



Positive or negative externalities? Exploring the spatial spillover and industrial agglomeration threshold effects of environmental regulation on haze pollution in China

Yihang Zhao¹ · Chen Liang¹ · Xinlong Zhang²

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Abstract

As one of the efficacious environmental governance instruments, environmental regulations usually have been adopted to control haze pollution in most developing countries. However, as proved in recent researches, the relationship between environmental regulation and haze pollution remains uncertain. This paper develops a conceptual model and attributes this phenomenon to two reasons: the spatial spillover effect and industrial agglomeration threshold effect of effective environmental regulation. Spatial durbin model (SDM), instrumental variable (IV) and panel threshold model are used to estimate these effects based on 277 cities data in China from 2012 to 2016. The results confirm the spatial spillover effects of environmental regulations and haze pollution, which could influence the pollutant reduction effect through positive and negative spatial spillover effects. It also validates the thresholds of industrial agglomeration of approximately 0.818 and 1.271. Nevertheless, only 1.271 represents the turning point of the environmental regulation effect changing and environmental regulations could significantly reduce haze, only if it exceeds this numerical value. Moreover, the results have regional heterogeneity regarding spillover effect and threshold effect as well. The environmental regulation intensity in central and western regions plays a “multi-stage promotion” role on haze pollution emission with the adjustment of industrial agglomeration threshold, while it turns out to be a “triple-stage downward” trend in eastern China. At last, we put forward differential policies suggestions according to their industrial agglomeration levels.

Keywords Environmental regulation intensity · Haze pollution · Industrial agglomeration level · Spatial Durbin model (SDM) · Panel threshold model · Instrumental variable (IV)

✉ Chen Liang
liangchen007@sjtu.edu.cn

Yihang Zhao
zhaoyihang@sjtu.edu.cn

Xinlong Zhang
471292873@qq.com

¹ School of International and Public Affairs, Shanghai Jiao Tong University, Shanghai 200030, China

² Institute of Photogrammetry and Remote Sensing, Technische Universität Dresden, Dresden, Germany

1 Introduction

The launch of the economic reforms at the end of the 1970s caused unprecedented urbanization and rapid growth of the economy (Zhang and Xu 2016). Meanwhile, it also led to high energy consumption and air pollution. Particularly, haze pollution caused by PM_{2.5} (fine particulate matter with diameter < 2.5 μm) is generally believed to be the major concern of such terrible air condition in China (Huang et al. 2010). Since the unique characteristics of PM_{2.5}, it could contribute to heavy smog with some important expressway stations having to be closed (Zhou et al. 2019). Serious air pollution in China has also caused heavy economic losses (Chen et al. 2013). The direct economic loss caused by heavy air pollution in China is equivalent to nearly 346.36 billion RMB per year (Xia et al. 2016). In order to control such sulfur dioxide emissions, it costs almost 192.95 thousand RMB for every ton reducing in haze pollution (Chen et al. 2018). Furthermore, increasingly serious air pollution adds people's health risk. It was proved to increase the percentage of people suffering respiratory diseases and lung cancer (Zhang et al. 2019b). Such severe haze pollution could be regarded as the negative externalities of industrial production (Ebenstein et al. 2017).

Unfortunately, the priority of economic growth over pollution control in China has contributed to inefficient environmental governance and even collusion between governments and enterprises (Nie et al. 2013). China is facing threats coming from the deterioration of haze pollution, mainly attributed to the disappointing performance in terms of industrial pollution control (Konisky 2008). As the new Chinese leadership took power in late 2012, circumstances have considerably improved after Premier Li acknowledged that the government had failed to achieve much progress in environmental regulation, and announced that China would solve environmental challenge with “an iron fist, firm resolution and tough measures”.¹

In order to address such haze pollution and other types of environmental harm, Chinese central government and local governments have taken measures to formulate a series of environmental protection policies, such as Command-and-Control policy (CACs, e.g., setting standards, targets, or process requirements) and market-based instruments (MBIs, e.g., ecotaxes or other Pigouvian taxes, tradable pollution permits or the Emission Trading System). However, compared with the agreement with different parties involved (private-sector) and MBIs with much more flexible policy implementation, the CACs such as environmental regulation measures are currently recognized as the most effective means to remedy the system failure of environmental governance and largely control haze pollution (Hashmi and Alam 2019; Yu et al. 2019), which also have been adopted to put into practice by a large number of scholars and environment protection departments (Zhang et al. 2019a).

Environmental regulations are able to achieve haze pollutant reduction in many ways. For example, enhancing people's awareness of environmental protection (Triebswetter and Hitchens 2005), forcing enterprises improving technology and adopting clean production equipment (Mani and Wheeler 1998; Costantini et al. 2013), defining the environmental responsibilities of local officials and implementing the accountability mechanism (Wu et al. 2018; Zhang and Wu 2018). Theoretically speaking, there is a strong causal relationship between environmental regulation and haze pollution reduction (Qu 2018). While the conclusions are unclear according to the existing researches. Even for the same

¹ Luna Lin, “Will China's new premier Li Keqiang improve the environment?”, *China Dialogue*, February 4, 2013, <https://www.chinadialogue.net/article/show/single/en/5847-Will-China-s-new-premier-Li-Keqiang-improve-the-environment>.

environment governance policy, the results vary with different policy assessment methods, the actual effects of policies are ambiguous in both developing and developed countries (Yu et al. 2018; Tietenberg 1998). Some scholar identified the non-linear effect of environmental regulation on haze pollution with panel data of Chinese cities (Zhou et al. 2019). Furthermore, the air pollutant reduction effect of environmental regulation could be adjusted by economic threshold because of the “pollute first and control later” mode (Pang et al. 2019). Unfortunately, the economic development level may have reverse causality with most social and economic indexes. Therefore, we could not avoid eliminating the strong endogenous error when it took economic development level as threshold variable.

The concept of "agglomeration" in regional economics brings us inspiration to find threshold variables of environmental regulation. Environmental pollution is an unexpected output brought by negative externality of industrial agglomeration, and the relationship between industrial agglomeration and environmental pollution has gradually become a popular topic in the field of resource and environmental economics and industrial economics (Pei et al. 2020). Until now, such progress has been made, but the research conclusions are considerably different. Some scholars have concluded that industrial agglomeration could aggravate pollutant emission (negative externalities). In early studies, Virkanen (1998) tested that the industrial agglomeration is a crucial factor contributing to serious air pollution in southern Finland. It was also confirmed that the significant correlation between industrial agglomeration and air pollution by analyzing the panel data of 200 cities in EU (Frank et al. 2001). In China, Ren et al. (2003) identified the causal relationship between industrial agglomeration and water pollution emission in early stage of industrial development using the data of Shanghai from 1947 to 1996. Other scholars have pointed out that industrial agglomeration could reduce pollutant emission (positive externalities). Firstly, if enterprises gather together and use the centralized pollutant recycling system, the total processing costs will be reduced (He et al. 2014). Secondly, local governments can set up specialized environmental protection departments in regions where the industrial enterprises are concentrated, so as to supervise the enterprises' emission behavior and punish the illegal behaviors (van Rooij and Lo 2010). Thirdly, industrial agglomeration can promote the communication concerning technology upgrading among enterprises (Lin et al. 2017). Research shows that innovative environmental technologies could be developed and promoted easier in industrial agglomeration regions. Therefore, cluster firms are more motivated to adopt advanced environmental protection technologies to reduce pollution (Cole et al. 2006). Some other studies believed that the relationship between industrial agglomeration and environmental pollution is still uncertain. When the industrial agglomeration level falls below the threshold, industrial enterprises are in the early stage of agglomeration and it will aggravate the environmental pollution. When the industrial agglomeration level exceeds the threshold, it will contribute to pollutant emission reduction (Liu et al. 2016; Yang 2015).

It can be concluded that the relationship among industrial agglomeration, environmental regulation and environmental pollution are complex, and it is uncertain to identify the role of industrial agglomeration and environmental regulation applied to environmental pollution. Based on the synergistic effect hypothesis of environmental regulation and industrial agglomeration, a study analyzed the interaction effect of these two factors on pollution and its regional heterogeneity (Zhang et al. 2019a). There is another literature integrating environmental regulation and industrial agglomeration into the social economic network to analyze the spatial spillover effect of these two factors on pollutant reduction (Wang et al. 2019a). However, the remaining literature is not related to the inner mechanism analysis of effective pollution reduction. There is a lack of theoretical model to support how these two

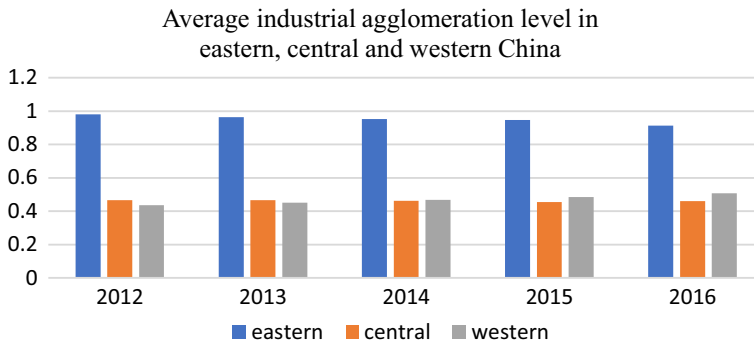


Fig. 1 The average industrial agglomeration levels in eastern, central and western China

factors affect environmental pollution emission. Our study makes marginal contribution to building a theoretical model which assumed the effect of pollution reduction to be the result of the game between “porter hypothesis” and “pollution shelter hypothesis”. With the method of SDM and panel threshold model, we attributed the non-linear relationship between environmental regulation and air pollution to the spatial spillover effect of environmental regulation and the threshold regulation effect of industrial agglomeration. At the same time, it is necessary for us to conduct heterogeneity analysis in terms of the relationship among environmental regulation, industrial agglomeration level and air pollution since the huge gap among industrial agglomeration levels in eastern, central and western China (as shown in Fig. 1, the average industrial agglomeration level in eastern China is much higher than these in central and western China).

The remainder of the paper is organized as follow. Section 2 introduces the theoretical framework and research hypothesis. The methods and model settings are presented in Sect. 3, including the data sources, sample, measurements and econometric models. Section 4 is the part of empirical analysis. At last, the complete discussion and conclusion are presented in Selection 5.

2 Theoretical framework and research hypothesis

It is generally believed that Henry Sidgwick conducted the initial study of externalities or “spillover effects” in his famous work *The Principles of Political Economy* (1883), and Arthur C. Pigou is credited with formalizing these concepts which was firstly applied in the field of environmental economics (Pigou 1920). In order to identify the externalities of environmental regulation and the decision-making behaviors of enterprises, two important hypotheses were raised, named “porter hypothesis” and “pollution shelter hypothesis”. Under the framework of porter hypothesis, strict and appropriate environmental regulation could promote technological innovation of enterprises in an industrial cluster, and then lead to pollutant reduction and pollution control cost saving (Porter and Linde 1995). The position of the pollution shelter hypothesis is polluting enterprises would choose to enter another regions with lower intensity of environmental regulation in order to cut down the pollution control costs when the governments strengthen the environmental regulation in previous region, which actually provides shelter for polluting enterprises and forms industrial agglomeration in areas with lower level of environmental regulation. (Walter and

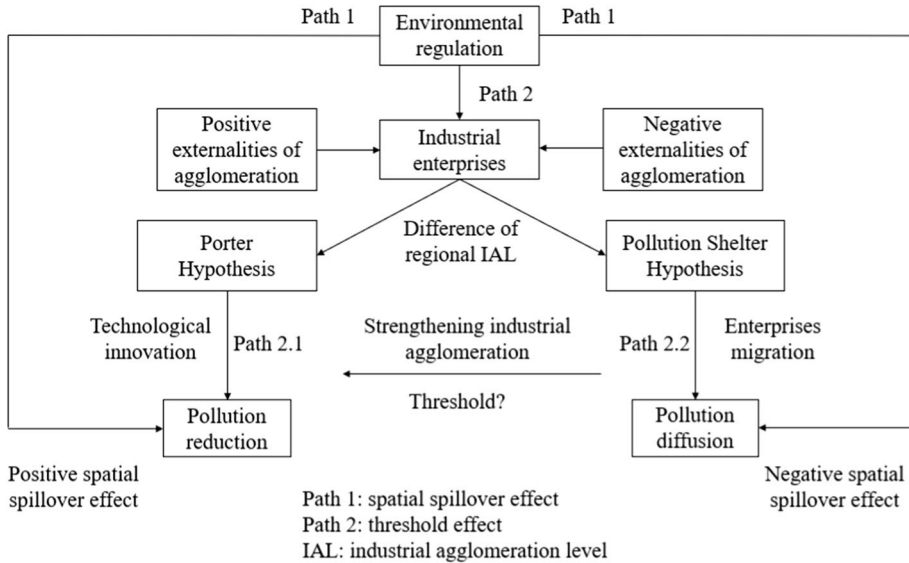


Fig. 2 Theoretical framework

Ugelow 1979). Due to the regional heterogeneity, different areas would appear differential pollutant reduction effects under the functions of these two hypotheses. Under the circumstances, industrial agglomeration is always the adjustment variable of enterprise migration or technological innovation all along. In addition to analyzing the spatial spillover effect of environmental regulation, this paper intends to adopt the industrial agglomeration level as an index to measure the heterogeneity among different regions, which could be used as a threshold variable to explore the relationship between environmental regulation and pollution reduction. The theoretical framework is shown in Fig. 2.

This paper puts forward such a theoretical framework as shown in Fig. 2: The non-linear relationship between environmental regulation and pollution reduction could be attributed to the following two reasons. Firstly, air pollution emission and environmental regulation in surrounding areas might have spatial spillover effect, which could make the policy effects of environmental regulation much more inconclusive (Path 1); Secondly, in the area where industrial agglomeration is developed, affected by the positive externality of agglomeration (Porter Hypothesis, Path 2.1), industrial enterprises would carry out technological innovation to reduce pollution emissions. At the same time, the unit cost of pollution control would be reduced because of agglomeration effect, and finally the innovative compensation mechanism would be formed (Ramanathan et al. 2017). Eastern area in China could support the porter hypothesis, but evidence from central and western areas in China could not be explained by porter hypothesis (Shen and Liu 2012). Due to negative externality of agglomeration dominating in central and western China, industrial enterprises would be transformed to other areas with lower intensity of environmental regulation that is able to strengthen the level of industrial agglomeration in neighboring regions based on pollution shelter hypothesis (Path 2.2). Environmental regulation intensity has become an important factor in the industrial layout of pollution intensive enterprises, which also leads to the deterioration of pollution levels in these areas (Chung 2014; Qiu et al. 2013). Concerning a huge gap among the industrial agglomeration levels in eastern, central and western China

(Fig. 1), we could assume an industrial agglomeration threshold existing due to the enterprise migration effect, which could become the applicable boundary of porter hypothesis and pollution shelter hypothesis.

3 Methodology and data

3.1 Variables selection and data sources

3.1.1 Explained variables

In order to exactly measure the regional haze pollution status, the paper used the concentration of PM_{2.5} as dependent variable, which has been adopted as the major haze pollution indicator of official Chinese department since 2012 (van Donkelaar et al. 2018). It can be got from the Globe Annual PM_{2.5} Grids at the *Socioeconomic Data and Application Center* (SEDAC) at Columbia University (including the data from 1998 to 2016).

3.1.2 Key explanatory variable and threshold variable

We adopted *environmental regulation intensity* (*env_regu*) as key explanatory variable, it can be measured by Investment in Anti-pollution Projects as Percentage of GDP with city level in China (Bai and Nie 2017; Guo et al. 2017); we used the *level of industrial agglomeration* (*ind_agg1*) as threshold variable. Referred to related literatures (Keeble et al. 1991; Yang 2013), we used the formula of *location entropy* to count, which could truly reflect the spatial distribution of geographical elements and eliminate regional differences in city scale to measure industrial agglomeration. As is shown in Eq. (1)

$$ind_{agg1} = \left(\frac{e_{ir}}{\sum_i e_{ir}} \right) / \left(\frac{\sum_i e_{ir}}{\sum_i \sum_r e_{ir}} \right) \quad (1)$$

In this formula, e_{ir} represents the total output of industry r in area i . We adopt industrial total output value of each prefecture level city to calculate the *location entropy*.

3.1.3 Control variables

This paper selected control variables from the aspects of economic factors, social factors, government regulation factors and natural factors which are represented by EV, SV, GV and NV, respectively. (Zhao et al. 2020; Yang and Chen 2019). Economic factors: (1) *Industrial level* (*second_gdp*): We took the proportion of secondary industries' added values in GDP to measure industrial level which could affect the industrial pollutant emissions directly (Wang et al. 2018b). (2) *Foreign direct investment* (*FDI*): In order to attract foreign investment, local government will relax environmental regulation to a certain extent (Lan et al. 2012), and we took the indicator of FDI quota. Social factors: (3) *Population density* (*pop_den*): Cities with higher population might have crowded living environment and severe pollution (Lang et al. 2016), and it is necessary for us to adopt *population density* as control variable. (4) *High education level* (*high_edu*): It could be measured by the ratio between the number of universities students and the population in a city. And cities with higher college student ratio might have less pollutant emissions (Kan et al. 2008).

Government regulation: (5) *Government fiscal ability* (*fis_gdp*): It could be indicated by the proportion of fiscal expenditure in GDP and affect environmental pollution significantly (Gupta and Barman 2009). Natural factors: (6) *Green plant's coverage rate* (*green*): As far as natural conditions, green plants can purify the air and change the meteorological factors in a city (Zhao et al. 2020). We believe they could control most extra factors affecting the atmospheric pollutant emissions.

Considering the accuracy and availability of data, panel data of 277 prefecture level cities (excluding some cities with missing data) in China from 2012 to 2016 are selected in our study. Ultimately, the dataset contained 1385 (277×5) sample data points. The social and economic data are coming from *China City Statistical Yearbook* and *China Environment Yearbook* from 2013 to 2017 and the concentration of $PM_{2.5}$ can be got from the Globe Annual $PM_{2.5}$ Grids at the *Socioeconomic Data and Application Center* (SEDAC) at Columbia University.² We matched the administrative boundaries of Chinese cities with the annual $PM_{2.5}$ grids data in every city. After matching and calculating with the Arcgis 10.4, we could extract the $PM_{2.5}$ concentration of 277 cities from 2012 to 2016, and it is more exact than data coming from Chinese official statistical yearbooks.

3.2 Methodology

3.2.1 Spatial econometric models

(1) Spatial autocorrelation model

The spatial autocorrelation model can be summarized by the first law of geography, which is indicated by Moran's index. Moran's index is divided into two categories: global Moran's index and local Moran's index. The global Moran's index is used to measure the inner relationship among spatial elements from a holistic perspective, which ranges from -1 to 1 . The calculation is as follows:

$$I(d) = \frac{\sum_{i=1}^n \sum_{j=1}^n W_{ij} (X_i - X) (X_j - X)}{S^2 \sum_{i=1}^n \sum_{j=1}^n W_{ij}} \quad (2)$$

In this formula, S^2 and X represent the sample variance and sample mean, respectively. X_i is a spatial element value in area i , and W_{ij} indicates the spatial weight matrix. Referring to Elhorst (2010), the methods of building spatial weight could be divided into three categories: binary contiguity matrix, distance function matrix (inverse distance matrix) and economic weight matrix. With frequent interregional activities, the distance and location between two cities might play more important role in exploring spatial spillover effects when compared with other factors. Thus, we adopt inverse distance matrix in this paper to measure the spillover effects of environmental regulation which based on interregional policy effects. It could be calculated by the reciprocal distance between cities. The specific form of the matrix is shown in Eq. (3), where W_{ij} stands for the inverse distance matrix and d_{ij} is the distance between city i and city j .

² The homepage of SEDAC is: <https://sedac.ciesin.columbia.edu/data/set/sdei-global-annual-gwr-pm2-5-modis-misr-seawifs-aod/data-download>.

$$W_{ij} = \begin{cases} \frac{1}{d_{ij}}, & i \neq j \\ 0, & i = j \end{cases} \quad (3)$$

In geography, value of the global Moran's index usually ranges from 0 to 1 based on adjacency or Euclidean distance. It is mainly used to describe the spatial correlation and pattern in a specific region from global and local perspectives. This study uses Moran's index to analyze the spatial agglomeration and evolution characteristics of the concentration of PM_{2.5} and industrial agglomeration level. At a given level of significance, the global Moran's index greater than zero represents that the pollution emission has a significant positive correlation in the spatial distribution, the adjacent space regions have similar properties, and vice versa. However, if the global Moran's index is not significantly different from zero, it means that there is no spatial dependence among the sample observations and the pollutant emissions shows a random spatial distribution.

(1) Spatial Durbin model (SDM)

In order to ensure the consistency of coefficient regression results, we adopt spatial Durbin model (SDM) which is the most general form of spatial econometric models to measure the spatial spillover effect of environmental regulation (Shao and Su 2017). The SDM model is shown in Eq. (4):

$$Y_{it} = \alpha + \beta \sum_{j=1}^n X_{it} + \rho \sum_{j=1}^n W_{ij} Y_{jt} + \sigma \sum_{j=1}^n W_{ij} X_{it} + \mu_i + \tau_t + \epsilon_{it} \quad (4)$$

In Eq. (4), we choose environmental regulation intensity as the key variable. Y_{it} represents the concentration of PM_{2.5} or industrial agglomeration level in city i at year t , X_{it} is the covariates. W_{ij} denotes the inverse distance matrix. μ_i are city-fixed effects, τ_t are year-fixed effects and ϵ_{it} is the error term. ρ is the spatial autoregressive parameter.

When it contains spatial autoregressive parameter in SDM, the coefficient cannot reflect the effect from explained variables to explanatory variables. According to the example from Griffith and Paelinck (2011), we estimated the indirect effects of the EPI, which could reflect the marginal effect of explanatory variables in a specific region on the explained variable of all other regions, it is also named as the spillover effect.

3.2.2 Instrumental variable (IV)

Since the *environmental regulation intensity* and *haze pollution* may have reverse causality (on one hand, environmental regulation could control the emission of PM_{2.5}, on the other hand, cities with higher PM_{2.5} concentration might implement more serious environmental regulation). In order to solve such endogenous problem, *promotion pressure on local officials* was selected as an instrumental variable (IV) for *environmental regulation intensity*. As we all known, the promotion of Chinese local officials is mainly dominated by economic growth instead of pollution control effects. As a result of it, the promotion pressure on local officials is not related to haze pollution directly, however, the local officials have a significant impact on environmental regulation (Zhou et al. 2019). Based on the *Database of Municipal Party Secretaries and Mayors of the People's Republic of China*, we could get the local official data. Following the study from Qian et al. (2011), we could also calculate the values of *promotion pressure of local officials* from the perspectives of *local GDP growth rate*, *local fiscal surplus* and *local unemployment rate*, which are usually adopted

Table 1 Descriptive statistics

Category	Variable	Observations	Mean	Std.Dev	Min	Max
DV	<i>pm2.5</i>	1385	39.003	16.838	7.237	86.479
KV	<i>envi_regu</i>	1385	1.364	1.319	0.102	11.189
TV	<i>ind_aggl</i>	1385	0.595	0.677	0.0252	4.661
EV	<i>lnsecond_gdp</i>	1385	3.871	0.236	2.705	4.393
	<i>lnfdi</i>	1385	10.055	1.811	2.773	14.941
SV	<i>lnpop_den</i>	1385	5.793	0.793	3.157	7.735
	<i>high_edu</i>	1385	171.477	212.68	0.592	1185.76
GV	<i>fis_gdp</i>	1385	0.174	0.0998	0.0082	1.106
NV	<i>lngreen</i>	1385	3.658	0.169	2.884	4.411

DV denotes the dependent variables, *KV* denotes the key explanatory variables, *TV* represents the threshold variable, *EV*, *SV*, *GV* and *NV* are control variables which represent some variables in economic development, social factors, government fiscal ability and natural factor, respectively

as the performance evaluation indicators of local officials. Furthermore, Entropy method was adopted to measure the composite index of promotion pressure of local officials. The computational processes of these indicators are easy to realize and we skip the calculation formulas to save space.

3.2.3 Panel threshold model

According to panel threshold model proposed by Hansen (1999), this paper constructs the threshold regression model with *industrial agglomeration level* as the threshold variable. As the changing of threshold variable, the relationship between environmental regulation and haze pollution varies nonlinearly. We took double thresholds model as an example in Eq. (5).

$$\begin{aligned}
 PM2.5_{i,t} = & \alpha + \beta_1 lnsecond_gdp_{i,t} + \beta_2 lnfdi_{i,t} + \beta_3 lnpop_den_{i,t} \\
 & + \beta_4 high_edu_{i,t} + \beta_5 exp_gdp_{i,t} + \beta_6 lngreen_{i,t} \\
 & + \theta_1 env_regu_{i,t} * I(ind_aggl) + \theta_2 env_regu_{i,t} * I(< ind_aggl) \\
 & + \theta_3 env_regu_{i,t} * I(ind_aggl) > \gamma_2 + \epsilon_{i,t}
 \end{aligned} \quad (5)$$

where *env_regu* represents environmental regulation, *ind_aggl* is the threshold, γ_n are the threshold values of *ind_aggl*. In this formula, *i* represents city, *t* represents year; α is the intercept. β_n are the coefficients of control variables. θ_n are the corresponding estimated coefficients of *environmental regulation* when ϵ is the error term.

4 Empirical results

4.1 Descriptive statistics

The descriptive statistics of all the dependent, explanatory and control variables are shown in Table 1. In order to weaken heteroscedasticity during the regression process, we took continuous variables to their natural logarithm.

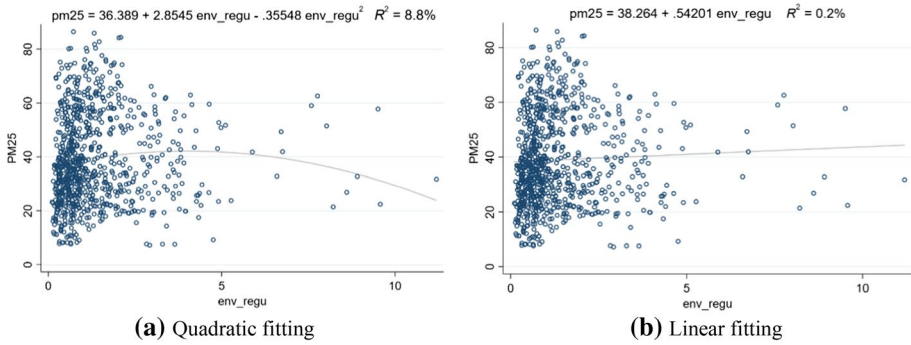


Fig. 3 The concentration of PM_{2.5} versus environmental regulation for 277 cities in China during 2012–2016

Table 2 The globe Moran’s index

Year	The concentration of PM _{2.5}		Industrial agglomeration level	
	Moran’s I	Prob	Moran’s I	Prob
2012	0.177	0.008***	0.1862	0.011**
2013	0.1232	0.023**	0.1952	0.01**
2014	0.1838	0.011**	0.202	0.006***
2015	0.1971	0.01**	0.2004	0.007***
2016	0.1928	0.007***	0.2061	0.008***

*indicates $p < 0.10$, **indicates $p < 0.05$, ***indicates $p < 0.01$

Before carrying out main econometric analysis, we take pretest to fit the scatter plot of the environmental regulation intensity and haze pollution values. As is shown in Fig. 3, the R -squared values of Fig. 3a is higher than Fig. 3b, which indicates that the relationship between environmental regulation and haze pollution is more suitable to be drawn by quadratic fitting. The result of pretest confirms our non-linear relationship assumption.

4.2 Spatial econometric analysis

4.2.1 Global Moran’s index

The most outstanding innovation of spatial econometric model is adding the spatial weight matrix (W_{ij}) to ordinary regression [Eq. (4)]. Using software Arcgis 10.4, we extracted the coordinates of 277 sample cities, then we transferred them into the inverse distance matrix (277×277) with Stata 15.0. The spatial autocorrelation analysis should be used to reveal the temporal and spatial characteristics of haze pollution and industrial agglomeration, which could be represented by global Moran’s index with Eq. (2). The result of spatial autocorrelation analysis is shown in Table 2.

From Table 2, we can find that the spatial agglomeration effects are all positive significantly at the 5% level. The globe Moran’s index analysis revealed that pollution emissions and industrial agglomeration have significantly spatial clustering phenomenon at the cities level,

which both implied that the standard OLS regressions of the environmental regulation effects may be not suitable for spatial panel data in this empirical analysis since the spillover effect might result to the estimation error (Wang et al. 2019b; Elhorst 2015). Thus, we adopt spatial durbin method (SDM) to further explore the spatial spillover effects of *environmental regulation intensity* in China.

4.2.2 Spatial regression analysis of environmental regulation effects on $PM_{2.5}$ (Path 1)

In order to prove Path 1, we need to confirm the non-linear effect of environmental regulation firstly and then identify its spatial spillover effect. As the city-level data is adopted in this study and each city has its own socio-economic characteristics, we controlled the city-fixed effects and year-fixed effects in all of the spatial regressions to eliminate the missing variables problems caused by unobservable factors. Considering the possible reverse causality between environmental regulation and haze pollution, although the dynamic spatial econometric model could alleviate the endogeneity to some extent, it could not completely eliminate the estimation error of reverse causality (Zhou et al. 2020). We used *promotion pressure of local officials* as the instrumental variable for *environmental regulation intensity* which could exactly identify the causal relationship with SDM used IV estimation. Table 3 reports the spatial econometric analysis results with SDM and 2SLS, of which columns (1)(3)(5)(7) and (2)(4)(6)(8) are the common SDM and spatial 2SLS model results, respectively.

According to the results from Table 3, all Adjusted- R^2 values could meet the model fitting requirements. The spatial autoregressive coefficient ρ ($W \times PM_{2.5}$) is positive and significant at the 1% level, which indicates that the $PM_{2.5}$ concentration have positive spillovers through all three regions in China. The coefficients of environmental regulation on haze pollution (*envi_regu*) are uncertain and insignificant, it is consistent with Fig. 3 and identify the non-linear effects of environmental regulation. Regarding the spillover effect of environmental regulation on haze pollution concentration, we found that the coefficients of $W \times enviro_regu$ are differential in eastern, central and western China: in eastern and central regions, $W \times enviro_regu$ are significantly negative in relation to $PM_{2.5}$ concentration, while they are significantly positive in western areas. This suggests that the increasing of environmental regulation intensity in eastern and central China could help to reduce the haze concentration in the surrounding areas, because strict environmental regulations have “deterrence effect” on enterprises in an industrial cluster and promote technological innovation diffusion with imitation behaviors in surrounding cities (positive spatial spillover effect). While in western areas, increasing environmental regulation intensity promote the enterprises migration which transfer the pollution emission to surrounding areas and actually deteriorate the haze pollution (negative spatial spillover effect). In addition, since the Wald-F statistical values all exceed 10, which confirms that promotion pressure on local officials could be adopted as an instrumental variable for environmental regulation intensity with empirical evidence. And the results of common SDM and 2SLS-SDM are robust, demonstrating the accuracy and effectiveness of the results. Concerning the function of control variables, it could ensure the overall fitness of the model.

Table 3 SDM regression results for environmental regulation and PM_{2.5} concentration

Variables (PM _{2.5})	(1)		(2)		(3)		(4)		(5)		(6)		(7)		(8)
	All	SDM	2SLS	SDM	Eastern	SDM	2SLS	Central	SDM	2SLS	Western	SDM	2SLS	SDM	2SLS
<i>envir_regu</i>	0.0261 (0.11)	0.0243 (0.10)	0.0243 (0.10)	-0.127 (-0.33)	-0.127 (-0.33)	-0.127 (-0.33)	-0.085 (-0.49)	-0.0135 (-0.04)	-0.0135 (-0.04)	-0.0273 (-0.15)	0.668 (0.95)	0.668 (0.95)	0.539 (0.61)	0.668 (0.95)	0.539 (0.61)
<i>Insecond_gdp</i>	-0.3603 (-0.17)	-0.267 (-0.15)	-0.267 (-0.15)	-2.503 (-0.69)	-2.503 (-0.69)	-2.503 (-0.69)	-4.91 (-0.76)	2.0597 (0.6)	2.0597 (0.6)	3.452 (0.238)	-9.239*** (-2.97)	-9.239*** (-2.97)	-7.986*** (-3.05)	-9.239*** (-2.97)	-7.986*** (-3.05)
<i>lnfdi</i>	0.105 (0.66)	0.076 (0.71)	0.076 (0.71)	-0.527* (-1.75)	-0.527* (-1.75)	-0.527* (-1.75)	-0.386* (-1.73)	0.134 (0.32)	0.134 (0.32)	0.266 (0.56)	-1.185*** (-3.42)	-1.185*** (-3.42)	-1.403*** (-2.99)	-1.185*** (-3.42)	-1.403*** (-2.99)
<i>lnpop_den</i>	0.574 (0.44)	0.631 (0.39)	0.631 (0.39)	2.815** (2.05)	2.815** (2.05)	2.815** (2.05)	5.621** (1.99)	-3.348 (-0.62)	-3.348 (-0.62)	-3.164 (-0.56)	3.610*** (3.61)	3.610*** (3.61)	2.909*** (3.91)	3.610*** (3.61)	2.909*** (3.91)
<i>high_edu</i>	0.012*** (2.85)	0.035*** (2.14)	0.035*** (2.14)	0.00538 (0.53)	0.00538 (0.53)	0.00538 (0.53)	0.0114 (0.41)	0.0101* (1.95)	0.0101* (1.95)	0.0127* (1.94)	-0.001 (-0.22)	-0.001 (-0.22)	-0.001 (-0.19)	-0.001 (-0.22)	-0.001 (-0.19)
<i>fis_gdp</i>	-0.249 (-0.13)	-0.671 (-0.24)	-0.671 (-0.24)	-3.912 (-0.49)	-3.912 (-0.49)	-3.912 (-0.49)	-2.854 (-0.78)	2.039 (0.44)	2.039 (0.44)	2.406 (0.52)	-2.673 (-0.56)	-2.673 (-0.56)	-2.043 (-0.43)	-2.673 (-0.56)	-2.043 (-0.43)
<i>lngreen</i>	-1.243 (-1.17)	-2.751 (-1.19)	-2.751 (-1.19)	-1.046 (-0.48)	-1.046 (-0.48)	-1.046 (-0.48)	-3.301 (-0.91)	-3.660** (-1.99)	-3.660** (-1.99)	-2.881** (-2.01)	1.636 (0.62)	1.636 (0.62)	1.371 (0.71)	1.636 (0.62)	1.371 (0.71)
<i>W × envir_regu</i>	-3.055** (-2.60)	-1.618*** (-2.94)	-1.618*** (-2.94)	-2.474* (-1.85)	-2.474* (-1.85)	-2.474* (-1.85)	-2.374* (-1.93)	-1.902* (-1.79)	-1.902* (-1.79)	-2.374 (-1.62)	11.12** (2.17)	11.12** (2.17)	10.011** (2.09)	11.12** (2.17)	10.011** (2.09)
<i>W × lnsecond_gdp</i>	-41.289*** (-4.08)	-25.363** (-2.71)	-25.363** (-2.71)	28.623*** (2.77)	28.623*** (2.77)	28.623*** (2.77)	31.129*** (3.98)	9.181 (1.2)	9.181 (1.2)	7.723* (1.83)	-42.09** (-2.38)	-42.09** (-2.38)	-19.77** (-2.11)	-42.09** (-2.38)	-19.77** (-2.11)
<i>W × lnfdi</i>	-0.468 (-0.47)	-0.587 (-0.52)	-0.587 (-0.52)	-2.033** (-2.03)	-2.033** (-2.03)	-2.033** (-2.03)	-1.436** (-2.12)	-2.099 (-1.15)	-2.099 (-1.15)	-3.125 (0.36)	-8.51*** (-3.13)	-8.51*** (-3.13)	-6.96*** (-3.61)	-8.51*** (-3.13)	-6.96*** (-3.61)
<i>W × lnpop_den</i>	7.681 (0.56)	4.831 (0.49)	4.831 (0.49)	49.92*** (4.34)	49.92*** (4.34)	49.92*** (4.34)	31.76*** (3.95)	-77.915** (-2.11)	-77.915** (-2.11)	-53.043** (-2.09)	32.157*** (4.26)	32.157*** (4.26)	61.287*** (5.08)	32.157*** (4.26)	61.287*** (5.08)

Table 3 (continued)

Variables (PM _{2.5})	(1)		(2)		(3)		(4)		(5)		(6)		(7)		(8)		
	All	SDM	2SLS	SDM	Eastern	SDM	2SLS	SDM	Central	SDM	2SLS	SDM	Western	SDM	2SLS	SDM	
<i>W × high_edu</i>	0.228*** (4.29)	0.538*** (3.19)	0.135** (2.08)	0.253*** (2.03)	0.095*** (2.94)	0.138*** (3.18)	0.095*** (2.94)	0.138*** (3.18)	0.095*** (2.94)	0.138*** (3.18)	0.095*** (2.94)	0.138*** (3.18)	0.095*** (2.94)	0.138*** (3.18)	0.095*** (2.94)	0.138*** (3.18)	0.095*** (2.94)
<i>W × fis_gdp</i>	16.324 (0.88)	9.652 (0.71)	-58.492*** (-3.37)	-41.278** (-2.52)	2.682 (0.39)	2.342 (0.56)	2.682 (0.39)	2.342 (0.56)	2.682 (0.39)	2.342 (0.56)	2.682 (0.39)	2.342 (0.56)	2.682 (0.39)	2.342 (0.56)	2.682 (0.39)	2.342 (0.56)	2.682 (0.39)
<i>W × lngreen</i>	-3.032 (-0.26)	-5.711 (-0.34)	2.318 (0.22)	2.389 (0.56)	-25.672** (-2.44)	-31.349** (-2.39)	-25.672** (-2.44)	-31.349** (-2.39)	-25.672** (-2.44)	-31.349** (-2.39)	-25.672** (-2.44)	-31.349** (-2.39)	-25.672** (-2.44)	-31.349** (-2.39)	-25.672** (-2.44)	-31.349** (-2.39)	-25.672** (-2.44)
ρ (<i>W × PM_{2.5}</i>)	0.976*** (89.76)	0.769*** (78.12)	0.742*** (8.38)	1.304*** (4.27)	0.946*** (41.42)	0.735*** (21.13)	0.946*** (41.42)	0.735*** (21.13)	0.946*** (41.42)	0.735*** (21.13)	0.946*** (41.42)	0.735*** (21.13)	0.946*** (41.42)	0.735*** (21.13)	0.946*** (41.42)	0.735*** (21.13)	0.946*** (41.42)
IV <i>F</i> value	-	24.17	-	29.88	-	17.52	-	17.52	-	17.52	-	17.52	-	17.52	-	17.52	-
Adjusted- <i>R</i> ²	0.231	0.702	0.445	0.679	0.337	0.695	0.337	0.695	0.337	0.695	0.337	0.695	0.337	0.695	0.337	0.695	0.337
Log <i>L</i>	-2059.429	-1861.964	-538.482	-398.349	-897.884	-542.644	-897.884	-542.644	-897.884	-542.644	-897.884	-542.644	-897.884	-542.644	-897.884	-542.644	-897.884
Observations	1385	1385	485	485	545	545	545	545	545	545	545	545	545	545	545	545	545
Number of groups	277	277	97	97	109	109	109	109	109	109	109	109	109	109	109	109	109

T statistics are in parentheses. *indicates $p < 0.10$, **indicates $p < 0.05$, ***indicates $p < 0.01$

4.3 Industrial agglomeration threshold analysis of effective environmental regulation (Path 2)

4.3.1 Spatial spillover analysis of environmental regulation on industrial agglomeration

In order to prove Path 2, it is necessary to identify the moderating function of industrial agglomeration which could reflect the enterprises migration characteristic at first. As in shown in Fig. 2, affected by the negative externalities of agglomeration, enterprises migration will increase industrial agglomeration level and turn out spatial spillover effects. Thus, we explored the spatial spillover effects of environmental regulation on industrial agglomeration with the method SDM in Table 4.

Table 4 shows that there is a significant positive correlation between the *environmental regulation intensity* and *industrial agglomeration level* in local cities according to the coefficients of *envir_regu*. Regarding the spatial spillover effect of environmental regulation, it can be found that the coefficients of $W \times \text{envir_regu}$ are significantly negative related to *industrial agglomeration level* in eastern and central China, while the results are positive significantly in the west. It demonstrates that even increasing the environmental regulation intensity in the eastern and central cities could syphon industrial enterprises from surrounding areas to promote their own industrial agglomeration level. And technological innovations have transitivity within industrial cluster to realize pollutant reduction (positive externalities of agglomeration). But such externalities of environmental regulation force local enterprises to migrate to other western cities which might aggravate the haze pollution in adjacent cities (negative externalities of agglomeration). SDM analysis confirms that industrial agglomeration adjusts environmental regulation influence on haze pollution through enterprises cross-regional diffusion. That is to say, *industrial agglomeration level* could be the threshold variable of *environmental regulation intensity*.

4.3.2 Panel threshold regression (full sample)

Before panel threshold regression, it is necessary to explore the number of thresholds and set basic regression equation correctly. This paper adopts *industrial agglomeration level* as the threshold variable of *environmental regulation intensity*. We carry out threshold effect tests for the hypotheses of single threshold, double thresholds and triple thresholds, respectively.

The threshold effect test results are obtained after 500 bootstrap iterations in estimating several equations (Table 5). The single threshold effect and double thresholds effect are significant at the 5% and 1% significance level, respectively. Therefore, this paper sets the econometric model as double thresholds model to get a more exact estimation (Eq. (5)).

Table 6 gives the specific threshold values and their corresponding 95% confidence intervals. Figure 4 shows the likelihood ratio (LR) function diagram of the double threshold estimators. The threshold estimators are the γ values when the likelihood ratio statistic equal to 0. With the assumption of single threshold, its threshold value 0.987 and the first value of double thresholds are similar. Moreover, the range of confidence interval when adopting single threshold model is wide. Therefore, it is unsuitable for us to use single threshold model to identify the threshold effect of industrial agglomeration. With the method of double thresholds model, we get the threshold estimators of *industrial*

Table 4 SDM regression results for environmental regulation and industrial agglomeration

Variables (ind_aggl)	Eastern	Central	Western
<i>envir_regu</i>	0.055*** (6.95)	0.071*** (12.44)	0.238*** (6.23)
<i>lnsecond_gdp</i>	0.131* (1.68)	0.368*** (6.23)	0.0647 (0.39)
<i>lnfdi</i>	0.0034 (0.49)	-0.0016 (-0.22)	0.187*** (10.01)
<i>lnpop_den</i>	0.0039 (0.14)	0.0304 (0.33)	-0.143*** (-2.66)
<i>high_edu</i>	0.0001 (0.65)	0.0001 (1.17)	-0.0004** (-2.27)
<i>fis_gdp</i>	0.288* (1.71)	-0.0898 (-1.12)	0.325 (1.26)
<i>lngreen</i>	-0.006 (-0.13)	-0.0002 (-0.01)	0.153 (1.07)
<i>W × envir_regu</i>	-0.0355* (-1.89)	-0.139*** (-6.52)	0.49* (1.78)
<i>W × lnsecond_gdp</i>	-0.201 (-0.34)	-0.286 (-1.25)	1.564 (1.58)
<i>W × lnfdi</i>	0.172*** (4.89)	-0.0432 (-0.88)	-0.263* (-1.85)
<i>W × lnpop_den</i>	-0.379 (-1.59)	1.01 (1.48)	1.500*** (3.8)
<i>W × high_edu</i>	-0.001 (-0.47)	-0.0032*** (-4.4)	0.003** (2.52)
<i>W × fis_gdp</i>	-3.235*** (-3.44)	-0.728 (-1.47)	0.492 (0.22)
<i>W × lngreen</i>	-0.158 (-0.4)	0.0777 (0.34)	1.693 (1.36)
ρ (<i>W × ind_aggl</i>)	-0.534* (-1.84)	0.362** (2.11)	-1.278*** (-3.32)
Adjusted- R^2	0.271	0.239	0.671
Log <i>L</i>	339.099	606.3655	-109.6203
Observations	485	545	355
Number of groups	97	109	71

T statistics are in parentheses. *indicates $p < 0.10$, **indicates $p < 0.05$, ***indicates $p < 0.01$

Table 5 The results of threshold effect test

Threshold	<i>F</i> stat	Prob	BS	Crit1	Crit5	Crit10
Single	8.817**	0.028	500	12.318	7.238	5.577
Double	62.647***	0.000	500	-5.711	-7.254	-8.858
Triple	0.000	0.913	500	0.000	0.000	0.000

*indicates $p < 0.10$, **indicates $p < 0.05$, ***indicates $p < 0.01$

Table 6 Threshold value estimation results

Threshold	Threshold estimator	95% confidence interval
Single threshold (γ_1)	0.987	(0.052, 3.523)
Double threshold (γ_1)	1.271	(1.262, 1.271)
Double threshold (γ_2)	0.818	(0.818, 1.157)
Triple threshold (γ_3)	1.157	(1.157, 1.157)

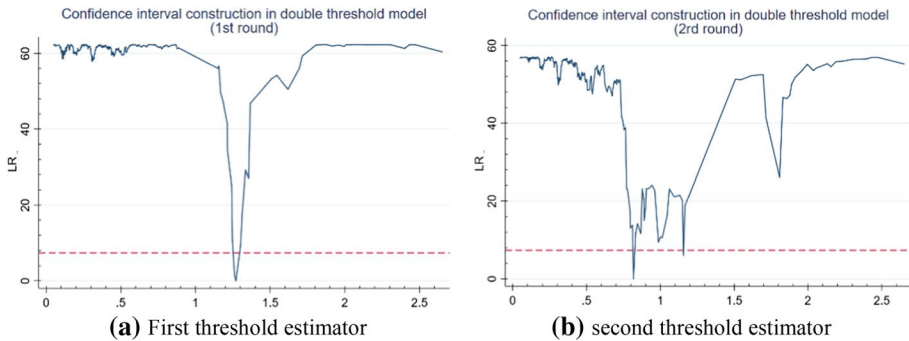


Fig. 4 Likelihood ratio function diagram of the threshold estimators

Table 7 Threshold model estimation results

Variables	Coefficient	Std. err	Prob
$env_regu \times I(ind_aggl \leq 0.818)$	-0.516	0.67	0.441
$env_regu \times I(0.818 < ind_aggl \leq 1.271)$	5.221***	0.851	0.000
$env_regu \times I(ind_aggl > 1.271)$	-0.613**	0.302	0.047
$lnsecond_gdp$	1.442	2.13	0.499
$lnfdi$	-0.271	0.295	0.360
$lnpop_den$	8.51***	0.792	0.000
$high_edu$	-0.0039	0.0029	0.178
fis_gdp	-9.434**	3.669	0.010
$lngreen$	-1.663	2.019	0.410
$_cons$	-5.0215	11.847	0.672
F-statistics	27.26***	-	0.000
Adjusted- R^2	0.399		

*indicates $p < 0.10$, **indicates $p < 0.05$, ***indicates $p < 0.01$

agglomeration level of 0.818 and 1.271. As is shown in Fig. 4, projection below the part of dotted line on the horizontal axis is the confidence interval at the 5% significance level.

Table 7 illustrates the panel regression results of double thresholds model. All of the model fitting estimates are satisfactory. There are three coefficients of *environmental regulation intensity* that change nonlinearly because of the values of the threshold variable (*industrial agglomeration level*). We classify the threshold effects of industrial agglomeration into three categories. When industrial agglomeration level is lower than the first threshold ($ind_aggl \leq 0.818$), the coefficient of environmental regulation effect is negative,

Table 8 Threshold effect test results in eastern, central and western regions of China

Threshold	Eastern	Central	Western
Threshold (γ_1)	0.690*** (10.072)	0.306*** (7.219)	0.184*** (17.095)
Threshold (γ_2)	1.529*** (35.233)	0.535*** (11.244)	–
BS	500	500	500

T statistics are in parentheses. *indicates $p < 0.10$, **indicates $p < 0.05$, ***indicates $p < 0.01$

but insignificant (-0.516), it means the environmental regulation will cause the “compliance” of enterprises at primary stage of industrial agglomeration, and environmental regulation will promote emission reduction effect to some extent. However, due to these environmental regulations don’t have binding effect, and the pollutant reduction effect is not significant. In the middle stage of industrial agglomeration ($0.818 < \text{ind_aggl} \leq 1.271$), the effect turns to positive significantly (5.221) which indicates strengthening environmental regulation might promote haze pollution emission. It means that the negative externality of industrial agglomeration is prominent, environmental regulations could only bring out enterprises migration and it cannot drive the green technology progress of enterprises. In this stage, agglomeration increases the consumption of resources and energy which aggravates the environmental pollution. When *industrial agglomeration level* exceeds the second threshold ($\text{ind_aggl} > 1.271$), negative externality of industrial agglomeration dominates and strengthening environmental regulation could reduce $\text{PM}_{2.5}$ concentration definitely. Regarding the second threshold, where the environmental regulation effects vary different on both sides. Only when the industrial agglomeration level exceeds the threshold, will the haze emission reducing effect of enhance environmental regulation significantly. The results also provide strong evidence for Pang et al. (2019) conclusion.

In addition, the estimated coefficients of control variables on haze pollution are essentially as expected. The population density is positively related with $\text{PM}_{2.5}$ concentration, which indicates the population growth will significantly increase the local environmental pressure and strict household registration policy should be adopted. Higher per GDP could promote technological innovation thus it results in lower haze pollution emission significantly. Alternately influenced by “pollution heaven” and “pollution halo” hypotheses, the coefficient of FDI appears to be negative, but not significant. At the same time, the effects of industrial structure, higher education level and the green coverage are all uncertain on haze pollution reduction.

4.3.3 Panel threshold regression (regional heterogeneity)

In order to explore the regional heterogeneity of industrial agglomeration threshold effect on effective environmental regulation, we also divided China into eastern, central and western areas to implement panel threshold regressions, respectively.

Tables 8 and 9 demonstrate the regional disparities of industrial agglomeration threshold effect on effective environmental regulation. All of the model fitting estimates are satisfactory and it could be concluded that double thresholds model should be adopted in eastern and central regions, while single threshold model used in western region. Table 9 reflects the threshold model estimation results in different areas. The environmental regulation intensity in central and western regions plays a “multi-stage promotion” role on

Table 9 Threshold model estimation results in eastern, central and western regions of China

Variables	Eastern	Central	Western
$env_regu \times I(ind_aggl \leq \gamma_1)$	-10.871*** (-4.60)	2.045** (2.07)	9.432*** (2.75)
$env_regu \times I(\gamma_1 < ind_aggl \leq \gamma_2)$	-6.247 (-0.17)	4.114*** (4.22)	-0.466 (-0.50)
$env_regu \times I(ind_aggl > \gamma_2)$	-3.809*** (-5.02)	0.577 (1.16)	-
$lnsecond_gdp$	12.030** (2.32)	-8.729*** (-2.72)	-10.14** (-2.13)
$lnfdi$	-0.508 (-0.79)	0.270 (0.45)	0.414 (1.03)
$lnpop_den$	8.697*** (3.54)	14.58*** (9.83)	2.485** (2.11)
$high_edu$	-0.010* (-1.86)	-0.007 (-1.60)	-0.008* (-1.97)
fis_gdp	-27.072* (-1.84)	-11.59* (-1.87)	-5.910 (-1.39)
$lngreen$	0.221 (0.05)	-0.903 (-0.23)	3.283 (1.17)
$_cons$	-33.482 (-1.07)	-8.901 (0.39)	39.73* (1.75)
F -statistics	11.21***	28.62***	13.85***
Adjusted- R^2	0.439	0.644	0.537
N	485	545	355

T statistics are in parentheses. *indicates $p < 0.10$, **indicates $p < 0.05$, ***indicates $p < 0.01$

haze pollution emission under the adjustment of industrial agglomeration threshold, which indicates the industrial development in central and western China is still at the expense of environmental pollution and far away from cleaner production (Cheng 2016). On the contrary, it turns out to be a “triple-stage downward” trend in eastern China, which illustrates that environmental regulation could promote haze pollution reduction due to the positive externality of agglomeration. But along with the increase in industrial agglomeration level, the coefficients (absolute values) of environmental regulation variable change to decrease (from 10.871 decreasing to 3.809) because of marginal diminishing effect of pollution reduction (Bommer 1999). In order to realize effective haze pollution reduction in eastern region, environmental regulation intensity should be addressed increasing, especially by means of market-based policy instruments (Blackman et al. 2018). Overall, according to the inverted U-shaped curve relationship between environmental regulation and pollution emissions (Wang et al. 2018a), the industrial agglomeration level in eastern China had exceeded the threshold where environmental regulation had positive externality, while industrial agglomeration level in central and western China were lower than the threshold where environmental regulation had negative externality. Heterogeneous environmental regulation is the solution to realize optimal scale of industrial agglomeration level.

5 Conclusions and policy implications

5.1 Conclusions

This paper explores the panel data of 277 Chinese cities from 2012 to 2016 and puts forward a new interpretation for the non-linear relationship between environmental regulation and haze pollution. We assume it could be attributed to the spatial spillover effects of environmental regulation and the industrial agglomeration threshold effect. With the method of spatial econometric model and panel threshold model, several findings can be concluded. First, using the SDM and instrumental variable (IV) methods, the spatial spillover effects of environmental regulation and haze pollution could be identified, which indicates the spillover effects of environmental regulation in eastern and central China are significantly negative in relation to $PM_{2.5}$ concentration, while they are conspicuously positive in western areas. Second, we confirmed the feasibility of industrial agglomeration threshold effect on effective environmental regulation through the analysis of environmental regulation and industrial agglomeration. Third, the three coefficients of environmental regulation intensity change non-linearly due to the value of the threshold variable (industrial agglomeration level). We also prove the environmental regulation intensity in central and western regions plays a “multi-stage promotion” role on haze pollution emission under the adjustment of industrial agglomeration threshold while it turns out to be a “triple-stage downward” trend in eastern China.

5.2 Policy implications

According to the spatial spillover effect of environmental regulation and the industrial agglomeration threshold effect on effective environmental governance, the following policy pathways are recommended to realize China's target for controlling haze pollution.

- (1) Implementing differentiated regional policies strictly. Due to the huge gaps in economic development, resource endowment, and technological innovation capabilities between different regions in China, policy makers must follow the principle of adjusting measures to local conditions when formulating industrial agglomeration policies. At the same time, the advantages and disadvantages of the industrial agglomeration development model should be scientifically evaluated according to the conditions of the comprehensive area. The government should absolutely prohibit sacrificing the environment for economic development.
- (2) Related departments should pay more attention to the spillover effect of environmental regulation on agglomeration and pollution. It is necessary to establish cross-region cooperation mechanisms in order to form a reasonable division of labor. We should not only think highly of pollution source governance, but also implement strict environmental regulation and effective governance on pollution end treatment. Simultaneous, we should promote the design and improvement of ecological compensation mechanism, and provide financial support to some areas with serious environmental pollution, in order to neutralize the losses caused by spillover in other cities.
- (3) The results of panel threshold analysis indicate that the role of environmental regulation is weak at low-industrial agglomeration levels relatively. Hence, we need to coordinate the relationships among industrial agglomeration, environmental regulation and

environmental pollution dynamically. For regions where industrial agglomeration level lower than the threshold value 1.271 (central and western cities in China), local governments should plan to attract investment to rationally guide the level of local industrial agglomeration to exceed thresholds, rather than blindly increasing the intensity of environmental regulation. For regions where industrial agglomeration exceeds the threshold value (eastern cities in China), market-based instruments of environmental regulation should be adopted to control haze pollution. Meanwhile, it is necessary to optimize industrial structure and promote green technology innovation, to ensure the sustainability of positive externality.

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