Economic Research-Ekonomska Istraživanja

ISSN: (Print) (Online) Journal homepage: https://www.tandfonline.com/loi/rero20

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To cite this article: Yuee Tang, Siyu Wu & Shuxing Chen (2023) Evaluating the influence of environmental R&D on the SO_2 intensity in China: evidence from dynamic spatial Durbin model analysis, Economic Research-Ekonomska Istraživanja, 36:1, 1886-1905, DOI: 10.1080/1331677X.2022.2094438

To link to this article: https://doi.org/10.1080/1331677X.2022.2094438

Published online: 11 Jul 2022.

ECONOMIC RESEARCH-EKONOMSKA ISTRAŽIVANJA
2023, VOL. 36, NO. 1, 1886–1905
https://doi.org/10.1080/1331677X.2022.2094438

Routledge
Taylor & Francis Group

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Evaluating the influence of environmental R&D on the SO_2 intensity in China: evidence from dynamic spatial Durbin model analysis

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ABSTRACT

Green technology is a significant means to improve the environment and achieve sustainable development goals. According to the data of Chinese provincial panel from 2000 to 2016, our study investigated the spatial effect of environmental research and development (R&D) activities on SO_2 intensity using the dynamic spatial Durbin model. First, SO_2 intensity in China was shown to have obvious spatial correlation, strong path dependence, and spatial agglomeration features of 'high-high' as well as 'low-low'. Second, both in the short- and long-term, environmental R&D activities had an essential negative influence on local SO_2 intensity, but no significant effect on SO_2 intensity in the neighbouring areas, indicating that the SO_2 intensity reduction effect of environmental R&D activities was confined to local areas. Moreover, the long-term effect of environmental R&D activities on SO_2 intensity was not enhanced, indicating that China's existing green technology is insufficient, which hinders the spillover influences of environmental R&D activities. Third, the short- as well as long-term effects of practical-type R&D on SO_2 intensity were significantly negative, indicating that practical-type R&D can effectively reduce SO_2 intensity. Invention-type R&D had a significant negative effect on local SO_2 intensity, but no significant effect on neighbouring areas.

ARTICLE HISTORY
Received 6 August 2021
Accepted 21 June 2022

KEYWORDS
SO_2 intensity; environmental R&D activities; dynamic spatial Durbin model

JEL CLASSIFICATIONS
B22; C23; O30

1. Introduction

In the past forty years, the fast economic development in China has caused some environmental problems. As one of the air pollutants, SO_2 can seriously hinder the photosynthesis of plants after entering the atmosphere, causing a series of environmental pollution problems such as acid rain and haze. In 2014, 723 million people in China were affected by haze, mainly in East and Central China (Han et al., 2018). With rising levels of environmental pollution, increased attention is being paid to reduction of SO_2 emissions.

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Numerous researchers have focused on the relative indicator of SO_2 emissions (SO_2 intensity), which is recognized as the proportion of SO_2 emissions in gross domestic product (GDP) units (Nan et al., 2020; Tian et al., 2022). SO_2 intensity is primarily affected by technological progress and structural changes (Tang et al., 2021). Over six decades, heavy industry has become the main contributor of pollutant emissions in China, and its stable economic structure is difficult to change (Li et al., 2020). In such a scenario, technological progress is a realistic path to improve environmental quality.

Thus, the use of technological innovation to control environmental pollution while promoting economic growth has been a hot issue. Environmental research and development (R&D) activities focus on environmental protection and energy saving, which is an R&D activity related to energy-saving technology[1]. Environmental R&D activities can not only lead to reduction of pollutant emissions per unit product, but also greatly improve total factor productivity (TFP), thereby improving the environment effectively without restricting economic development (Acemoglu et al., 2012). Therefore, environmental R&D activities are an important factor in achieving the sustainable development goals.

Since 2000, environmental R&D activities have developed rapidly in China. However, the quality of environmental R&D activities is still low (Wang & Zhao, 2019). In addition, there are few inter-regional green innovation cooperation activities; neither an inter-regional platform for green technology innovation exchange nor a pollution control platform has been formed. Increased and efficient input–output relationship, knowledge diffusion, and technology spillover are the main methods to promote regional economic efficiency. Particularly, environmental R&D activities are conducive to improving energy efficiency and achieving emission reduction goals owing to few technical obstacles and mass technology flow as well as diffusion (Bataille et al., 2018). In addition, through cross-regional technical cooperation and strict environmental regulation, emission intensity can be decreased further (Gries et al., 2018). While some studies have discussed the spatial correlation of SO_2 intensity, the relationship between environmental R&D activities and SO_2 intensity has not been considered so far. Besides, the heterogeneity of environmental R&D activities has been ignored. Therefore, we realise the necessity to systematically research the spatial effect of environmental R&D activities on SO_2 intensity.

Therefore, our research's key goal was to assess the spatial effects of environmental R&D activities on SO_2 intensity. First, based on diverse spatial weight matrices, the spatial correlation of SO_2 intensity in China from 2000 to 2016 was examined. Second, considering that SO_2 emissions have the characteristics of 'path dependence' and 'spatial correlation', we used the dynamic spatial Durbin model (DSDM) to examine the influence of environmental R&D activities and its spatial spillover on SO_2 intensity. Third, given the heterogeneity of environmental R&D activities, this study further estimated the influences of various environmental R&D activities on SO_2 intensity in the short- and long-term.

2. Literature review

Theoretically, technological progress has a uncertain influence on the environment. Technological progress will result in more energy-intensive economic activities, thereby leading to more energy consumption and more emissions. Besides, technological progress reduces emissions by upgrading products and improving energy-saving technologies. Therefore, the environmental influence of technological progress is indeterminate and depends on the net effect. For economically developed countries, a relatively consistent view is that technological progress is beneficial to improving environmental quality (Fernández-Fernández et al., 2018; Weimin et al., 2021; Petrovic & Lobanov, 2020). For China, technological progress and structural change are important elements affecting SO_2 intensity (Tang et al., 2021). Due to the high cost of optimising the economic and energy structures, improving technological progress has become an important tool to decrease SO_2 intensity in China (Liu et al., 2019; Zhou et al., 2017).

Green technology was first mentioned by Ernest and David (1994); It is aimed at realising clean production, promoting environmental performance, improving the comprehensive utilisation of resources and energy of various technologies, processes or products (de Oliveira et al., 2018). As an important part of green technology, environmental R&D activities are R&D activities related to energy-saving technologies, which can reflect the 'bias' of technological progress (Hicks, 1932). According to the concept of induced innovation, enterprise innovation is a profit-driven investment activity (Acemoglu et al., 2012). If an enterprise's R&D investment is more inclined towards utilising emission reduction technology, then such R&D activities reduce SO_2 intensity more directly; these are known as environmental R&D activities. The factors affecting environmental R&D activities were discussed. First, environmental regulation (environmental policy) has been regarded as a key tool to directly promote environmental performance or affects it indirectly by raising environmental R&D activities (Ngo, 2022). Second, the business cycle also has an impact on environmental R&D activities and the environment (Ahmad & Zheng, 2021). The relatively consistent conclusion is the relationship between environmental R&D activities and pollutants emissions is asymmetric and counter-cyclical, and environmental R&D activities reduce pollutant emissions overall (Khattak & Ahmad, 2021;Khattak et al., 2022; Xin et al., 2021). Third, institutional pressure, second-order social capital, and government R&D subsidies also influence environmental R&D activities (Chen et al., 2018; Wu & Zhao, 2021; Zhao et al., 2021).

However, there is a relative lack of literature on environmental R&D activities and SO_2 intensity. You et al. (2022) investigated the relationship between domestic environmental innovation and CO_2 emissions in the United States between the first quarter of 1990 and fourth quarter of 2018 and found that domestic environmental innovation could reduce long-term CO_2 emissions. Hou et al. (2020) takes emissions trading scheme for SO_2 (SO_2 ETS) as the research object, and uses DID methods to verify the policy influence on green total factor productivity and SO_2 intensity. The results show that the policy can significantly reduce SO_2 intensity, but inhibit the development of green total factor productivity. Thus, we need to clarify the relationship between environmental R&D and SO_2 intensity.

A comprehensive environmental R&D activity encompasses different fields and stages. R&D based on various categories may result in differentiated environmental performance. Du et al. (2021) divided green innovation into green utility innovation and green invention innovation, and estimated the emission trading policy influence on green innovation. The results show that different green innovations have different environmental effects. However, most research use environmental R&D activities to investigate the environmental effects, rarely further considering the heterogeneity of environmental R&D activities and their differential influence on SO_2 intensity.

Lastly, air pollutant emissions have obvious spatial diffusion and spillover effects. On the one hand, air pollutant emissions are easily transferred from one area to the neighbouring areas with the movement of air or water, and local emissions are affected by emissions from the neighbouring areas. On the other hand, adjacent areas may imitate one another's development pattern, which means that environmental quality may also be influenced by neighbours. More importantly, pollutant emissions also have obvious path dependence; that is, districts with heavy air pollution at present will still have relatively high air pollution levels in the future. As an air pollutant, SO_2 emission has significant spatial correlation (Nan et al., 2020). Few studies have simultaneously considered the characteristics of spatial correlation and path dependence when studying the relationship between environmental R&D activities and SO_2 intensity.

3. Model design and description of variables

3.1. Spatial econometric model

3.1.1. Spatial correlation test

Moran's I Index includes global Moran's I Index (GMI) and local Moran's I Index (LMI). The GMI is adopted to determine spatial correlations or dependencies between different regions (Moran, 1948), as follows:

$$GMI = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{i,j}(SOI_i - \overline{SOI})(SOI_j - \overline{SOI})}{S^2 \sum_{i=1}^{n}\sum_{j=1}^{n} w_{i,j}} \tag{1}$$

where SOI represents SO_2 intensity in China at a provincial level, $\overline{SOI}$ represents the mean value of SO_2 intensity of the sample, n denotes the number of samples, and $w_{i,j}$ denotes binary spatial weight matrix;

S^2 denotes the sample variance and can be written as

$$S^2 = \sum_{i=1}^{n}(SOI - \overline{SOI})^2/n \tag{2}$$

The LMI is used as a method to test the existence of clustering in observed samples. Accordingly, the LMI of SO_2 intensity can be calculated as follows:

$$LMI = \frac{(SOI_i - \overline{SOI})\sum_{j=1}^{n} w_{i,j}(SOI_j - \overline{SOI})}{\sum_{i=1}^{n}(SOI_i - \overline{SOI})^2/n} \tag{3}$$

3.1.2. Spatial weight matrix

The definition of the spatial weight matrix (W) is a key step in capturing the interactions between different provinces. This study uses three of the most common spatial matrices, namely the spatial adjacent matrix (W1), geographic distance matrix (W2), and economic distance matrix (W3), with the following basic forms:

3.1.3. Spatial adjacent matrix (W1).
If the province i and province j are geographically adjacent, the corresponding factor in the matrix is 1. Otherwise, it is 0, as shown below:

$$e_{ij}{}^{1} = \begin{cases} 1, & i \neq j \\ 0, & i = j \end{cases} \tag{4}$$

3.1.4. Geographic distance matrix (W2).
This is an extension of W1. According to the latitude and longitude of the provincial capital, the spherical distance between each point is calculated. Then, the geographical distance weight matrix is constructed with its reciprocal element as follows:

$$e_{ij}{}^{2} = \begin{cases} 1/d_{ij}, & i \neq j \\ 0, & i = j \end{cases} \tag{5}$$

3.1.5. Economic distance matrix (W3).
According to Feng et al. (2019), this study adopts the reciprocal of the economic level gap between the two provinces as W3, where $\bar{Y_i}$ is the annual average per capita GDP of a province from 2000 to 2016.

$$e_{ij}{}^{3} = \begin{cases} 1/\left|\bar{Y_i} - \bar{Y_j}\right|, & i \neq j \\ 0, & i = j \end{cases} \tag{6}$$

3.1.6. Spatial econometric model

As a generalised form of a spatial econometric model, the spatial Durbin model (SDM) entails spatial lags of pollutant emissions and socio-economic elements; these can effectively resolve estimation problems, such as spatial heterogeneity and omission of variables (Elhorst, 2014). Therefore, the traditional SDM can be expressed in the following manner:

$$\begin{aligned} \ln SOI_{i,t} = {} & \rho W.\ln(SOI_{i,t}) + \eta_1 \ln SIN_{i,t} + \eta_2 \ln EM_{i,t} + \eta_3 \ln UR_{i,t} + \eta_4 \ln SRD_{i,t} \\ & + \theta_1 W.\ln(SIN_{i,t}) + \theta_2 W.(\ln EM_{i,t}) + \theta_3 W.(\ln UR_{i,t}) \\ & + \theta_4 W.(\ln SRD_{i,t}) + \mu + \partial_t l_N + \mu_t \end{aligned} \tag{7}$$

where ρ is the spatial autoregressive coefficient of SO_2 intensity, reflecting the spatial spillover effect of SO_2 intensity, where *SOI* denotes SO_2 intensity; *SRD* denotes total environmental R&D activities; *SIN*, *EM*, and *UR* represent economic structure, energy structure, and urbanisation, respectively; $\eta_i (i = 1, 2 \ldots, 4)$ is the regression coefficient of different variables.$\theta_i (i = 1, 2 \ldots, 4)$ signifies the spatial lag term of the corresponding variable, μ symbolises the vector of space fixed or space random effect, and ∂_t denotes the fixed or random effect of time period (t = 1,2, … ,T).

However, SO_2 intensity also has the characteristic of path dependence; in other words, SO_2 intensity in the present period is also influenced by the SO_2 intensity in the preceding period. Thus, the DSDM is introduced to study the dynamic characteristics of SO_2 intensity:

$$\begin{aligned}\ln SOI_{i,t} = {} & \phi \ln SOI_{i,t-1} + \rho W.\ln(SOI_{i,t}) + \eta_1 \ln SIN_{i,t} + \eta_2 \ln EM_{i,t} \\ & + \eta_3 \ln UR_{i,t} + \eta_4 \ln SRD_{i,t} + \theta_1 W.\ln(SIN_{i,t}) + \theta_2 W.(\ln EM_{i,t}) \\ & + \theta_3 W.(\ln UR_{i,t}) + \theta_4 W.(\ln SRD_{i,t}) + \mu + \partial_t l_N + \mu_t \end{aligned} \tag{8}$$

where ϕ represents the lagging term of SO_2 intensity.

Based on the above analysis, models (7) and (8) can evaluate the influence of environmental R&D on SO_2 intensity under the spatial effect. The magnitudes of the coefficients η_4 and θ_4 are of prime importance.

However, significant diversities exist between environmental R&D activities, as discussed in the **Literature review**, leading to different influences on SO_2 intensity. Thus, environmental R&D activities are categorised based on various purposes (e.g., practical-type and invention-type). Then, the experimental model can be showed as

$$\begin{aligned}\ln SOI_{i,t} = {} & \rho W.\ln(SOI_{i,t}) + \eta_1 \ln SIN_{i,t} + \eta_2 \ln EM_{i,t} + \eta_3 \ln UR_{i,t} \\ & + \eta_4 \ln CRD_{i,t} + \eta_5 \ln URD_{i,t} + \theta_1 W.\ln(SIN_{i,t}) + \theta_2 W.(\ln EM_{i,t}) \\ & + \theta_3 W.(\ln UR_{i,t}) + \theta_4 W.(\ln CRD_{i,t}) + \theta_5 W.(\ln URD_{i,t}) \\ & + \mu + \partial_t l_N + \mu_t \end{aligned} \tag{9}$$

where model (9) is a static SDM; *URD* denotes practical-type R&D, *CRD* denotes invention-type R&D, the coefficients η_4 and θ_4 are of prime importance.

Likewise, the DSDM is presented below:

$$\begin{aligned}\ln SOI_{i,t} = {} & \phi \ln SOI_{i,t-1} + \rho W.\ln(SOI_{i,t}) + \eta_1 \ln SIN_{i,t} + \eta_2 \ln EM_{i,t} \\ & + \eta_3 \ln UR_{i,t} + \eta_4 \ln CRD_{i,t} + \eta_5 \ln URD_{i,t} \\ & + \theta_1 W.\ln(SIN_{i,t}) + \theta_2 W.(\ln EM_{i,t}) + \theta_3 W.(\ln UR_{i,t}) \\ & + \theta_4 W.(\ln CRD_{i,t}) + \theta_5 W.(\ln URD_{i,t}) + \mu + \partial_t l_N + \mu_t \end{aligned} \tag{10}$$

where Model (10) is based on the SDM under different environmental R&D, in which the coefficients $\eta_4, \eta_5, \theta_4, \theta_5$ are of prime importance.

3.2. Variable selection and data source

In accordance with previous studies, the present study classified the factors affecting SO_2 intensity into technological progress and structural change, wherein the latter refers to the shift in economic structure and energy structure. In the process of rapid urbanisation, energy demand and energy consumption patterns triggered by urbanisation will also have an impact on SO_2 intensity. Considering the availability of data, we obtained balanced panel data for 30 provinces from 2000 to 2016. Tables 1 and 2

Table 1. Definitions and descriptive statistics of the variables.

Variables	Description	Proxy variables	Mean	Std.Dev	Min	Max
ln *SOI*	SO_2 intensity	Sulphur dioxide emission divided by GDP in logarithm	1.855	0.487	0.112	3.164
ln *SRD*	The total environmental R&D activities	Number of the total environmental patents in logarithm	4.817	1.676	0	8.634
ln *CRD*	The invention-type of environmental R&D activities	Number of invention-type patents in logarithm	4.152	1.746	0	8.108
ln *URD*	The practical-type of environmental R&D activities	Number of practical-type patents in logarithm	4.036	1.617	0	7.898
ln SIN	Economic structure	Ratio of secondary sector added value to GDP in logarithm	3.64	0.248	2.477	3.970
ln *EM*	Energy mix	Ratio of coal in energy consumption in logarithm	4.117	0.314	2.163	4.572
ln *FDI*	FDI	Ratio of FDI to the total fixed asset investment in logarithm	3.474	1.222	0.941	8.176
ln *EX*	Export	Ratio of export divided by GDP in logarithm	−2.38	0.991	−4.785	−0.007
ln *UR*	Urbanization	Ratio of urban population to the total population in logarithm	3.867	0.297	2.976	4.496

Source: Research results.

Table 2. Correlation matrix.

	ln *SOI*	ln *SRD*	ln *CRD*	ln *URD*	ln SIN	ln *EM*	ln *UR*	ln *EX*	ln *FDI*
ln *SOI*	1								
ln *SRD*	−0.753	1							
ln *CRD*	−0.761	0.987	1						
ln *URD*	−0.731	0.979	0.943	1					
ln SIN	0.164	0.201	0.164	0.252	1				
ln *EM*	0.477	−0.101	−0.14	−0.060	0.524	1			
ln *UR*	−0.700	0.648	0.667	0.602	0.073	−0.342	1		
ln *EX*	−0.307	0.376	0.364	0.369	0.212	−0.117	0.561	1	
ln *FDI*	0.315	−0.196	−0.196	−0.185	−0.045	0.215	−0.451	−0.641	1

Source: Research results.

present the definitions of the variables and the correlation matrix, respectively. All indicators are described below.

3.3. Explained variable

For the explained variable, SO_2 intensity (unit: kg/10^4 RMB) is described by the proportion of SO_2 emissions to GDP. SO_2 emissions and GDP data were obtained from the *China Energy Statistical Yearbook (CESY)* and the *China Provincial Statistical Yearbooks (CPSY)*, respectively. GDP is showed in 2000 constant prices.

3.4. Core explanatory variable

This study selected environmental R&D activities as the core explanatory variable. There are three ways to measure environmental R&D activities. First, in terms of innovation input, they are expressed through R&D investment (Ahmad et al., 2020).Second, from the perspective of innovation output, they are represented by green patents. Third, from the perspective of innovation performance, they are expressed by TFP (Miao et al., 2021). However, due to data limitations, R&D and TFP have certain disadvantages (Tumelero et al., 2019). Consistent with most literature, we use the number of green patents to show environmental R&D activities (Du et al., 2021; Zhang et al., 2019).

For the construction of green patents, first, we defined the scope of environmental R&D activities. According to the World Intellectual Property Organization (WIPO), there are seven fields related to emission reduction and energy conservation technologies[2], and the innovative technologies in these areas can be considered as environmental R&D activities. Second, we collected all patent data from the Chinese Patent database, which publishes all valid patent application information. Third, we identified green patents by combining the classification code of each patent with the IPC Green Inventory. The total environmental R&D activities would be the sum of the green patents in seven environmental fields. Additionally, based on the search keywords of each patent, it was possible to distinguish whether it was a practical-type or an invention-type patent. The number of practical R&D activities and invention R&D activities in environmental technology could also be obtained by following an identical method. Finally, given the time-lag of the impact of patents on the environment, the patent data from 1999 to 2015 were selected.

3.5. Control variables

3.5.1. Economic structure

Numerous researchers have confirmed the positive association between industrialisation and pollutant emissions. As SO_2 is an air pollutant, an economic structure dominated by the secondary industry will lead to elevated levels of SO_2 and SO_2 intensity. Similar to previous studies, this study defined the economic structure as the rate of the added value by industries to the GDP (Han & Amira,2021; Zhu et al., 2021), and the data were sourced from the *CPSY*. We expected the economic structure to increase SO_2 intensity.

3.5.2. Energy structure

China uses more coal compared to cleaner energy (natural gas or petroleum), and the rate of coal in entire energy consumption was 56.8% in 2020 (National Bureau of Statistics, China). The combustion of coal emits large quantities of sulphide. Therefore, a coal-based energy structure is not beneficial to reducing pollutant emissions (Wang et al., 2019). As in most literature, the rate of coal consumption to entire energy consumption was considered as the energy consumption structure (Li et al., 2020; Zhao et al., 2018), the corresponding data was obtained from the *CESY*. The effect of energy structure on SO_2 intensity was expected to be positive.

3.5.3. Urbanisation

Urbanisation can affect SO_2 emissions through aggregation and scale effects; therefore, its impact primarily relies on the size of the two effects. In empirical research, some researchers consider urbanisation to have worsened environmental pollution (Salahuddin et al., 2019). However, other studies confirmed the positive effects of urbanisation on the environment (Liu et al., 2019). Referring to Salahuddin et al. (2019) and Wang et al. (2019), urbanisation refers to the ratio of the urban population to total population, which from *CPSY*. We assumed urbanisation to have a uncertain impact on SO_2 intensity.

4. Results and discussion

4.1. Spatial auto-correlation test

The annual change in the GMI for SO_2 intensity was calculated based on three spatial weight matrices. In Table 3, the GMI was greater than 0 at a high level of 5%. The outcomes showed that SO_2 intensity in China had highly spatial correlation characteristics or global spatial dependence among different provinces. The annual GMI also showed an inverted U-shaped trend. To further explore this problem, this study used dynamic spatial econometric model to evaluate the impact of different environmental R&D activities on SO_2 intensity.

To identify the characteristics of local spatial autocorrelation and spatial agglomeration, we drew Moran's index scatter diagrams for 2005 and 2015 (Figure 1). Most provinces occurred in the first and third quadrants, showing that there was an important positive local spatial dependence of SO_2 intensity. In addition, according to the local Moran's index scatter diagrams and LISA, the 'high-high' cluster areas were mainly distributed in Gansu, Qinghai, Shanxi, and Ningxia from 2005 to 2015. The 'low-low' agglomeration areas were mainly in the eastern coastal areas, including Jiangsu, Zhejiang, Fujian, Guangdong, Shanghai, and other regions. Heilongjiang, Hunan, and Anhui were in the clustering characteristic of 'high-low'. The 'low- high'-type regions were mainly distributed in parts of Gansu, Shaanxi, Shanxi, and Inner Mongolia. In summary, China's SO_2 intensity not only has significant spatial agglomeration, but also presents unbalanced spatial heterogeneity within provinces.

Table 3. The global Moran *I* index of China's SO_2 intensity between 2000 and 2016.

Year	W1	W2	W3
2000	0.061**	0.065**	0.077***
2001	0.065***	0.068***	0.081***
2002	0.069***	0.072***	0.085***
2003	0.087***	0.091***	0.103***
2004	0.099***	0.098***	0.115***
2005	0.1***	0.11***	0.116***
2006	0.103***	0.107***	0.12***
2007	0.105***	0.109***	0.123***
2008	0.108***	0.11***	0.125***
2009	0.108***	0.112***	0.124***
2010	0.119***	0.117***	0.131***
2011	0.127***	0.125***	0.14***
2012	0.126***	0.124***	0.139***
2013	0.124***	0.123***	0.138***
2014	0.126***	0.128***	0.141***
2015	0.13***	0.131***	0.146***
2016	0.124***	0.125***	0.142***

Notes: (a)The results are based on the stata command 'spatgsa'. (b) ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.
Source: Research results.

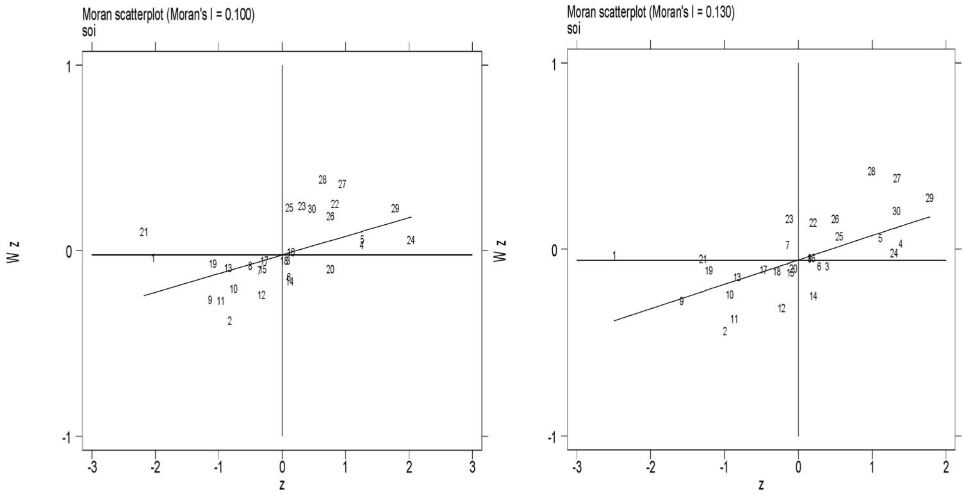

Figure 1. Moran scatter chart of China's SO_2 intensity in 2005 and 2015.

Notes: (a) The left figure shows the reported results of SO_2 intensity in 2005, and the right figure shows the reported results of SO_2 intensity in 2015. (b) The provinces represented by the figures are： 1 - Beijing, 2 - Tianjin, 3 - Hebei, 4 - Shanxi, 5 - Inner Mongolia, 6 - Liaoning, 7 - Jilin,8 - Heilongjiang, 9 - Shanghai, 10 - Jiangsu, 11 - Zhejiang, 12 - Anhui, 13 - Fujian, 14 - Jiangxi, 15 - Henan,16 - Shandong ,17 - Hubei, 18 - Hunan, 19 - Guangdong, 20 - Guangxi, 21 - Hainan, 22 - Chongqing, 23 - Sichuan, 24 - Guizhou, 25 - Yunnan, 26 - Shaanxi, 27 - Gansu, 28 - Qinghai, 29 - Ningxia, 30 - Xinjiang. (c) For simplicity, we only report the Moran's index scatter diagrams based on W1. Due to space limitation, the other weight matrices (W2,W3) are quite relatively consistent with the results of W1.
Source: Research results.

Table 4. Statistical tests results for form selection.

Statistic	W1	W2	W3
LM-lag	6.088**	6.026**	6.111**
LM-error	7.638***	7.988***	5.112***
Robust- LMlag	5.012**	6.065**	8.615***
Robust -LM error	5.633**	5.894**	6.182**
Wald_spatial_lag	68.232***	66.468***	80.76***
Wald_spatial_error	62.129***	61.31***	85.72***
LR_spatial_error	56.122***	50.432***	85.11***
LR_spatial_lag	59.172***	59.071***	84.18***

Notes: ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.
Source: Research results.

4.2. Spatial regression results

4.2.1. Analysis of general environmental R&D activities and SO_2 intensity

Before empirical analysis, we used statistical tests to select the appropriate econometric model. Table 4 reports the results. First, it was assumed that there was no correlation between individual effects and variables. We used Hausman test to decide whether to adopt the fixed effects model (FE) or the random effects model (RE). The Hausman test showed that FE was better than RE, which passed the test at the 5% significance level. Second, FE, static spatial Durbin model (FSDM), and DSDM were compared. We found that most p-values of Lagrange Multiplier (LM) test—LM-Lag, LM-error, Robust-LM-error, and Robust LM-lag—passed the test at the 5% significance level, which means that spatial correlation should be considered in the econometric model. In addition, both likelihood ratio test and Wald test also passed the

Table 5. Regression results of general environmental R&D activities to SO_2 intensity.

Variables	1 FE	2 FSDM1	3 DSDM1	4 DSDM2	5 DSDM3
ln *SRD*	−0.207***	−0.026**	−0.040***	−0.039***	−0.038***
	(0.010)	(0.012)	(0.002)	(0.005)	(0.003)
ln SIN	0.202***	0.068	0.063***	0.067***	0.065***
	(0.052)	(0.042)	(0.006)	(0.01)	(0.008)
ln *EM*	0.520***	0.352***	0.353***	0.354***	0.365***
	(0.045)	(0.033)	(0.005)	(0.004)	(0.005)
ln *UR*	−0.434***	−0.066	−0.065	−0.059	−0.062
	(0.080)	(0.065)	(0.061)	(0.058)	(0.068)
L. ln *SOI*			0.753***	0.775***	0.766***
			(0.067)	(0.069)	(0.068)
W ∗ ln *SOI*		0.155**	0.258**	0.247**	0.254**
		(0.075)	(0.112)	(0.102)	(0.111)
W ∗ ln *SRD*		0.017	0.015	0.011	0.022
		(0.024)	(0.023)	(0.025)	(0.024)
Hausman	13.05**				
ρ		0.621***	0.65***	0.713***	0.681***
		(0.061)	(0.17)	(0.103)	(0.041)
N	510	480	480	480	480

Notes: (1). ***, **, and * denote the significance at the 1%, 5%, and 10% level. (2). Values in ( ) denote the std.error for the coefficient. (3). L.ln*SOI* stands for the first-order lag of dependent variable (i.e., SO_2 intensity). (4). W is the spatial weight matrix. W*X stands for the product of W and the variable X, representing the spillover effect of the variable X on SO_2 intensity.
Source: Research results.

test at the 1% significance level; therefore, the FSDM was more suitable. Compared with the FSDM, the DSDM has both spatial and time lag effect, and could estimate parameters more accurately. In summary, we adopted the DSDM in this study.

Based on Equation (8), the quasi-maximum likelihood approach (Yu et al., 2008) was adopted to evaluate the influence of environmental R&D activities on SO_2 intensity in China from 2005 to 2015. The estimation outcomes are presented in Table 5. For comparison, Table 5 also lists the evaluated results of FE (Column 1), FSDM (Column 2), DSDM based on the spatial matrix W1 (Column 3), DSDM based on the spatial matrix W2 (Column 4), and DSDM based on the spatial matrix W3 (Column 5).

In Table 5, under three diverse spatial weight matrices, the time lag coefficient of SO_2 intensity (L.lnSOI) was significantly positive at 1% level. This indicates that China's SO_2 intensity has significant 'time inertia' and has certain pathing dependence; that is, if the SO_2 intensity is currently at a high level, the SO_2 intensity may increase continuously in the next period, showing a 'snowball effect'. From the spatial dimension, the spatial lag coefficient of SO_2 intensity (W*lnSOI) was significantly positive under three different spatial matrixes, indicating that SO_2 intensity had the characteristics of spatial agglomeration in different regions, which was in line with the outcomes of previous spatial autocorrelation tests.

The coefficient of environmental R&D (lnSRD) was largely negative at the 1% level, implying that the promotion of environmental technology would be conducive to decreasing SO_2 intensity in China. A 1% increase in general environmental technology activities would result in reducing SO_2 intensity by about 0.039%. Environmental R&D activities will allow companies to develop more energy-efficient technologies to enhance energy efficiency to save power. However, the spatial lag coefficient of environmental R&D (W*lnSRD) was positive, and it was not significant.

Table 6. Results of spatial effect decomposition.

Variables	Short-run			Long-run		
	Direct effects	Indirect effects	Total effects	Direct effects	Indirect effects	Total effects
ln *SRD*	−0.040***	0.015	−0.025***	−0.040***	0.015	−0.025***
	(0.002)	(0.023)	(0.003)	(0.002)	(0.023)	(0.003)
ln SIN	0.061***	−0.083*	−0.022	0.068***	−0.091*	−0.023
	(0.005)	(0.041)	(0.132)	(0.007)	(0.042)	(0.135)
ln *EM*	0.352***	0.155**	0.507***	0.360***	0.157**	0.517***
	(0.049)	(0.068)	(0.101)	(0.006)	(0.069)	(0.111)
ln *UR*	−0.062	−0.244	−0.306	−0.069	−0.247	−0.316
	(0.057)	(0.236)	(1.082)	(0.062)	(0.239)	(1.102)

Notes: (a) ***, **, and * denote the significance at the 1%, 5%, and 10% level. (b) The table reports the short-run and long-run effects under the DSDM model based on W1.
Source: Research results.

Possible reasons include (1) regional green technology innovation activities are not closely linked, and the mechanism to jointly improve the green technology innovation development has not yet been formed; (2) In terms of technology maturity, the green technology in China is of low quality and insufficient. As a result, it cannot give full play to its technology spillover effect, which has an obvious impact on neighbouring provinces.

According to Lesage and Pace (2009), the influence of various factors on SO_2 intensity can be divided into direct effect and indirect effect. In this study, the DSDM was adopted. According to time dimension, direct and indirect effects could be separated into short-term and long-term effects, respectively reflected the short-term impact of immediate and the long-term impact of considering time lag. Next, we examined the spatial effect decomposition of the explanatory variables using spatial adjacency matrix (W1), as W1 corresponded to the most ideal model (Table 6).

Regardless of direct effect or indirect influence, the absolute value of the coefficient of long-term effect was larger than that of short-term effect overall, indicating that each factor had a more profound long-term influence on SO_2 intensity. The effect of environmental R&D on local SO_2 intensity in the short- as well as long-term was negative in the same direction. Both short- and long-term direct influences were negative and passed the 1% significance level. The long-term effect did not change significantly. China's green innovation activities will help solve the problem of emission reduction. The reason the long-term effect of SO_2 intensity reduction was not strengthened may be that China's existing green technology still mainly involves incremental improvement, and it does not have sufficient time to develop. Meanwhile, the indirect influence of environmental R&D in both short- and long-term was positive, but not significant; this shows that the green technology innovation was mainly limited locally, and there was a lack of regional linkage.

4.2.2. Analysis of different purposes of environmental R&D activities and SO_2 intensity

When environmental R&D activities were categorised based on different aims (i.e., lnURD and lnCRD), we further estimated the spatial effect of different environmental R&D activities on SO_2 intensity (Table 7).

Table 7. Regression results of different environmental R&D activities to SO_2 intensity.

Variables	1 FE	2 FSDM1	3 DSDM1	4 DSDM2	5 DSDM3
ln *URD*	−0.127***	−0.017	−0.116***	−0.112***	−0.118***
	(0.014)	(0.012)	(0.013)	(0.014)	(0.016)
ln *CRD*	−0.094***	−0.021	−0.017	−0.014	−0.011
	(0.013)	(0.011)	(0.012)	(0.015)	(0.018)
ln SIN	0.159***	0.068	0.061**	0.062***	0.069***
	(0.051)	(0.042)	(0.027)	(0.025)	(0.028)
ln *EM*	0.477***	0.352***	0.355***	0.365***	0.375***
	(0.045)	(0.033)	(0.032)	(0.037)	(0.041)
ln *UR*	−0.340***	−0.062	−0.075	−0.077	−0.074
	(0.079)	(0.065)	(0.078)	(0.075)	(0.073)
L. ln *SOI*			0.792***	0.785***	0.796***
			(0.066)	(0.059)	(0.065)
W ∗ ln *SOI*			0.219**	0.224**	0.235**
			(0.102)	(0.103)	(0.108)
W ∗ ln *URD*		−0.04	−0.049**	−0.051**	−0.053**
		(0.037)	(0.022)	(0.024)	(0.025)
W ∗ ln *CRD*		−0.014	−0.012	−0.014	−0.015
		(0.042)	(0.072)	(0.074)	(0.076)
W ∗ ln SIN		−0.083	−0.084***	−0.082***	−0.083***
		(0.109)	(0.027)	(0.028)	(0.021)
W ∗ ln *EM*		0.153**	0.154**	0.151**	0.153**
		(0.063)	(0.064)	(0.062)	(0.069)
W ∗ ln *UR*		−0.291	−0.247	−0.241	−0.245
		(0.195)	(0.484)	(0.489)	(0.494)
Hausman	13.95**				
ρ		0.608***	0.615***	0.621***	0.617***
		(0.062)	(0.134)	(0.135)	(0.137)
sigma2_e		0.008***	0.007***	0.009***	0.008***
		(0.001)	(0.000)	(0.000)	(0.000)
N	510	510	480	480	480

Notes: (1) ***, **, and * denote the significance at the 1%, 5%, and 10% level. (2) Values in ( ) denote the std.error for the coefficient. (3) L.ln*SOI* stands for the first-order lag of dependent variable (i.e., SO_2 intensity). (4) W is the spatial weight matrix. W*X stands for the product of W and the variable X, representing the spillover effect of the variable X on SO_2 intensity.
Source: Research results.

It is worth noting that different types of green innovation activities had different influences on SO_2 intensity. First, practical-type innovation activities (lnURD) had a significant positive impact on the SO_2 intensity reduction. A 1% increase in practical innovation activities significantly reduced local SO_2 intensity by about 0.11%. In addition, its effect of technology spillover on SO_2 intensity was significantly negative, indicating that practical innovation activities can help reduce SO_2 intensity in neighbouring provinces. Second, although invention-type innovation activities (lnCRD) could reduce local SO_2 intensity, their direct and spatial effects on SO_2 intensity were insignificant. Third, practical green innovation activities (lnURD) had a more obvious effect on SO_2 intensity, and the impact was greater. The possible reasons are that invention-type innovation activities (lnCRD) are more inclined towards theoretical innovation, and the influence on the environment is relatively indirect. Their spatial spillover effect is not obvious, which may be due to most innovation activities focusing on frontier theories, and the confidentiality of high-tech ventures makes regional technical cooperation difficult, thus affecting SO_2 intensity in neighbouring provinces. In addition, invention-type innovation activities (lnCRD) are insufficient in China.

Practical innovation activities (lnURD) pay more attention to the practical operation of green technology, their product maturity is higher, and technology is easier to flow between different regions, thus resulting in a positive technology spillover effect on the decrease of SO_2 intensity.

Among other control variables, first, the coal-dominated energy structure (lnEM) had a significant positive impact on local SO_2 intensity. This shows that the long-term energy consumption structure in China has been sacrificing the environment; therefore, it is extremely important to optimise the current energy consumption structure. The indirect effects of energy structure (W*lnEM) on SO_2 intensity were all positive and passed the significance level test of 5%, demonstrating the local energy consumption structure increased the SO_2 intensity of neighbouring areas. The possible reason is the local energy consumption structure has greatly promoted local economic development, and the neighbouring areas will also highly rely on coal for economic development based on competition, resulting in increase of SO_2 intensity in the neighbouring areas. Second, the direct effect of industrial structure (lnSIN) on local SO_2 intensity was positive, but its indirect effect (W*lnSIN) was negative. From the perspective of the rapid industrialisation process, the increase in the proportion of industry may be caused by high-energy-consuming industries or unreasonable trade division in the surrounding area, which increases the local SO_2 intensity, while the SO_2 intensity in neighbouring areas relatively decrease. Finally, urbanisation (lnUR) had a negative effect on SO_2 intensity, though insignificant. Rapid urbanisation will increase residents' income and make them have higher requirements for environmental quality. At the same time, neighbouring provinces will also imitate this consumption pattern; therefore, the spatial effect of urbanisation (W*lnUR) will lead to reduction of SO_2 intensity.

4.3. Results of Robustness test

4.3.1. Robustness test of endogeneity W

There may be endogeneity problems in previous estimates, which may bias the estimated results. The possible reasons for endogeneity are as follows: First is the problem of omitted variables. Some important variables affecting SO_2 intensity may be missing from the model. Second is the interaction effect: environmental R&D activities and SO_2 intensity are likely to interact. Third, the problem of endogeneity is not only how to build spatial weights but also involves the spatial lag of control variables in SDM that is considered to be endogenous (Delgado et al., 2018). Referring to Zhang and Wu (2022), the Spatial Panel Autoregressive Generalised Method of Moments Regression (Spatial GMM) was used in this study. First, the instrumental variables of spatial GMM estimation were selected. We used W*lnSRD as the instrumental variable of spatial GMM method to estimate the influence of general environmental R&D activities on SO_2 intensity. When estimating the impact of various types of environmental R&D activities on SO_2 intensity, W*lnSRD and W*lnURD were selected as instrumental variables of spatial GMM estimation. Second, Hansen J test was used to test the rationality of instrumental variables. Finally, the SAR model was used for GMM estimation of the above models, and the outcomes can be seen in

Table 8. The effects of environmental R&D activities on SO_2 intensity (Robustness test).

Variables	1 SGMM1	2 SGMM2	3 DSDM4	4 DSDM5
ln *SRD*	−0.039***		−0.042***	
	(0.005)		(0.001)	
ln *URD*		−0.113***		−0.118***
		(0.014)		(0.017)
ln *CRD*		−0.016		−0.016
		(0.015)		(0.017)
ln SIN	0.061**	0.06*	0.067***	0.069***
	(0.026)	(0.028)	(0.022)	(0.023)
ln *EM*	0.343***	0.345***	0.357***	0.0356***
	(0.015)	(0.04)	(0.002)	(0.011)
ln *UR*	−0.069	−0.071	−0.078	−0.074
	(0.062)	(0.09)	(0.063)	(0.059)
ln *EX*				
ln *FDI*			0.083***	0.080***
			(0.014)	(0.015)
L. ln *SOI*	0.748***	0.782***	0.795***	0.794***
	(0.067)	(0.076)	(0.025)	(0.024)
W ∗ ln *SOI*	0.258**	0.219*	0.217***	0.219***
	(0.112)	(0.106)	(0.027)	(0.037)
W ∗ ln *SRD*	0.015		0.013	
	(0.024)		(0.04)	
W ∗ ln *URD*		−0.046*		−0.047**
		(0.023)		(0.018)
W ∗ ln *CRD*		−0.013		−0.013
		(0.077)		(0.037)
W ∗ ln SIN	−0.09**	−0.081***	−0.089***	−0.087***
	(0.032)	(0.03)	(0.024)	(0.023)
W ∗ ln *EM*	0.159**	0.151*	0.155**	0.156**
	(0.069)	(0.072)	(0.068)	(0.068)
W ∗ ln *UR*	−0.245	−0.237	−0.245	−0.241
	(0.238)	(0.256)	(0.237)	(0.238)
W ∗ ln *EX*				
W ∗ ln *FDI*			−0.008***	−0.009**
			(0.002)	(0.003)
ρ	0.68***	0.625***	0.066***	0.068***
	(0.19)	(0.131)	(0.022)	(0.025)
sigma2_e			0.002***	0.002***
			(0.000)	(0.000)
Hansen J	0.199	0.203		

Notes: (1). ***, **, and * denote the significance at the 1%, 5%, and 10% level..(2) The variables EX and FDI represent the openness, denoted by the ratio of export in GDP and the share of FDI in fixed asset investment, respectively. (3) The regression results of column 1 and column 2 are obtained by the spregdpd and xtdpdsys commands of Stata14.0; columns (3)-(6) based on W1.
Source: Research results.

columns 1 and 2 of Table 8. The empirical results show that the regression results are consistent with those in Table 5 (DSDM1) and Table 7 (DSDM1).

4.3.2. Robustness tests of different variables

We added control variable to verify the robustness. Openness is one of the most significant elements influencing the environment. Consistent with most studies, foreign direct investment (FDI) was taken as a proxy variable of openness and expressed by the rate of FDI in the total fixed-asset investment (Huang & Chen, 2020). Relevant data were sourced from *CPSY*. The results in columns 3 and 4 of Table 8 show that the magnitude and direction of the effects of core variables and other influencing factors on SO_2 intensity are similar to the previous results. Thus, the robustness of the regression outcomes in this research was confirmed.

5. Conclusions and policy recommendations

Our research empirically tested the effects of environmental R&D activities on SO_2 intensity by using spatial econometric model according to the 2005–2015 panel data of Chinese provinces. The major conclusions include: (1) China's SO_2 intensity is path-dependent in the temporal dimension. In terms of spatial agglomeration, SO_2 intensity presents a spatial correlation of 'high-high' and 'low-low', and the regional SO_2 intensity will be positively affected by surrounding areas. (2) The direct influence of environmental R&D on local SO_2 intensity is negative both in the short- and long-term, indicating that it has a continuous inhibition effect on local SO_2 intensity, but the effect does not show a long-term strengthening trend. The indirect effects of environmental R&D on neighbouring areas are all positive, but insignificant, showing that the spatial spillover influences of China's green technology are not yet apparent and there are spatial limitations. (3) There is obvious heterogeneity in environmental R&D. Compared with invention-type R&D, utility-type R&D has more effect on SO_2 intensity. (4) The coal-based energy structure and the industrial economic structure will significantly increase SO_2 intensity in China. Although urbanisation has a positive effect on improving the environment, the effect is not significant.

The corresponding policy recommendations are as follows: (1) SO_2 emission reduction and environmental protection need 'collaborative governance' of provinces. Provincial governments are supposed to control local SO_2 intensity. Besides, 'emissions alliance' should be formed between neighbouring provinces. (2) Environmental R&D is beneficial to controlling regional SO_2 intensity, indicating that the government should continue to support R&D related to green technology and continuously increase financial support for cleaner production technology. (3) Environmental R&D should give full play to its spatial spillover effect. A regional linkage platform should be provided to high-tech enterprises of emission reduction and energy conservation; in addition, the technical personnel exchanges between regions should be strengthened. (4) Although the influence of practical-type R&D on SO_2 intensity is far higher than that of invention-type R&D, it does not indicate that invention-type R&D is not essential. In fact, invention-type R&D represents high-quality green technology and deserves more investment. Thus, China should make full use of these differential characteristics of environmental R&D to reduce SO_2 intensity more effectively.

This study pays attention to the influence of green technology on environmental performance. Several extensions of this analysis are possible: (1) We use green patents instead of green technologies, and the proxy variable problem arises. We can calculate the biased technological progress in China and further research the influence of biased technological progress on environmental performance. (2) Green technology may not change linearly owing to environmental regulation and business cycle. An extension of this study may consider the nonlinear influence of environmental regulation, business cycle, and human capital on green technology. (3) This study can be extended to industry data and city data.

Disclosure statement

No potential conflict of interest was reported by the authors.

Notes

1. For environmental R&D, please see Literature Review Section.
2. According to the IPC Green Inventory published by WIPO, these seven areas are (a) Waste management; (b) Administrative, regulatory, or design aspects; (c) Energy conservation; (d) Transportation; (e) Alternative energy production; (f) Agriculture/forestry; and (g) Nuclear power generation.

Acknowledgement

The authors gratefully acknowledge comments and suggestions by all referees.

Funding

No funding was received for conducting this study.

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