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The influential factors of urban $PM_{2.5}$ concentrations in China: a spatial econometric analysis

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ABSTRACT

Based on the data of $PM_{2.5}$ concentrations and Air Quality Index of 73 Chinese cities in 2013, this study empirically investigates the socioeconomic influential factors of urban $PM_{2.5}$ concentrations in China. Specifically, it examines whether and how the socioeconomic development indicators such as GDP per capita, industry and transport would affect the air quality. Due to the existence of spatial autocorrelation of air pollution, conventional regression techniques that ignore the spatial autocorrelation would yield biased and inconsistent estimation results. Therefore, in this study two spatial econometric models, namely Spatial Lag Model (SLM) and Spatial Error Model (SEM), are utilized to control for spatial effects. According to the estimation results, the relationship between $PM_{2.5}$ concentrations and per capita GDP is inverted U-shaped, suggesting the existence of the inverted-U shaped Environmental Kuznets Curve (EKC) for air quality in China. In addition, the vehicle population and the secondary industry have significant and positive influences on urban $PM_{2.5}$ concentrations. As a result, a series of comprehensive measures in both social and economic aspects as well as the regional coordination of environmental policies are needed to hold China's air pollution in check.

1. Introduction

Since the reform and opening up, China's economy has been growing at a remarkable speed. However, meanwhile the environmental pollution has also become increasingly significant in China. In recent years, the contradiction between economic development and the environment intensified, which has seriously threatened China's sustainable development. Since 2012 spring, many regions in northern and eastern China have been repeatedly hit by severely hazardous haze and fog. The main component of the haze and fog pollution is fine particles (diameter of 2.5 μm or less, $PM_{2.5}$). Because $PM_{2.5}$ can easily enter the lungs and even the blood stream, and because the fine particles can persist in the air for a long time and easily move to other places with wind, $PM_{2.5}$ pollution has posed serious threats to human health and the atmospheric environment. Recently, China's air pollution has become a focus of public attention and has even provoked concerns of the international community. On January 24, 2013, Ministry of Environmental Protection (MEP) of China announced the requirements for the reduction of the total emissions of major pollutants during the "twelfth Five-Year Plan" period (2011–2015). MEP required that the air quality of all Chinese cities should reach the national secondary standard by 2030. According to the new ambient air quality standards which were in effect in 2013, the annual average concentrations of $PM_{2.5}$ should be reduced to 35 $\mu g/m^3$ or less.[1]

A large body of literature has investigated the causes and harms of $PM_{2.5}$ in the aspects of environmental science and physiology. For instance, Pope and Dockery (2006) and Semple et al. (2010) have pointed out that the high concentrations of $PM_{2.5}$ are particularly harmful to human cardiovascular and respiratory systems, and $PM_{2.5}$ pollution is also an important cause of premature death. Many existing studies focused on a certain city at a specific time spot and examined the main resources of $PM_{2.5}$ in the atmosphere. For example, Yang et al. (2013) identified the main sources and causes of $PM_{2.5}$ using observations obtained from Dec. 2007 to Oct. 2008 in Jinan, a highly polluted city in Northern China. Huang et al.

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[1] For more details of the requirements of MEP, see http://english.mep.gov.cn/News_service/Photo/201301/t20130129_245653.htm.

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(2011) developed an emission inventory method for major anthropogenic air pollutants and VOC species in the Yangtze River Delta region for the year 2007 and found that the industrial sources including power plants, other fuel combustion facilities, and non-combustion processes are the major contributors to the $PM_{2.5}$ emissions in the YRD region. These sources accounted for as much as 91% of total $PM_{2.5}$ emissions in that region. However, so far the researches on the relationship between $PM_{2.5}$ and socioeconomic development using rigorous quantitative empirical tools are still scarce. Given the fact that China is facing extensive air pollution, such empirical analyses are direly needed, because they can shed some light on the principles and reasons for the occurrence of haze and fog, and the estimation results are very useful for policy makers to formulate proper policies to reduce China's air pollution.

Based on the data of $PM_{2.5}$ and Air Quality Index (AQI) in 73 different Chinese cities, this study examines the relationship between urban air quality and the socioeconomic development in China. Concretely, the spatial econometric models are employed to investigate the influences of the level of economic development, industrial structure, transport and population on urban $PM_{2.5}$ concentrations. According to Chan and Yao (2008), China's air pollution exhibits some typical regional characteristics. Specifically, the haze and fog in one city may probably affect the air quality of its neighboring cities; therefore there might be strong spatial correlations in air quality of geographically nearby cities. For this reason, the traditional econometric techniques, including ordinary least square (OLS) and generalized least square (GLS), would lead to biased estimations because of ignoring the spatial correlations. To address this problem, in this paper the suitable spatial econometric techniques are utilized to control the potential spatial correlations in air pollution. As a result, the empirical study of this paper fills the academic gap in this field and is therefore one of the main contributions of this research.

2. Literature review

The number of literature on the relationship between economic development and environmental quality has increased rapidly since the early 1990s. Most of the empirical studies are based on the Environmental Kuznets Curve (EKC) which was first raised by Grossman and Krueger (1991, 1995). EKC is an empirical hypothesis that describes an inverted U-shaped relationship between economic development and the environment: In the early stage of economic development, the pollution increases and the environment deteriorates; after the turning point of the pollution is achieved, the pollution decreases and the environment improves as the economy continues to grow. Since the early 1990s, heated contentions have been made on the EKC hypothesis. Although a plenty of studies support the existence of inverted-U EKC (e.g., Culas, 2007; Song et al., 2008; Auffhammer and Carson, 2008; Bertinelli et al., 2008; Diao et al., 2009; Halkos and Paizanos, 2013), some researches challenged these estimation results and found evidence against the existence of EKC (e.g., Caviglia-Harris et al., 2009; Kearsley and Riddel, 2010; He and Richard, 2010). Hence the empirical results are mixed and no accordant conclusion has been drawn. In the studies supporting the existence of inverted-U EKC, for instance, Culas (2007) found significant evidence of an EKC relationship for deforestation in Latin American countries. Song et al. (2008) have found EKC relationships for three different pollutants (waste gas, waste water and solid wastes) in China, but the peaks of these pollutants appeared at different time. Bertinelli et al. (2008) developed a vintage capital model to model the possible inverted-U shaped EKC and verified the theory using footprint and biological capacity data. Diao et al. (2009) examined the EKC relationship in Jiaxing a Chinese city for six pollutants, and their results suggested that four of them (IWWD, IWGD, SD and IDD) followed EKC, while the other two (SOD and ISWP) did not. Auffhammer and Carson (2008), and Halkos and Paizanos, 2013 supported the existence of an inverted EKC for CO_2. On the other hand, some researches challenged these estimation results and found evidence against the existence of EKC. Caviglia-Harris et al. (2009) found no empirical evidence of an EKC relationship between the Ecological Footprint and economic development. Kearsley and Riddel (2010) estimated EKC relations for seven often-studied pollutants (CO_2, greenhouse gases, CO, NO_x, SO_x, PM, and VOCs) and found that confidence intervals around EKC turning points were very wide. He and Richard (2010) used semiparametric and flexible nonlinear parametric modeling methods and found little evidence in favor of the EKC hypothesis for CO_2 in Canada. For more explanations and analyses, see the reviews by Stern (2004), Dinda (2004), Müller-Fürstenberger and Wagner (2007) and Carson (2010). Generally speaking, EKC has been estimated using a wide variety of pollutants including sulfur dioxide, carbon dioxide, biological oxygen demand, nitrogen oxides, smoke, water pollution, deforestation, hazardous waste and particulate matter. However, despite the growing number of empirical studies on EKC, the researches on the relationship between $PM_{2.5}$ pollutants and the socioeconomic development are still scarce. To the best of our knowledge, the very recent study of Xu and Lin (2016) that utilized cointegration analysis with China's provincial data to investigate the key driving forces of $PM_{2.5}$ emissions at the regional level is the only exception. The reason for the lack of studies on the socioeconomic influential factors of $PM_{2.5}$ pollution is twofold. First, compared with conventional pollutants such as SO_2 and NO_x, $PM_{2.5}$ is not a big environmental problem in most developed countries, therefore the attention on $PM_{2.5}$ pollutants is not high.[2] Second, in many developing countries where $PM_{2.5}$ pollutants pose a greater threat to environment and human beings, the data for $PM_{2.5}$ pollutants are usually unavailable. Considering the fact that $PM_{2.5}$ is the main component of haze and fog in China, to investigate the relationship between the concentrations of fine particles ($PM_{2.5}$) and the economic development is very valuable and important to Chinese policy makers. Therefore in this research $PM_{2.5}$ is chosen as the main research subject.

Given the fact that haze and fog usually occurred in many areas of China at the same time, there probably exists spatial correlation within $PM_{2.5}$ concentrations of neighboring regions. According to the First Law of Geography (Tobler, 1970), all attributed values of different indicators on a geographic surface are related to one other, but closer indicators are more strongly related than the more distant ones. Since 1990s, the importance of spatial dimensions in researches on environmental issues has been pointed out by several scholars. Anselin (1988, 2001) stressed the necessity of applying the specialized techniques of spatial econometrics in environmental and resource economics. Giacomini and Granger (2004) also noted that spatial effects were important when evaluating the influences of economic growth on environmental quality. Maddison (2007) suggested that the spatial relationship incorporated in the data used to estimate EKC relations should be taken into consideration, because the cities and countries located nearby can interact with each other strongly through international trade, FDI, capital flows and environmental policies. Letchumanan and Kodama (2000) and Cole (2004) stated that some countries could acquire more environmentally-friendly technology through international trade and foreign direct investment. Keller (2004) found

[2] Several famous incidents involved with $PM_{2.5}$ pollutants in developed countries occurred in the mid-20th century, such as the smog pollution in London in 1952, and the Los Angeles photochemical smog episode in 1940s and 1950s.

that geographical distance was a major determinant of technology diffusion. Besides, most air pollutants (including $PM_{2.5}$) showed typical regional characteristics due to their high flowability (Xue et al., 2014). As Maddison (2006) pointed out, the spatial relationship incorporated in the data would cause potential spatial autocorrelation problem. Due to the high flowability of $PM_{2.5}$ and the First Law of geography, $PM_{2.5}$ pollutants in China may probably have strong spatial effects. Therefore, when utilizing the conventional econometrics techniques like ordinary least square (OLS) and generalized least squares (GLS) methods, the estimation results would be biased and invalid.[3] Compared with conventional estimation techniques, the spatial econometric approach could also help researchers to explore whether or not the regional environmental performance is dependent on the characteristics of neighboring districts. Thus, this paper utilized a spatial econometric approach to estimate the relationship between $PM_{2.5}$ and socioeconomic development.

Up to date, there have been some empirical studies on the influential factors of environmental pollution employing the spatial econometric approach that addresses the spatial autocorrelation problem. For instance, Rupasingha et al. (2004) examined the relationship between toxic pollutants and per capita income at county-level using a comprehensive EKC model and found spatial effects to be important in understanding toxic pollution in US. Maddision (2006) found that per capita emissions for two important pollutants were a function of the spatially weighted averages of the per capita emissions of neighboring countries. Hossein and Kanek (2013) studied the spatial spillover of the institutional qualities of the countries on their neighbors and found that the impact of spatial spillover on the environmental quality in neighboring countries was significant in recent decades. Wang et al. (2013) used a spatial econometric approach to re-examine the relationship between economic growth and environmental impact that is represented by ecological footprint. The results did not support the existence of inverted U-shaped EKC. In a recent research, Li et al. (2014) utilized spatial error model (SEM) and spatial lag model (SLM) to evaluate the effects of economic development, population density and industrial structure on the environment. Their results indicated that these factors were all highly correlated with the levels of SO_2 and COD emissions. However, as mentioned previously, the relationship between pollutant emissions and economic development may be nonlinear when EKC exists, but Li et al. (2014) simply ignored the possibility of linear EKC relationship. Moreover, the research subjects Li et al. (2014) focused on are the conventional pollutants (SO_2 and COD). However, as haze and fog pollution has become one of the most serious environmental threats for China today, a research on the impact of socioeconomic development on the concentrations of $PM_{2.5}$ and air quality is direly needed.

As a result, comparing with previous studies, this paper has two main contributions. First, we estimate the relationship between socioeconomic development and $PM_{2.5}$ in China, especially the EKC relationship between $PM_{2.5}$ concentrations and economic development. To the best of our knowledge, this study is the first empirical estimation for the influential factors of urban $PM_{2.5}$ concentrations in China with EKC framework using the city-level data. Second, the proper spatial econometric techniques are utilized in this study so that the spatial effects of $PM_{2.5}$ could be fully considered. By utilizing spatial error model (SEM) and a spatial lag model (SLM), the estimation bias caused by ignoring spatial correlation of air pollutants could be avoided. The results obtained by different spatial econometric estimators could also be used for robustness check.

The remainder of the paper is organized as follows. Section 3 describes the data used in the empirical part of the paper and the spatial econometric techniques. Section 4 presents the econometric empirical results of the EKC augmented by spatially weighted variables and discusses the results obtained. Section 5 presents the conclusions and corresponding policy recommendations.

3. Data and empirical method

3.1. Data

Currently, the monitoring data of urban $PM_{2.5}$ concentrations are updated every hour. Because the socioeconomic indicators are yearly data, and because the urban PM2.5 concentrations began to be regularly reported since 2013, the annual average values of urban $PM_{2.5}$ concentrations in the year 2013 are utilized in this study.[4] On 1st January 2013, the Chinese new air quality standards came into effect. According to the new standards, the concentrations of six common pollutants ($PM_{2.5}$, PM_{10}, SO_2, NO_2, O_3 and CO) are measured to calculate the Air Quality Index (AQI). Because $PM_{2.5}$ has become the main air pollutant in most of Chinese cities, the level of AQI is highly related with $PM_{2.5}$ concentrations. Therefore, the annual average of AQI is also used as a dependent variable for the robust analysis.[5] The data of $PM_{2.5}$ concentrations and AQI of 73 Chinese cities are provided by Fresh-Ideas Studio.[6]

To show the spatial characteristics of $PM_{2.5}$ concentrations in our sample cities intuitively, Fig. 1 presents the annual average of $PM_{2.5}$ concentrations of all 73 sample cities. We use circles of different sizes to represent different levels of $PM_{2.5}$ concentrations. The larger circle corresponds to the higher level of the $PM_{2.5}$ concentrations.

As shown in Fig. 1, most of the sample cities concentrated in the three most developed regions of China: Beijing-Tianjin-Hebei Region (including Beijing city, Tianjin city and Hebei province), Yangtze River Delta (including Shanghai city and provinces of Jiangsu and Zhejiang), and the Pearl River Delta (including Guangzhou city and a large part of Guangdong province). In general, the neighboring cities have similar $PM_{2.5}$ concentrations, suggesting the spatial correlation of $PM_{2.5}$ pollutants may probably exist. Concretely, the cities in the Beijing-Tianjin-Hebei Region suffer more serious haze and fog pollution than the other regions. A number of studies have partly attributed the higher $PM_{2.5}$ concentrations in the North region to the coal-based industries such as coal-fired power plants, iron and steel manufacturing (e.g., Zhang et al., 2009; Zhao et al., 2012). Comparatively, partly thanks to the developed tertiary industry which produces little pollution, the $PM_{2.5}$ concentrations in the cities of the Pearl River Delta are the lowest in the three main economic zones.

[3] The technical details of OLS and GLS could be found in a modern econometric textbook like Wooldridge (2012).

[4] At the end of 2012 China began to monitor the $PM_{2.5}$ concentration. In 2013, the observation stations in 73 Chinese cities were established and the urban $PM_{2.5}$ concentrations were regularly reported for the first time. The number of cities whose air quality is monitored has been growing steadily. In 2013 this umber was 73, in 2014 161 cities were monitored, since the beginning of 2015 all 338 prefecture-level cities in mainland China have been monitored.

[5] In fact, the AQI is a more comprehensive index that measures air quality. According to its definition, the concentration of $PM_{2.5}$ is an important but not solo influential factor of AQI. The concentrations of some other main air pollutants, such as SO_2, NO_x and PM_{10}, are all considered when the level of AQI is calculated.

[6] Fresh-Ideas Studio is a China-based professional IT group. They developed and maintained a mobile phone application (*app*) named "China Air Quality Index". At present, this *app* provides real-time data of urban $PM_{2.5}$ concentrations and AQI for more than 200 Chinese cities.

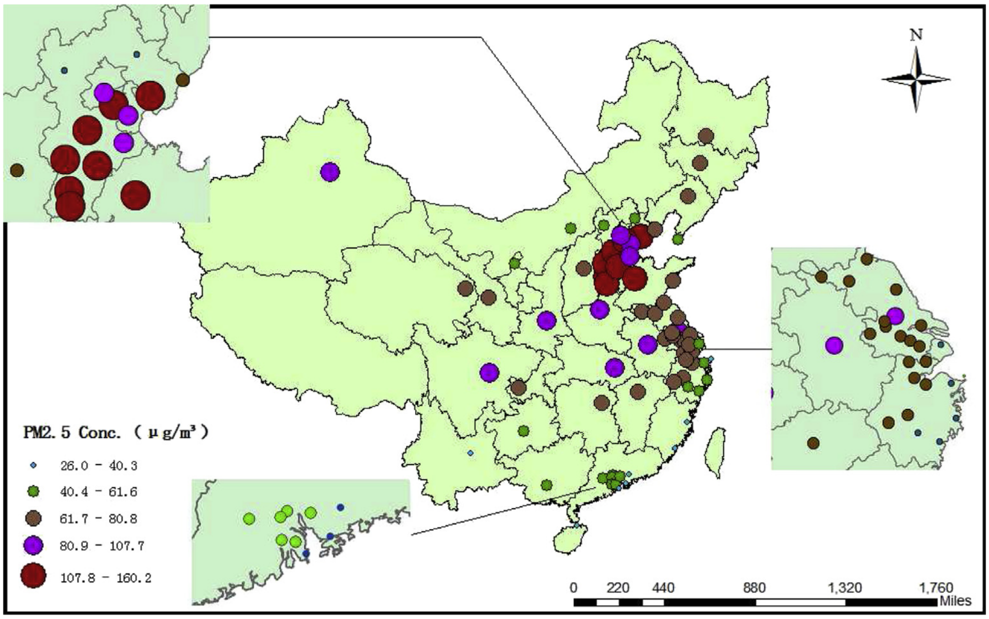

Fig. 1. The annual average $PM_{2.5}$ concentrations of 73 Chinese cities in 2013.

The possible influential factors of $PM_{2.5}$ concentrations are introduced as explanatory variables. Considering the availability of data at city level, we chose four indicators, which are listed as follows.[7]

3.1.1. *GDP per capita*

Previous empirical researches of EKC and the researches on the socioeconomic influential factors of environmental quality have indicated that the concentrations and/or emissions of pollutants are closely related to the average income (e.g., Auffhammer and Carson, 2008; Xu and Lin, 2015). Given the fact that the haze and fog also occurred in some developed countries during the process of industrialization, it is possible that the burst of the haze and fog pollution is an unavoidable stage China has to experience during its economic development. If this is true, the relationship between China's $PM_{2.5}$ concentrations and GDP per capita should also be inverted-U shaped, as the conventional EKC hypothesis predicts. To test this hypothesis, per capita GDP of the sample cities in 2013 is used as an explanatory variable, and the squared term of GDP per capita is also incorporated to capture the possible nonlinear relationship between $PM_{2.5}$ concentrations and GDP per capita.

3.1.2. *Industrial structure*

In China, the secondary industry contributes greatly to the emissions of various pollutants that affect the air quality. Therefore, the relative size of the secondary industry has a direct and significant effect on the air quality (e.g., He, 2009). Hence, the share of secondary industry in GDP is introduced as an explanatory variable in this study.

3.1.3. *Vehicle population*

The vehicle population has increased dramatically in many Chinese cities in recent years. Scientific studies have already indicated that the vehicular gas contains organic hydrocarbons, nitrogen oxides, black carbon, and many other pollutants, which are the main components of $PM_{2.5}$ (Xue et al., 2014). As a result, the number of vehicles may have considerable impact on a city's $PM_{2.5}$ concentrations (Auffhammer and Carson, 2008). Therefore, vehicle population is also used as an explanatory variable.

3.1.4. *Population density*

The population density is commonly used as a control variable in EKC studies (e.g., Auffhammer and Carson, 2008; Halkos and Paizanos, 2013). However, the total effects of population density on $PM_{2.5}$ concentrations are ambiguous. On the one hand, higher population density would lead to higher the degree of urbanization and industrialization; therefore the urban air quality may be affected. On the other hand, high population density makes it possible for the intensive use of energy, which reduces total pollutant emissions and is therefore beneficial to the environment. To find out which of the two effects prevail, the urban population density is utilized as an additional explanatory variable.

The data for all variables except the vehicle population are collected from the National Economic and Social Development Statistics Bulletin of the sample cities. The vehicle population variable is acquired from the Traffic Management Bureau of the corresponding city. Due to the data availability, the 2013 annual average of urban $PM_{2.5}$ concentrations and AQI are utilized. Therefore, similar to previous influential researches like Grossman and Krueger (1991, 1995) and Wang (2013), this study uses cross-sectional data. In fact, considering the remarkable development imbalance among different regions of China, China's city-level data is to some extent parallel to the international multi-country data in terms of development disparity. In other words, the differences in levels of development between different regions within China can be compared to the development gaps between developed and

[7] It is noteworthy that, besides the influential factors of socio-economy development, the natural influential factors such as climate, topography may also contribute to the $PM_{2.5}$ spatial variation in China. However, due to lack of data, we simply ignore these factors. Nevertheless, the ignorance of the natural factors may not cause serious estimation bias, because using the logarithmic transformations of the variables could efficiently reduce the potential heteroskedasticity, the most prominent estimation problem that may be caused by these city-specific natural factors (Wooldridge, 2012). Moreover, in previous similar researches on the influential factors of air pollution (including $PM_{2.5}$), the natural influential factors are rarely accounted for (e.g., Song et al., 2008; Li et al., 2014). As a result, the exclusion of the natural factors may probably not severely reduce the explanatory power of the basic findings of this study.

developing countries (Fan and Sun, 2008). Thus, the estimation results based on the cross-sectional date are also reasonable. As a summary, the descriptive statistics of these variables used in this study are presented in Table 1.

3.2. Method: spatial econometric models

As mentioned previously, there might be spatial correlations in air pollution among adjacent cities. The application of the spatial econometric techniques is necessary in environmental and resource economics. For a brief introduction to spatial econometrics, one could refer to LeSage (1997), Dubin (1998) and Anselin (2003, 2002) and Florax and Vlist (2003) provided classic reviews of early literature. Spatial autocorrelation could be measured by Moran's I statistics, which depend on the spatial weight matrices that reflect the intensity of the geographic relationship between observations in a neighborhood (Anselin, 1998). The Moran's I is calculated using the following formula:

$$I = \frac{n\sum_i \sum_{j\neq i} w_{ij}(y_i - \bar{y})\left(y_j - \bar{y}\right)}{\left(\sum_i \sum_{j\neq i} w_{ij}\right)\sum_i (y_i - \bar{y})^2} \tag{1}$$

where w_{ij} is the element in the spatial weights matrix W corresponding to the geographic districts (i, j), y is the variable of interest. The Moran's I index ranges from −1 to 1. A positive value of Moran's I indicates a positive spatial autocorrelation; a negative value implies a negative autocorrelation; and 0 means no spatial correlation. The spatial econometric models for spatial autocorrelation could be considered as the extensions of conventional regression models by incorporating the spatial effects explicitly. Specifically, we focus on the following two most frequently used spatial econometric models: spatial lag model (SLM) and spatial error model (SEM).

The spatial lag model (SLM) can be written as:

$$Y = \alpha + \rho WY + X\beta + \varepsilon \tag{2}$$

where Y is a vector of dependent variables, X is a matrix of explanatory variables, W is the spatial weight matrix, and WY is a vector of spatial lag dependent variable. ρ is a spatial regression coefficient that reflects the spatial dependence of the sample observations. β is a vector of parameters and ε is a normally distributed disturbance term with a diagonal covariance matrix.

The spatial error model (SEM) could be expressed as:

$$Y = \alpha + X\beta + \varepsilon \qquad \varepsilon = \lambda W\varepsilon + \mu \tag{3}$$

where μ is an *i.i.d* residual. The parameter λ is the spatial autoregressive coefficient that reflects the influences of the residuals of adjacent area on the residuals of the local area. The main difference between the two parameters ρ and λ lies in the way how the spatial dependence is introduced into the regression equation.

Due to the introduction of space-weighted matrix in the explanatory variables or residuals, if the spatial econometric models are still estimated by OLS, the coefficients would be biased (for SLM) and/or inefficient (for SEM). The maximum likelihood (ML) method is a more appropriate estimation method for spatial econometric models. In this study, spatial lag and spatial error models as well as the Moran's I statistics and the corresponding test are all estimated using the corresponding programs in LeSage's Spatial Econometrics MATLAB toolbox.[8]

The setting of spatial weights matrix is also important for the accurate estimations (LeSage and Pace, 2010; Plümper and Neumayer, 2010). Following Plümper and Neumayer (2010) and Klemm and Van Parys (2012), in this study we use the reciprocal of the geographic distance between two cities i and j as the corresponding element w_{ij} of the spatial weight matrix, and then the matrix is row standardized to get rid of the effect of the unit. In order to check the robustness of the estimation results, we have also tested two alternative spatial matrix, including the contiguity spatial matrix in which the value of w_{ij} is based on the comparison of the distance between the two cities and a threshold distance and the spatial matrix in which the element w_{ij} is calculated using the square of the reciprocal of the geographic distance between cities i and j.[9] The estimation results using the alternative spatial matrixes are quite similar to the results shown in this paper, which implies that our estimation is quite robust.[10]

Poon et al. (2006) claimed that the specification of EKC with cubic term of GDP per capita is more appropriate for industrialized countries but performs not very well for developing countries. As a result, a quadratic EKC-type model is utilized as the benchmark regression equation for our empirical study. In other words, GDP per capita and its squared term (both in logarithmic form) are incorporated in the regression equation. Specifically, the benchmark regression equation utilized in this paper could be expressed as:

$$\mathrm{LogY_i} = \beta_0 + \beta_1 \mathrm{Log(GDP/POP)_i} + \beta_2 \mathrm{Log(GDP/POP)_i^2} + \beta_3 \mathrm{X_i} + \varepsilon_i \tag{4}$$

where Y is dependent variable ($PM_{2.5}$ concentrations and AQI in this study); Log(GDP/POP) is the natural logarithm of GDP per capita; X_i represents the vector of other explanatory variables including the industry structure, vehicle volume and population density.

According to the definitions, the SLM and SEM models utilized in this study are in the following forms:

3.2.1. Spatial lag model (SLM)

$$\mathrm{LogY_i} = \beta_0 + \rho \mathrm{WLogY_i} + \beta_1 \mathrm{Log(GDP/POP)_i} + \beta_2 \mathrm{Log(GDP/POP)_i^2} + \beta_3 \mathrm{X_i} + \varepsilon_i \tag{5}$$

Where $WLogY_i$ is the spatial lag that is obtained by multiplying a row-standardized weight matrix W with $LogY_i$; ρ is the spatial autocorrelation parameter.

Table 1
Descriptive statistics.

Variable	Unit	Mean	Std. Dev	Min	Max
$PM_{2.5}$	$\mu g/m^3$	72.667	27.856	26.029	160.179
AQI	–	104.071	36.192	44.12	218.93
GDP	yuan	65,920.21	27,036.46	11,150	218.93
r-sec	%	0.479	0.073	0.223	0.619
veh	10,000 vehicles	134.862	89.239	14.8	534.7
pop	person/km^2	846.567	934.796	95.618	5322.434

[8] The toolbox could be downloaded at http://www.spatial-econometrics.com/ (accessed on 04 May, 2015).

[9] The criterion for the contiguity matrix is that if the distance between city i and city j is over the threshold level, then $w_{ij} = 1$, otherwise $w_{ij} = 0$ (Maddison, 2006; Wang et al., 2013). To ensure there is at least one contiguous city for each city, we chose the threshold level to be 1439 km, the distance between Urumqi and Xining. It is noteworthy that this distance is a little smaller than the cut–off parameter of 1624 km above which interactions are assumed to be negligible (Abreu et al., 2005; Madariaga and Poncet, 2007).

[10] Due to space limits, the estimation results using alternative spatial weights are not reported in this paper but available upon request.

3.2.2. Spatial error model (SEM)

$$\mathrm{LogY_i} = \beta_0 + \beta_1 \mathrm{Log(GDP/POP)_i} + \beta_2 \mathrm{Log(GDP/POP)_i^2} + \beta_3 \mathrm{X_i} + \varepsilon_i \quad (6)$$

Where $\varepsilon = \lambda \mathrm{WLogY_i} + \mathrm{u}$. W is the row-standardized weight matrix, λ is the spatial autoregressive coefficient, and u is an *i.i.d* distributed terms as defined in Eq. (4).

4. Estimation results and discussion

4.1. Spatial autocorrelation test

According to the results of the tests for Moran's I statistics, the p-values are positive and considerably lower than the 1%, indicating that the existence of spatial autocorrelation in $PM_{2.5}$ and AQI is statistically significant at any given significant level. The spatial associations could also be intuitively depicted by the Moran scatterplot, which plots the spatial lag of the variable against the original variable. As Anselin (1996, 2002) has pointed out, the Moran's I scatterplot is a visual tool to illustrate spatial autocorrelation intuitively. The spatial lag refers to the values of a location's neighbor. In the Moran scatterplot, x axis denotes the concentration of $PM_{2.5}$/AQI and y axis is the spatial lagged values of $PM_{2.5}$/AQI and all the values are standardized variables, not the raw data. Therefore both $\times$ and y axes have no units. The four quadrants in the graph provide a classification of four types of spatial autocorrelation: high–high (upper right), low–low (lower left), for positive spatial autocorrelation; high-low (lower right) and low-high (upper left), for negative spatial autocorrelation. In Fig. 2, the scatterplots for $PM_{2.5}$ and AQI of all 73 cities in the sample are drawn. As shown in Fig. 2, for each variable there are more than 50 cities appearing in the upper right and lower left quadrants. This result suggests that the cities in the high–high quadrants have a high potential for exporting pollution to their neighboring cities, and conversely cities with low air pollution "cluster together" with other low polluted cities. The slope of the simple trend line is Moran's I. For $PM_{2.5}$ and AQI the Moran's I statistics are 0.33 and 0.38, respectively.

4.2. Spatial econometric regression results

To determine which spatial econometric model is more appropriate for the estimation, at first we conduct the conventional OLS estimations and perform the corresponding (robust) LM lag and LM error tests for the two spatial econometric estimators. The results are presented in Table 2.

From Table 2, all quadratic income terms for $PM_{2.5}$ and AQI are statistically significant which supports the EKC hypothesis for both $PM_{2.5}$ and AQI. The coefficients of vehicle population and industry structure are significantly positive, indicating that more vehicles and a higher ratio of secondary Industry to GDP would increase the urban $PM_{2.5}$ concentrations, respectively. However, population density appears to be insignificant. Given the presence of spatial autocorrelation in $PM_{2.5}$ and AQI, the OLS models just reveal the relationships between relationship between socioeconomic development and $PM_{2.5}$ to some extent.

The LM (Lagrange Multiplier) and robust LM tests are applied to determine whether spatial relationships should be considered and which econometric models are preferred. As shown in Table 2, the statistics of most LM tests and robust LM tests for the two estimation techniques of SLM and SEM are significant for both AQI and $PM_{2.5}$. Concretely, all of the robust LM tests for SLM are significant and most are significant for SEM (except model (3)). The test results indicate that both of the two spatial relationships exist. Therefore, to obtain robust results, SLM and SEM estimators are both employed in following estimations.

The estimation results of SLM and SEM are reported in Tables 3 and 4 below.

First of all, it is noteworthy that all of the spatial autocorrelation parameters ρ and spatial autocorrelation coefficients λ in both SLM and SEM estimations for $PM_{2.5}$ concentrations and AQI are statistically significant at 1% level, indicating that the spatial dependence presented in the datasets has been captured by both spatial econometric models. Moreover, the high values for both λ and ρ also indicate the apparent spatial spillover effects of $PM_{2.5}$ and AQI. These results suggest that an increase in the $PM_{2.5}$ concentrations of neighboring cities by 1% would cause the rising of $PM_{2.5}$ concentrations in the city by approximately 0.9%, other things being equal. For AQI, the corresponding level of spatial dependence is a little higher. These findings are basically consistent with the intuitive conclusions drawn from the Moran's I scatterplots shown in Fig. 2 that there exists positive spatial correlations in $PM_{2.5}$ and AQI in Chinese cities. Moreover, considering the remarkable differences in the styles of economic and social development among different areas in China, the urban $PM_{2.5}$ concentrations have clear regional specific patterns. Comparatively, the concentrations of $PM_{2.5}$ are higher in the cities located in Beijing-Tianjin-Hebei region while

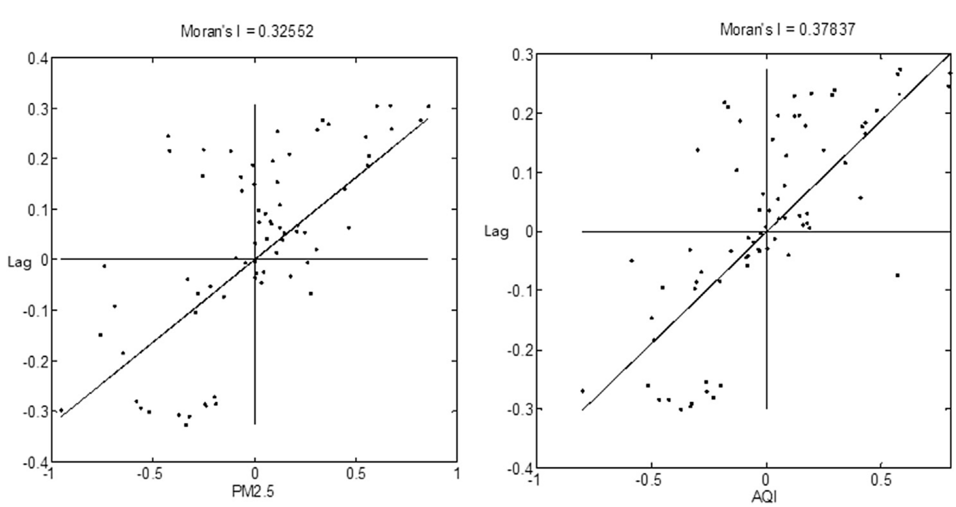

Fig. 2. Moran's I scatterplots for $PM_{2.5}$ and AQI of 73 Chinese cities, 2013.

Table 2
OLS estimation results for Eq. (4).

Dep. Var	Ln($PM_{2.5}$)						ln(AQI)					
Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
lngdp	0.954***	0.862***	0.830***	0.929***	0.716***	0.223***	1.054***	0.994***	0.981***	1.054***	0.911***	0.322***
	(9.594)	(7.591)	(8.374)	(9.067)	(6.3751)	(4.314)	(12.413)	(10.169)	(11.098)	(11.955)	(9.026)	(6.3625)
$lngdp^2$	−0.052***	−0.047***	−0.049***	−0.053***	−0.043***		−0.058***	−0.055***	−0.056***	−0.058***	−0.051***	
	(-5.756)	(-5.069)	(-5.820)	(-5.846)	(-4.793)		(-7.520)	(-6.831)	(-7.483)	(-7.396)	(-6.365)	
r-sec		0.970			1.172**	2.003***		0.636			0.782	1.773***
		(1.623)			(2.112)	(3.310)		(1.238)			(1.568)	(2.987)
lnveh			0.217***		0.242***	0.304***			0.129**		0.164***	0.238***
			(3.491)		(3.597)	(4.011)			(2.323)		(2.714)	(3.200)
lnpop				0.068	−0.033	−0.098				0.002	−0.067	−0.145**
				(1.030)	(-0.490)	(-1.311)				(0.028)	(-1.117)	(-1.974)
R^2	0.038	0.073	0.1803	0.052	0.232	−0.0273	0.063	0.095	0.142	0.076	0.184	−0.302
DW	1.341	1.308	1.328	1.350	1.318	1.147	1.390	1.370	1.345	1.391	1.331	1.138
Obs	73	73	73	73	73	73	73	73	73	73	73	73
LM lag	5020.3	2002.3	3260.6	2846.7	1004.1	67.392	1876.8	9002.5	14,416	3106	4490.5	75.614
	($p = 0$)	($p = 0$)	($p = 0$)	($p = 0$)	($p = 0$)	($p = 0$)	($p = 0$)	($p = 0$)	($p = 0$)	($p = 0$)	($p = 0$)	($p = 0$)
Robust	20.556	24.665	12.788	15.203	18.873	16.173	26.276	29.869	24.163	26.605	30.809	23.777
LM lag	($p = 0$)	($p = 0$)	($p = 0$)	($p = 0$)	($p = 0$)	($p = 0$)	($p = 0$)	($p = 0$)	($p = 0$)	($p = 0$)	($p = 0$)	($p = 0$)
LM error	59.892	61.644	62.617	71.531	61.237	72.997	75.566	78.606	74.830	75.903	64.256	71.462
	($p = 0$)	($p = 0$)	($p = 0$)	($p = 0$)	($p = 0$)	($p = 0$)	($p = 0$)	($p = 0$)	($p = 0$)	($p = 0$)	($p = 0$)	($p = 0$)
Robust	8.116	10.030	0.134	5.676	1.205	21.779	6.496	8.178	2.787	6.782	4.148	19.625
LM error	($p = 0.004$)	($p = 0.002$)	(0.715)	(0.017)	($p = 0.272$)	($p = 0$)	($p = 0.011$)	($p = 0.004$)	($p = 0.095$)	($p = 0.009$)	($p = 0.042$)	($p = 0$)

Note: In parentheses the t-values are given. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively. For the dependent variables, ln($PM_{2.5}$) and ln(AQI) indicate the logarithmic $PM_{2.5}$ concentrations and logarithmic AQI index, respectively.

Table 3
The SLM estimation results for Eq. (5).

Dep. Var	ln($PM_{2.5}$)						ln(AQI)					
Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
lngdp	0.162*	0.013	0.051	0.117	−0.070	−0.134***	0.124**	0.091	0.122	0.156**	0.044	−0.075***
	(1.702)	(0.144)	(0.550)	(1.247)	(-0.732)	(-3.985)	(1.962)	(1.175)	(1.517)	(1.988)	(0.506)	(-2.522)
$lngdp^2$	−0.011	−0.003	−0.008	−0.013*	−0.004		−0.010*	−0.009	−0.012*	−0.014**	−0.008	
	(-1.163)	(-0.480)	(-1.182)	(-1.787)	(-0.526)		(-1.827)	(-1.456)	(-1.989)	(-2.323)	(-1.371)	
rsec		0.955**			1.041***	1.054***		0.665*			0.746**	0.859***
		(2.002)			(2.554)	(2.75)		(1.814)			(2.118)	(2.577)
lnveh			0.183***		0.176***	0.173***			0.101***		0.104***	0.109***
			(3.872)		(3.552)	(3.603)			(2.532)		(2.438)	(2.619)
lnpop				0.114**	0.042	0.045				0.055	0.011	0.006
				(2.297)	(0.848)	(0.943)				(1.342)	(0.254)	(0.150)
ρ	0.884***	0.884***	0.891***	0.887***	0.903***	0.962***	0.969***	0.937***	0.910***	0.914***	0.912***	0.965***
	(11.776)	(11.271)	(12.670)	(12.108)	(14.251)	(37.99)	(46.37)	(22.32)	(15.464)	(16.130)	(15.797)	(41.476)

Note: The same as in Table 2 ρ is the spatial autocorrelation parameter.

relatively lower in the cities located in Pearl River Delta (see Fig. 1). Some existing studies also have similar findings that the $PM_{2.5}$ pollution is to some extent a regional problem (e.g., Hu et al., 2014). The serious air pollution in Beijing-Tianjin-Hebei region have aroused great concerns of the China government, because China's capital city of Beijing locates in this highly populous region. Some studies have showed that the burning of biomass and fossil energy (especially coal) for the heating in the winter generated huge $PM_{2.5}$

Table 4
The SEM estimation results for Eq. (6).

Dep. Var	ln($PM_{2.5}$)						ln(AQI)					
Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
lngdp	0.744***	0.666***	0.642***	0.661***	0.537***	−0.094	0.807***	0.810***	0.809***	0.807***	0.745***	−0.072
	(7.273)	(5.896)	(5.808)	(5.157)	(4.686)	(-1.328)	(5.578)	(8.422)	(7.867)	(6.048)	(7.389)	(-1.140)
$lngdp^2$	−0.035***	−0.031***	−0.034***	−0.036***	−0.030***		−0.040***	−0.034***	−0.042***	−0.040***	−0.039***	
	(-4.542)	(-3.828)	(-4.491)	(-4.326)	(-3.989)		(-4.800)	(-5.874)	(-6.208)	(-5.353)	(-5.889)	
rsec		0.758*			0.985***	0.971***		0.574			0.700**	0.684**
		(1.736)			(2.554)	(2.539)		(1.617)			(2.067)	(2.017)
lnveh			0.179***		0.165***	0.162***			0.095***		0.091**	0.087**
			(3.855)		(3.382)	(3.339)			(2.386)		(2.113)	(2.031)
lnpop				0.147***	0.078	0.072				0.079	0.041	0.031
				(2.820)	(1.498)	(1.402)				(1.185)	(0.902)	(0.673)
λ	0.905***	0.916***	0.932***	0.944***	0.937***	0.990***	0.962***	0.925***	0.941***	0.959***	0.937***	0.990***
	(15.161)	(17.255)	(21.519)	(26.358)	(23.300)	(150.899)	(39.368)	(19.429)	(24.963)	(36.409)	(23.318)	(152.899)

Note: The same as in Table 2 λ is the spatial autocorrelation coefficient.

emissions and therefore caused high $PM_{2.5}$ concentrations in the Beijing-Tianjin-Hebei region (e.g., Chai et al., 2014; Yang et al., 2013). Besides, cities in this area are mostly located in the North China Plain which is not geographically separated by mountain ranges; therefore the pollutants can easily flow from one city to its nearby cities when wind conditions permit.

For all specifications of the SEM estimations for $PM_{2.5}$ and AQI, the coefficients of per capita GDP and its squared term are both significant. The coefficient of per capita GDP is positive while the squared term carries a negative sign. These results indicate that an inverted-U EKC relationship for $PM_{2.5}$ concentrations indeed exists. Because the coefficients of the SLM model do not directly reflect the marginal relationship between variables (LeSage and Pace, 2010), the coefficients of SEM estimations are utilized for the quantitative analyses and comparisons. It is noteworthy that the SLM estimates of GDP per capita and its squared term are insignificant for most of the specifications, although the signs of per capita GDP and its squared term are consistent with the SEM estimates. Because the SEM estimates are similar to the OLS estimates represented in Table 2, the inverted-U relationship between $PM_{2.5}$ concentrations and GDP per capita is estimated to be quite robust. To verify the necessity of introducing the squared GDP per capita, we also made estimations with only the first degree of GDP per capita for both SLM and SEM, and the results are reported in the last columns for each dependent variable (columns (6) and (12) in Tables 2–4). When the squared term of GDP per capita is excluded, the coefficients of lnGDP are negative but only significant for SEM estimations, indicating that the impact of GDP per capita on air quality is negative, other conditions being equal. However, this conclusion is contrary to our observations as China's air pollution becomes more serious alongside rapid economic growth of China. Moreover, this finding is contrary to Xu and Lin (2015), who have found that economic growth is a decisive factor of $PM_{2.5}$ emissions. The unreasonable results without the squared term in essence suggest that the real relationship between air quality and GDP per capita should be inverted-U shaped, and therefore it is necessary to introduce the square term of GDP per capita.[11]

The effect of vehicular volume on haze pollution has been a public concern for long. Some cities in the U.S. suffered from severe air pollution in the 1950s and 1960s due to the fast growth of energy consumption and the number of motor vehicles (e.g., Pui, 2014). Lonati et al. (2005) conducted a research on the compositions of $PM_{2.5}$ pollution generated from the automobile exhaust for the period between August 2002 and November 2003 in Milan of Italy. They have found that the average annual concentrations of $PM_{2.5}$ in the tunnel portals and downtown were 204.5 $\mu g/m^3$ and 32.8 $\mu g/m^3$, respectively. These results indicate that the motor vehicle is one of the most important influential factors of the urban $PM_{2.5}$ concentrations. According to the results shown in Tables 3 and 4, the estimated coefficients of vehicles volume in all the specifications of SLM and SEM are significantly positive, suggesting that vehicle is also a key cause of $PM_{2.5}$ pollution in China. Based on the SEM estimation results presented in Table 4, an increase in vehicle population by 1% would lead to an increase in urban $PM_{2.5}$ concentrations by approximately 0.17% or an increase in AQI by 0.1%, other conditions held constant. For the readers' better understanding of the important role of vehicle population in $PM_{2.5}$ pollution, in Fig. 3 the urban $PM_{2.5}$ concentrations and AQI against logarithmic vehicle population are plotted, and the two simple linear trend lines for the relationship between $PM_{2.5}$ concentrations and vehicle population and the nexus of AQI and vehicle population are also presented. As shown clearly in Fig. 3, the two trend lines both have positive slopes, indicating the positive impacts of vehicle population on urban air pollution. Given the fact that the China's vehicle population has grown very fast over the past a few years and that China's economy may continue to grow at a relative high speed, the trend of rapid increase in urban vehicle population may probably persist in the near future. As a result, the urban air pollution caused by automobile exhaust would become an important environmental challenge for China.

Similar to vehicle population, the secondary industry is also an important source of urban $PM_{2.5}$ pollution, because the coefficients of explanatory variable rsec are significantly positive in most of the specifications of Tables 3 and 4 (except in model (8) where the coefficient of rsec is positive but insignificant with p value being 0.11). The estimation results indicate that a higher share of secondary industry added to GDP would contribute to higher $PM_{2.5}$ concentrations. These results are broadly in line with our prediction because the development of secondary industry accompanies the rapid growth of energy consumption in China. According to the statistics of the Chinese Ministry of Information Industry in 2013, nearly 70% of China's energy was consumed in the secondary industry. Because coal is the dominating energy source for the secondary industry in China, the fast growth of secondary industry demands a huge increase in coal consumption. As Xue et al. (2014) have pointed out, the combustion of coal especially mineral coal with low degree of coalification is one of the most important sources of $PM_{2.5}$ pollutants. Therefore, the surge in coal consumption caused by the development of secondary industry in recent years contributed significantly to rising urban $PM_{2.5}$ concentrations. The close relationship between the secondary industry and $PM_{2.5}$ concentrations could also be observed intuitively in Fig. 4. Similar to Fig. 3, in Fig. 4 the scatterplots of $PM_{2.5}$ concentrations and AQI against the share of secondary industry to GDP and the corresponding simple linear trend lines are drawn. The two trend lines are upward sloping, and the slopes are relatively high in magnitude, suggesting that the positive relationship between $PM_{2.5}$ pollution and the importance of the secondary industry to the economy.

However, the effect of population density on $PM_{2.5}$ is ambiguous. For most of the specifications, the coefficients of population density turned out to be positive but statistically insignificant. Only in two models (model (4) in Table 3 and model (4) in Table 4), the estimated coefficients of population density are significantly positive. These results suggest that the population gathering tends to increase urban $PM_{2.5}$ concentrations, but the effects are not strong enough to be statistically significant. As a result, the rapid urbanization in China, especially the dramatic expansion of big cities with high population density may bring about more urban haze and fog pollution, although the severity of the impacts of population gathering on air pollution is still controversial.

[11] The estimated negative signs of GDP per capita in the SLM and SEM estimation results when the squared term of GDP per capita is absent do not mean the actual relationship between air quality and economic development is negative. In fact, to some degree, the negative coefficients of lnGDP indicate that the $PM_{2.5}$ concentrations should be decreased and the air quality should be improved as GDP per capita continues to grow for the sample cities. It is noteworthy that the levels of GDP per capita for most of the sample cities were considerably higher than the national average at 2013, therefore the theoretical turning point for most sample cities should have been reached. However, because of the positive spatial correlation in $PM_{2.5}$ concentrations, and due to relatively high dependence on secondary industry and the rapid increase in the number of cars, the $PM_{2.5}$ concentrations in the vast majority of sample cities remain high in the near future, even when GDP per capita in these cities keeps rising (note that the coefficients of the industrial structure and vehicle population for SLM and SEM estimations are both significant and positive, and the coefficients of these two variables are considerably large in magnitude).

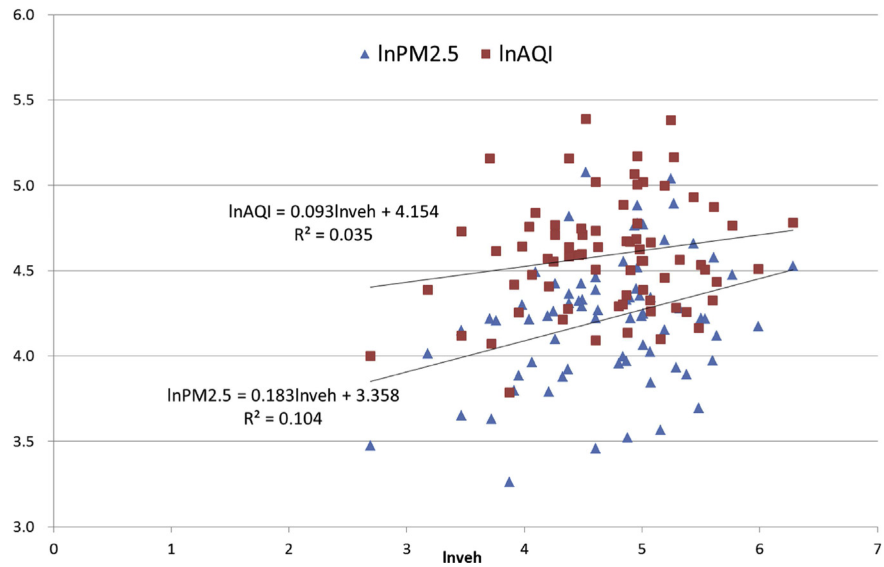

Fig. 3. The scatterplots of urban logarithmic $PM_{2.5}$ concentrations (blue triangles) and AQI (red squares) against logarithmic vehicle population (lnveh). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

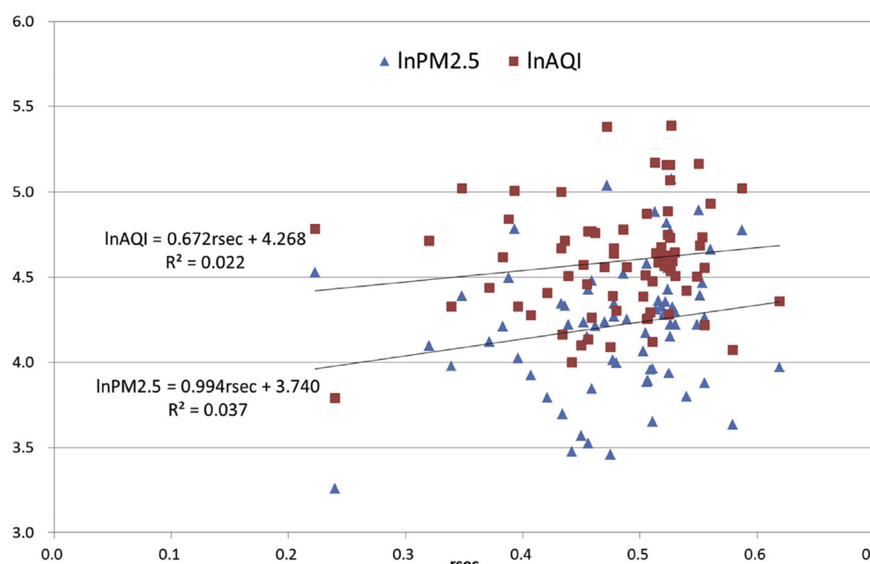

Fig. 4. The scatterplots of urban logarithmic $PM_{2.5}$ concentrations (blue triangles) and AQI (red squares) against the share of the secondary industry to GDP (rsec). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

5. Conclusions and policy implications

This study for the first time investigates the economic and social influential factors of urban $PM_{2.5}$ concentrations in China. Moran's I scatterplot and statistics verify the existence of significant spatial autocorrelation; therefore the Spatial Lag Model (SLM) and Spatial Error Model (SEM) are utilized to perform the empirical estimations in this research.

Using the annual average levels of $PM_{2.5}$ concentrations and AQI in 73 Chinese cities at 2013, the hypothesis of inverted U-shaped EKC between air pollution and GDP per capita is verified. This existence of inverted-U shaped EKC for $PM_{2.5}$ concentrations indicates that, to some extent, the burst of haze and fog in China nowadays is an inevitable phenomenon in China's current stage of development. According to the experiences of some developed countries which have also experienced serious urban air pollution, it might take some time for China to improve air quality.

Besides, the estimation results suggest that urban $PM_{2.5}$ concentrations are also strongly influenced by the secondary industry. Since China's economy is still heavily relying on the secondary industry especially heavy industry, the urban $PM_{2.5}$ concentrations may keep being relatively high in the near future. As a result, the policy implications are straightforward: to efficiently reduce urban $PM_{2.5}$ concentrations, China should speed up structural transformation of the economy and reduce the reliance on secondary industry especially heavy industries. Besides, the energy structure of the secondary industry should also be improved by reducing coal consumption and increasing the consumption of cleaner energy such as gas and renewable energy. This conclusion is also consistent with the findings of Fujii et al. (2013) that the improvement of energy efficiency in the industrial sector is crucial for the air pollution control in China.

Besides, according to the Moran scatterplots and the estimation results of the spatial econometric models, there are positive spatial correlations of $PM_{2.5}$ concentrations in nearby cities. As a result, the industrial restructuring requires the improvement of regional cooperation and a more appropriate plan for the whole country. For instance, the high energy-consuming industries should not concentrate geographically within a particular region (like Beijing-Tianjin-Hebei region nowadays), so that the environmental pressures caused by spatial effects of air pollution could be effectively reduced. In the short run, some administrative means could be used to control for the spatial effects of the $PM_{2.5}$ concentrations. For example, the energy intensive factories and industries have to be temporarily shut down when the air pollution is serious or when the weather condition is not suitable for the diffusion of the pollutants. Some of these restrictions and political regulations were carried out during the 22nd APEC summit held in Beijing in November 2014, and they proved to be effective in improving the short-term air quality.

The estimation results also indicate that the vehicular population contributes positively and significantly to urban $PM_{2.5}$ concentrations. According to the statistics of National Bureau of Statistics (NBS) of China, the sale of road vehicles in China ranked the 1st in the world for 6 consecutive years from 2009 to 2014. At 2014, the total vehicle population in China had reached 264 million. The surge in the number of vehicles caused not only severe urban air pollution but also serious traffic congestions. As a result, the Chinese authorities should pay close attention to the excessively rapid growth of vehicles, especially in several mega cities where there are massive air pollution and high traffic pressures. In the near future, the most important and feasible measures for air quality control include limiting the growth of vehicle population and to strictly restricting the amount of exhaust gas. When the $PM_{2.5}$ concentrations become hazardously high, some specific regulations such as even and odd-numbered license plate rule could be conducted. However, in the long run, the improvement of urban air quality depends on whether the waste gas pollution could be reduced more effectively. The possible measures include developing new energy and low-emission cars, promoting hybrid buses and electric taxis and encouraging the green commuting.

All in all, this research is an initial attempt to investigate the economic and social influential factors of urban $PM_{2.5}$ concentrations in China. The purpose of this study is to arouse the attention of researchers to investigate the reasons of severe air pollution burst frequently in China nowadays from the macro perspective. Due to data availability, the annual data of the year 2013 is utilized to make a cross-section analysis. As a result, this study could be considered as the first step for future more sophisticated researches in this field when more data are accessible.

Acknowledgments

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