Spatial Analysis of Environmental Regulations: Evidence from Chinese Provinces

Xueming Liu¹, Li Li¹,², Jiaoju Ge¹ and Dengli Tang²

¹School of Economics and Management, Harbin Institute of Technology, Shenzhen, China
²School of Business Administration, Guangdong University of Finance and Economics, Guangdong, China

*Corresponding author e-mail: lxmngu@163.com

Abstract. This research focuses on the spatial distribution and spatial correlation of environmental regulations (ERS) with exploratory spatial data analysis technique (ESDA). The panel data of 31 provinces in China during the period of 2005-2015 is used. Finds show that the most intensive ERS region is located around Beijing-Tianjin-Hebei region. The values of global Moran’s I vary from 0.1104 to 0.2145, indicating that ERS in China is not distributed randomly, but has spatial agglomeration effects. The High–High agglomeration type is mainly distributed in north China.

1. Introduction

Recently, a satellite photo, taken by NASA in 2013 releasing the latest distribution of China’s haze-fog pollution, shocked all Chinese citizens. Rapid industrialization, urbanization and economic growth have resulted in an increase in energy consumption, air pollution, and associated health effects [1]. The China National Environmental Monitoring Center (CNEMC) reported that, in 2015, about 265 out of 338 cites could not meet the National Ambient Air Quality Standards of China, accounting for 78.4%. The population-weighted mean of PM2.5 in Chinese cities reached 61 μg/m³, about 3 times as high as global mean [2]. These showed the fact that not only China’s haze pollution problem is serious but also the ability to control it is limited. Despite of a certain degree of meteorological factors, in China, haze/smoke events are ultimately arising from inefficient environmental regulations (ERS), unbalanced industry structures, as well as irrational energy structures.

In March 2017, Premier Li first mentioned “fighting against the blue skies” at the fifth meeting of the Twelfth National People’s Congress, especially emphasized the importance of strict environmental enforcement and supervision. It shows the control of environmental pollution depends largely on the intensity, supervision and execution of ERS. Although the haze's cross-border nature and spillover characteristics make the management of haze complex, the incidents of “APEC Blue” and “Olympic Blue” have fully demonstrated that ERS is very effective in a special period. Therefore, ERS should be regarded as a necessary mean in addressing the serious air pollution.

ERS can be divided into formal regulation and informal regulation, including market-based tools and command-control tools [3]. Zeyi Zhang and Baoliang Xu (2017) [4] researched the effects of ERS on environmental pollution with introducing hidden economy. Based on the mediating effect method,
Chenyue Liu and Yingzhi Xu (2017) [5] analyzed the influence path of ERS on haze pollution and its heterogeneity. Shubin Wang and Yingzhi Xu (2015) [6] studied the decoupling effect of ERS and haze pollution from the perspective of enterprise investment preferences. Danhe Liu and Xiaochen Wang (2017) [3] reviewed studies on ERS theory, including the game of ERS based on different political systems and market mechanisms, and the effectiveness of ERS tools and regulation policies. While many studies have investigated the effects, paths, heterogeneities, policies, mechanisms of ERS, its spatial analysis in China is largely neglected.

2. Method

2.1. Data sources
To analyze ERS, the panel data of 31 provinces in China during the period of 2005-2015 is used in this study. All the original economic and regulated data are taken from National Statistical Yearbook and China Statistical Yearbook for Regional Economy.

2.2. Exploratory spatial data analysis (ESDA)
The technology of ESDA is an effective method to analyze the spatial spillover effect of environmental regulations [7], including global spatial auto-dependence (GSA) and local spatial auto-dependence (LSA).

2.2.1. Global spatial auto-dependence. Usually, GSA is applied to describe spatial distribution characteristics in the entire study area and is measured by the indices of global Moran’s $I$, as:

$$global\text{ }Moran’s\text{ }I = \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij} (x_{i} - \bar{x}) (x_{j} - \bar{x})}{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}}$$

\[ (1) \]

Where Moran’s $I$ (values between -1 and 1) reflects the degree of similarity of attribute values of each neighboring spatial regions. Further, $n$ presents the 31 provinces and regions in mainland China. $x_{i}$ and $x_{j}$ are observed annual averaged ERS concentrations from regions $i$ and $j$, respectively. $w_{ij}$ is a spatial weight matrix. $\bar{x}$ is the average observed variables in different regions while $S^2$ is the corresponding variance. Standardize Moran’s $I$ as:

$$Z(I) = \frac{Moran’s\text{ }I - E(I)}{\sqrt{Var(I)}}, \text{ where } E(I) = -\frac{1}{n-1}, \text{ } Var(I) = \frac{n^2w_0 + nw_1 + 3w_2}{w_0(n^2 - 1)} - E^2(I)$$

\[ (2) \]

$$w_0 = \sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}, \text{ } w_1 = \frac{1}{2} \sum_{i=1}^{n} \sum_{j=1}^{n} (w_{ij} + w_{ji})^2, \text{ } w_2 = \sum_{i=1}^{n} \sum_{j=1}^{n} (w_{ij} + w_{ji})^2$$

$E(I)$ is the expected value and $Var(I)$ is the variance. $Z(I)$ follows the standard normal distribution if there is no spatial dependence, vice versa.

2.2.2. Local spatial auto-dependence. In this article, both Moran scatter plot (MSP) and local indicator of spatial association (LISA) are used to investigate the local spatial dependence of ERS in China. As one of LISA methods, local Moran’s $I$ is expressed as:
\[
local \text{ Moran's } I_j = \frac{(x_j - \bar{x})}{S^2} \sum_{j=1}^{n} w_{ij} (x_j - \bar{x})
\]  
(3)

Where \(x_j, \bar{x}, n, w_{ij}, \) and \(S^2\) are the same as calculation of global Moran's I index.

2.2.3. Spatial weight matrix. In order to investigate the spatial correlation of ERS systematically, a spatial weight matrix \(w_{ij}\) is necessary with reference to spatial layout of observation variables between different regions. In this study, a spatial-adjacency-relationship based spatial weight matrix is introduced, where \(w_{ij} = 1\) if region \(i\) and \(j\) are adjacent cells; otherwise, \(w_{ij} = 0\). \(n\) is the total number of regions. \(w_{ij}\) is calculated as follows:

\[
w_{ij} = \begin{bmatrix}
    w_{11} & w_{12} & \cdots & w_{1n} \\
    w_{21} & w_{22} & \cdots & w_{2n} \\
    \vdots & \vdots & \ddots & \vdots \\
    w_{n1} & w_{n2} & \cdots & w_{nn}
\end{bmatrix}
\]  
(4)

3. ERS Measurement

The measurement for ERS is challenging due to the large number of missing and unavailable data in the field of air pollution. In the existing literature, there are several common approaches, including concentrations or emissions[8], per capita GDP[9], industry’s annual operating cost associated with pollution control[10], pollution abatement control expenditures (PACE)[11], pollution abatement fees and pollution discharge fees[12]. Obviously, the shortcoming of above methods is the single indicator can only reflect a certain aspect of ERS, which can be problematic in our case. Therefore, in order to accurately measure the intensity of ERS in various regions of China, in this paper, we use comprehensive index assessment method (CIAM) to estimate ERS. The system of CIAM consists of one target layer (ERS composite index), three evaluation index layers (waste water, waste gas and solid waste), and a number of individual indicator layers. The calculation steps are as below:

First, standardize individual indicators

\[
UE^*_{ij} = \frac{UE_j - \text{min}(UE_j)}{\text{max}(UE_j) - \text{min}(UE_j)}
\]  
(5)

Where \(UE_j\) is the original value of the indicator, \(\text{max}(UE_j)\) and \(\text{min}(UE_j)\) are maximum and minimum values, respectively, in terms of major pollutant \(j\) in all regions, \(UE^*_{ij}\) is the normalized value.

Second, calculate the adjustment factor of each evaluation index. The role of the adjustment factor \(C_j\) is similar to the weight, which can approximately reflect the changes in the governance of major pollutants in each region, as:

\[
UE_{ij}^n = \frac{UE_j - \text{min}(UE_j)}{\text{max}(UE_j) - \text{min}(UE_j)}
\]  
(6)
Where $E_{ij} / \sum_{i} E_{ij}$ denotes the ratio of the emission of pollutant $j$ in $i$ industry ($E_{ij}$) and the total amount of similar pollutants ($\sum_{i} E_{ij}$) in the country. While $P_{i} / \sum_{i} P_{i}$ indicates the proportion of $i$ industry’s output value ($P_{i}$) to the entire industrial output value ($\sum_{i} P_{i}$). Through the identity transformation, $C_{j}$ is concluded as the ratio of unit $E_{ij}$ ($UE_{ij}$) and national average unit $E_{ij}$ ($UE_{ij}$).

Finally, calculate the environmental regulation of each single index and the comprehensive index, $S_{i}$, and ERS, respectively as:

$$S_{i} = \frac{1}{n} \sum_{j=1}^{n} C_{j} \times UE_{ij}^{5}; \quad ERS = \sum_{i=1}^{n} S_{i}$$  \hspace{1cm} (7)

### 4. Results and analysis

#### 4.1. Global Spatial Correlation Analysis

The results of standardized global Moran’s I values are listed in Table 1. Except for the year of 2014, Global Moran’s I values of ERS are generally above 0.1 and pass the significant test of $p<0.05$, indicating the significant positive correlation of spatial distribution for ERS in China rather than distributing randomly. In addition, ERS put up a spatial agglomeration phenomenon in some regions, that is, a high ERS region is often adjacent to a high ERS region, and vice versa. Meanwhile, global Moran’s I values vary from 0.1104 to 0.2145, and higher value means better agglomeration effect.

| Year | Moran’s I | E(I) | Mean | Sd. | Z (I) | P-value |
|------|-----------|------|------|-----|-------|---------|
| 2005 | 0.2135    | -0.0333 | -0.0310 | 0.0995 | 2.4561 | 0.016 |
| 2006 | 0.2145    | -0.0333 | -0.0313 | 0.1006 | 2.4429 | 0.017 |
| 2007 | 0.2070    | -0.0333 | -0.0312 | 0.1008 | 2.3618 | 0.017 |
| 2008 | 0.1899    | -0.0333 | -0.0308 | 0.0997 | 2.2150 | 0.021 |
| 2009 | 0.1802    | -0.0333 | -0.0311 | 0.1005 | 2.1032 | 0.025 |
| 2010 | 0.1713    | -0.0333 | -0.0302 | 0.1000 | 2.0151 | 0.030 |
| 2011 | 0.1772    | -0.0333 | -0.0288 | 0.1020 | 2.0196 | 0.036 |
| 2012 | 0.1685    | -0.0333 | -0.0288 | 0.1021 | 1.9327 | 0.040 |
| 2013 | 0.1618    | -0.0333 | -0.0287 | 0.1026 | 1.8577 | 0.040 |
| 2014 | 0.1104    | -0.0333 | -0.0320 | 0.1027 | 1.3862 | 0.094 |
| 2015 | 0.1823    | -0.0333 | -0.0277 | 0.1003 | 2.0934 | 0.034 |

#### 4.2. Local Spatial Correlation Analysis

To get a better understanding of spatial characteristics of ERS in China, the local spatial correlation is analyzed in this study including MSP and LISA.

#### 4.2.1. MSP.

Local Moran’s $I$ values and MSP were got from 2005 to 2015. As space is limited, only examples of the year of 2012 and 2015 are given (see Fig.1). MSP of ERS indicates that most of regions are located in the first three quadrants while only two to four regions fall in the fourth quadrant. Specifically, 9 and 7, 10 and 10, as well as 10 and 10 regions are contained in the first three quadrants, respectively, for the year of 2012 and 2015. The results confirmed the significant positive spatial correlation of ERS in China.
4.2.2. LISA. LISA is applied to check spatial aggregation type of local areas (see Fig. 2). In the local spatial distribution, ERS forms different aggregation areas. High ERS agglomeration regions are centered on Inner Mongolia and Shanxi in 2012. ERS in the regions located in high clustered areas are intensive, which can drive the increase in ERS levels in neighbouring regions through cooperation. For example, it gradually approached Hebei in 2015. Note that low-low, low-high and high-low concentration areas are not appeared.

5. Conclusions
This research studies spatial distribution and spatial correlation of ERS in China by using ESDA method. Results indicate that high ERS regions are expending to Beijing-Tianjin-Hebei region due to the different spatial distribution of ERS in every year. Global spatial correlation analysis shows that ERS in China from 2005 to 2015 exists significant positive correlation, which illustrates that high ERS regions tend to be adjacent to high ERS regions and vice versa. In addition, agglomeration phenomenon is obvious and stable, where High–High aggregation type is mainly distributed in north China, and low-low, low-high and high-low concentration areas are not appeared during the study year. Nowadays, China can no longer avoid the air pollution problem along with its getting worse, Chinese government is keen to tackle the detrimental health impact from air pollution through implementing a policy of environmental regulations. Findings in this study could provide reference for the formulation of ERS governance policies.

Acknowledgments
This work was financially supported by National Social Science Fund (No.17BJL041).
References

[1] C.K. Chan, X. Yao, Air pollution in mega cities in China, Atmospheric environment, 42(2008) 1-42.

[2] Y. Zhang, F. Cao, Fine particulate matter (PM2.5) in China at a city level, Scientific reports, 5(2015) 14884.

[3] D. LIU, X. Wang, Review on the Environmental Regulation Policy Under the Constraint Object of Economic Growth, Research on Economics and Management, 8(2017) 9.

[4] Z.Y.Zhang and B.L.Xu, Regulation Strength, Shadow Economy and Pollution Emissions, Research on Economics and Management, (2017) 100-111.

[5] C.Y.Liu and Y.Z.Xu, How dose Environmental Regulation Affect the Governance of Haze Pollution? Journal of China University of Geosciences (Social Sciences Edition), (2017) 41-53.

[6] S.B.Wang and Y.Z.Xu, Environmental Regulation and Haze Pollution Decoupling Effect—based on the Perspective of Enterprise Investment Preference, China Industrial Economics, (2015) 18-30.

[7] L. Anselin, Local indicators of spatial association—LISA, Geographical analysis, 27(1995) 93-115.

[8] M.A. Cole, R.J. Elliott, Determining the trade - environment composition effect: the role of capital, labor and environmental regulations, Journal of Environmental Economics and Management, 46(2003) 363-383.

[9] M. Mani, D. Wheeler, In search of pollution havens? Dirty industry in the world economy, 1960 to 1995, The Journal of Environment & Development, 7(1998) 215-247.

[10] W.B. Gray, The cost of regulation: OSHA, EPA and the productivity slowdown, The American Economic Review, 77(1987) 998-1006.

[11] E. Berman, L.T. Bui, Environmental regulation and productivity: evidence from oil refineries, Review of Economics and Statistics, 83(2001) 498-510.

[12] R. Xie, Y. Yuan, J. Huang, Different Types of Environmental Regulations and Heterogeneous Influence on "Green" Productivity: Evidence from China, Productivity: Evidence from China, 132(2017) 104-112.