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Environmental regulation and synergistic effects of $PM_{2.5}$ control in China

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A R T I C L E I N F O

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A B S T R A C T

In recent years, haze pollution has been widespread across China, and the intensity of environmental regulation has been continuously strengthened. Differences in regional environmental regulation intensity brought about the spillover effect of air pollution. In this study, we analyze the spatiotemporal variation trends and distribution of provincial environmental regulation in China from 2004 to 2017. Considering the spatiotemporal lag effect of haze pollution, the dynamic spatial Durbin model was employed to study the spatial impact of environmental regulation tools of different pollutants on $PM_{2.5}$ (fine particulate matter with aerodynamic diameters $\leq$2.5 μm). We found that $PM_{2.5}$ is significantly negatively related to the environmental regulation intensity and synergy, showing a lag effect of 1–2 periods. The environmental regulation level is high in Eastern China but low in western areas, however, most regions lack an important understanding of environmental regulation. Overall, only 19.8%, 23.0%, and 28.1% of the regions exceeded the average level of the environmental regulation intensity of SO_2, smoke/dust (SD), and NO_X, respectively. $PM_{2.5}$ yields a spatial spillover effect and is also negatively correlated to the environmental regulation tools of various pollutants. For every 1% increase in the environmental regulation intensity (synergy) of above three pollutants, $PM_{2.5}$ will be significantly ($p < 0.05$) reduced by 0.02% (0.04%), 0.05% (0.10%) and 0.04% (0.08%), respectively. Inter-regional collaboration has a profound and long-term impact on $PM_{2.5}$ and is conducive to improving the efficiency of environmental governance.

1. Introduction

In China, extensive economic growth along with the continuous urbanization causes severe environmental problems, especially haze pollution (Chen et al., 2017; Liao et al., 2017; Song et al., 2021; Xue et al., 2021a; Wei et al., 2021a, 2021b, 2022). Fine particulate matters have become the major air pollutants that can cause a large number of diseases, e.g., cancer, cardiovascular and respiratory diseases (Lu et al., 2021; Ma et al., 2016; Wei et al., 2019, 2020, 2021c; Zhang et al., 2020; Zheng et al., 2015). As stated in the Bulletin on the State of China's Ecological Environment in 2019 issued by the Ministry of Ecology and Environment, among 337 prefecture-level and above cities in China, 46.6% of cities fail to meet the air quality standard, and $PM_{2.5}$ (particulate matters with an aerodynamic diameter <2.5 μm), is the primary air pollutant. Environmental regulation (ER) is considered to be an effective way to reduce $PM_{2.5}$ concentrations (Yu et al., 2017). However, spatial heterogeneities of ER exist in China, which may cause the transfer of air pollution, thus reducing the efficiency of ER (Johnson, 2020). Therefore, exploring the impacts of regional environmental regulation intensity (ERI) and environmental regulation synergy (ERS) on $PM_{2.5}$ is crucial in China.

The relationships between ER by local governments and $PM_{2.5}$ pollution have been attracted by the public because it is an important part of government management (Dasgupta et al., 2012; Hao et al., 2018; Zhang et al., 2020). Two viewpoints are mainly expressed now, first of all, the Porter Hypothesis (Porter and Linde, 1995). This view

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indicated that an appropriate ER would promote technological innovation (Hille and Mobius, 2019), which can offset the cost increase caused by ER. However, based on the data on environmental protection in Mexico, Blackman and Kildegaard (2010) found that the promotion effect of ER on green technology innovation is not significant, and the pollution emissions will be enhanced by contraries. The other viewpoint is that a low level of ER can provide shelter for air pollution (Bartik, 2015; Bildirici and Gokmenoglu, 2020). Konisky (2007) indicated that the regional environmental standards would be cheapened to attract more foreign investment. Due to the profiting maximization and avoid the increase of production costs caused by ER, local enterprises are more inclined to move to lower-level ER areas (Li et al., 2021). In short, some scholars have pointed out the important relationship between ER, enterprise cost, and regional economy, that is, environmental regulation can alleviate pollution. However, many problems, e.g., cross pollution, repeated control, and low-efficiency government, are still existed in China for environmental management, especially for the spillover effect of $PM_{2.5}$.

The spatial effects of $PM_{2.5}$ are mainly co-affected by geographical attributes and regional economic linkages (Cheng et al., 2017; Ma et al., 2016). Although ER can alleviate $PM_{2.5}$, spatial adjacency of $PM_{2.5}$ are existed in most areas of China due to the action of atmospheric circulation, which could form an isolated 'pollution basin' through the transporting of air masses (Qin et al., 2015). The spatial spillover effect of air pollution will cause the definition of responsibility for regional environmental governance ambiguous. However, it is impossible to avoid the phenomenon of inter-regional air cross-pollution and repeated governance, which makes the regional governance mode inefficient (Yamagishi, 2019). Thus, the spatial spillover effect of $PM_{2.5}$ is not conducive to the local environmental governance nor the improvement of the environment. Therefore, exploring the spatial relationship between ER and $PM_{2.5}$ is necessary, which is of practical significance.

The control of air pollution in different regions will inevitably be transformed from the traditional control by administrative division to collaborative governance. This paper conducts a quantitative analysis on the inter-governmental synergy governance of air pollution in China, from the perspective of local government ERI and regional ERS. The secondary source is the main source of atmospheric particulate matters ($PM_{2.5}$) in China (Lu et al., 2020; Quan et al., 2011; Yang et al., 2011). In addition, the secondary sources of $PM_{2.5}$ are mainly the precursors discharged into the air, including sulfur dioxide, nitrogen oxides, smoke dust, and volatile organic compounds produced by energy consumption in factories. The nitrate, sulfate, and secondary organic aerosol produced by chemical reactions lead to the increase of $PM_{2.5}$ concentrations. $PM_{2.5}$ pollution will also increase under the conditions of high concentrations of SO_2, SD, and NO_X smoke. Therefore, the environmental regulation of those pollutants will directly affect the emission of $PM_{2.5}$. Based on this, we conducts a causal identification of the relationship between ER and $PM_{2.5}$ to verify the impact of ER tools of different pollutants on $PM_{2.5}$ concentration and whether the difference in ERI between neighboring regions affects the overall effect of environmental governance. After that, the dynamic spatial Durbin model (SDM) is selected to deal with endogenous problems and explore the background effect of environmental pollution in China. This provides the key theoretical evidence for regional environmental joint governance.

2. Data and methods

2.1. Datasets

2.1.1. $PM_{2.5}$ and emission data

The annual high-resolution (1 km) and high-quality $PM_{2.5}$ data for China (i.e., ChinaHigh$PM_{2.5}$) from 2004 to 2017 are collected from the ChinaHighAirPollutatns (CHAP) dataset, which is generated using satellite remote sensing and machine learning (Wei et al., 2020, 2021a; 2021b). The emission data, including the SO_2, SD, and NO_X emissions, are obtained from the "China Statistical Yearbook". Here, only the SO_2 data for the available period 2004–2017, and SD and NO_X data for the available period 2011–2017 are employed.

2.1.2. Other analysis data

In the control variables, gross domestic product (GDP) per capita was used to measure the level of economic development of the province and is represented by GDP in this paper. The regional industrial structure is measured by the proportion of industrial added value in GDP (Wu et al., 2019) and expressed by IS. The regional technical level was represented by the number of patents granted, expressed as Patent. Technological innovation ability is helpful to improve factor utilization efficiency and reduce pollution emission intensity (Omri and Hadj, 2020). The total population of the region is represented by Pop. The degree of opening up of an area also affects its environmental pollution (Zeng and Zhao, 2009). In this paper, the proportion of foreign direct investment in the GDP of each province is used to measure the openness of a region, which is represented by FDI. The main data of this paper is from China Statistical Yearbook from 2004 to 2017.

2.2. Methodology

2.2.1. Environment regulation and synergism

Quantitative measurement of the enforcement degree of regulation has always been the focus of the existing literature. In this paper, the ratio of air pollutant emission to air environmental governance investment is used to measure the intensity of air environmental regulation (Xue et al., 2020), and it is shown as follows:

$$ERI_i = Invest_i \;/\; Emission_i \qquad [1]$$

where *ERI* represents the intensity of environmental regulation, *i* represents the province, and *Invest* represents the investment in environmental control of air pollution. *Emission* represents the concentration of air pollutants, including SO_2, SD, and NO_X emission.

Furthermore, the degree of ERS is calculated based on the intensity of regional atmospheric environmental regulations as follows (Liu et al., 2009; Hu et al., 2019).

$$ERS = \left\{ \left[\prod_{i=1}^{n} ERI_i \Big/ \left(\frac{1}{n} \sum_{i=1}^{n} ERI_i \right)^n \right]^k \left(\sum_{i=1}^{n} \alpha_i ERI_i \right) \right\}^{\frac{1}{2}} \qquad [2]$$

where *ERS* represent the synergy of environmental regulation between two provinces. *k* is the adjustment coefficient, $k \geq 2$, this paper takes $k = 2$, and all regions are equally empowered. α represents weights, and *i* represents the province. *n* indicates the number of regions in the area.

2.2.2. Temporal and spatial correlation

The mean value of factors (ERI and ERS) for each province from 2011 to 2017 was calculated. Then, the spatial correlation among provinces was investigated according to the spatial distribution of provincial values. Besides, the annual factors of all provinces are calculated, and the temporal correlation between these factors based on time series is studied. To distinguish whether ER has a lag effect, spatial correlation and temporal correlation both consider the current period, one period, and two periods of lag. Pearson correlation coefficient is selected here and the T-test method is employed to test the statistical significance.

2.2.3. Spatial autocorrelation test

Moran's I describes the spatial autocorrelation characteristics of $PM_{2.5}$, which is usually between −1 and 1, and the values > (<0) indicate positive (negative) spatial autocorrelation (Moran, 1948):

$$I = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}(X_i - \overline{X})(X_j - \overline{X})}{S^2 \sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}} \qquad [3]$$

where n indicates the number of provinces. X_i and X_j are the $PM_{2.5}$ concentrations for province i and j, respectively. $\overline{X}$ indicates the average $PM_{2.5}$ concentration of all provinces and W_{ij} is the spatial weight matrix. s^2 is the variance value of $PM_{2.5}$, namely $s^2 = \frac{\sum_{i=1}^{n}(X_i-\overline{X})^2}{n}$. Besides, at a certain level of significance, the larger the absolute value of Moran's I, the higher the spatial correlation. Among them, the significance of Moran's I is tested by $Z_I = \frac{I-E[I]}{\sqrt{V[I]}}$, where $E[I]$ is the expectation of Moran's I and $V[I]$ represents the standard deviation of the variable.

2.2.4. Dynamic SDM and decomposition effect

Due to ER and environmental pollution may produce trans-regional spatial spillover. Therefore, we used the spatial econometric model for empirical study. Before that, the LR and LM tests methods were used to select the suitable spatial econometric model for our study (Anselin and Florax, 1995; Lv et al., 2019; Shurui et al., 2019; Zhang et al., 2018).

By LM Test and LR test (Table 1), LM-lag and robust LM-lag of SO_2 ERI and ERS were significant at 1% level, which rejected the original hypothesis. In addition, the Robust LM-error value was not significant, indicating that the spatial lag model (SAR) was more suitable than the spatial error model (SEM). However, the LR (SAR) value is significant ($P < 0.01$), which indicates the SDM cannot degenerate into SAR. Meanwhile, the LR tests of SD and NO_X environmental regulation were also significant at 1%. Therefore, SDM is chosen to test the causal relationship between ER (ERI and ERS) and $PM_{2.5}$, and it is shown as follows (Anselin, 1980; Elhorst and Freret, 2009):

$$Y_{it} = \beta X_{it} + \theta W X_{it} + \rho W Y_{it} + u_i + \lambda_t + \varepsilon_{it} \quad [4]$$

where Y_{it} represents the $PM_{2.5}$ concentration of i province in t year. X represents ER, represented by the ERI (ERS) of SO_2, SD, and NO_X. β is the coefficient of ERI (ERS), and W represents the spatial weight matrix. u_i and λ_t represent province fixed effect and year fixed effect, respectively, and ε_{it} indicates random disturbance term.

Since $PM_{2.5}$ is time-dependent, $PM_{2.5}$ concentration with a lag of one period was added as an instrumental variable to deal with the endogenies of the model and discuss the environmental background effect of $PM_{2.5}$. The model was constructed as follows:

$$Y_{it} = \beta X_{it} + \theta W X_{it} + \rho W Y_{it} + \tau Y_{i,t-1} + u_i + \lambda_t + \varepsilon_{it} \quad [5]$$

where τ represents the time lag coefficient of $PM_{2.5}$. If it is significantly positive, it indicates that the $PM_{2.5}$ of the previous year has an impact on the $PM_{2.5}$ of the current year.

At the same time, the spatial and temporal correlation of $PM_{2.5}$ was considered, the temporal and spatial lag terms of $PM_{2.5}$ are added to the right side of the model (5) to construct dynamic SDM, and it is shown as follows:

$$Y_{it} = \beta X_{it} + \theta W X_{it} + \rho W Y_{it} + \tau Y_{i,t-1} + \eta W Y_{i,t-1} + u_i + \lambda_t + \varepsilon_{it} \quad [6]$$

where η indicates the spatiotemporal lag coefficient of $PM_{2.5}$. In addition, the dynamic SDM can be written as follows:

$$I - \rho W Y_{it} = X_{it}\beta + W X_{it}\theta + \tau I + \eta W Y_{i,t-1} + u_i + \lambda_t + \varepsilon_{it} \quad [7]$$

And then:

$$Y_{it} = I - \rho W^{-1} X_{it}\beta + W X_{it}\theta + I - \rho W^{-1}\tau I + \eta W Y_{i,t-1} + I - \rho W^{-1} u_i + \lambda_t + \varepsilon_{it} \quad [8]$$

Among them, $I - \rho W^{-1} u_i + \lambda_t + \varepsilon_{it}$ represents the constant term. Furthermore, take the partial derivative with respect to X_{it}.

$$\left[\frac{\partial E(Y_{1t})}{\partial X_{iK}} \cdots \frac{\partial E(Y_{Nt})}{\partial X_{NK}}\right] = I - \rho W - \tau I - \eta W^{-1}\beta I + W\theta = [(1-\tau)I - (\rho+\eta)W]^{-1}\beta I + W\theta \quad [9]$$

Assume $\tau = 0$ and $\eta = 0$ as follows:

$$\left[\frac{\partial E(Y_{1t})}{\partial X_{iK}} \cdots \frac{\partial E(Y_{Nt})}{\partial X_{NK}}\right] = I - \rho W^{-1}\beta I + \theta W \quad [10]$$

Accordingly, the short (long) term direct, indirect, and total effects of the dynamic SDM can be calculated (Elhorst, 2014a). The short-term direct effect is $[I - \rho W^{-1}\beta_K I_N + \theta_K W]^{\bar{d}}$, the indirect effect is $[I - \rho W^{-1}\beta_K I_N + \theta_K W]^{\overline{rsum}}$, and the total effect is $[I - \rho W^{-1}\beta_K I_N + \theta_K W]^{\bar{d}} + [I - \rho W^{-1}\beta_K I_N + \theta_K W]^{\overline{rsum}}$. In addition, the long-term direct effect is $\{[(I-\tau) - (\rho+\eta)W]^{-1}\beta_K I_N + \theta_K W\}^{\bar{d}}$; the indirect effect is $\{[(I-\tau) - (\rho+\eta)W]^{-1}\beta_K I_N + \theta_K W\}^{\overline{rsum}}$, and the total effect is $\{[(I-\tau) - (\rho+\eta)W]^{-1}\beta_K I_N + \theta_K W\}^{\bar{d}} + \{[(I-\tau) - (\rho+\eta)W]^{-1}\beta_K I_N + \theta_K W\}^{\overline{rsum}}$. Where I represents the identify matrix, the superscript $\bar{d}$ denotes the operator for calculating the average diagonal element of the matrix, and the superscript $\overline{rsum}$ denotes the operator that calculates the mean row sum of the non-diagonal elements.

2.2.5. Spatial weight matrix

W_{ij} is spatial weight matrix, which is used to describe the spatial proximity between different regions. The geographical distance weight matrix can consider the relationship between the farther spatial units (Cliff and Ord, 1973; Kelejian and Prucha, 2010), and it is shown as follows:

$$W_{ij} = \begin{cases} 0, & i = j \\ \frac{1}{(d_{ij})^2}, & i \neq j \end{cases} \quad [11]$$

where d_{ij} represents the greater-circle distance calculated according to longitude and latitude between province i and province j. To simplify the model and make the results easier to interpret, W_{ij} is normalized after dividing each element by the sum of its row, ensuring that the sum of each row is 1 (Anselin, 1988).

3. Results and discussions

3.1. Spatiotemporal trends of ERI and ERS

To explore the development trend of environmental regulation status under different pollutant concentrations, and the time trend analysis of ERI (ERS) of SO_2, SD, and NO_X was conducted, respectively (Fig. 1). In recent years, the environmental regulations of various pollutants have

Table 1
LM Test and LR test.

Variables	SO_2_ERI	SO_2_ERS	SD_ERI	SD_ERS	NO_X_ERI	NO_X_ERS
LM-lag	463.082***	463.082***	16.710**	16.710**	368.648***	368.646***
Robust LM-lag	116.784***	116.084***	282.686***	282.687***	72.885***	72.884***
LR(SAR)	25.040***	25.040***	35.785***	35.785***	18.440***	18.440***
LM-error	346.718***	346.717***	275.909***	275.911***	295.934***	295.932***
Robust LM-error	0.420	0.420	29.008***	29.009***	0.170	0.170
LR(SEM)	29.010***	29.000***	19.030***	19.030***	20.580***	20.580***

Note: *, **, *** represent significance at 10%, 5%, and 1% level, respectively.

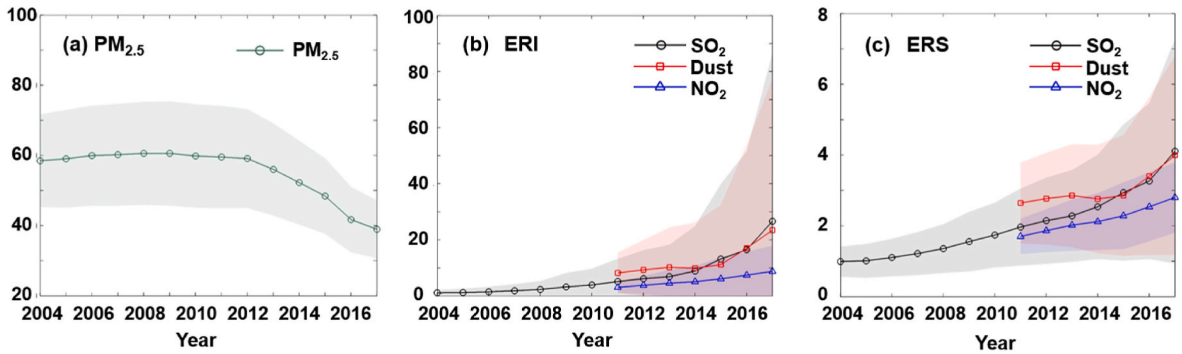

Fig. 1. Temporal trends of $PM_{2.5}$ concentration and ERI (ERS) of SO_2, SD, and NO_X from 2004 to 2017: (a) $PM_{2.5}$, (b) ERI, and (c) ERS.

shown an upward trend, and the $PM_{2.5}$ concentration has shown a downward trend. The average $PM_{2.5}$ concentration was 55.71 μg/m^3 (48% of the samples exceeded the average), with the highest value in Henan Province in 2011 (96.19 μg/m^3) and the lowest value in Heilongjiang Province in 2016 (24.81 μg/m^3). The $PM_{2.5}$ concentration has been well controlled in recent years. From 2004 to 2012, it gradually developed and remained at 60.0 ± 5.0 μg/m^3, and then a downward trend was observed since 2013. $PM_{2.5}$ concentration has dropped significantly from 59.37 μg/m^3 to 38.94 μg/m^3 from 2013 to 2017.

The mean value of SO_2 ERI (ERS) was 6.51 (1.97), the lowest value was 0.10 (0.32), which was found in Guizhou Province in 2005, and the highest value was 331.29 (18.20), which appeared in Beijing in 2017. The reason is that the SO_2 emission is well controlled in Beijing, e.g., the national average SO2 is 662.9 thousand tons, while it is only 110.5 thousand tons in Beijing in 2017. In addition, the investment in pollution control in Beijing is relatively large, accounting for 41.25% and 5.34% of those in the Beijing-Tianjin-Hebei region and the whole country, respectively. The ERI (ERS) of SO_2 increased year by year during the sample period, from 1.16 (0.99) in 2004 to 26.59 (4.11) in 2017, indicating that China has paid more attention to the ER of SO_2. Due to data limitations, the temporal trend of SD and NO_X began in 2011. The ERI (ERS) of SD and NO_X averaged 12.53 (3.02) and 5.56 (2.19), respectively, and fluctuated from 2011 to 2015, ranging from 8.12–11.45 (2.60–3.05). The ERI (ERS) of SD began to rise steadily after 2016, to 16.07 (3.39), indicating that compared with SO_2, the awareness and effective work of environmental regulation on SD started later. Although the trend of ERI (ERS) of NO_X is relatively flat, it has been steadily increasing, with an average annual increase of 19.3% (8.6%). The average fluctuation of ERI (ERS) of NO_X from 2011 to 2017 ranged from 3.16 to 8.43 (1.71–2.77). The highest value was 70.14 (8.38) in Beijing in 2016, and the lowest value was 0.90 (0.95) in Tibet in 2012.

Fig. 2 shows the spatial distribution of ERI and ERS of various pollutants. The SO_2 ER in more than 70% of provinces are not optimistic. Only 19.8% of the provinces have exceeded the average value of SO_2 ER, indicating that there is a big gap in environmental regulation levels among the provinces, and most provinces lack important awareness of environmental regulations (Peng et al., 2016). The ERI of eastern regions is generally high (11.26), while the ER level of central and western regions is low (3.67 and 4.06). In addition, the situation of collaborative governance among regional governments is also weak in the western area (Ren et al., 2018). The ERI of eastern, central, and western regions were 2.61, 1.68, and 1.58, respectively.

For SD, 23.0% of the provinces exceeded the average value of environmental regulation. It can be seen that the ERS in the southern region is significantly better than that in the northern region, with the mean ERS of 3.16 and 2.89, respectively. The main reason is due to a large amount of SD caused by heating in the north in winter (Almond et al., 2009; Chen et al., 2013). Therefore, with the same total investment in environmental governance, the ER of SD in northern China is weaker than that of SO_2 and NO_X. By region, Northeast China has the lowest environmental regulation status of SD, at 3.62 (1.87), while East China has a better general environmental regulation status with an average of 22.68 (4.02). The main reason is that the economic development level of eastern region is much higher than that of the central and western regions, and the average investment in environmental governance is 1.59 and 2.44 times that of the central and western

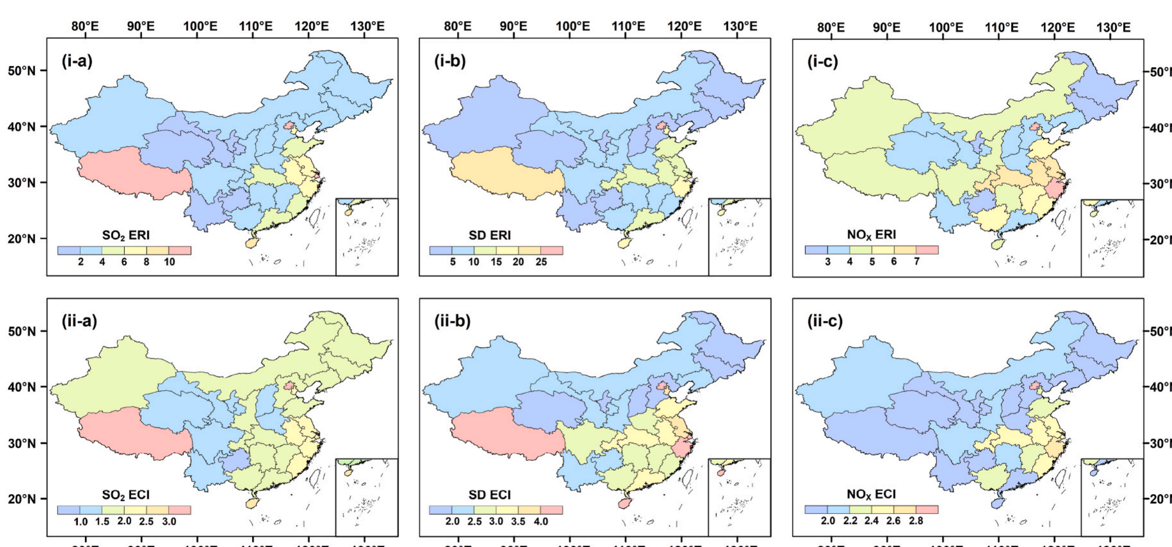

Fig. 2. Spatial distribution of ERI (upper) and ERS (bottom) of (a) SO_2, (b) SD, and (c) NO_X.

regions, respectively. In addition, compared with SO_2 and NO_X, SD emission is much lower in eastern China; thus, with the same investment in environmental governance, SD's environmental regulation intensity is higher.

The NO_X environmental regulations of 28.1% of provinces are above the average. The ER of NO_X in the western region is still worse than that in the eastern and central regions. The ERI (ERS) of eastern, central, and western NO_X was 7.95 (2.55), 4.43 (2.02), and 4.13 (1.96), respectively. Although the ER of NO_X in the eastern region is better, the overall environmental coordination governance of the regions still needs to be further improved. From Fig. 2, we can see that there may be a negative correlation between $PM_{2.5}$ and the environmental regulation level of various pollutants.

3.2. Relationship between $PM_{2.5}$ and environment regulation

3.2.1. Spatial relevance

Fig. 3 shows the correlation coefficient between ER of various pollutants and $PM_{2.5}$, which are the results of the current period, the first lag period, and the second lag period respectively. From this, we can see that the ERI and ERS increased year by year in the beginning, and this spatial correlation gradually decreased when $PM_{2.5}$ concentration was effectively controlled. Moreover, in the early stage, the spatial correlation between ER and $PM_{2.5}$ in the current period is stronger, while in the later stage, the ER and $PM_{2.5}$ are gradually changed to lag a period with a stronger spatial correlation. Especially in 2017, when the environmental regulation was lagging two periods, the ERI (ERS) of all pollutants had the highest spatial correlation with $PM_{2.5}$. The ERI (ERS) correlation coefficients of SO_2, SD and NO_X were 0.07 (0.12), 0.11 (0.17) and 0.14 (0.18), respectively. It shows that the effectiveness of environmental regulation in the reduction of $PM_{2.5}$ concentration is not limited to the current period but also plays an important role in the next 1–2 years. Moreover, the correlation between ERS and $PM_{2.5}$ is greater than the correlation coefficient of ERI, indicating that each region can improve governance efficiency through environmental coordination while paying attention to its environmental regulation (Li et al., 2018).

The ERI and ERS of SO_2 maintained a consistent trend on the whole (Table S1). Before 2014, the ERI of SO_2 was negatively correlated with $PM_{2.5}$, with an average correlation coefficient of −0.06 from 2004 to 2013. In particular, a significant turning point occurred in 2014, when the negative correlation changed to a positive correlation, indicating that the early $PM_{2.5}$ concentration was high, however, the local government had not yet formed a good awareness of air control (Chan and Yao, 2008). Compared with ERI, the ERS of SO_2 and $PM_{2.5}$ has a positive correlation before 2014 (Fig. 3 ii-a), but the overall level was still close to 0, indicating that the government had a preliminary awareness of the governance of the air environment, but the governance may not be effective or not in place (Wang et al., 2019).

The correlation coefficient of SD ERI is greater than 0, the average correlation coefficient is 0.11, the highest is 0.18 in 2015, and the lowest is 0.04 in 2011 (Table S2). For 2015 and before, the correlation coefficient increased by 48% per year on average, indicating that high pollution was accompanied by high governance. However, from 2015 to 2017, the correlation coefficient of ERI (ERS) decreased year by year, which was 0.18 (0.23), 0.15 (0.20), and 0.11 (0.17), respectively. The reason is that after the initial success of air environmental governance, $PM_{2.5}$ concentration has been effectively controlled, and the ERI has eased. Moreover, from 2015 to 2017, there was a higher correlation between ER and $PM_{2.5}$ with a lag of two periods. This shows that the early treatment of SD not only has a mitigation effect on the haze level of the year, even after the mitigation of pollution is effectively controlled, the early treatment will also play a mitigation effect in the later stage (Lv et al., 2019).

The spatial correlation of NO_X ERS was consistent with the trend of ERI (Fig. 3), and the datastet was available in Table S3. In general, the spatial correlation of NO_X ERI (ERS) was positive from 2011 to 2017. Among them, the environmental governance of NO_X from 2011 to 2014 was timely, and the average correlation coefficient was 0.14 (0.19). During this period, the correlation coefficient between $PM_{2.5}$ and ERI (ERS) of the current year was significantly greater than that of the first lag period and the second lag period. In addition, the correlation coefficients of ERI (ERS) in the current period, one lag period and two lag periods had no significant difference in 2015, while the correlation of environmental regulations with a lag of two periods is significantly higher after 2015.

3.2.2. Temporal relevance

Fig. 4 shows the different performances of the time correlation between ERI and $PM_{2.5}$ of various pollutants in the current period, one lag period, and two lag periods. The time correlation of ERI of all pollutants in different provinces in each period is significant at the level of 1% or 5%, which can be seen by us, indicating that ERI has a strong time correlation.

In the current period, the temporal correlation between the ERI of SO_2 and $PM_{2.5}$ was negative in all provinces, with an average correlation coefficient of −0.75, indicating that SO_2 ERI is conducive to slow down $PM_{2.5}$ concentration. In central China (−0.73) and eastern coastal China (−0.76), the environmental regulation effect is higher. In terms of

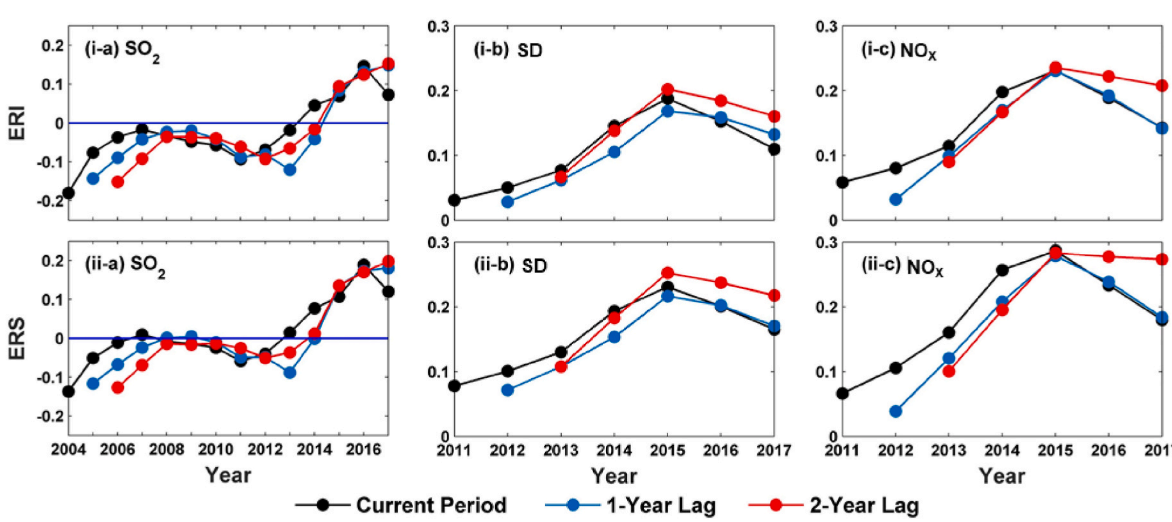

Fig. 3. Spatial correlation between (i) ERI and $PM_{2.5}$. and (ii) ERS and $PM_{2.5}$, respectively.

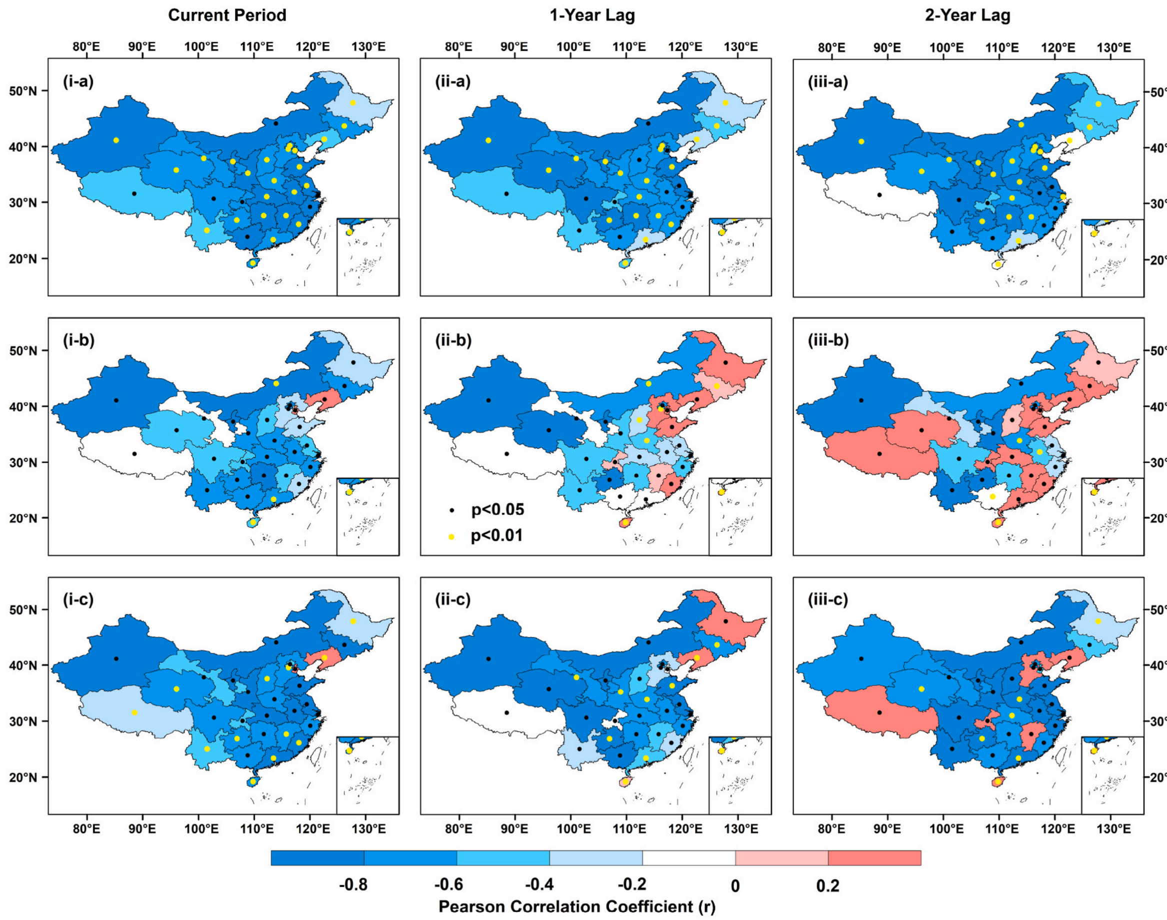

Fig. 4. Temporal correlation between ERI of three pollutants (SO_2, SD, and NO_X) and $PM_{2.5}$. (i-iii) represent the current period, one lag period, and two lag periods, respectively. (a–c) Represent SO_2, SD, and NO_X, respectively. The yellow dots indicate significant confidence levels at the 1% level, and the black dots indicate significant confidence levels at the 5% level. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

geographic area, the correlation is low in Northeast China (average −0.50). Among them, Heilongjiang has a stronger correlation with the two-period lag of ERI, indicating that the governance effect needs a certain period. The correlation of current governance in Jilin was higher, which decreased in the second year and kept after that. The governance relevance of Liaoning decreased year by year and was even close to 0 in the third year. In contrast, the temporal correlation of environmental regulation in South China and East China is generally strong (−1.0~-0.8), indicating the effectiveness of governance. In South China and the southern part of East China, the temporal correlation of ERI in the current period is higher than that of the first lag period, and the performance of the two lag periods is consistent with that of the one lag period.

Most areas of China need to pay attention to the control of SD, especially in the Northeast (- 0.25) and North China (−0.34). The temporal correlation between SD ERI and $PM_{2.5}$ differs from that of SO_2 due to the presence of provinces with positive correlations, i.e., Liaoning and Tianjin, with correlation coefficients of 0.32 ($p > 0.1$) and 0.94 ($p < 0.01$), respectively. The correlation between SD ERI and $PM_{2.5}$ in these two locations indicates that the higher the pollution intensity, the stricter the environmental regulation (Domazlicky and Weber, 2004), and the correlation does not change significantly between the first and second lagging periods. It is possible that the government is not aware of the environmental management of SD or that it is inadequate (Xue et al., 2021b; Zhang et al., 2020). Both Heilongjiang and Jilin, which are located in the same Northeast China region as Liaoning Province, also show positive correlations in the year after treatment, which may be temporary or short-term treatment, considering only the solution of the problem in the current year, without paying attention to the sustainability of air pollution. Furthermore, for the provinces located in North China together with Tianjin, there are two scenarios: the correlation between ERI and $PM_{2.5}$ has decreased (i.e., Beijing and Inner Mongolia), and the correlation coefficient has turned from negative to positive (i.e., Hebei and Shanxi). East China also shows different degrees of performance, except for Shanghai, where the correlation is strong and stable (Table 4). The ERI correlations of Jiangsu, Anhui, and Zhejiang provinces show the highest correlations in the current year (−0.56, −0.69, and −0.78, respectively), but the decline in the second year (−0.20, −0.33, and −0.59, respectively).

The governance status of NO_X performs better than SD, and similarly, there is a regional correlation in the temporal correlation of NO_X. Nationally, only a few provinces showed a positive correlation in different lag periods (less than 6.5%), and there was no clustering. Precisely, 93.6% of the provinces have a negative time correlation for environmental regulations, and the mean value of the national correlation

Table 2
Spatial autocorrelation of $PM_{2.5}$.

Variable	2004	2005	2006	2007	2008	2009	2010
Moran'I	0.10	0.09	0.10	0.10	0.09	0.10	0.07
P	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01
Variable	2011	2012	2013	2014	2015	2016	2017
Moran'I	0.11	0.09	0.08	0.12	0.10	0.10	0.10
P	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01

Table 3
Spatial Durbin results for SO_2.

Variable	ERI			ERS		
	SDM	Dynamic SDM	Dynamic SDM	SDM	Dynamic SDM	Dynamic SDM
SO_2	−0.013*(0.008)	−0.021***(0.008)	−0.020**(0.008)	−0.027*(0.015)	−0.043***(0.016)	−0.041**(0.016)
P	0.573***(0.104)	0.558***(0.112)	0.533***(0.111)	0.573***(0.104)	0.558***(0.112)	0.533***(0.111)
Sigma2_e	0.003***(0.000)	0.003***(0.000)	0.003***(0.000)	0.003***(0.000)	0.003***(0.000)	0.003***(0.000)
W*SO_2	−0.085(0.062)	−0.151**(0.068)	−0.120*(0.068)	−0.170(0.125)	−0.303**(0.137)	−0.240*(0.137)
L.pm		0.207***(0.050)	0.296***(0.056)		0.207***(0.050)	0.296***(0.056)
W*L.pm			−1.305***(0.369)			−1.305***(0.369)
Control Variable	Yes	Yes	Yes	Yes	Yes	Yes

Note: The regression includes the regression results of the constant term, time fixed effect, region fixed effect, and control variables, which are not reported due to the limitation of space. ***, ** and * indicate significant at the level of 1%, 5% and 10%, respectively. In parentheses are standard errors for heteroscedasticity robustness.

Table 4
Spatial Durbin results for SD.

Variable	ERI			ERS		
	SDM	Dynamic SDM	Dynamic SDM	SDM	Dynamic SDM	Dynamic SDM
SD	−0.044***(0.015)	−0.044***(0.017)	−0.048***(0.017)	−0.087***(0.029)	−0.088***(0.033)	−0.096***(0.033)
P	0.543***(0.156)	0.550***(0.169)	0.500***(0.165)	0.543***(0.156)	0.550***(0.169)	0.500***(0.165)
Sigma2_e	0.004***(0.000)	0.004***(0.000)	0.004***(0.000)	0.004***(0.000)	0.004***(0.000)	0.004***(0.000)
W*SD	−0.304***(0.115)	−0.228(0.142)	−0.245*(0.140)	−0.607***(0.230)	−0.457(0.284)	−0.490*(0.281)
L.pm		0.203**(0.081)	0.328***(0.086)		0.203**(0.081)	0.328***(0.086)
W*L.pm			−2.322***(0.627)			−2.322***(0.627)
Control Variable	Yes	Yes	Yes	Yes	Yes	Yes

Note: *, **, *** represent significance at 10%, 5%, and 1% level, respectively.

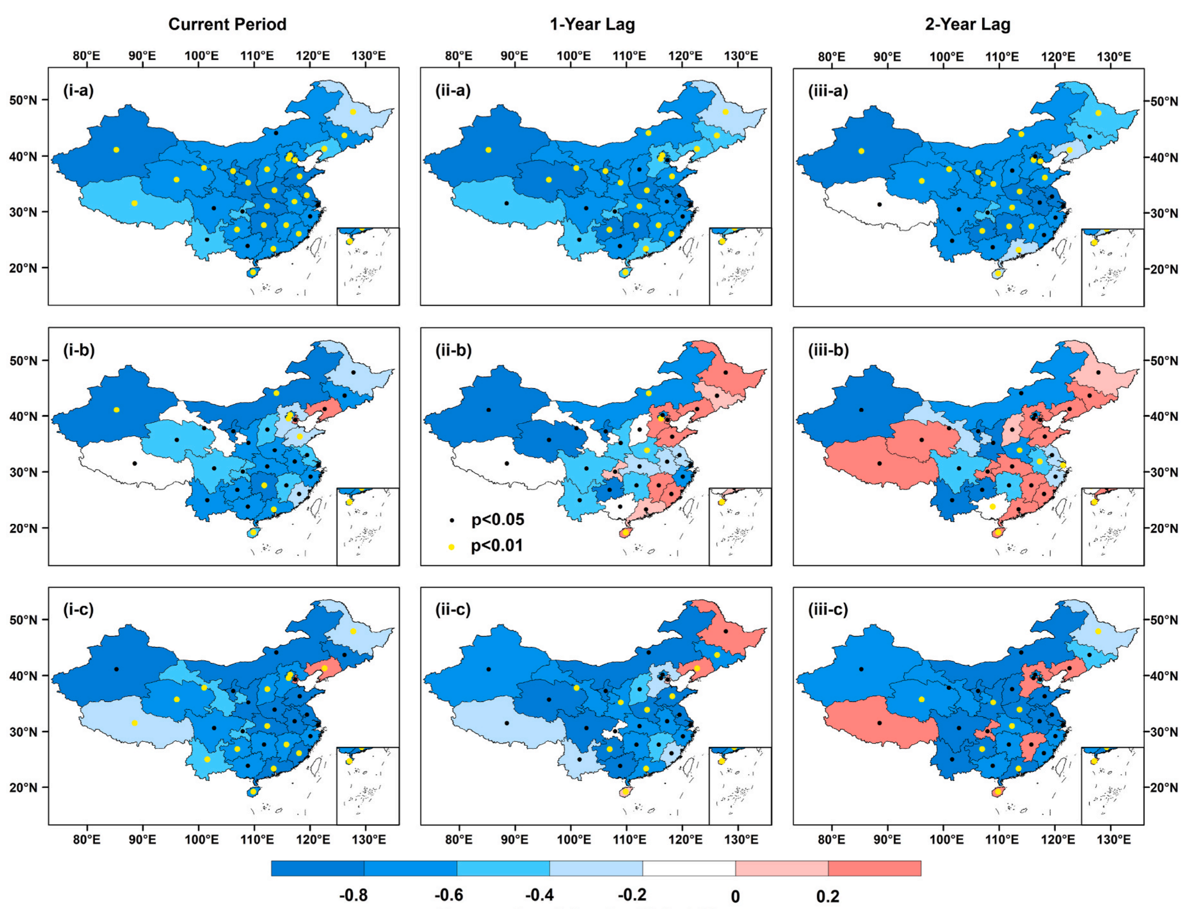

Fig. 5. Same as Fig. 4 but for ERS.

coefficient of ERI is −0.66. The correlations between NO_X ERI and $PM_{2.5}$ are relatively high with R values of −0.72, −0.76, −0.82, and −0.79 in central, southern, eastern and northwestern regions, respectively.

Fig. 5 shows the temporal correlation between SO_2 ERS and $PM_{2.5}$, and the R values of each province are all list in Table S5. In general, the temporal correlation is high in China, with an average of −0.73 and 83.9% of the provinces have a correlation coefficient less than −0.6. Regionally, the temporal correlation of ERS is higher in Central China with a mean value of −0.82, indicating that high governance mitigates high pollution. Among them, the performance of Henan remains stable in the first and second lagging periods (−0.81 and −0.82, $p < 0.01$), while the correlation of Hubei Province decreases at first lag, but also remains stable at second lag (−0.76 and −0.72, $p < 0.01$). In addition, most provinces in North China showed a high negative correlation (−0.73 on average), and the environmental synergies remained stable over the two-year period. The validity decreased only in Hebei in the second year but still improved to the original level in the third year (−0.69, −0.60, and −0.62, $p < 0.01$).

Consistent with the ERI performance of SD, three provinces in Northeast China showed a positive correlation in the current year and one year lagged, respectively. It shows that the environmental regulation of SD may be inadequate by the regional government, and the environmental coordination between governments should be paid more attention to. The same problem has occurred in the Beijing-Tianjin-Hebei city cluster, which borders the northeastern region, as well as in the provinces of Shanxi and Shandong. These areas are geographically close to each other and have a relatively consistent environmental synergy. Fig. 5 shows that in addition to the northern region, the regions with positive co-correlation of SD environment all have geographical neighborhood characteristics. For example, starting from Chongqing, through Hubei, Jiangxi, Fujian, Guangdong to Hainan, as well as Tibet and its neighboring Qinghai region, all have such characteristics. The reason is that SD has the characteristics of spatial overflow and can flow between regions. Therefore, if the local environmental governance cannot be coordinated with the governments of the surrounding areas, the fundamental problems cannot be solved (Zhou et al., 2021).

The NO_X ERS with $PM_{2.5}$ is better than that of SD globally, but at the same time, it does not have the obvious geographic proximity characteristics of SD. In general, the time correlation of Northwest, North, Central, and East China is relatively high, which is −0.80, −0.65, −0.77, and −0.83, respectively. The high level of environmental coordination in these regions is accompanied by the mitigation of pollution. In contrast, the environmental co-correlation in Southwest China is relatively low, at −0.55.

In general, environmental regulation in most regions has achieved some effectiveness, and the pattern of collaborative governance in some regions has sprouted, but more substantial progress is lacking. Thus, the spatial relationship between ERI (ERS) and $PM_{2.5}$ was empirically examined after considering the spatial spillover effect of $PM_{2.5}$.

3.3. Synergistic variations of $PM_{2.5}$ and environmental management

3.3.1. Spatial autocorrelation analysis

The global Moran index was calculated based on the geographical distance weight matrix, which was used to explore the spatial autocorrelation of $PM_{2.5}$ in China from 2004 to 2017, and the analysis results are shown in Table 2. Moran's I values were all positive ($p < 0.01$), which indicates that the $PM_{2.5}$ distribution in different provinces had a high spatial correlation. Therefore, the spatial spillover effect must be considered when exploring the impact of ERI (ERS) on $PM_{2.5}$ in China.

3.3.2. Synergistic relationship among $PM_{2.5}$-ERI-ERS

Table 3 shows the estimated result of the SO_2 ERI and ERS on $PM_{2.5}$. The first column is the regression results of SDM, the second column is the regression results of dynamic SDM with time lag items added, and the third column is the regression results of dynamic SDM with a time lag and spatiotemporal lag term added. It can be found that the environmental regulation intensity of SO_2 is negatively correlated with $PM_{2.5}$, and it is significant at the level of 10%. However, endogeneity is also an important issue that we need to pay attention to, and adding a time lag term can alleviate the endogeneity problem, which leads to more robust estimation results. Therefore, on the basis of the SDM, the lagged term of the explained variable is added into the explanatory variable, and the unconditional maximum likelihood estimation (MLE) is used to regression the model (Elhorst, 2014b). Furthermore, the Hausman test was performed on the model, and the statistical results rejected the original hypothesis of random effects, so the fixed-effects SDM should be chosen.

Table 3 shows that the coefficient results of the dynamic spatial panel model are similar to those of the static spatial panel in terms of symbol and significance, showing good robustness. In addition, the spatial spillover coefficient ρ is lower, which indicates that the static model overestimates the effect of explanatory variables. The regression results of the dynamic SDM with time lag are shown in the third column of Table 3. The coefficient of ERI (ERS) of SO_2 is significantly negative ($p < 0.01$), indicating that the SO_2 ERI (ERS) is conducive to the reduction of $PM_{2.5}$. The estimated coefficient of $PM_{2.5}$ with a 1-year lag is significantly positive, indicating that there is an environmental background effect of regional $PM_{2.5}$, and the time dependence significantly increases the concentration of $PM_{2.5}$ in China (Zhang et al., 2020).

The regression results of the temporal lag term and the spatiotemporal lag term are shown in column 4 of Table 3. Among them, ρ is greater than 0 ($p < 0.01$), indicating that $PM_{2.5}$ in the province has an obvious spatial spillover effect, and the area with more $PM_{2.5}$ will aggravate the $PM_{2.5}$ in the surrounding areas (Chen et al., 2019). Not only that, it will also force local provinces to strengthen the enforcement of regulations, thus reducing the concentration of $PM_{2.5}$. The negative coefficient of SO_2 environmental regulation indicates that enhanced environmental regulation is beneficial to mitigate $PM_{2.5}$ concentrations. In addition, the negative coefficient of the spatial lag term of ER (W^*SO_2) indicates that the ER in neighboring areas has a mitigating effect on $PM_{2.5}$ in the region. The results of the control variables (Table S6) show that the coefficients of per capita GDP and FDI are both significantly negative ($p < 0.01$), indicating that these two variables significantly alleviate the concentration of $PM_{2.5}$. On the one hand, the rapid economic development in China has brought more green technology innovation and equipment sharing, which helps to reduce emissions. On the other hand, the adjustment of industrial structure caused by foreign investment has resulted in the transfer of heavily polluting industries (Feng and Wang, 2020).

The coefficient of SD environmental regulation is negative under all three models ($p < 0.01$). It shows that the higher SD ERI, the lower the regional $PM_{2.5}$ concentration. Moreover, Table 4 shows the regression coefficient of the dynamic SDM of ERS is −0.096, that is, after controlling for time and spatiotemporal lag terms, when the environmental synergy of SD increases by 1 unit, local pollution emissions will decrease by 0.096 units. The low degree of ERS between local governments will lead to little joint treatment effect, which is not conducive to the improvement of environmental pollution.

Table 5 shows the regression results of NO_X ERI (ERS) and $PM_{2.5}$. The estimated coefficient of $PM_{2.5}$ lagged by one period remains significantly positive, confirming the existence of a time-lagged effect of $PM_{2.5}$. Moreover, the estimated coefficient of ERI (ERS) of NO_X is −0.039 (−0.078), which is significantly negative ($p < 0.05$), indicating that ER of NO_X is conducive to reducing $PM_{2.5}$ concentration. For each unit increase in NO_X ERI (ERS), $PM_{2.5}$ concentration decreased by 0.039 (0.078) units. The environmental regulation coefficients in the dynamic SDM of SO_2, SD, and NO_X are −0.020(−0.041), −0.048(−0.096), and −0.039(−0.078), respectively, indicating that the ER of SD is more conducive to the reduction of $PM_{2.5}$ compared with the other two pollutants. Environmental regulation of SD and inter-regional joint management should receive attention from all regions.

Table 5
Spatial Durbin results for NO_X.

Variable	ERI			ERS		
	SDM	Dynamic SDM	Dynamic SDM	SDM	Dynamic SDM	Dynamic SDM
NO_X	−0.033**(0.015)	−0.033*(0.018)	−0.039**(0.018)	−0.065**(0.030)	−0.066*(0.037)	−0.078**(0.036)
P	0.516***(0.164)	0.536***(0.174)	0.485***(0.171)	0.516***(0.164)	0.536***(0.174)	0.485*** (0.171)
Sigma2_e	0.004***(0.000)	0.004***(0.000)	0.004***(0.000)	0.004***(0.000)	0.004***(0.000)	0.004***(0.000)
W*NO_X	−0.352***(0.119)	−0.249(0.154)	−0.241(0.152)	−0.705***(0.238)	−0.498(0.308)	−0.482(0.305)
L.pm		0.200**(0.083)	0.327***(0.088)		0.200**(0.083)	0.327***(0.088)
W*L.pm			−2.287***(0.633)			−2.287***(0.633)
Control Variable	Yes	Yes	Yes	Yes	Yes	Yes

Note: *, **, *** represent significance at 10%, 5%, and 1% level, respectively.

3.3.3. *Effects of spatial decomposition*

The dynamic SDM model can be decomposed into direct, indirect, and total effects (Fig. 6). Among them, the direct effect measures the effect of each unit change in the explanatory variable on the explained variable in the region. The indirect effect (spillover effect) measures the impact of each unit change in the explanatory variable on the explained variables in other relevant areas. In addition, the total effect is the sum of the direct and indirect effects, indicating the overall effect of changes in the explanatory variables on the explained variables (Qiang et al., 2020).

The estimation results of parameters showed that the direct effects of SO_2, SD, and NO_X ERI were negative both in the short and long term, indicating that the effect of previous regulation of various pollutants on the current $PM_{2.5}$ concentration was negative. In addition, the intensity of early-period environmental regulation will also express a negative spatial spillover effect on $PM_{2.5}$ in the surrounding areas. The direct (indirect) effects of the environmental synergies of all pollutants are also negative, indicating that the synergies between different regions are not only beneficial to the development of the region in the current period, but also have a long-term impact on the environmental quality of neighboring regions. Fig. 6 shows that the long-term effects of direct effects, indirect effects, and total utility are all greater than the short-term effects (absolute value), indicating that the ERI and ERS of each pollutant have a more far-reaching long-term impact on $PM_{2.5}$.

4. Conclusion and policy suggestion

Atmospheric pollution seriously affected economic development, especially in China. However, due to the spatial spillover effect of $PM_{2.5}$, the traditional administrative division becomes limited and thus the importance of joint air pollution control gradually emerges. The ERI (ERS) of SO_2, SD, and NO_X were used to quantitatively analyze the effects of intra-provincial governance and co-governance in China. Moreover, the spatial and temporal trends of ER of three pollutants and the impact of ERI (ERS) on $PM_{2.5}$ from 2004 to 2017 were investigated. The results show that ERI (ERS) varies greatly among provinces, and most regions still lack the important awareness of ER. In addition, the ERI (ERS) of the three pollutants have the characteristics of spatial contiguity, which is highly consistent with the main administrative division in China. From the perspective of regional heterogeneity, the level of ERI tends to be higher in the east (11.26) and lower in the west (4.06). ER and $PM_{2.5}$ are spatially and temporally correlated, and a lag effect exist. Furthermore, $PM_{2.5}$ has spatial spillover characteristics. The environmental regulation in this region is not only conducive to the current local haze pollution situation but also improves the environmental level of neighboring regions. When the environmental synergy of the three pollutants increased by 1 unit, $PM_{2.5}$ was reduced by 0.04 ($p < 0.05$), 0.1 ($p < 0.01$), and 0.08 ($p < 0.05$) units. In general, the low degree of ERS between local governments will lead to a poor joint treatment effect, which is not conducive to the reduction of $PM_{2.5}$.

Air pollution control, especially $PM_{2.5}$, has become the focus of environmental protection in China. The source analysis and control of air pollution is an important practical issue. All kinds of pollutants must be controlled collaboratively in order to maximize the benefits of pollution control. In addition, the top-level design of indicators and policies should be carried out by the country, further improve relevant standards and technical guidelines, and establish a collaborative control technology system. Local governments need to strengthen environmental governance and expand the jurisdictional of environmental regulation. Collaborative regulatory consensus among geographically adjacent local governments should be promoted to avoid duplication of related infrastructure and waste of resources. On this basis, the government should formulate targeted environmental supervision measures according to the actual situation and characteristics of the specific region. Finally, joint prevention and control of air pollution should be carried out among regions to prevent and reduce urban air pollution as a whole.

CRediT authorship contribution statement

Xinyao Li: designed the research, carried out the research and wrote the initial draft. **Wenhao Xue:** designed the research. **Kai Wang:** helped

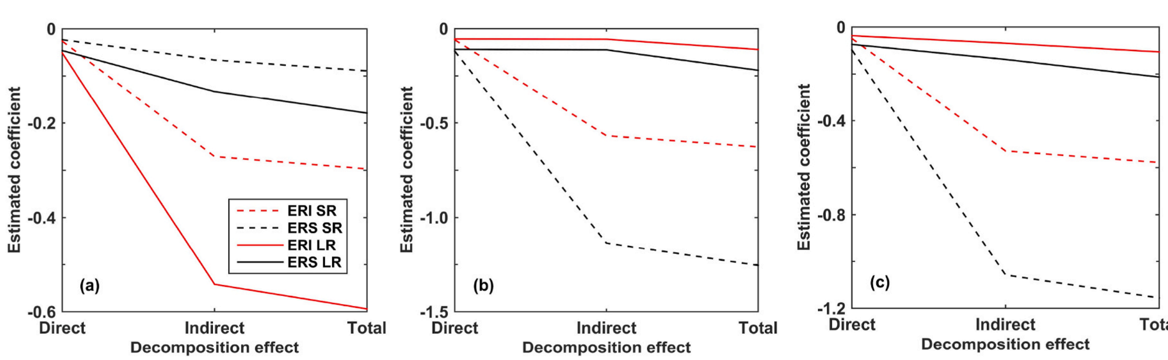

Fig. 6. Decomposition effect of dynamic SDM, where (a–c) represent SO_2, SD, and NO_X, respectively. The solid line represents the long-term effect, and the dotted line represents the short-term effect.

collected and processed the data. and. **Yunfei Che:** helped collected and processed the data. **Jing Wei:** designed the research. and, helped review and editing the draft, All authors contributed to the interpretation of the results.

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.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jclepro.2022.130438.

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