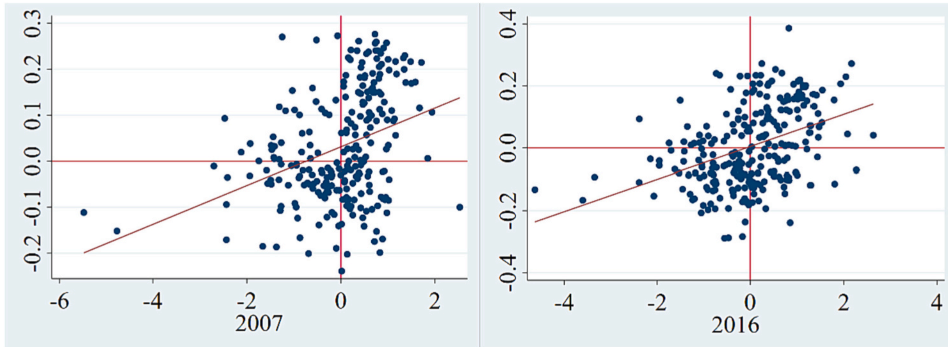

Fig. 1. Local Moran's I scatterplots (SO_2 and $\mathbf{W}_1$).

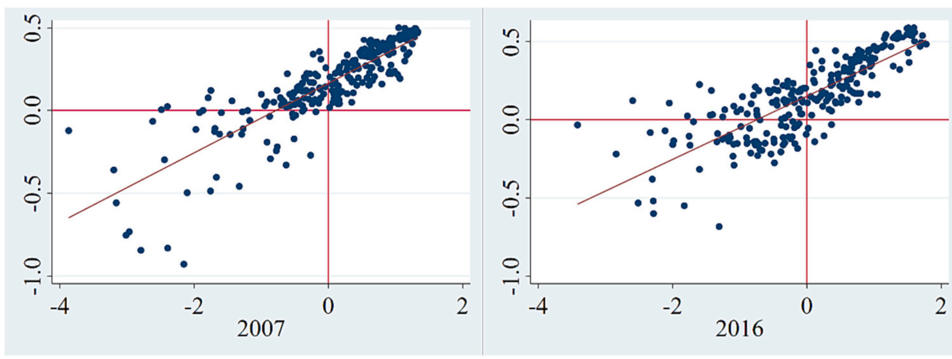

Fig. 2. Local Moran's I scatterplots ($PM_{2.5}$ and $\mathbf{W}_1$).

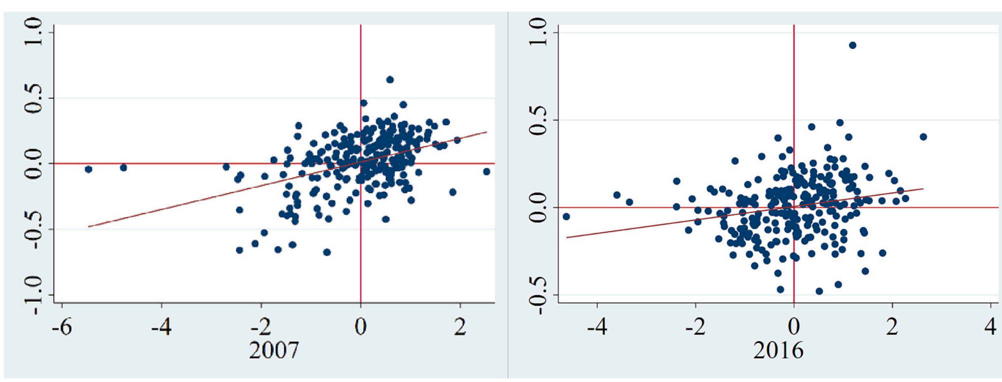

Fig. 3. Local Moran's I scatterplots (SO_2 and $\mathbf{W}_2$).

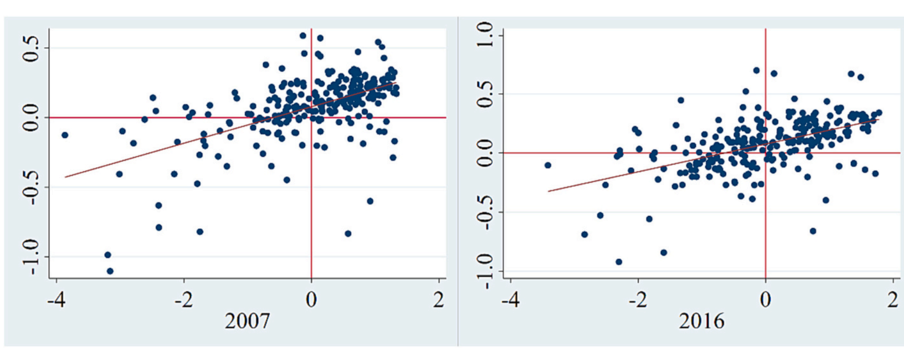

Fig. 4. Local Moran's I scatterplots ($PM_{2.5}$ and $\mathbf{W}_2$).

Table 4
LM test results.

			Statistic	*p*-value
SEM	SO_2	$\mathbf{W}_1$	1707.928	0.000
		$\mathbf{W}_2$	530.983	0.000
	$PM_{2.5}$	$\mathbf{W}_1$	5203.946	0.000
		$\mathbf{W}_2$	940.390	0.000
SLM	SO_2	$\mathbf{W}_1$	1281.511	0.000
		$\mathbf{W}_2$	459.883	0.000
	$PM_{2.5}$	$\mathbf{W}_1$	4434.810	0.000
		$\mathbf{W}_2$	1049.969	0.000

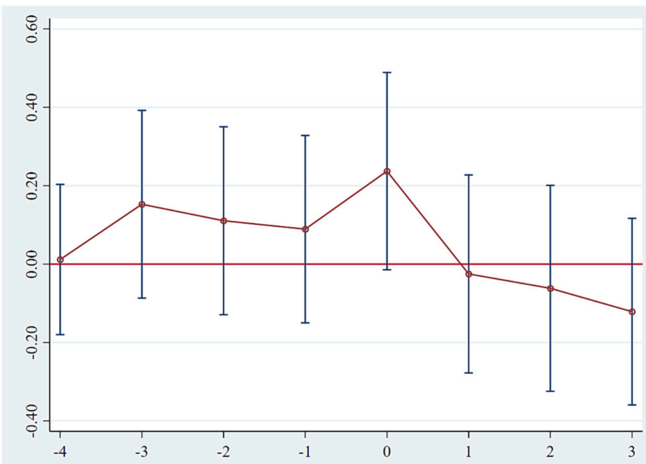

Fig. 5. Parallel trend test (SO_2).

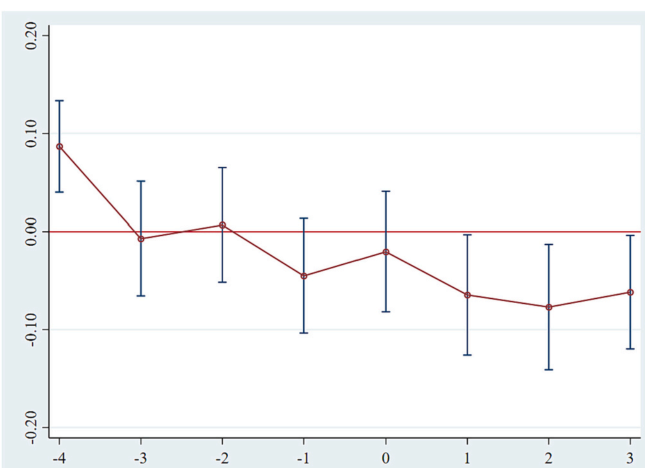

Fig. 6. Parallel trend test ($PM_{2.5}$).

2020). Although there are differences in the ex-post dynamic effects, the ex-ante parallel trends are consistent with the requirements of the DID model.

4.2. Baseline regression results

The baseline regression results are shown in Table 5, with Columns (1) and (2) reporting the estimated results obtained using $\mathbf{W}_1$, and Columns (3) and (4) provide the estimates obtained using $\mathbf{W}_2$. First, both the coefficients of the spatial lagged terms of SO_2 and $PM_{2.5}$ are statistically significant, suggesting that their spatial correlation can be attributed to natural factors and economic mechanisms, thereby displaying "both prosperity and loss" distribution characteristics in the pilot cities and their neighboring regions. Second, the coefficient of the spatial lag of *ETS* is significant at the 5% level at least, signifying that the policy can influence SO_2 emissions and haze pollution in the neighboring areas.

It should be noted that SO_2 emissions and haze pollution not only have certain natural characteristics, but are influenced by regional economic factors as well. Therefore, utilizing a weight matrix based only on geographical distance has limitations. According to the construction method of $\mathbf{W}_1$ and $\mathbf{W}_2$, $\mathbf{W}_2$ reflects not only the spatial distance at the geographic level but also the economic connection between cities. Hence, $\mathbf{W}_2$ is a better fit for our model. Therefore, in the analysis and discussion that follows, we concentrate on the findings obtained using $\mathbf{W}_2$ for empirical examination. Table 6 indicates that the direct effects of *ETS* on the two air pollutants are negative at the 10% significance level at least. These findings indicate that the policy can reduce SO_2 emissions and help to manage haze pollution in the pilot areas, thereby verifying Hypothesis 1.

Additionally, Table 6 indicates that the indirect effect of *ETS* on SO_2 is significantly positive, while the indirect effect on the $PM_{2.5}$ concentrations is negative. These findings suggest that implementing the ETS pilot policy increases SO_2 emissions but contributes to reducing $PM_{2.5}$ concentrations in neighboring areas. The current research identifies three key factors that contribute to the spatial spillover effects: industrial structure upgrading, energy structure optimization, and green technology innovation. Upgrading a region's industrial structure increases production costs for highly polluting industries, prompting their relocation to peripheral areas and creating a "leakage" effect that pollutes the surrounding environment. Optimizing the energy structure can increase the cross-regional flow of fossil fuels, hindering the clean energy transformation of neighboring areas and exacerbating air pollution. The ETS pilot policy stimulates innovative activities in the pilot regions (Zhang et al., 2020), promoting interregional trade and patent transfers (Hübler, 2011; Parrado and Cian, 2014; Verdolini and Galeotti, 2011), thereby reducing air pollution in adjoining areas. The above regression results suggest that different factors contribute varyingly to the ETS pilot policy's effects on the two air pollutants, resulting in the different directions of the effects of the policy. In Section 5.1, we identify the mechanism through which the ETS pilot policy generates heterogeneous spatial spillover effects on the two air pollutants.

From the estimation results of the total effects presented in Table 6, it is evident that the impact of the ETS pilot policy on SO_2 emissions is either statistically insignificant ($\mathbf{W}_1$) or positive at the 5% significance level ($\mathbf{W}_2$). Conversely, the total effect on $PM_{2.5}$ concentrations is significantly negative at the 1% level. These findings suggest that the implementation of the ETS pilot policy exacerbates overall SO_2 pollution, and demonstrate a collaborative-governance effect on haze pollution. Analyzing the direct and indirect effects, it becomes apparent that the increase in SO_2 emissions in the total effect is mainly due to the indirect effect. This spatial spillover effect of SO_2 emissions highlights the need for examining the collaborative-governance effects of the ETS pilot policy on air pollution and the mechanism of the spatial spillover effect.

Notably, as previously stated, our estimation results demonstrate that the ETS pilot policy exacerbates SO_2 pollution in the neighboring areas. However, the increase of pollution emissions in the surrounding areas will inevitably react to the pilot areas, thereby weakening the emission reduction effect of the policy on the pilot areas. Ignoring such a spatial spillover effect would attribute the above weakening effect to the policy itself, leading to an underestimation of its impact on the local area. Similarly, according to the results in Columns (2) and (4) of Table 5, the coefficients of *WETS* exhibit higher significance and larger absolute values compared to the coefficients of *ETS*. Hence, the policy's impact on haze governance in the pilot city primarily stems from its "feedback" effect on spatially collaborative environmental governance effect in the neighboring areas. In other words, the policy benefits the neighborhood, subsequently leading to its own reduction in haze

Table 5
Baseline regression results.

	(1) $SO_2(W_1)$	(2) $PM_{2.5}(W_1)$	(3) $SO_2(W_2)$	(4) $PM_{2.5}(W_2)$	(5) SO_2	(6) $PM_{2.5}$
ETS	−0.223***	0.020	−0.118*	−0.050***	−0.021	−0.131***
	(0.076)	(0.015)	(0.060)	(0.014)	(0.055)	(0.014)
LS	0.461***	−0.034**	0.275***	−0.034*	0.313***	−0.036*
	(0.085)	(0.017)	(0.089)	(0.020)	(0.081)	(0.020)
PD	0.046	−0.017	0.051	−0.022	0.068	−0.045**
	(0.075)	(0.015)	(0.073)	(0.016)	(0.076)	(0.019)
HC	−0.049***	−0.013***	−0.049***	−0.020***	−0.046***	−0.022***
	(0.015)	(0.003)	(0.015)	(0.003)	(0.016)	(0.004)
GI	0.277***	0.015	0.170***	0.023*	0.228***	0.059***
	(0.058)	(0.012)	(0.059)	(0.013)	(0.057)	(0.014)
ID	−0.087***	−0.008	−0.103***	−0.001	−0.119***	0.000
	(0.027)	(0.005)	(0.027)	(0.006)	(0.028)	(0.007)
EE	−0.355***	−0.003	−0.297***	−0.042***	−0.286***	−0.075***
	(0.070)	(0.014)	(0.068)	(0.015)	(0.070)	(0.018)
WETS	0.692**	−0.374***	0.753***	−0.411***		
	(0.303)	(0.061)	(0.284)	(0.064)		
WLS	−1.544***	0.072	−0.328	−0.038		
	(0.504)	(0.102)	(0.391)	(0.088)		
WPD	0.067	−0.350***	0.284	−0.426***		
	(0.554)	(0.112)	(0.454)	(0.102)		
WHC	0.096	−0.308***	0.419***	−0.047**		
	(0.157)	(0.032)	(0.094)	(0.021)		
WGI	−0.648	0.210**	0.419	0.198***		
	(0.417)	(0.085)	(0.273)	(0.061)		
WID	−0.869***	−0.281***	−0.151	0.006		
	(0.296)	(0.060)	(0.161)	(0.036)		
WEE	0.961*	−1.058***	0.830**	−0.518***		
	(0.577)	(0.117)	(0.404)	(0.091)		
ρ	0.835***	0.978***	0.333***	0.935***		
	(0.041)	(0.006)	(0.060)	(0.017)		
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Wald SLM	39.85***	275.86***	35.34***	105.58***		
Wald SEM	31.43***	328.51***	34.50***	144.70***		
N	3500	3500	3500	3500	3500	3500
R^2	0.003	0.000	0.000	0.000	0.824	0.942

Notes: ***, **, * denote 1%, 5%, and 10% significance levels, respectively; values in square brackets below the coefficients are standard errors; ρ is the coefficient of the spatial lag term of *AP*; same as in the following tables.

Table 6
Direct and indirect effects of the baseline regression.

			ETS	*LS*	*PD*	*HC*	*GI*	*ID*	*EE*
Direct effect	SO_2	W_1	−0.207*** (0.074)	0.426*** (0.079)	0.057 (0.069)	−0.048*** (0.015)	0.266*** (0.054)	−0.113*** (0.030)	−0.335*** (0.071)
		W_2	−0.107* (0.060)	0.269*** (0.084)	0.062 (0.069)	−0.045*** (0.015)	0.176*** (0.056)	−0.104*** (0.027)	−0.288*** (0.070)
	$PM_{2.5}$	W_1	−0.051* (0.028)	−0.026 (0.022)	−0.088** (0.036)	−0.077*** (0.023)	0.060** (0.024)	−0.067** (0.027)	−0.213*** (0.074)
		W_2	−0.092*** (0.016)	−0.041** (0.019)	−0.060*** (0.020)	−0.026*** (0.004)	0.044*** (0.014)	−0.001 (0.008)	−0.092*** (0.020)
Indirect effect	SO_2	W_1	3.112* (1.864)	−7.111* (3.768)	0.722 (3.522)	0.297 (1.020)	−2.537 (2.839)	−6.109** (2.723)	4.458 (3.802)
		W_2	1.042** (0.405)	−0.300 (0.560)	0.468 (0.676)	0.593*** (0.145)	0.724* (0.419)	−0.281 (0.245)	1.122* (0.617)
	$PM_{2.5}$	W_1	−17.382*** (6.487)	2.223 (4.855)	−17.713** (8.704)	−15.701*** (5.637)	11.084* (5.777)	−14.331** (6.509)	−51.244*** (18.496)
		W_2	−7.424*** (2.519)	−1.027 (1.420)	−7.139** (2.895)	−1.064** (0.469)	3.596** (1.513)	0.050 (0.649)	−8.884*** (3.051)
Total effect	SO_2	W_1	2.905 (1.828)	−6.685* (3.764)	0.779 (3.520)	0.249 (1.023)	−2.270 (2.837)	−6.222** (2.738)	4.123 (3.805)
		W_2	0.935** (0.381)	−0.031 (0.535)	0.530 (0.674)	0.548*** (0.147)	0.900** (0.409)	−0.385 (0.250)	0.834 (0.621)
	$PM_{2.5}$	W_1	−17.432*** (6.510)	2.198 (4.870)	−17.800** (8.736)	−15.779*** (5.659)	11.145* (5.798)	−14.398** (6.536)	−51.457*** (18.569)
		W_2	−7.516*** (2.529)	−1.068 (1.423)	−7.199** (2.908)	−1.090** (0.472)	3.639** (1.519)	0.049 (0.654)	−8.975*** (3.063)

pollution. Neglecting the spatial spillover effect would attribute the aforementioned spatial collaborative-governance effects solely to the policy's impact on the local area, resulting in an overestimation of the policy's effectiveness. The estimation results under the traditional DID model are presented in Columns (5)–(6) of Table 5. The results indicate that without considering the spatial spillover effects of air pollution, the ETS pilot policy does not have a significant effect on SO_2 pollution in the pilot cities; however, it does significantly contribute to haze governance. Thus, the utilization of the SDID model is crucial.

4.3. Robustness tests

4.3.1. PSM-SDID model

We employ the propensity score matching SDID (PSM-SDID) model for robustness testing to address the issue of self-selection bias. First, to ensure similarity between the control and treatment groups, we employ the following matching variables: living standard (*LS*), population density (*PD*), human capital (*HC*), government intervention (*GI*), energy efficiency (*EE*), foreign direct investment (*OP*), and science and technology level (*ST*). Second, we estimate propensity scores based on logit models, dummy variables, and the matching variables. Third, we conduct propensity score matching using a put-back-sampling nearest neighbor method with a 1:4 ratio. Lastly, we perform a PSM-SDID estimation using the matched samples.

Table 7 presents the detailed matching results, which indicate insignificant *t*-tests for all matched variables after matching. The results in Table 8 reveal that the directions and magnitudes of the ETS pilot policy's effects on the two air pollutants, estimated using the PSM-SDID method, aligns with the baseline regressions. This further validates the robustness of our results.

4.3.2. Placebo test

Next, we use a placebo test following the methodology conducted by Jia et al. (2021b) to determine if the baseline regression results are attributable to chance findings or omitted variables. To perform this test, we first extract the variable *ETS* and create 200 dummy variables, ETS^{false}, in a random order. Second, we replace the *ETS* with ETS^{false} to create 200 new samples. Lastly, we employ Eq. (1) and the 200 new samples to estimate the direct and indirect effects of ETS^{false}.

After repeating the placebo test 200 times, we check whether the means of the direct and indirect effects of 200 ETS^{false} differ significantly from zero. The one-sample *t*-test results show that the means of the direct and indirect effects of ETS^{false} on SO_2 emissions are 0.0021 and −0.0360, with *p*-values of 0.519 and 0.219, respectively. Meanwhile, the means of the direct and indirect effects on $PM_{2.5}$ concentrations are 0.0007 and 0.0103, with *p*-values of 0.456 and 0.911, respectively. Figs. 7 and 8 present the probability density distributions of the placebo-tested regression coefficients for SO_2 and $PM_{2.5}$, respectively. Fig. 7 shows that the actual direct effect (−0.107) of the SO_2 baseline regression is located at the end of the left tail, while the indirect effect (1.042) is located at the end of the right tail. Furthermore, Fig. 8 shows that the $PM_{2.5}$ baseline regression's actual direct (−0.092) and indirect effect (−7.424) are both located at the end of the left tail. Therefore, the placebo test results confirm the reliability of the baseline regression.

Table 7
PSM matching balancing test results.

Variables	Matching status	Mean: Treatment group	Mean: control group	Sd. (%)	t-test: t	t-test: p
LS	Before	10.647	9.879	118.0	12.44	0.000
	After	10.638	10.597	6.3	0.61	0.541
PD	Before	6.205	5.794	57.0	5.93	0.000
	After	6.189	6.170	2.6	0.26	0.797
OP	Before	0.019	0.022	−11.1	−1.19	0.234
	After	0.020	0.019	4.2	0.44	0.660
HC	Before	10.816	10.273	34.3	3.75	0.000
	After	10.837	10.727	7.0	0.60	0.551
GI	Before	−2.081	−2.249	39.7	4.34	0.000
	After	−2.093	−2.017	−18.0	−1.43	0.155
EE	Before	1.391	0.807	127.5	16.70	0.000
	After	1.366	1.297	15.2	1.18	0.241
ST	Before	−0.272	−0.879	43.1	6.26	0.000
	After	−0.274	−0.437	11.6	0.97	0.334

5. Mechanism identification and heterogeneity analysis

5.1. Mechanism identification

According to the theoretical mechanism analysis in the preceding section, the ETS pilot policy may affect regional air pollution by promoting industrial structure upgrading, optimizing energy structure, and enhancing green innovation levels. To further investigate this, we employ the mediating effect model as follows:

$$\begin{aligned} AP_{it} = {} & \alpha'' + \rho\sum_j w_{ij}AP_{jt} + \beta'' ETS_{it} + \boldsymbol{\gamma}''\mathbf{X}_{it} + \theta\sum_j w_{ij}ETS_{jt} \\ & + \boldsymbol{\psi}\sum_j w_{ij}\mathbf{X}_{jt} + \mu_i'' + v_t'' + \varepsilon_{it}'' \end{aligned} \tag{5}$$

$$\begin{aligned} M_{it} = {} & \alpha_1'' + \rho_1\sum_j w_{ij}M_{jt} + \beta_1'' ETS_{it} + \boldsymbol{\gamma}_1''\mathbf{X}_{it}' + \theta_1\sum_j w_{ij}ETS_{jt} \\ & + \boldsymbol{\psi}_1\sum_j w_{ij}\mathbf{X}_{jt} + \widetilde{\mu}_i'' + \widetilde{v}_t'' + \widetilde{\varepsilon}_{it}'' \end{aligned} \tag{6}$$

$$\begin{aligned} AP_{it} = {} & \alpha_2'' + \rho_2\sum_j w_{ij}AP_{jt} + \beta_2'' ETS_{it} + \upsilon M_{it} + \boldsymbol{\gamma}_2''\mathbf{X}_{it} + \pi\sum_j w_{ij}M_{jt} \\ & + \theta_2\sum_j w_{ij}ETS_{jt} + \boldsymbol{\psi}_2\sum_j w_{ij}\mathbf{X}_{jt} + \widehat{\mu}_i'' + \widehat{v}_t'' + \varepsilon_{it}'' \end{aligned} \tag{7}$$

where *M* includes industrial structure (*IS*), energy structure (*ES*), and green innovation (*GT*). Other variables are as previously described.

In Tables 9 and 10, estimates based on Eq. (5) are presented in Column (1), while Columns (2)–(3), (4)–(5), and (6)–(7) display estimates based on Eq. (6) and (7) and utilize *IS*, *ES*, and *GT* as mediating variables, respectively.

First, regarding the influence of industrial structure upgrading, Column (2) in Table 9 demonstrates that the ETS pilot policy's implementation promotes industrial structure upgrading within the pilot area, with a statistically significant level of 10%. The results presented in Columns (3) in Tables 9 and 10 indicate that industrial structure upgrading has a significantly negative direct influence on SO_2 emissions but no significant impact on $PM_{2.5}$ concentrations. Components that cause haze are more complex than those that cause SO_2, including sand, soot, sulfate, and nitrate aerosols, among others. Furthermore, transportation, postal, and real estate industries produce a substantial amount of sand and dust, which is a significant contributor to haze. Therefore, while the ETS pilot policy facilitates the substitution of tertiary industries for secondary industries in the pilot regions, it does not improve the haze pollution in these areas.

Second, regarding the effect of optimizing energy structure, results from Columns (4) and (5) in Tables 9 and 10 indicate that implementing the ETS pilot policy significantly decreases the electricity consumption ratio within pilot cities with statistical significance at the 1% level. This reduction has a significant impact, with a statistical significance of at least 10%, on lowering both SO_2 emissions and haze pollution in pilot areas. However, these results differ from our expectations. In fact, during the sample period, China's share of installed coal power capacity was maintained at the high level of over 50%.[4] Therefore, the electricity consumption ratio, to some extent, indicates the reliance on non-clean

[4] See http://www.gov.cn/xinwen/2021-02/07/content_5585511.htm.

Table 8
Results based on PSM-SDID model.

		ETS	*LS*	*PD*	*HC*	*GI*	*ID*	*EE*
X	SO_2	−0.159**	0.390***	0.022	−0.052***	0.190***	−0.153***	−0.223***
		(0.069)	(0.106)	(0.089)	(0.017)	(0.067)	(0.032)	(0.077)
	$PM_{2.5}$	−0.048***	−0.023	−0.017	−0.014***	0.022	−0.003	−0.050***
		(0.015)	(0.022)	(0.019)	(0.004)	(0.014)	(0.007)	(0.016)
WX/WY	SO_2	1.012***	−0.846**	0.547	0.294**	0.572*	−0.149	0.473
		(0.304)	(0.410)	(0.483)	(0.121)	(0.338)	(0.183)	(0.440)
	$PM_{2.5}$	−0.347***	−0.057	−0.342***	−0.101***	0.197***	−0.067*	−0.362***
		(0.065)	(0.087)	(0.102)	(0.026)	(0.072)	(0.039)	(0.093)
Direct effect	SO_2	−0.148**	0.380***	0.036	−0.049***	0.195***	−0.153***	−0.219***
		(0.069)	(0.100)	(0.084)	(0.016)	(0.064)	(0.032)	(0.080)
	$PM_{2.5}$	−0.084***	−0.031	−0.048**	−0.025***	0.042***	−0.009	−0.087***
		(0.016)	(0.021)	(0.021)	(0.005)	(0.015)	(0.009)	(0.020)
Indirect effect	SO_2	1.218***	−0.918*	0.714	0.351**	0.791*	−0.234	0.574
		(0.377)	(0.506)	(0.611)	(0.152)	(0.448)	(0.236)	(0.569)
	$PM_{2.5}$	−4.719***	−0.867	−4.238**	−1.378***	2.641**	−0.856	−4.816***
		(1.558)	(1.032)	(1.832)	(0.500)	(1.191)	(0.615)	−4.816***
	City FE	Year FE	Wald SLM	Wald SEM	R^2	N		
SO_2	Yes	Yes	24.83***	24.72***	0.017	2646		
$PM_{2.5}$	Yes	Yes	85.17***	120.12***	0.000	2646		

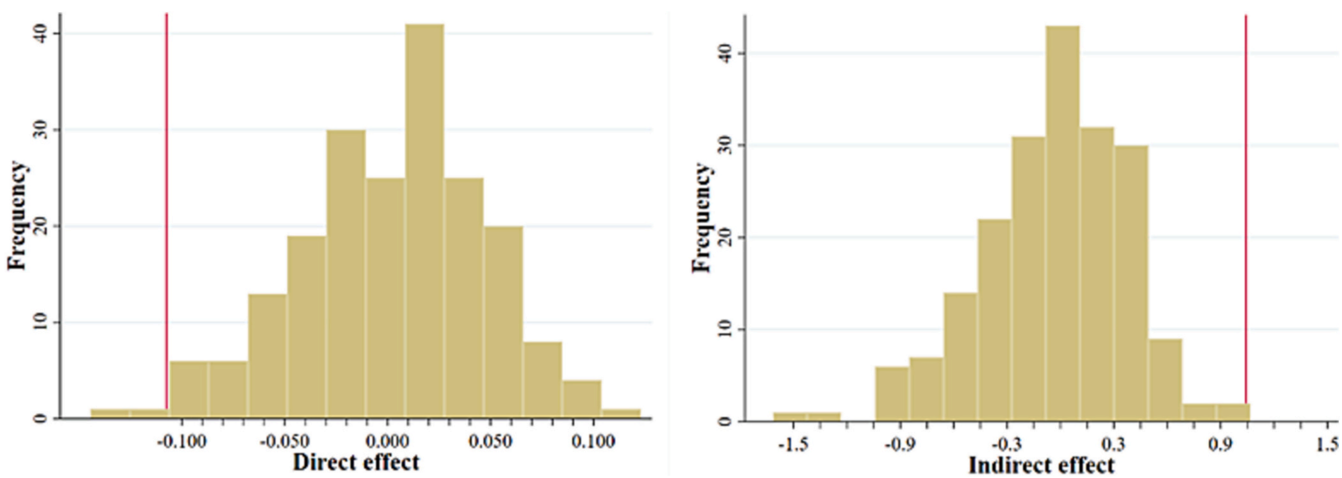

Fig. 7. Placebo test results (SO_2).

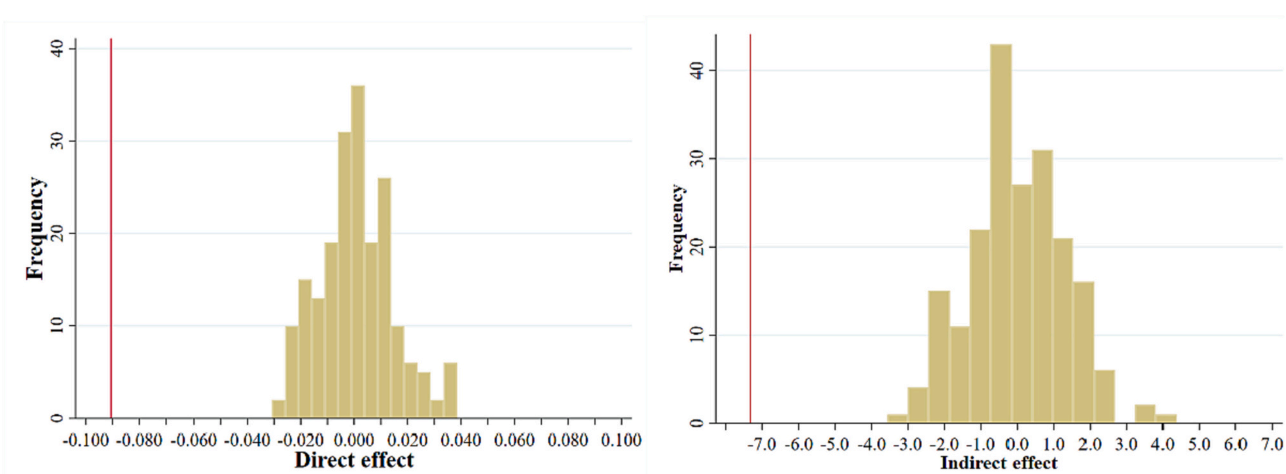

Fig. 8. Placebo test results ($PM_{2.5}$).

Table 9
Mechanism testing results (SO_2).

		M = IS		M = ES		M = GT	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Direct effect							
ETS	−0.107* (0.060)	0.031* (0.019)	−0.096 (0.060)	−0.097*** (0.032)	−0.097 (0.061)	0.031** (0.015)	−0.105* (0.061)
IS			−0.357*** (0.053)				
ES					0.088*** (0.031)		
GT							−0.554*** (0.082)
Indirect effect							
ETS	1.042** (0.405)	−0.517*** (0.197)	0.996** (0.407)	−0.165 (0.172)	1.127*** (0.413)	9.009*** (2.723)	1.509*** (0.411)
IS			−0.012 (0.424)				
ES					0.014 (0.283)		
GT							−0.055 (0.440)

energy sources in the region. Consequently, the ETS pilot policy facilitates a transition toward cleaner energy sources in the region, resulting in lower SO_2 emissions and $PM_{2.5}$ concentrations.

Finally, the results from Columns (6) in Tables 9 and 10 suggest that the ETS pilot policy facilitates green technology innovation progress within pilot cities with a statistical significance exceeding the 5% level. Moreover, the results from Columns (7) in Tables 9 and 10 indicate that green innovation contributes to a reduction in SO_2 emissions and $PM_{2.5}$ concentrations in pilot areas with statistical significance of at least 10%. Thus, the ETS pilot policy's implementation can effectively reduce SO_2 emissions and haze pollution by increasing green technology innovation, consistent with our expectations.

In conclusion, implementing the ETS pilot policy can positively impact SO_2 and haze governance in the pilot areas through the development of green technologies and the optimization of the energy structure. Additionally, although the policy successfully reduces SO_2 emissions in the pilot regions by facilitating industrial structure upgrading, it has not yet fully achieved its expected effect on haze pollution control. Therefore, Hypothesis 2 is only partially validated.

For the indirect effects, the estimation results in Columns (2) of Tables 9 and 10 demonstrate a significant negative indirect effect of the ETS pilot policy on the upgrading of industrial structure. This suggests that the secondary industry in the pilot area relocates to neighboring regions. Furthermore, Columns (3) of Tables 9 and 10 reveals that the introduction of the secondary industry with high pollution levels exacerbates SO_2 pollution in the neighboring cities. However, it does not lead to an increase in haze pollution in these cities. This indicates that the change in industrial structure has divergent effects on haze and SO_2. As previously mentioned, the tertiary industry, known for generating substantial quantities of sand and dust, constitutes a significant contributor to haze formation. Consequently, the introduction of the secondary industry in the neighboring cities does not exert a substantial influence on haze pollution; however, it notably exacerbates SO_2 pollution.

The results in Columns (4) of Tables 9 and 10 indicate that the indirect effect of the ETS pilot policy on the energy structure is statistically insignificant, suggesting that the policy does not have a significant impact on air pollution in the pilot neighborhood through the change of energy structure. Finally, based on the results of the indirect effect in Columns (6) and the direct effect in Columns (7) of Tables 9 and 10, it is evident that the ETS pilot policy leads to the diffusion of green technologies from the pilot areas to the neighboring areas, resulting in an improvement in the air pollution of the neighboring areas.

Table 10
Mechanism testing results ($PM_{2.5}$).

		M = IS		M = ES		M = GT	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Direct effect							
ETS	−0.092*** (0.016)	0.031* (0.019)	−0.093*** (0.018)	−0.097*** (0.032)	−0.090*** (0.017)	0.031** (0.015)	−0.084*** (0.017)
IS			0.011 (0.014)				
ES					0.017* (0.009)		
GT							−0.033* (0.019)
Indirect effect							
ETS	−7.424*** (2.519)	−0.517*** (0.197)	−7.757** (3.159)	−0.165 (0.172)	−7.450** (3.042)	9.009*** (2.723)	−6.847** (2.773)
IS			0.760 (1.167)				
ES					2.343** (1.157)		
GT							−4.205** (1.879)

Table 11
Geographic location heterogeneity analysis results (SO_2).

Geographic location	Eastern region		Central-western region	
	Direct effect	Indirect effect	Direct effect	Indirect effect
	(1)	(2)	(3)	(4)
ETS	0.043	0.505	−0.190**	1.039*
	(0.132)	(0.444)	(0.080)	(0.586)
LS	0.512***	−0.088	0.107	−1.450*
	(0.142)	(0.720)	(0.103)	(0.864)
PD	0.034	0.334	0.149	−0.472
	(0.093)	(0.538)	(0.115)	(1.291)
HC	−0.144**	−1.149**	−0.036**	0.615***
	(0.058)	(0.510)	(0.014)	(0.158)
GI	0.020	−1.493**	0.215***	0.372
	(0.117)	(0.740)	(0.060)	(0.501)
ID	−0.326***	−1.601***	−0.006	0.235
	(0.055)	(0.379)	(0.030)	(0.282)
EE	−0.485***	0.027	−0.202***	0.837
	(0.147)	(0.869)	(0.078)	(0.790)
City FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Wald SLM	25.50***	25.50***	25.77***	25.77***
Wald SEM	28.85***	28.85***	22.35***	22.35***
N	1274	1274	2226	2226
R^2	0.012	0.012	0.022	0.022

In summary, the ETS pilot policy effectively reduces haze pollution in the neighboring areas by promoting the transfer of green technologies from the pilot areas to the periphery. However, the introduction of the secondary industry and changes in the energy structure do not significantly impact haze pollution in the pilot periphery. Regarding SO_2 pollution, the spillover of green technologies from the pilot areas partially mitigates the pollution in the neighboring cities. However, the introduction of the secondary industry significantly worsens SO_2 pollution, leading to an overall positive spatial spillover effect of the ETS pilot policy on SO_2 emissions in the neighboring areas.

5.2. Heterogeneity analysis

Owing to the existence of certain differences in terms of geographical location, policy background, and resource endowments among the various cities in China, we categorize the samples further into three groups: geographic location, whether they are key environmental protection (EP) cities, and whether they are energy-oriented cities. We adopt this approach to avoid masking regional variations in our regression analysis.

Table 12
Geographic location heterogeneity analysis results ($PM_{2.5}$).

Geographic location	Eastern region		Central-western region	
	Direct effect	Indirect effect	Direct effect	Indirect effect
	(1)	(2)	(3)	(4)
ETS	−0.065***	−0.788**	−0.067***	−2.766**
	(0.016)	(0.358)	(0.024)	(1.141)
LS	0.004	−0.051	−0.132***	−4.675**
	(0.019)	(0.567)	(0.031)	(1.846)
PD	−0.033**	−1.390**	−0.016	−2.641
	(0.014)	(0.611)	(0.036)	(2.066)
HC	−0.065***	−1.745***	−0.025***	−0.613**
	(0.012)	(0.621)	(0.005)	(0.268)
GI	−0.006	−0.159	0.054***	1.490*
	(0.017)	(0.596)	(0.018)	(0.807)
ID	0.000	−0.040	−0.003	−0.115
	(0.009)	(0.297)	(0.010)	(0.449)
EE	−0.084***	−2.663***	−0.080***	−4.400***
	(0.024)	(0.994)	(0.024)	(1.594)
City FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Wald SLM	49.17***	49.17***	48.44***	48.44***
Wald SEM	85.78***	85.78***	68.32***	68.32***
N	1274	1274	2226	2226
R^2	0.000	0.000	0.003	0.003

Table 13
Results of heterogeneity analysis of key EP cities (SO_2).

	Key EP cities		Non-key EP cities	
	Direct effect	Indirect effect	Direct effect	Indirect effect
	(1)	(2)	(3)	(4)
ETS	−0.221***	0.053	0.007	1.310***
	(0.085)	(0.374)	(0.072)	(0.387)
LS	−0.066	−0.233	0.294***	−1.392*
	(0.120)	(0.517)	(0.113)	(0.727)
PD	−0.017	0.041	0.102	0.617
	(0.124)	(0.648)	(0.083)	(0.622)
HC	−0.090**	0.550**	−0.054***	0.335***
	(0.036)	(0.244)	(0.016)	(0.102)
GI	0.271***	1.432***	0.051	−1.711***
	(0.082)	(0.454)	(0.073)	(0.514)
ID	−0.146***	−0.192	−0.052	−0.091
	(0.038)	(0.202)	(0.038)	(0.234)
EE	−0.241**	1.085*	−0.240**	0.213
	(0.099)	(0.570)	(0.095)	(0.546)
City FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Wald SLM	21.16***	21.16***	36.56***	36.56***
Wald SEM	21.75***	21.75***	35.75***	35.75***
N	1554	1554	1946	1946
R^2	0.032	0.032	0.001	0.001

5.2.1. Geographical location

The results in Table 11 indicate that there is heterogeneity in the ETS pilot policy's impact on SO_2 emissions and their spatial spillover effects across different regions. Specifically, *ETS* promotes local SO_2 emission reduction but worsens SO_2 emissions in surrounding areas in the central-western region. Nevertheless, in the eastern region, the ETS policy's impacts on local and surrounding SO_2 emissions are not significant. The heterogeneity in the direct effects of *ETS* can be justified through two reasons. First, the "two control zones" policy, which mainly covered the eastern cities, was implemented by the Chinese government in 1998 to control SO_2 emission levels. Consequently, the SO_2 emission levels in the eastern region was already reasonable during our sample period. Second, the eastern region has a more optimized industrial structure, a more reasonable energy structure, and advanced technologies compared to the central-western regions (Yang et al., 2023). Additionally, its residents demonstrate a greater demand for improving environmental quality (Shao et al., 2019a). These factors lead to lower SO_2 emissions in the eastern region, thereby largely weakening the marginal improvement effect of the ETS pilot policy on SO_2 pollution. Furthermore, differences in the local impacts of the policy on the central-western and eastern regions are responsible for the heterogeneity of spatial spillover effects of the ETS pilot policy in different geographical locations.

The results in Table 12 suggest that the policy can improve haze pollution across various regions without heterogeneity. Compared to SO_2 pollution, haze pollution is a comparatively new type of pollution in China during our sample period. Although the eastern region has superior industrial structure, energy structure, and green technology, the short duration of haze pollution during our sample period maintains that the haze pollution levels in all regions are severe, which limit the potential of these advantages to control haze effectively. Therefore, implementing the ETS pilot policy can be a successful approach to promote efficient haze control in pilot cities across all regions.

Table 14
Results of heterogeneity analysis of key EP cities ($PM_{2.5}$).

	Key EP cities		Non-key EP cities	
	Direct effect	Indirect effect	Direct effect	Indirect effect
	(1)	(2)	(3)	(4)
ETS	−0.105***	−0.796**	−0.113***	−2.335***
	(0.020)	(0.312)	(0.018)	(0.731)
LS	0.013	0.481	−0.074**	−1.894*
	(0.027)	(0.375)	(0.029)	(1.011)
PD	−0.057*	−1.650***	−0.042**	−0.758
	(0.031)	(0.604)	(0.021)	(0.806)
HC	−0.031***	−0.030	−0.018***	−0.261*
	(0.009)	(0.186)	(0.004)	(0.135)
GI	0.008	−0.180	0.085***	1.979***
	(0.020)	(0.339)	(0.019)	(0.740)
ID	−0.016*	−0.010	0.015	0.259
	(0.010)	(0.162)	(0.011)	(0.310)
EE	−0.048*	−1.322***	−0.100***	−0.911
	(0.025)	(0.492)	(0.024)	(0.676)
City FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Wald SLM	27.00***	27.00***	34.06***	34.06***
Wald SEM	36.47***	36.47***	59.01***	59.01***
N	1554	1554	1946	1946
R^2	0.016	0.016	0.005	0.005

5.2.2. Key EP city or not

Tables 13 and 14 present the results of a heterogeneity analysis conducted between cities categorized as key and non-key EP cities.[5] The ETS pilot policy's direct effect on SO_2 emissions indicates a significant reduction in key EP cities and an insignificant influence in non-key EP cities. Conversely, the indirect effect is insignificant in key EP cities and significant in non-key EP cities. These results demonstrate the existence of heterogeneity in the effects of the ETS pilot policy on SO_2 emissions and their surrounding areas in both types of cities. These findings can be attributed to the superior environmental infrastructure and policy background in key EP cities, making the collaborative effect of the ETS pilot policy on SO_2 governance differ from its effect in non-key EP cities. In contrast, non-key EP cities struggle to achieve the desired effect due to inadequate facilities and other limitations. Furthermore, key EP cities often use cleaner production techniques, end-of-pipe treatment, and cleaner production equipment optimization and upgrades to control SO_2 emissions, rather than expelling polluting industries. Meanwhile, the beggar-thy-neighbor approach used by non-key EP cities increases SO_2 emissions in neighboring regions.

Regarding the ETS pilot policy's impact on regional $PM_{2.5}$ concentrations, the results show that the policy contributes to controlling haze in both types of cities, and there is no heterogeneity in the impacts of the policy on areas surrounding the two types of cities. The underlying reason behind this homogeneity is the emergence of the haze problem in China around 2013, whereas the establishment of key EP cities began in 2003 and ended in 2010 with no objective set for controlling haze.[6] This implies that being a key EP city does not have a significant influence on haze pollution. Therefore, the ETS pilot policy's impact on haze control is independent of whether an area is a key EP city.

[5] See https://www.ndrc.gov.cn/fggz/fzzlgh/gjjzxgh/200804/P020191104623762904948.pdf.

[6] See https://www.mee.gov.cn/gkml/zj/wj/200910/t20091022_172229.htm?keywords=.

Table 15
Results of heterogeneity analysis of energy-oriented cities (SO_2).

	Energy-oriented cities		Non-energy-oriented cities	
	Direct effect	Indirect effect	Direct effect	Indirect effect
	(1)	(2)	(3)	(4)
ETS	−0.241***	0.532	−0.018	0.614*
	(0.087)	(0.763)	(0.089)	(0.358)
LS	0.204*	0.749	0.361***	−0.480
	(0.116)	(0.652)	(0.127)	(0.465)
PD	0.218**	0.261	0.006	0.371
	(0.105)	(0.758)	(0.094)	(0.494)
HC	−0.025	0.479***	−0.110***	0.281*
	(0.016)	(0.107)	(0.030)	(0.144)
GI	0.157**	−0.115	0.248***	0.144
	(0.074)	(0.440)	(0.082)	(0.355)
ID	−0.015	−0.386	−0.164***	−0.533**
	(0.035)	(0.267)	(0.042)	(0.233)
EE	−0.472***	−0.155	−0.124	−0.055
	(0.104)	(0.717)	(0.100)	(0.477)
City FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Wald SLM	29.55***	29.55***	13.77**	13.77**
Wald SEM	28.50***	28.50***	14.00**	14.00**
N	1750	1750	1750	1750
R^2	0.083	0.083	0.048	0.048

Table 16
Results of heterogeneity analysis of energy-oriented cities ($PM_{2.5}$).

	Energy-oriented cities		Non-energy-oriented cities	
	Direct effect	Indirect effect	Direct effect	Indirect effect
	(1)	(2)	(1)	(2)
ETS	−0.120***	−2.195**	−0.067***	−1.108***
	(0.028)	(1.034)	(0.016)	(0.209)
LS	−0.142***	−1.596*	0.025	−0.053
	(0.034)	(0.872)	(0.023)	(0.197)
PD	−0.043	−1.327	−0.036**	−0.844***
	(0.033)	(0.981)	(0.018)	(0.250)
HC	−0.018***	−0.105	−0.032***	−0.220***
	(0.005)	(0.120)	(0.006)	(0.073)
GI	0.049**	0.793	0.032**	0.247
	(0.021)	(0.528)	(0.015)	(0.159)
ID	0.014	0.160	−0.009	−0.097
	(0.012)	(0.331)	(0.008)	(0.108)
EE	−0.118***	−1.308	0.005	−0.297
	(0.032)	(0.866)	(0.019)	(0.217)
City FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Wald SLM	11.49***	11.49***	64.56***	64.56***
Wald SEM	22.57***	22.57***	87.88***	87.88***
N	1750	1750	1750	1750
R^2	0.018	0.018	0.000	0.000

5.2.3. Energy-oriented city or not

We analyze the heterogeneity of energy- and non-energy-oriented cities based on the geographic and economic distance nested matrix $\mathbf{W}_2$.[7] The estimation results are exhibited in Tables 15 and 16.

Regarding the ETS policy's effect on SO_2 emissions, energy-oriented cities exhibit a significantly negative direct effect and an insignificant indirect effect, while non-energy-oriented cities display an insignificant direct effect and a significantly positive indirect effect. This difference causes heterogeneity in the policy's impact on SO_2 emissions within and around energy- and non-energy-oriented cities. A possible explanation for this variance is as follows. Previous studies have found that the economic and environmental "resource curse" effect affects energy-

[7] A city is energy-oriented if its resource dependency is higher than the sample mean. Resource dependency is the share of the number of people employed in mining in the secondary industry in the number of people employed in urban units.

oriented cities that provide energy supply in China (Shao et al., 2021). The effects of crowding-out on human capital, technological innovation, and excessive government intervention in energy-oriented cities make them less market-oriented in terms of air pollution governance mechanisms compared to non-energy-oriented cities (Zhang and Da, 2015). However, the ETS pilot policy, serving as a market-oriented policy instrument, amplifies the marketization of air pollution governance in energy-oriented cities, thus alleviating the “resource curse” effect to some extent. Consequently, compared with non-energy-oriented cities, the results in Tables 15 and 16 show more significant promotion of SO_2 reduction and haze control in energy-oriented cities. Additionally, according to prior analyses, the backward technological innovation level and unreasonable industrial and energy structures of energy-oriented cities cause greater pollution, industrial extrusion, and energy structure deterioration in their neighboring non-energy-oriented cities. Furthermore, there are almost no green technology spillovers. All these reasons result in the energy-oriented cities’ positive spatial spillover effects of SO_2 pollution to their neighboring cities while they receive emission reduction effects themselves.

6. Conclusions and policy implications

In the context of promoting the national carbon emissions trading market, it is essential to accurately identify the collaborative air pollution governance effects of ETS pilot policy. This study employs an SDID model, which embeds SDM into the traditional DID model. We conduct a systematic empirical analysis on the collaborative-governance effects of ETS pilot policy on air pollutants represented by SO_2 and $PM_{2.5}$, while controlling for spatial spillover effects. Our major findings are as follows: (1) the ETS pilot policy reduces SO_2 emissions in the pilot area but worsens SO_2 pollution in surrounding areas, indicating a negative spatial spillover effect. However, the ETS pilot policy lowers haze pollution in both the pilot and surrounding areas. These conclusions remain valid even after the robustness tests conducted using PSM-SDID models and placebo tests. (2) The ETS pilot policy mainly improves SO_2 pollution via three ways: industrial structure upgrading, energy structure optimization, and green technology innovation. The latter two ways help to achieve collaborative haze pollution governance. (3) The ETS pilot policy’s effects on the two air pollutants are heterogeneous. Specifically, the collaborative governance effect of the policy in central-western regions is more obvious than that in eastern regions. The policy has a collaborative effect on haze control in key and non-key EP cities, energy- and non-energy-oriented cities. However, it is challenging to improve SO_2 emissions in non-key EP cities and non-energy-oriented cities, thereby worsening the surrounding areas of these cities’ SO_2 pollution problem.

The above research findings have several policy implications. First, China’s carbon market’s top-level design requires gradual improvements with the consideration of multiple objectives such as air pollution collaborative governance. The study findings indicate that the ETS pilot policy significantly suppresses air pollution, providing empirical support for incorporating air pollution collaborative governance objectives into the ETS pilot policy system. Therefore, it is imperative for China to devote enough attention to the collaborative impact of air pollution control in designing the national carbon market. This should be done by incorporating air pollution reduction objectives in the decision-making process of carbon quota allocation and carbon price design, thus facilitating mutually beneficial outcomes for both carbon and pollution abatement.

Second, establishing a mechanism for cross-regional cooperation consultation and joint prevention and air pollution control should be done while ensuring the orderly operation of the carbon market. The implementation of a regional cooperation consultation mechanism is important for China to strengthen the positive influence of the ETS pilot policy on haze pollution in neighboring regions. Furthermore, China should establish regional joint prevention mechanisms to avoid the “leakage” effect of SO_2 emissions in neighboring regions to ensure regional sharing of air pollution control results.

Finally, global planning of the carbon market must be customized to local conditions, focusing on setting market parameters that can efficiently improve the effectiveness of environmental collaborative governance within the national carbon market. Our findings indicate that the collaborative governance effect of the ETS pilot policy demonstrates considerable regional heterogeneity. Therefore, it is critical to consider the unique characteristics of each region, including geographical location, policy background, and resource endowment, while designing policies of varying intensities and paths of implementation. This approach can prevent the loss of carbon market efficiency due to a single, standardized institutional design.

CRediT authorship contribution statement

Shuai Shao: Conceptualization, Supervision, Data curation, Formal analysis, Methodology, Writing – original draft. **Silu Cheng:** Conceptualization, Data curation, Investigation, Formal analysis, Visualization, Writing – original draft. **Ruining Jia:** Conceptualization, Supervision, Data curation, Methodology, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Acknowledgments

We acknowledge the financial support from the National Natural Science Foundation of China (Nos. 72243004, 72203164, and 71773075), the Fundamental Research Funds for the Central Universities (No. XJSJ23111), Shaanxi Provincial Social Science Foundation (No. 2023D085), and Shaanxi Philosophy and Social Science Special Youth Project (No. 2023QN0052).

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