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ORIGINAL ARTICLE

Effects of environmental regulation on air pollution control in China: a spatial Durbin econometric analysis

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Abstract

Based on provincial panel date of China for the period 2001–2014, this study empirically adopts the slacks-based measure of directional distance function model and spatial Durbin model to explore the impacts of environmental regulation and its spatial spillover effect on air pollution control. The results show that the increase of environmental regulation stringency will help to improve air pollution control efficiency or reduce air pollutant emissions. In terms of spatial effect, evidence has been found to support environmental regulation has significantly spatial spillover effects. Specifically, the increase of environmental regulation in other provinces will decrease local air pollution control efficiency or increase local air pollutant emissions, which implies that there is strategic interaction of environmental regulation among local governments. Moreover, the results of the time interval test indicate that the effects of environmental regulation on air pollution control have improved in recent years, and with the increase of environmental regulation stringency, its spatial spillover effects have increased.

Keywords Environmental regulation · Air pollution control · Strategic interaction · Spatial Durbin model · Local government

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1 Introduction

Since the 1980s, China's economy has seen remarkable growth. However, environmental issues have become the most hazardous social problem affecting Chinese life, especially air pollution (Shi et al. 2017). The conflict between the environment and economic growth is more complex and intense than ever before. The Chinese government has implemented environmental regulations to control air pollution; a series of policies have been formulated and much money has been invested for the purpose of emissions reduction, but there has been no significant reduction. Numerous economists and policymakers have focused on this issue (Ma et al. 2016). Environmental regulation as a public service is vital to the sustainable development of a country, though it may inevitably increase unemployment rates and lower economic growth by replacing "productive investment." However, the vital issue is whether it can promote environmental governance efficiency (Li and Wu 2017).

Environmental quality depends on two aspects: one is the direct discharge of human production activities, such as economic development (Li et al. 2016), advancement of industrialization (Gan et al. 2018), energy consumption (Khan et al. 2016), and urbanization (Yilmaz et al. 2016), etc., being the main pollution sources. The Environmental Kuznets Curve theory provides a detailed analysis of this aspect (Grossman and Krueger 1991). The other is pollution control, including treatment of pollutant emissions and construction of environmental protection infrastructure. If emissions are large and environmental investment is insufficient, the environment will deteriorate. Different methods are used to investigate the effects of regulation on environmental protection (Laplante and Rilstone 1996; Vargas-Vargas et al. 2010; Levinson 2003), highlighting three different perspectives: (1) Blackman and Kildegaard (2010) explore inspections enforced by an environmental agency in Mexico, finding that regulatory pressure is not related to pollution reduction; (2) Lanoie et al. (2011) argue that regulation will add the cost of pollution control and discharge to firms, squeeze out productive resources, and reduce productivity and market competitiveness, rendering environmental problems unmanageable; (3) Zheng et al. (2015) investigates the effects of environmental regulation on air quality by using provincial-level data of China during 2002–2011, suggesting that environmental regulation greatly improve the local air quality.

Though these researches provide an opportunity to understand the relationship between environmental quality and regulation, they pay little attention to the interaction between regional economies, usually assuming that the regional variables are independent of each other. This is flawed and inconsistent with the real economy. According to the First Law of Geography, "everything is related to everything else" (Tobler 1970). In the real economy, the regional economy has a wide range of links, and the closer the distance is, the closer the regional connection is. In addition, the atmosphere characterized by fluidity and diffusivity can spread from one region to another, so it is necessary to take spatial factors into account when investigating the spillover effects of economic activities and atmosphere (Case et al. 1993; Lundberg 2006; Deng et al. 2012). In terms of environmental regulation, there may be strategic interaction among regions (Claude et al. 2012; Nauleau 2014; Chen et al. 2017). For example, the increase of local environmental protection investment will benefit neighboring areas, inducing free-riding in response (Delmas and Keller 2005; Konisky and Woods 2012). Such free-riding behavior may lead to the phenomenon of "if you invest more, I will invest less." In addition, under the pressure of regional finance, if a government lowers local environmental standards, then the surrounding governments may also lower their environmental standards, which may eventually lead to a fierce environmental standards "race to the bottom" in attracting 'mobile' foreign industries and enterprises (Zhu et al. 2014; Chirinko and Wilson 2017; Chen et al. 2017). Therefore, the spillover effect is an indispensable factor in studying the relationship between environmental regulation and environmental governance. Based on this logic and the perspective of spillover effect, we endeavor to investigate the effects of environmental regulation on environmental governance.

Under the decentralization system of China, local officials must offer necessary public services within their jurisdictions, making independent decision-making difficult to imagine (Kurian et al. 2016). Local governments seek to facilitate their local economy by attracting high-pollution and high-emission industries, with little incentive to protect the environment or decrease emissions, which do not enhance their political careers (Li and Zhou 2005; Zheng et al. 2014). Therefore, they incline to compete in productive expenditure (e.g. infrastructure) promoting local economic development but ignore environmental protection expenditure (e.g. air pollution prevention) deeming it of no use to local economic performance (Yu et al. 2016). Driven by competitive strategic interaction amongst political opponents, free-riding behavior, mimicking, competition, and externality spillovers are likely to happen and change the strategies of surrounding governments (Zhao and Sun 2016; Chen et al. 2017). Thus, strategic interaction may have strong spatial effects in China (Yu et al. 2016; Zhao and Sun 2016).

Anselin (1988) finds that the spatial Durbin model (SDM) is a novel method for analyzing regional spatial spillover effects. We attempt to empirically estimate the influences of environmental regulation on environmental governance by using the SDM. This is our major contribution. In addition, we fully consider the spatial correlations of environmental pollution, economic activities, and environmental regulation in the empirical estimations, which effectively address the potential spatial deviations. Finally, we formulate corresponding policies. Specifically, we first adopt a slacks-based measure of directional distance function (SBM-DDF) model that considers undesired output in the data envelopment analysis (DEA) method to measure the efficiency of air pollution control. Besides, we apply the SDM to investigate the spatial spillover effect.

The remainder of the paper is structured as follows. Section 2 introduces the estimation methodology. Section 3 presents data and calculates dependent and independent variables. Section 4 reports and discusses our findings. Section 5 presents conclusions and provides some policy recommendations.

2 Empirical analysis

2.1 Econometric model

Considering air pollution and other economic activities may be transmissible and spill over into neighboring areas, spatial correlation cannot be ignored and the non-spatial econometric model is not applicable. The spatial econometric model is considered a good tool to analyze regional spatial interaction (Anselin 1988). Spatial econometric models can be divided into three categories: spatial error model (SEM), spatial lag model (SLM) and spatial Durbin model (SDM). LeSage (2008) believes that SDM contains many widely used models, which are more comprehensive than SEM and SLM. It can also capture the spatial spillover effect of independent variables and the spatial correlation of dependent variables, which mitigates the biases associated with unobservable and omitted factors. Besides, Anselin and Le Gallo (2006) argue that introducing explanatory variables with spatial weights could solve the possible endogenous problems. Therefore, we use the SDM to test the influences of environmental regulations on air pollution control and its spillover effects. The general form of the SDM is expressed as follows:

$$Y = \rho WY + \beta X + \theta WX + \varepsilon \tag{1}$$

where Y is the dependent variable, X is the independent variables, ρ is the spatial auto-correlation coefficient, ε is an error term, W denotes the spatial weight matrix, which stands for the spatial connection between each provincial unit, and β and θ are the spatial regressive coefficients. WY and WX represent the spatial lag effects of dependent and independent variables, respectively.

In this study, we select two dependent variables (*eff* and *poll*) as indicators of air pollution control, the core explanatory variable is environmental regulation (er). Regarding other impact factors, based on the Stochastic Impacts by Regression on Population, Affluence, and Technology (STIRPAT) model (York et al. 2003), and referring to the related research of Ma et al. (2016), Liu et al. (2017a, b), Feng et al. (2016), and Zhang et al. (2017), we introduce urbanization (*urb*), foreign direct investment (*fdi*), and energy consumption intensity (*eci*) as control variables. The specific spatial econometric model can be given as follows:

$$\begin{aligned} eff_{it} = \rho \sum\nolimits_{j \neq i}^{N} W_{ij} eff_{jt} + \alpha_1 er_{it} + \alpha_2 urb_{it} + \alpha_3 fdi_{it} + \alpha_4 eci_{it} + \beta_1 \sum\nolimits_{j \neq i}^{N} W_{ij} er_{jt} + \beta_2 \sum\nolimits_{j \neq i}^{N} W_{ij} urb_{jt} \\ + \beta_3 \sum\nolimits_{j \neq i}^{N} W_{ij} fdi_{jt} + \beta_4 \sum\nolimits_{j \neq i}^{N} W_{ij} eci_{jt} + \xi_{it} \end{aligned} \tag{2}$$

$$\begin{aligned} poll_{it} = \rho^1 \sum\nolimits_{j \neq i}^{N} W_{ij} poll_{jt} + \alpha_1^1 er_{it} + \alpha_2^1 urb_{it} + \alpha_3^1 fdi_{it} + \alpha_4^1 eci_{it} + \beta_1^1 \sum\nolimits_{j \neq i}^{N} W_{ij} er_{jt} + \beta_2^1 \sum\nolimits_{j \neq i}^{N} W_{ij} urb_{jt} \\ + \beta_3^1 \sum\nolimits_{j \neq i}^{N} W_{ij} fdi_{jt} + \beta_4^1 \sum\nolimits_{j \neq i}^{N} W_{ij} eci_{jt} + \xi_{it} \end{aligned} \tag{3}$$

where i denotes a province, j is nearby provinces, t is a year. *eff* and *poll* stand for the air pollution control efficiency and the relative emissions level of air pollutants, respectively. W_{ij} is a spatial weight matrix that corresponds to the spatial connectivity assigned to province j and i. The other variables are defined as before.

2.2 Estimation method

Before estimating parameters, the spatial weight matrix needs to be set since it is the formal representation of regional spatial correlation (Anselin 1988). Some researchers adopt a binary weight matrix to determine the spatial weight (Zheng et al. 2014). However, some sample provinces are not adjacent, and they are prone to be affected by adjacent and non-adjacent areas. Thus, the binary weight matrix is replaced by the geographic distance weight matrix. A geographic distance weight matrix is chosen to determine $W_{ij} = w_{ij}^{Dis\tan ce}$. Following Caldeira (2012), we further construct a GDP per capita weight matrix ($W_{ij} = w_{ij}^{Pgdp}$) since correlation with each province's economic structure might not be of a simple geographic nature. Thus, Eqs. (2) and (3) are estimated twice by using two sets of weights. The specific form of the matrix is as follows:

$$w_{ij}^{Dis\tan ce} = \begin{cases} 1/d_{ij}, & i \neq j, \quad i = 1, \dots, N; \quad j = 1, \dots, N; \\ 0, & i \neq j, \quad i = 1, \dots, N; \quad j = 1, \dots, N \end{cases} \tag{4}$$

$$w_{ij}^{Pgap} = \begin{cases} 1/(|pgdp_{it\_}pgdp_{jt}|), & i \neq j, \quad i = 1, \dots, N; \quad j = 1, \dots, N; \\ 0, & i \neq j, \quad i = 1, \dots, N; \quad j = 1, \dots, N \end{cases} \tag{5}$$

where d_{ij} is the Euclidian distance between the capitals of the province i and j. Note that we allow w_{ij}^{Pgdp} to be time variant.

Owing to the existence of dependent and independent spatial lag variables in the SDM model, Eqs. (2) and (3) may produce endogenous problems, which goes against the classical assumptions of the ordinary least squares (OLS) method. Therefore, it is necessary to use viable methods to estimate parameters. According to Lesage and Pace (2010) and Li and Wu (2017), we employ the maximum likelihood (ML) method to effectively address the endogenous problem and decompose the values of the effects of independent variables on dependent variables into direct and indirect effects. The specific derivation processes are given as follows:

$$Y = (I - \delta W)^{-1}(X\beta + WX\theta + \mu_I + \varepsilon_{it}), \tag{6}$$

$$(I - \delta W)^{-1} = I + \delta W + \delta^2 W^2 + \delta^3 W^3 + \cdots, \tag{7}$$

$$\partial Y / \partial x_{ir} = (I - \delta W)^{-1}(I\beta_r + (W)_{ii}\theta_r), \quad \textit{for all i and for all r}, \tag{8}$$

$$\partial Y / \partial x_{jr} = (I - \delta W)^{-1}(I\beta_r + (W)_{ij}\theta_r), \quad \textit{for all } i \neq j \textit{ and for all r} \tag{9}$$

where I is an $N \times 1$ unit matrix, N is the number of provinces, $(I - \delta W)^{-1}$ is a spatial Leontief inverse matrix, β_r denotes the coefficient of the rth explanatory variable, θ_r represents its spatial lag coefficient, $\partial Y / \partial x_{ir}$ is the direct effect, and $\partial Y / \partial x_{jr}$ is the indirect effect. All estimations are performed by STATA (version 14) software.

3 Data

3.1 Dependent variables

Two opposite indicators are selected as dependent variables: the efficiency of air pollution control (*eff*) and the relative emissions level of air pollutants (*poll*). The former is calculated by SBM-DDF and is a positive index. The larger the value, the better. The latter is calculated by weighted average method and is a negative index. The smaller the value, the better. If the regression coefficients of the two indicators are completely opposite, it proves that the conclusions are robust.

3.1.1 Calculating method of efficiency of air pollution control

Scholars use two methods of efficiency measurement, namely nonparametric and parametric. The nonparametric method is favored because it can eliminate function setting subjectivity without specific function form. Among them, DEA is a commonly used method for environmental efficiency measurement.

When there are redundant inputs or insufficient outputs, radial DEA may overestimate efficiency, and oriented DEA efficiency measurement may overlook inputs or outputs. Therefore, efficiency may be calculated inaccurately. In order to overcome the two defects, Fukuyama and Weber (2009) developed a more general non-radial and non-oriented directional distance function (DDF), based on the non-radial, non-oriented, slacks-based measure (SBM) function proposed by Tone (2004). Therefore, based on Fukuyama and Weber (2009), we employ SBM-DDF to estimate air pollution control efficiency.

Each province is taken as a production decision-making unit (DMU) to set up the best practice boundary of China's production at each period. As resources can be incorporated into the structure of the production boundary, the difficulty in constructing is considering environmental factors. Following definitions set by Chung et al. (1998) and Färe et al. (2007), we assume that there are k DMUs at time t and each DMUk ($k = 1, \dots, K$) transforms n types of inputs, $x = \left(x_1, \dots, x_n\right) \in R_n^+$, into m types of desirable outputs ('goods'),$y = \left(y_1, \dots, y_m\right) \in R_m^+$, and l types of undesirable outputs ('bads'), $b = \left(b_1, \dots, b_l\right) \in R_l^+$. Further, null-jointness and weak disposability of outputs are assumed. The production possibility set is denoted as:

$$p^t(x^t) = \left\{ (y^t, b^t) : \sum_{k=1}^{K} \lambda_k^t y_{km}^t \geq y_{km}^t, \forall m; \sum_{k=1}^{K} \lambda_k^t x_{kn}^t \leq x_{kn}^t, \forall n; \right. \\ \left. \sum_{k=1}^{K} \lambda_k^t b_{kl}^t = b_{kl}^t, \forall l; \sum_{k=1}^{K} \lambda_k^t = 1, \lambda_k^t \geq 0, \forall k \right\} \tag{10}$$

where λ_k^t is the intensity variable. When setting up the production possibility frontier, λ_k^t is the weight assigned to each observed input and output. The constraint that the sum of λ_k^t is 1 assumes variable returns to scale (VRS).

According to research of Tone (2004) and Fukuyama and Weber (2009), a directional slacks-based measure is used to estimate a production frontier. The SBM under consideration of undesirable outputs is defined on the DEA technology set, as:

$$\vec{S}_v^t(x^{t,k}, y^{t,k}, b^{t,k}; g^x, g^y, g^b) = \frac{1}{3}\max_{s^x,s^y,s^b}\left(\frac{1}{N}\sum_{n=1}^{N}\frac{s_n^x}{g_n^x} + \frac{1}{M}\sum_{m=1}^{M}\frac{s_m^y}{g_m^y} + \frac{1}{L}\sum_{l=1}^{I}\frac{s_l^b}{g_l^b}\right)$$
$$s.t. \sum_{k=1}^{K}\lambda_k^t x_{kn}^t + s_n^x = x_{kn}^t, \forall n; \quad \sum_{k=1}^{K}\lambda_k^t y_{km}^t - s_m^y = y_{km}^t, \forall m; \quad \sum_{k=1}^{K}\lambda_k^t b_{kl}^t + s_l^b = b_{kl}^t, \forall l;$$
$$\sum_{k=1}^{K}\lambda_k^t = 1; \quad \lambda_k^t \geq 0, \forall k; \quad s_n^x \geq 0, \forall n; \quad s_m^y \geq 0, \forall m; \quad s_l^b \geq 0, \forall l \tag{11}$$

where $\vec{S}_v^t$ is the SBM with VRS. The vector $(x^{t,k}, y^{t,k}, b^{t,k})$ is the k th DMU$_\text{k}$'s inputs, desirable outputs and undesirable outputs vector at time t; (g^x, g^y, g^b) is the directional vector that indicates reduction of inputs and bad outputs, but an increase in good outputs; (s_n^x, s_m^y, s_l^b) is the slack vector of inputs and outputs. $(s_n^x, s_m^y, s_l^b) > 0$ suggests that the actual inputs and bad outputs are greater than their relative boundary value, but the actual good outputs are less than the boundary production. Therefore, when (s_n^x, s_m^y, s_l^b) is not completely zero, there is room for improvement in air pollution control efficiency in the inputs, and good and bad outputs. If and only if $s_n^x = s_m^y = s_l^b = 0$, then efficiency is optimal. By solving the above linear programming, we obtain the inefficiency value of province i at time t under environmental considerations. Then the air pollution control index can be constructed according to the inefficiency value. In order to clarify the specific sources of inefficiency, this study refers to the research of Cooper and Seiford (2004) and Fukuyama and Weber (2009) to decompose inefficiency into:

$$IE = \vec{S}_v^t = IE_v^x + IE_v^y + IE_v^b \tag{12}$$

where the inefficiency of inputs, good outputs and bad outputs can be written as:

$$IE_x = \frac{1}{3N}\sum_{n=1}^{N}\frac{s_n^x}{g_n^x}; \quad IE_y = \frac{1}{3M}\sum_{m=1}^{M}\frac{s_m^y}{g_m^y}; \quad IE_b = \frac{1}{3L}\sum_{l=1}^{L}\frac{s_l^b}{g_l^b} \tag{13}$$

In this study, the bad outputs are sulfur dioxide emissions, industrial waste gas emissions, and industrial smoke and dust emissions. Based on this, air pollution control inefficiency can be calculated as:

$$IE_b^{APUE} = IE_b^{so_2} + IE_b^{waste\_gas} + IE_b^{smoke\_dust} \tag{14}$$

Based on the SBM-DDF model theorem, let the directional vectors $g_n^x = x_n^{\max} - x_n^{\min}, \forall n$ and $g_m^y = y_m^{\max} - y_m^{\min}, \forall m$, then $0 \leq \vec{S}_v^t(x^{t,k}, y^{t,k}, b^{t,k}; g^x, g^y, g^b) \leq 1$, then the objective can be written as: $0 \leq (IE_x, IE_y, IE_b) \leq 1$, and then the efficiency value of air pollution control (*eff*) can be constructed according to the inefficiency value:

$$\begin{aligned} & eff = 1 - IE_b^{APUE} \\ & s.t.g_n^x = x_n^{\max} - x_n^{\min}, \forall n; \\ & g_m^y = y_m^{\max} - y_m^{\min}, \forall m; \end{aligned} \tag{15}$$

As IE_b^{APUE} is between 0 and 1, *eff* is also between 0 and 1. The larger the *eff*, the higher the efficiency of air pollution control in this province. On the contrary, the smaller the *eff*, the lower the efficiency of air pollution control in this province.

3.1.2 Inputs and outputs

This study adopts SBM-DDF method to calculate air pollution control efficiency of 30 provinces in China over the period 2001–2014. The inputs include labor force, capital stock, and energy consumption. The capital stock is measured by using the perpetual inventory method. Shan (2008) gives specific methods and procedures for measuring initial capital and depreciation rates. The labor force is calculated by the total employment of the primary, secondary and tertiary industry. Given that the energy consumption structure in each province is quite different, the primary energy consumption is selected as the energy input data and linear interpolation is used to supplement data deficiency in some years. The desirable output is given by real gross domestic product (GDP). Besides, the undesirable outputs are the emissions of sulfur dioxide, industrial waste gas, and industrial smoke and dust. All relevant data can be obtained from *China Labor Statistical Yearbook, China Statistical Yearbook, China Energy Statistical Yearbook,* and *China Environmental Yearbook*. Additionally, all nominal variables are deflated to the 2001 constant price. Table 1 presents definitions and descriptive statistics for inputs and outputs.

3.1.3 Measurement results analysis

Based on the SBM-DDF model, the efficiency of air pollution control in each province from 2001 to 2014 is estimated (see Table 2). As shown in Table 2, the average efficiency of air pollution control in China has decreased from 0.8996 in 2001 to 0.8903 in 2014, and the average annual efficiency of air pollution control is 0.8909. In addition, China's air pollution control efficiency fluctuated from 2001 to 2014. According to the ranking of each province, the top five provinces are Beijing, Hainan, Tianjin, Qinghai, and Shanghai, while Inner Mongolia, Henan, Shandong, Shanxi and Hebei are the last. Of the 30 provinces, only Beijing's air pollution control efficiency value is 1, reaching the efficiency frontier of air pollution control. The average efficiency of Hainan, Tianjin, Qinghai, and Shanghai is over 0.95, which is close to the efficiency frontier of air pollution control. The average efficiency of Shandong, Shanxi, and Hebei is less than 0.8.

Table 1 Definitions and descriptive statistics for inputs and outputs

	Definition	Obs	Mean	SD	Min	Max	Unit
Inputs	Capital stock	420	7303.86	6765.16	195.81	35,189.88	Hundred million RMB
	Labor force	420	2462.69	1654.32	277.25	6593.45	Ten thousand people
	Energy consumption	420	10,594.33	7465.79	520.00	38,899.25	Tons of standard coal
Outputs	Real gross domestic product	420	8637.13	8323.17	300.13	50,825.78	Hundred million RMB
	Industrial waste gas emissions	420	13,791.18	12,527.27	502.00	79,121.30	Hundred million standard cubic meters
	Sulfur dioxide emissions	420	73.45	44.39	2.00	200.20	Ten thousand tons
	Industrial smoke and dust emissions	420	47.49	34.92	1.07	160.50	Ten thousand tons

Table 2 Measurement results of air pollution control efficiency

Provinces	2002	2004	2006	2008	2010	2012	2014	Ranking
Beijing	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1
Hainan	0.9889	0.9979	0.9981	0.9957	0.9963	0.9954	0.9939	2
Tianjin	0.9683	0.9818	0.9744	0.9745	0.9738	0.9853	0.9722	3
Qinghai	0.9867	0.9816	0.9780	0.9715	0.9622	0.9679	0.9664	4
Shanghai	0.9536	0.9544	0.9734	0.9615	0.9637	0.9710	0.9700	5
Ningxia	0.9570	0.9604	0.9573	0.9466	0.9183	0.9402	0.9410	6
Fujian	0.9731	0.9597	0.9527	0.9368	0.9262	0.9383	0.9289	7
Jilin	0.9437	0.9476	0.9384	0.9314	0.9299	0.9429	0.9358	8
Gansu	0.9399	0.9403	0.9418	0.9334	0.9261	0.9274	0.9234	9
Yunnan	0.9484	0.9434	0.9393	0.9196	0.9268	0.9007	0.9094	10
Chongqing	0.9299	0.9226	0.9184	0.8999	0.9106	0.9407	0.9397	11
Heilongjiang	0.9337	0.9343	0.9309	0.9087	0.9108	0.9117	0.9164	12
Jiangxi	0.9471	0.9227	0.9208	0.8995	0.8983	0.9137	0.9103	13
Xinjiang	0.9599	0.9404	0.9364	0.9084	0.8846	0.8630	0.8570	14
Zhejiang	0.9160	0.9043	0.9222	0.9041	0.9040	0.9202	0.9115	15
Hubei	0.9019	0.8987	0.9061	0.8904	0.9078	0.9130	0.9045	16
Anhui	0.9299	0.9151	0.9096	0.8739	0.8754	0.8917	0.8861	17
Guangdong	0.8977	0.8879	0.9050	0.8626	0.8720	0.9067	0.8990	18
Shaanxi	0.9054	0.8978	0.8989	0.8699	0.8860	0.8884	0.8844	19
Guizhou	0.8513	0.8748	0.8741	0.8473	0.8734	0.8862	0.8754	20
Hunan	0.8652	0.8607	0.8652	0.8189	0.8442	0.9137	0.9072	21
Guangxi	0.8503	0.8244	0.8611	0.8260	0.8362	0.8990	0.9141	22
Sichuan	0.8084	0.8286	0.8626	0.8206	0.8432	0.8948	0.8949	23
Jiangsu	0.8517	0.8514	0.8631	0.8535	0.8503	0.8485	0.8179	24
Liaoning	0.8382	0.8600	0.8097	0.7492	0.8121	0.8251	0.8126	25
Inner Mongolia	0.8817	0.8045	0.8089	0.7830	0.7614	0.7971	0.7902	26
Henan	0.7833	0.7875	0.7920	0.7485	0.7829	0.8238	0.8122	27
Shandong	0.7696	0.7926	0.8186	0.7821	0.7824	0.7894	0.7558	28
Shanxi	0.7478	0.7451	0.7630	0.7456	0.7350	0.7580	0.7746	29
Hebei	0.7597	0.7460	0.7403	0.7315	0.7324	0.7055	0.7040	30
Mean	0.8996	0.8956	0.8987	0.8765	0.8809	0.8953	0.8903	–

3.1.4 Calculating relative emissions level of air pollutants

Using weighted average method, the emissions of air pollutants (sulphur dioxide, industrial waste gas, and industrial smoke and dust) are selected to construct a dimensionless relative emissions level index. The relative emissions level of air pollutants (*poll*) is defined as:

$$A_{li} = \frac{E_{li}}{\sum E_{li}} \Bigg/ \frac{O_i}{\sum O_i}, \quad l = 1, 2, 3; \quad i = 1, \ldots, N, \tag{16}$$

$$poll_i = \frac{1}{l}\sum_{l}^{3} A_{li}, \quad i = 1, \ldots, N \tag{17}$$

where i denotes a province, l denotes an air pollutant. A_{li} is the adjustment coefficient of each evaluation index. The emissions of air pollutants varies greatly amongst different regions, and the emissions of different pollutants in the same region also varies. Therefore, the effect of the adjustment coefficient is similar to the weight, giving different weights to different air pollutants in each region, thus reflecting the intensity of air pollution in each region. E_{li} is the emissions of air pollutant l in province i; O_i is the gross value of industrial output in province i. $poll_i$ is the relative emissions level of air pollutants in province i.

3.2 Explanatory variables

3.2.1 Core explanatory variable

Environmental regulation is a core explanatory variable. Presently, scholars mainly measure environmental regulation from the following aspects: (1) single indicators are used as proxies for environmental regulation stringency, including the number of environmental laws, policies, and standards (Lindstad and Eskeland 2016), pollution control expenditure (Hamamoto 2006; Jaffe and Palmer 1997), environmental investment (Deng et al. 2012); environmental tax (Marco and Giménez 2013), standard discharge rates (Xu et al. 2016), pollutant emissions intensity (Cole et al. 2005; Zhou et al. 2017), the ratio of pollution control investment in the total cost of material or industrial added value (Lanoie et al. 2008; Levinson and Taylor 2008), and the level of per capita income (Antweiler et al. 2001); (2) a composite index is used as a proxy for environmental regulation stringency; Lin and Sun (2016) construct total discharge of waste water, waste gas, and corresponding taxes to calculate environmental regulation stringency; (3) a comprehensive type index. For example, the comprehensive index composed of air, water resources, and land indicators (Xu and Song 2000); the composite index composed of removal rates of pollutants (Li and Wu 2017; Zhao and Sun 2016). Considering the relative perfection of indicators and the availability of data, we choose the third method, and construct a comprehensive index to measure the stringency of environmental regulation (*er*). The corresponding index system is shown in Table 3.

According to Table 3, the index system consists of four evaluation indicators, including comprehensive utilization rate of industrial solid waste, removal rate of industrial smoke and dust emissions, removal rate of industrial sulfur dioxide emissions and standard rate of industrial waste water discharge. In order to eliminate the dimension effect between indicators, we first use the Min–Max Normalization method to standardize the raw data. After that, the weighted method is adopted to integrate the indicators (Zhao and Sun 2016). The specific method is as follows:

Table 3 Environmental regulation stringency index

Criteria	Sub-criteria	Indicators
Comprehensive index of environmental regulation stringency	Waste water	Standard rate of industrial waste water discharge
	Waste gas	Removal rate of industrial smoke and dust emission
		Removal rate of industrial sulfur dioxide emission
	Waste solid	Comprehensive utilization rate of industrial solid waste

Step 1 Standardize the raw data of four indicators (q^*).

$$q^*_{i\tau} = \frac{q_{i\tau} - \min(q_\tau)}{\max(q_\tau) - \min(q_\tau)} \tag{18}$$

where $q_{i\tau}$ is the original value of indicator τ in province i, $\max(q_\tau)$ and $\min(q_\tau)$ are the maximum and minimum of indicator τ in all provinces respectively, and $q^*_{i\tau}$ is the standardized value of indicator τ.
Step 2 Calculate the weight (h). We assign weights to four evaluation indicators in each province. The calculation method is as follows:

$$\varpi_{i\tau} = \left(c_{i\tau} \Big/ \sum_i c_{i\tau}\right) \Big/ \left(o_i \Big/ \sum_i o_i\right) \tag{19}$$

$$h_{i\tau} = \varpi_{i\tau} \Big/ \sum_\tau \varpi_{i\tau} \tag{20}$$

where $\varpi_{i\tau}$ is the adjustment coefficient of indicator τ in province i. $h_{i\tau}$ is the weight of indicator τ in province i. $c_{i\tau}$ is the discharge amount of indicator τ in province i.$\sum c_{i\tau}$ is the sum of $c_{i\tau}$ in all provinces. o_i is the gross value of industrial output in province i. $\sum o_{i\tau}$ is the sum of o_i in all provinces.
Step 3 Calculate the total stringency of environmental regulation index (er).

$$er_i = \sum_\tau h_{i\tau} \times q^*_{i\tau} \tag{21}$$

where er_i is the stringency of environmental regulation in province i, which is the sum of all four indicators' environmental regulation index.

In Fig. 1, the average and growth rate trends of environmental regulation stringency are clearly shown. It can be seen that the average value of environmental regulation stringency remained at the level of 0.5–0.7 from the year 2001–2014, and reached a maximum of 0.6820 in 2011. Growth rates of environmental regulation stringency fluctuated between −5 and 6%, and declined in 2003, 2005 and 2013, while the rest years were on the rise. It reached the maximum (5.99%) in 2010, while reached the minimum (−4.11%) in 2013.

3.2.2 Control explanatory variables

1. Urbanization (*urb*). In the new economic geography, urbanization is a major factor affecting air pollution control (Zheng et al. 2015). The mechanism behind how it influences environmental quality is complicated and uncertain. Regional environmental quality has a close relationship with its urbanization (Ma et al. 2016), resulting in greater environmental degradation through increased resource

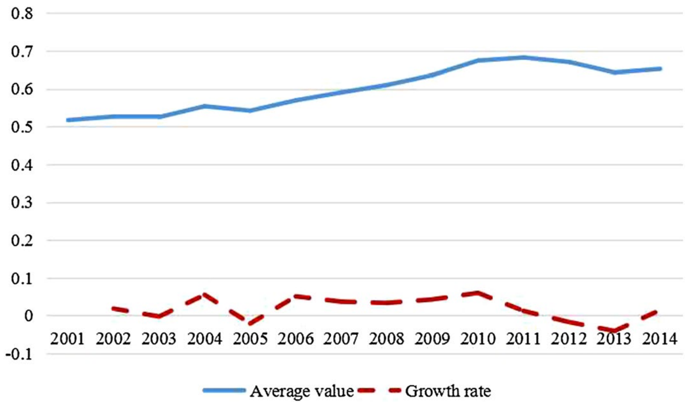

Fig. 1 The average and growth rate trends of environmental regulation stringency

consumption and pollutant emissions. However, it may produce the agglomeration effect, which may effectively increase the comprehensive resource utilization efficiency and reduce environmental pollution (Deng et al. 2012). We take the proportion of the urban population in the total population of each province as an indicator of the urbanization rate.

2. Foreign direct investment (*fdi*). On the basis of pollution haven theory, FDI is a vital environmental quality determinant (Zeng and Zhao 2009; Zhu et al. 2014; Liu et al. 2017a, b; Bagayev and Lochard 2017). It can introduce a sophisticated management theory or advanced environmental technologies, which may contribute to abatement. Alternately, it may produce more pollution, as pollution-intensive industries usually concentrate in regions or countries with relatively low environmental standards.
3. Energy consumption intensity (*eci*). Energy consumption plays a crucial role in China's economy and environmental pollution. Although energy is the foundation of human development, it is also harmful and limits sustainability (Feng et al. 2016). Nasreen et al. (2017) pointed out that increased energy consumption is detrimental to long-term environmental quality. We use the proportion of primary energy consumption to GDP to represent energy consumption intensity.

Table 4 summarizes the variables' descriptive statistics. Provincial-level data of 30 Chinese provinces (Tibet is excluded because of missing data) during the period 2001–2014 is collected mainly from the *China Statistical Yearbook*, *China Energy Statistical Yearbook*, and *China Environmental Yearbook*. All missing data are supplemented according to the moving average method.

Table 4 Descriptions and definitions of variables in econometric model

Variable	Definition	Obs	Mean	SD	Min	Max
eff	Air pollution control efficiency	420	0.8923	0.0702	0.7004	1.0000
poll	Relative emissions level of air pollutants	420	1.7603	1.3383	0.2086	7.8927
er	Environmental regulation stringency	420	0.5992	0.2018	0.0181	0.9239
urb	Urbanization	420	0.4835	0.1501	0.1931	0.8960
fdi	Foreign direct investment	420	0.3107	0.4162	0.0010	2.3572
eci	Energy consumption intensity	420	1.6212	0.8832	0.5036	4.9826

4 Results

4.1 Spatial autocorrelation test

Moran's I statistic is applied to test the spatial air pollution control characteristics. The formula is as follows:

$$Moran'sI = \left[\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}\left(Y_i - \bar{Y}\right)\left(Y_j - \bar{Y}\right)\right] \bigg/ \left[S^2 \sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}\right] \tag{22}$$

$$S^2 = \frac{1}{N}\sum_{i=1}^{n}\left(Y_i - \bar{Y}\right)^2, \bar{Y} = \frac{1}{N}\sum_{i=1}^{n} Y_i \tag{23}$$

where i and j denote the province i and j, respectively. Y_i and Y_j are air pollution control efficiency in province i and j, respectively. $\bar{Y}$ represents the average air pollution control efficiency, N is the number of provinces, and W_{ij} is the spatial weight matrix. The values of $Moran'sI$ range from -1 to 1. If $Moran'sI > 0$, then there is positive spatial correlation, which indicates that the attributes of the spatial unit are similar to those of the adjacent units, namely, the high value is adjacent to the high value, and the low value is adjacent to the low value; inversely, if $Moran'sI < 0$, then there is negative correlation, which indicates that the attributes of the spatial unit are not similar to those of the adjacent units, namely, the high value is adjacent to the low value; while $Moran'sI = 0$, there is no spatial correlation.

Table 5 reports the results of *Moran's I* statistical test in two types of spatial weight matrices. As shown in Table 5, the values of *Moran's I* are greater than zero, suggesting that both air pollution control efficiency and relative emissions level of air pollutants have positive spatial correlation. This means that high or low air pollution control efficiency (relative emissions level of air pollutants) are clustered together. In other word, high (low) efficiency or pollution level in one province correlate with high (low) efficiency or pollution level in nearby provinces. Low p values indicate that the values of *Moran's I* are statistically significant over the entire sample period.

Table 5 Moran's I indices of two dependent variables

Variables	*eff*				*poll*			
Spatial weight	$W^{Distance}$		W^{Pgdp}		$W^{Distance}$		W^{Pgdp}	
Year	Moran's I	*P* value	Moran's I	*P* value	Moran's I	*P* value	Moran's I	*P* value
2001	0.224	0.036	0.182	0.095	0.203	0.025	0.273	0.017
2002	0.224	0.035	0.205	0.064	0.205	0.024	0.272	0.017
2003	0.231	0.030	0.255	0.024	0.169	0.054	0.236	0.035
2004	0.198	0.058	0.270	0.018	0.153	0.076	0.224	0.044
2005	0.268	0.014	0.308	0.008	0.138	0.098	0.213	0.05
2006	0.265	0.014	0.320	0.006	0.219	0.018	0.291	0.012
2007	0.244	0.022	0.328	0.005	0.241	0.01	0.306	0.008
2008	0.234	0.030	0.310	0.008	0.272	0.004	0.347	0.003
2009	0.232	0.029	0.318	0.006	0.294	0.002	0.37	0.002
2010	0.217	0.040	0.345	0.003	0.22	0.01	0.296	0.005
2011	0.264	0.010	0.375	0.001	0.296	0.002	0.384	0.001
2012	0.239	0.021	0.392	0.001	0.269	0.004	0.354	0.003
2013	0.213	0.034	0.372	0.001	0.263	0.005	0.342	0.004
2014	0.242	0.021	0.372	0.001	0.257	0.006	0.343	0.004

4.2 Estimation results analysis

The empirical results of SDM estimated by the Quasi-maximum Likelihood method are shown in Tables 6 and 7. To acquire robust results, we apply the fixed effect model and random effect model to test the effects of environmental regulation on two dependent variables in two types of spatial weight, yielding 8 columns estimated results. The fixed-effect estimators are used to control unobserved heterogeneity. It is apparent that the spatial correlation coefficients ($W * eff$, $W * poll$) are all significantly positive in eight models, indicating spatial correlation in air pollution control does exist across Chinese provinces and rationality of spatial econometric model selection.

According to the Hausman test, the values are 20.93 (p values = 0.0130) in Models (1) and (2) and 23.99 (p values = 0.0043) in Models (3) and (4) of Table 6, indicating that the fixed effect models are accepted. Moreover, as shown in Table 6, values of the log likelihood of Models (2) and (4) are large than Models (1) and (3), which means a fixed effect should be applied. Thus, we focus on two fixed effect models. Models (2) and (4) show that the environmental regulation coefficients (*er*) are estimated to be positive (0.0689, 0.0682) at the 1% significance level, indicating that the positive influence of environmental regulation on air pollution control, namely, the increase of environmental regulation stringency will help to improve air pollution control efficiency. The recent implementation of a series of environmental regulations during the Eleventh Five-Year Plan sees China's industry developing energy-saving and environment-friendly growth. The increasing attention of central and local governments to environmental protection has meant continuously

Table 6 Regression results for the entire sample (dependent variable: *eff*)

Spatial weight	$W^{Distance}$		W^{Pgdp}	
Model	(1)	(2)	(3)	(4)
Variable	Random effect	Fixed effect	Random effect	Fixed effect
er	0.0670*** (0.0102)	0.0689*** (0.0099)	0.0666*** (0.0103)	0.0682*** (0.0099)
fdi	0.0248*** (0.0047)	0.0263*** (0.0045)	0.0244*** (0.0046)	0.0260*** (0.0045)
eci	−0.0165*** (0.0043)	−0.0171*** (0.0042)	−0.0158*** (0.0042)	−0.0166*** (0.0042)
urb	−0.0356 (0.0275)	−0.0484* (0.0268)	−0.0314 (0.0274)	−0.0435 (0.0267)
*W*er*	−0.0759*** (0.0213)	−0.0752*** (0.0206)	−0.0661*** (0.0188)	−0.0642*** (0.0183)
*W*fdi*	−0.0093 (0.0078)	−0.0095 (0.0076)	−0.0117* (0.0069)	−0.0117* (0.0067)
*W*eci*	0.0277*** (0.0070)	0.0283*** (0.0068)	0.0270*** (0.0062)	0.0279*** (0.0061)
*W*urb*	0.0093 (0.0403)	0.0146 (0.0392)	0.0082 (0.0352)	0.0106 (0.0345)
*W*eff*	0.3594*** (0.0595)	0.3635*** (0.0586)	0.388*** (0.0547)	0.3791*** (0.0546)
Constant	0.5700*** (0.0609)		0.5396*** (0.0551)	
R^2	0.1854	0.1858	0.1822	0.1827
Log-likelihood	1044.8360	1144.2166	1048.5705	1146.6833
Observation	420	420	420	420

Standard errors are shown in parentheses

*$p<0.1$, **$p<0.05$, ***$p<0.01$

increasing environmental investment and regulation stringency in air pollution control. From 2001 to 2014, the environmental regulation stringency grew at an average annual rate of 1.85%. In 2010, the stringency of environmental regulation was 0.68, an increase of 5.99% over the previous year. Generally speaking, environmental regulation has played an essential role in improving air quality.

The coefficients of the spatial spillover effects of environmental regulation ($W * er$) are significantly negative (−0.0752, −0.0642) in Models (2) and (4). The finding is an interesting result. The increase of environmental regulation stringency in neighboring provinces will decrease local air pollution control efficiency, indicating a government's decision-making on environmental regulation has a positive external effect on its surrounding regions, and local government inclines to respond to higher environmental regulation stringency from neighboring provinces with lower environmental regulation stringency, which inevitably leads to a decline in local air pollution control efficiency. This finding suggests that provincial governments are engaging in strategic interaction of environmental regulation. Yardstick competition in economic growth and spatial spillover effects might be the root cause of such free-riding behavior (Fredriksson and Millimet 2002; Konisky and Woods 2012; Yu et al. 2016). Environmental governance is characterized by long effective cycles, large investment demand, and many historical debts. Based on promotion considerations, officials are more inclined to invest in short-term and obvious growth effect fields during their tenure, such as urban public infrastructure construction. However, fiscal decentralization means that local governments undertake the

Table 7 Regression results for the entire sample (dependent variable: *poll*)

Spatial weight	$W^{Distance}$		W^{Pgdp}	
Model	(5)	(6)	(7)	(8)
Variable	Random effect	Fixed effect	Random effect	Fixed effect
er	−2.1585*** (0.2761)	−2.1810*** (0.2780)	−2.1347*** (0.2833)	−2.1667*** (0.2835)
fdi	−0.5974*** (0.1290)	−0.5896*** (0.1287)	−0.5247*** (0.1299)	−0.5325*** (0.1291)
eci	0.4362*** (0.1185)	0.1633 (0.1186)	0.3526*** (0.1222)	0.1164 (0.1198)
urb	−2.4188*** (0.7073)	−1.8358** (0.7483)	−2.4227*** (0.7297)	−2.0596*** (0.7603)
W^*er	3.0139*** (0.5816)	2.9337*** (0.5837)	2.3540*** (0.5203)	2.3412*** (0.5265)
W^*fdi	−0.4449** (0.2173)	−0.5958*** (0.2160)	−0.3446* (0.1952)	−0.4870** (0.1935)
W^*eci	−0.8509*** (0.1823)	−0.7439*** (0.1913)	−0.7342*** (0.1654)	−0.6757*** (0.1736)
W^*urb	3.2962*** (1.0633)	2.9901*** (1.0861)	3.2983*** (0.9407)	3.1712*** (0.9781)
W^*poll	0.3269*** (0.0753)	0.2412*** (0.0788)	0.3137*** (0.0656)	0.2398*** (0.0676)
Constant	1.3183** (0.5931)		1.5897*** (0.5585)	
R^2	0.6563	0.4298	0.4061	0.2532
Log-likelihood	−323.5933	−251.2003	−329.9710	−254.1072
Observation	420	420	420	420

Same as in Table 6

main local construction, and most have tight budgets. Compared with other budgetary projects, it is difficult to get priority approval for environmental protection investment. In addition, compared with the general public infrastructure investment, environmental pollution control has a greater spillover effect. When environmental pollution control in surrounding regions increases, the surrounding environment improves to a certain extent and the positive externality of their environmental governance increases, resulting in a greater incentive to decrease environmental regulation stringency in other regions.

In Models (2) and (4), in terms of the control variables, the estimated coefficients of FDI (*fdi*) are significantly positive (0.0263, 0.0260) at 1% level, indicating that higher FDI in local and surrounding areas may increase air control efficiency. The coefficients of the spatial spillover effects of FDI ($W * fdi$) are not significantly negative (−0.0095) in Model (2) but significantly negative (−0.0117) at 10% level in Model (4). The estimated coefficients of energy consumption intensity (*eci*) are significantly negative (−0.0171, −0.0166) at 1% level, and the coefficients of its spatial spillover effects ($W * eci$) are significantly positive (0.0283, 0.0279), suggesting that energy consumption intensity is an essential factor limiting local air pollution control efficiency, while the energy consumption intensity of surrounding areas is conducive to local air pollution control. As for urbanization (*urb*), the estimated coefficients are negative (−0.0484) at 10% significance level in Model (2) and not significantly negative (− 0.0435) in Model (4), while the coefficients of its spatial spillover effects ($W * urb$) are not significantly positive.

Table 6 reports the results of the impacts of environmental regulation on air pollution control. Table 7 displays the results of the effects of environmental regulation on air pollutant emissions. As shown in Table 7, the significance of coefficients of core independent variables are similar to those in Table 6, but the symbols of coefficients are completely opposite, which is in line with our expectations and suggesting the above conclusions are robust. Similarly, according to the Hausman test, and based on values of the log likelihood, fixed effect models are applied. In Models (6) and (8), the environmental regulation coefficients (er) are estimated to be negative (− 2.1810, − 2.1667) at the 1% significance level, indicating that the environmental regulation has significantly negative influence on air pollutant emissions, namely, the increase of environmental regulation intensity contributes to the reduction of air pollutant emissions. The coefficients of the spatial spillover effects of environmental regulation ($W * er$) are significantly positive (2.9337, 2.3412) in Models (6) and (8), indicating environmental regulation has significantly positive spatial spillover effects. The increase of local environmental regulation stringency promotes the increase of air pollutant emissions in other regions. This once again confirms the existence of strategic interaction. In terms of other variables, in Models (6) and (8), both the coefficients of FDI (fdi) and its spatial spillover effects ($W * fdi$) are significantly negative (− 0.5896, − 0.5325, − 0.5958, − 0.4870), suggesting that improving FDI in one province is conducive to reducing both the local and neighboring air pollutant emissions. The coefficients of energy consumption intensity (eci) are not significantly positive (0.1633, 0.1164), but its spatial spillover effects are significantly negative (− 0.7439, − 0.6757). The coefficients of urbanization (urb) are significantly negative (− 1.8358, − 2.0596), and its spatial spillover effects ($W * urb$) are significantly positive (2.9901, 3.1712). This implies that the development of urbanization can exert a positive agglomeration effect and contribute to the reduction of local air pollution, but it is not conducive to the treatment of air pollution in surrounding areas.

4.3 Direct, indirect and total effects

Based on Eqs. (6)–(9) and the coefficients of SDM in Tables 6 and 7, we obtain the direct, indirect, and total effects, respectively. The regression results are presented in Table 8. As we can see from Table 8, the results are similar to the corresponding results in Tables 6 and 7, indicating that the results are effective and robust. In addition, it confirms the rationality of applying SDM to study the spatial spillover effects of environmental regulation in various provinces. It should be noted that in Model (2) of Table 8, the direct effect is positive, the indirect effect is negative, and the latter dominates the former, so the total effect is negative, and vice versa. Concretely, in Models (2) and (4), a one-unit increase (decrease) in the local environmental regulation stringency will directly result in a 0.0650 and 0.0639 increase (decrease) in air pollution control efficiency in this province, and indirectly result in a 0.0746 and 0.0571 decrease (increase) in air pollution control efficiency in other neighboring

Table 8 The direct, indirect and total effects for the entire sample

Spatial weight	$W^{Distance}$			W^{Pgdp}		
Model	(2)			(4)		
Variable	Direct effect	Indirect effect	Total effect	Direct effect	Indirect effect	Total effect
eff						
er	0.0650*** (0.0104)	−0.0746** (0.0296)	−0.0096 (0.0334)	0.0639*** (0.0107)	−0.0571** (0.0263)	0.0068 (0.0312)
fdi	0.0262*** (0.0043)	0.0009 (0.0109)	0.0271** (0.0119)	0.0257*** (0.0043)	−0.0020 (0.0095)	0.0237** (0.0109)
eci	−0.0147*** (0.0040)	0.0330*** (0.0099)	0.0182* (0.0106)	−0.0135*** (0.0039)	0.0323*** (0.0085)	0.0188* (0.0095)
urb	−0.0490* (0.0259)	−0.0057 (0.0564)	−0.0546 (0.0601)	−0.0445* (0.0261)	−0.0104 (0.0503)	−0.0548 (0.0576)
Model	(6)			(8)		
poll						
er	−2.0409*** (0.2886)	3.0771*** (0.7350)	1.0362 (0.8210)	−2.0261*** (0.2967)	2.2781*** (0.6331)	0.2520 (0.7396)
fdi	−0.6343*** (0.1221)	−0.9417*** (0.2790)	−1.5760*** (0.2987)	−0.5813*** (0.1224)	−0.7661*** (0.2392)	−1.3474*** (0.2637)
eci	0.1379 (0.111)	−0.9073*** (0.2337)	−0.7694*** (0.2452)	0.0826 (0.1120)	−0.8205*** (0.2024)	−0.7378*** (0.2176)
urb	−1.7098** (0.7246)	3.2080** (1.3719)	1.4982 (1.4155)	−1.8778** (0.7370)	3.3147*** (1.2164)	1.4369 (1.3392)

Same as in Table 6

provinces, respectively. This implies that higher environmental regulation stringency would encourage a province to increase its air pollution control efficiency, while owing to the existence of spatial spillover effects, free-riding behavior caused by strategic interaction of environmental regulation has restrained air pollution control efficiency in other provinces. The government should implement joint prevention and control to promote air pollution control efficiency (Feng and Liao 2016).

In Models (6) and (8) of Table 8, the direct effects of environmental regulation on the relative emissions level of air pollutants are significantly negative, while the indirect effects are significantly positive, and the latter dominates the former, so the total effects are positive. Specifically, in Models (6) and (8), a one-unit increase (decrease) of local environmental regulation stringency will directly decrease (increase) relative emissions level of air pollutants by 2.0409 and 2.0261 unit in this province, and indirectly increase (decrease) relative emissions level of air pollutants by 3.0771 and 2.2781 unit in other neighboring provinces, respectively. This indicates that the increase of environmental regulation stringency in a certain region might actually reduce the relative emissions level of local air pollutants, but increase the relative emissions level of air pollutants in surrounding areas.

4.4 Reexamination at different intervals

Considering that the central and local governments are paying more attention to environmental protection, especially after 2008, we re-examined the samples at different periods. To compare the changes of environmental regulation in different periods and avoid the effects of environmental policy changes on empirical conclusions, we take 2008 as the time boundary. Meanwhile, it can be used as a sensitivity analysis. Based on the Hausman test and values of the log likelihood, fixed effect models are applied. The results are shown in Tables 9 and 10.

As shown in Tables 9 and 10, the estimated coefficients and signs of major variables are similar to those in Tables 6 and 7. As we can see from Table 9, the signs of estimated coefficients variables have not changed significantly at different intervals, but the influence degree of environmental regulation has. Specifically, the estimated coefficients of environmental regulation are significantly positive, indicating the environmental regulation has a positive correlation with air pollution efficiency. The estimated coefficients of environmental regulation (0.0819, 0.0855) in Models (10) and (12) increase significantly compared with those (0.0523, 0.0486) in Models (9) and (11), which implies that the effects of environmental regulation on air pollution control have improved in recent years. The absolute values of the coefficients of the spatial spillover effects of environmental regulation (0.0514, 0.0421) in Models (10) and (12) are larger than those (0.0293, 0.0345) in Models (9) and (11), but most of the coefficients are not significant.

The results in Table 10 confirm similar conclusions. As shown in Table 10, the signs of the estimated coefficients are opposite to those in Table 9, which is in line with our expectations. Concretely, the estimated coefficients of environmental regulation are significantly negative, illustrating environmental regulation can effectively inhibit the emissions of air pollutants. The absolute values of estimated

Table 9 Regression results of samples at different time intervals (dependent variable: *eff*)

Spatial weight	$W^{Distance}$		W^{Pgdp}	
Model	(9)	(10)	(11)	(12)
Variable	2001–2007	2008–2014	2001–2007	2008–2014
er	0.0523*** (0.0137)	0.0819*** (0.0151)	0.0486** (0.0243)	0.0855*** (0.0155)
fdi	0.0307*** (0.0107)	0.0487*** (0.0082)	0.0452** (0.0200)	0.0511*** (0.0083)
eci	−0.0116** (0.0048)	−0.0400*** (0.0094)	−0.0115 (0.0098)	−0.0389*** (0.0098)
urb	−0.0479** (0.0244)	−0.1901* (0.1046)	−0.0395 (0.0343)	−0.1292 (0.1077)
W^*er	−0.0293 (0.0290)	−0.0514* (0.0309)	−0.0345 (0.0347)	−0.0421 (0.0285)
W^*fdi	−0.0120 (0.0142)	−0.0086 (0.0170)	−0.0392 (0.0338)	−0.0080 (0.0147)
W^*eci	0.0005 (0.0113)	0.0865*** (0.0191)	0.0046 (0.0090)	0.0586*** (0.0170)
W^*urb	−0.0160 (0.0347)	0.4050** (0.1711)	−0.0116 (0.0360)	0.1929 (0.1425)
W^*eff	0.2434*** (0.0787)	0.3824*** (0.0846)	0.1451* (0.0798)	0.3722*** (0.0789)
R^2	0.1577	0.3689	0.1804	0.3377
Log-likelihood	651.2770	614.2600	551.0023	610.1632
Observation	210	210	210	210

Same as in Table 6

Table 10 Regression results of samples at different time intervals (dependent variable: *poll*)

Spatial weight	$W^{Distance}$		W^{Pgdp}	
Model	(13)	(14)	(15)	(16)
Variable	2001–2007	2008–2014	2001–2007	2008–2014
er	−1.5966*** (0.3634)	−1.9815*** (0.3257)	−1.5499*** (0.3656)	−1.9442*** (0.3336)
fdi	−0.3402 (0.3481)	−0.5351*** (0.1669)	−0.3352 (0.3477)	−0.4779*** (0.1700)
eci	0.0177 (0.1309)	1.0717*** (0.1446)	0.0205 (0.1326)	1.0962*** (0.1574)
urb	0.2172 (0.6281)	−2.1512 (1.3122)	0.2920 (0.6304)	−2.0300 (1.2923)
W^*er	1.6100* (0.9501)	2.0466*** (0.6650)	0.4286 (0.7915)	1.5239** (0.5958)
W^*fdi	−0.0737 (0.5182)	−0.3758 (0.3264)	0.1798 (0.4270)	−0.1529 (0.2766)
W^*eci	−0.8712*** (0.3069)	−1.3297*** (0.2771)	−0.6817*** (0.2604)	−1.1510*** (0.2417)
W^*urb	1.2358 (0.9407)	2.8494 (2.2603)	1.1520 (0.8368)	2.2515 (1.7798)
W^*poll	0.3196*** (0.1038)	0.4040*** (0.1006)	0.2847*** (0.0890)	0.3783*** (0.0909)
R^2	0.1423	0.1739	0.1193	0.1416
Log-likelihood	−43.9757	−118.4847	−46.0750	−123.6158
Observation	210	210	210	210

Same as in Table 6

coefficients of environmental regulation (1.9815, 1.9442) in Models (14) and (16) larger significantly compared with those (1.5966, 1.5499) in Models (13) and (15), which illustrates that the effects of environmental regulation on air pollutant emissions reduction during 2008–2014 are greater than that during 2001–2007. The coefficients of spatial spillover effects of environmental regulation (2.0466, 1.5239) in Models (14) and (16) are significantly positive and larger than those (1.6100, 0.4286) in Models (13) and (15), suggesting that the increase of environmental regulation in a province might promote the increase of air pollutant emissions in neighboring province, and the positive influence has recently increased. This again implies the existence of strategic interaction, and with the increase of environmental investment, this kind of strategic interaction leads to more serious free-riding behavior.

5 Conclusions

Using Chinese provincial-level panel data for the period 2001–2014 and controlling for energy consumption intensity, foreign direct investment and urbanization, this study establishes a spatial Durbin model to addresses three fundamental, yet crucial, questions: Can environmental regulation promote air pollution control in China? Whether local governments in China participate in strategic interaction of environmental regulation regarding air pollution control? If so, what impact does it have? The results show that environmental regulation has a positive correlation with air pollution control efficiency and a negative correlation with air pollutant emissions, namely, environmental regulation can significantly improve air pollution control efficiency and reduce air pollutant emissions. In terms of spatial effect, evidence has been found to support environmental regulation has significantly spatial spillover effects. Specifically, the increase of environmental regulation in other provinces will decrease local air pollution control efficiency or increase local air pollutant emissions. This indicates that provincial governments are engaging in strategic interaction of environmental regulation: local governments incline to respond to stricter environmental regulation from neighboring provinces with looser environmental regulation, which inevitably leads a decline in local air pollution control efficiency or an increase in air pollutant emissions. Additionally, the results of the time interval test indicate that the effects of environmental regulation on air pollution control have improved in recent years. With the increase of environmental regulation intensity, its spatial spillover effects have increased and led to more serious free-riding behavior. Based on these findings, some relevant policy implications are provided as follows:

1. The implementation of environmental regulation is conducive to improving air quality. Local governments should not worry too much about the restriction of environmental regulation on the short-term growth of the local economy, but should promote the sustainable development of economy and environment from a long-term perspective. Thus, local governments should strengthen environmental regulation rather than weaken it, and implement it scientifically according to

local conditions. The setting of regulation intensity should take into account the carrying capacity of enterprises and the reality of regional development.
2. The significant spatial correlation of regional air pollution control indicates that joint prevention and control is imperative. Regional governments should promote mechanisms for joint prevention and control of air pollution and fiscal responsibility. Implementation has begun, but many obstacles such as regional differences in emissions still exist, making the division of responsibility for pollution control difficult to determine. A regional environmental governance co-development fund and a strong inter-regional environmental management coordination agency may reduce the cost of cooperative transactions and ease the free-riding tendency in environmental governance.
3. As for the spatial spillover effects of environmental regulation on air pollution control, the central government should play a crucial role in alleviating these spillover effects, reducing its negative environmental effects. It is important to continue to lower the weight of the GDP in local officials' promotion assessment, increase the weight of environmental protection, promote the diversification of official assessment, strictly implement the lifelong responsibility system of resources and environment. Moreover, it is necessary to re-examine the social and economic value of environmental protection by changing the opposing concept between economic growth and environmental protection of local governments, and instead ensure synchronous growth through legislation, such as setting the proportion of environmental protection to GDP.

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