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Impacts of air pollution and its spatial spillover effect on public health based on China's big data sample

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ABSTRACT

Although the existing studies have paid much attention to the issue on the impacts of air pollution on public health, they fail to consider the spatial spillover effect and externality of air pollution as a significant influencing factor of public health, causing the biased results. This paper employs a spatial Durbin model (SDM) to investigate the impacts of both air pollution and its spatial spillover effect on public health in 116 cities of China over 2006–2012. We use the survey data of lung cancer mortality and respiratory diseases mortality from 161 sites of mortality censoring spots in China to measure public health and use the statistical data of industrial emissions of sulfur dioxide and soot from the corresponding cities to measure air pollution. Compared with the existing studies, from the perspective of the scale and scope of dataset, our dataset can be regarded as a big data sample in the fields of environmental and health economics. We estimate the direct and indirect effects of air pollution to distinguish the local and neighbors' impacts of air pollution on the mortalities caused by the two diseases. The empirical results provide the evidence for the adverse impacts of air pollution and its spatial spillover effect on public health. On average, an increase of ten thousand tonnes in industrial sulfur dioxide emissions in certain city will lead to an increase of 0.035 and 0.03 per ten thousand persons in local mortalities from lung cancer and respiratory diseases, respectively, and a total increase of 0.217 and 1.543 per ten thousand persons in the mortalities of all its neighbors from lung cancer and respiratory diseases, respectively. On an annual average, due to the air pollution, more than 200 billion RMB are spent on the medical treatment for curing health damages, and approximate hundred thousand lives were taken away.

1. Introduction

In the recent three decades, the whole world has witnessed the great achievement of China's economic development. At the beginning of the reform and opening up in 1978, China's gross domestic product (GDP) only ranked the 15th in the world. Shortly after thirty years, China surpassed Japan and became the second largest economy in 2010. China's GDP increased by over fifty folds from around $189 billion in 1980 to more than $10 trillion in 2014.[1] However, the indices and figures measuring the public welfare of China, such as environmental condition, public health, life expectancy, are not as well-performed as its pure economic growth ones. For example, the Chinese life expectancy at birth increased only by 8.3 years in the period of 1980–2013. Meanwhile, compared with its several neighboring countries, such as India, Thailand, Singapore, South Korea, and even Cambodia and Mongolia, the life expectancy increment of China in recent two decades has lagged behind.[1] A more surprising result shows that the increase in the average life span of China in that period was lower than those of middle income and even lower income countries.

Furthermore, all kinds of striking and horrifying scenes and news concerning environmental pollutions and ecological disasters in China are increasingly commonly witnessed in the past decades. Especially after the 2008 Beijing Olympic Games, more frequent and severe air pollution incidents and scenes can be seen across the

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[1] See World Bank Database, http://data.worldbank.org/.

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vast regions of China. In recent years, dozens of provinces and major metropolises are smothered and shrouded in severe smog and haze for several months every year. Some international cosmopolitan cities like Beijing and Shanghai are not excluded from the miserable and awkward air conditions. In particular, Beijing, the capital city of China, after suffering from serious sand storm problems for many years, is currently perplexed by unprecedented smog ravage. Since Beijing were severely engulfed with smog for several weeks in early 2013, elevating air pollution struck the public awareness to an unprecedented level. In December of 2015, for the first time, Beijing issued its "red alert", the highest level for heavy air pollution, and particulate readings soared dozens of times above the daily maximum level recommended by the World Health Organization. Hence, the specific and accurate investigation on air pollution and public health nexus in China is urgent and necessary.

In the wake of the emerging environmental and public health issues of China, the attentions of medical scientists and researchers are drawn to the impacts of environmental pollution on public health. Traditionally, the subject of pollution and health nexus is extensively studied by scholars from medical and public health fields (e.g., Goldsmith and Kobzik, 1999; Pope, 1999; Gilmour et al., 2001; Brunekreef and Holgate, 2002; Peng et al., 2008; To et al., 2012; Cai et al., 2014). Kan and Wu (2013) reviewed the existing literature on air pollution and human health in China from three perspectives: the acute health effects, chronic health effects, and intervention effects, and they also found that the vast majority of the literature confirmed the adverse impacts of air pollution on health. Most recently, several studies investigated the relationship between public health and air pollution indices from relatively novel and innovative perspectives. Zheng et al. (2015) used the aerosol optical depth (AOD) dataset from 2001 to 2012 in Beijing and the ground-based PM2.5[2] observations from the US Embassy in Beijing from 2010 to 2011 to explore the relationship between PM2.5 and AOD. This study can lead to a series of new researches with the AOD dataset. Using 75 communities' data of lung cancer incidence in China from 1990 to 2009, Guo et al. (2016) established a spatial age-period-cohort model to examine the relative risks of lung cancer incidence associated with air pollutants. Such investigations in natural scientific fields have confirmed the adverse impacts of air pollution on public health.

However, notable defects can be found in those existing medical and public health studies. Firstly, existing studies mainly focused on the pathological mechanism of the impacts of the air pollutants on public health, but policy-makers and researchers of social and economic fields are more concerned with social and economic costs from a more general and macro perspective. Elevated air pollution is generally beyond the scope of individual control and falls to the public sector (Tanaka, 2015). Secondly, many medical related studies are at the individual level and only pay attention to the interrelationship between air pollution and public health, without considering that the other significant factors also influence health conditions, such as population density, sanitary conditions, and the standard of living, etc. This may lead to an endogeneity problem in the estimation process, causing the biased and inconsistent estimated results. Thirdly, previous studies mostly employ the data from a specific county or city, with daily observations, but the pollution and health nexus could be a much more complex process, because the impacts from neighboring regions other than the local itself could also cast a shadow on the public health condition. Moreover, the daily time-series analysis cannot provide the conclusive evidence of the causal relationship between pollution and health, while the panel data with both time-series and cross-section information are seldom adopted in the medical literature.

Nowadays, policy-makers and researchers from social and economic fields have a strong interest in such an inter-disciplinary issue. Enormous findings and insights could be spotted in recent studies on the pollution and health nexus from a health economics perspective. In view of the potential health and sanitary costs associated with air pollution, issues on the relationship between air pollution and health have been a field of fierce debate in the past decades. Owing to relatively higher development level, better public awareness, and higher household living standard, studies focusing on the developed countries are more commonly witnessed. Francesca et al. (2002) used a dataset of air pollution and mortality in 88 US cities from 1987 to 1994 to analyze the relationship between the concentration of inhalable particles and mortality. They found that the emissions of air pollutants were strongly correlated with the industrial structure and development stage of a country, and to some extent, the economic recession period could function as a perfect timing for the reduction in air pollution level as well as the mortality induced by pollution. During the 1980–1982 recession in the United States, a remarkable decline in Total Suspended Particulates (TSPs) could be witnessed. As a perfect external shock, Chay and Greenstone (2003a) employed the substantial reduction in air pollution across sites to evaluate the impact of TSPs on infant mortality in the US. A similar research could be found in Heutel and Fischer (2013). After matching the air pollutant indices with the unemployment rate and economic fluctuation, they confirmed certain transmission mechanism between economic fluctuation and mortality through air pollution. Since the nature of immobility and vulnerability of newly-borne children is helpful to avoid endogeneity risks, various studies have focused on the impacts of air pollution on infant mortality (Chay and Greenstone, 2003b; Currie and Walker, 2011; Coneus and Spiess, 2012; Lavaine and Neidell, 2013; Tanaka, 2015).

However, due to the data availability in other countries, more studies conducted the investigations on the relationship between ordinary population and air pollution. Moretti and Neidell (2011) used daily arrivals and departures of boats in major ports of Los Angeles as an instrumental variable for the city-level ozone concentrations to estimate the health influence caused by local ozone level. Recently, the researchers in developing countries like China have contributed to the literature on such an issue with China's background and national characteristics. Taking Taiyuan as an example, Zhang et al. (2010) adopted an alternative method for the monetization of health impacts to estimate the total health costs, which amounted to 0.8–1.7 billion RMB and is 2.4–4.9% of the city's GDP in 2000. Chen et al. (2013) evaluated a quasi-external policy in China for the winter central heating system. They employed a regression discontinuity design to estimate the discrepancy of life expectancy caused by air pollution in the north and south of Huai River. In addition, some studies on the health expenditures and social costs resulted from air pollution can be found. Zhang et al. (2008) estimated the health effects of pollution caused by PM10 in 111 China's cities in 2004 by using epidemiological exposure–response functions. Their results showed that the total economic cost caused by PM10 pollution was approximately US$ 29,178.7 million. Cao and Han (2015) investigated the health impacts and social costs caused by haze in Beijing. They found that the growth of socio-economic costs caused by haze is much faster than the growth of GDP in Beijing. Obviously, the existing studies are either confined in a specific sample city or too short in research interval, and fail to reflect the spatial effects of air pollution.

Detailed mortality data in developing countries are usually unavailable or available only at a national level and in some metropolises. For this reason, the previous studies using the data of developing

[2] Small particulate refers to the particulate with less than 2.5 μm aerodynamic diameter.

countries from the perspective of health economics mainly used focused on provincial level or a certain specific city as a case (Arceo et al., 2012; Cai et al., 2014; Cao and Han, 2015). Hence, an accurate assessment of the effects of air pollution on public health is often difficult. This requires the introduction of big data sample to obtain more accurate information on both air pollution and public health. This paper examines the health effects of air pollution using China's city-level mortality data of lung cancer and respiratory diseases from the Chinese Disease Surveillance Points (DSP) system. The DSP is a mortality-monitoring system covering the nationally representative samples of cities and counties, including 161 sites in various geographic areas across 31 provinces, autonomous regions, and municipalities in China. Since the DSP data is high-capacity, it has been used in some recent studies (Chen et al., 2013; Ebenstein et al., 2015). However, the spillover effect and environmental externality of air pollution are generally ignored in the previous studies, causing serious biased and inconsistent estimated results. In this paper, we establish a spatial econometric model to overcome this problem.

We match the mortality data with the data of air pollution, economic development, and other relevant variables at the city level. With the assistance of the environmental and public health big data sample, this paper fills such a gap by investigating the spatial spillover effect of air pollution on public health in 116 major cities in China during 2006–2012. To our knowledge, our dataset is the largest in existing economic studies. Our observation amounts to 812, which can be regarded as a big data sample in the fields of environmental and health economics. In detailed, we attempt to answer the following questions: (i) Are there any impacts of air pollution from the neighboring regions on public health besides its impacts within local region? (ii) If the answer for the first question is affirmative, then to what extent are such impacts? (iii) Are there any other important influential factors of public health? (iv) How many would the death toll and medical costs from the health damage induced by air pollution be?

Correspondingly, the potential contributions of this paper present from three aspects. First, in terms of the problem of official statistical data unavailability, we use more exact survey data of lung cancer and respiratory diseases mortalities to measure the public health of China's prefecture-level city, which can be regarded as a big data sample compared with the existing studies. Second, a spatial Durbin model (SDM) is established to examine the damaging impacts of air pollution and its spillover effect on health in China's cities for the first time. Last but not least, we further estimate the loss from the health damage caused by air pollution, including the total death toll and medical expenses.

The rest of the paper is organized as follows. Section 2 describes the used method and data. Section 3 provides a detailed discussion of the results of our econometric analysis and medical expenses estimation. Section 4 presents research conclusions and policy implications.

2. Methodology and data

2.1. Econometric model and estimation method

Based on the health production function (Grossman, 1972), we first establish a non-spatial panel data model to analyze the impacts of air pollution on public health, the model is represented as follows:

$$\ln M_{it} = c + \alpha \ln AP_{it} + \beta X_{it} + f_i + \mu_{it}, \tag{1}$$

where i denotes city, t represents year, M stands for public health condition measured by the mortality of certain disease closely related to air pollution, AP represents the index of air pollution, X are some control variables, f stands for city fixed effect, and μ is the error term. All the variables in Eq. (1) are in logarithmic form.

Since air pollutants are apt to diffuse and migrate across different regions, air pollution generally has an obvious spillover effect geographically by nature. The health condition of certain region is not only affected by the local air pollution level, but also by those of its neighboring regions. Meanwhile, the influential factors of health, such as economic development level and medical condition, can also be diffusible and spilled over the neighboring regions. Thus, the sample data we use are not independent in space, but spatially dependent. This means that the observations from certain city could be affected by those from its neighboring cities. Therefore, the estimated results of non-spatial econometric model will be biased as it assumes that there is no spatial correlation between observations. In order to obtain accurate results, it is necessary to establish a spatial econometric model. Because the previous studies only used the ordinary panel data without considering spatial factors, they can hardly capture the spatial spillover effects across regions and their results are biased. Therefore, we construct a spatial Durbin model (SDM) to consider the impacts of air pollution and its spatial spillover effect on public health. LeSage and Pace (2009) argued that the SDM could be a perfect tool to capture the externalities and spillover effects from different sources. The SDM is able to capture the impacts of the spatial lagged independent variables on the dependent variable, where the spillover of air pollution can be measured by the spatial lagged coefficient of air pollution. Therefore, we can employ the SDM to examine the impacts of air pollution per se and its spatial spillover effect on public health. The common spatial panel Durbin model takes the form as follows:

$$y_{it} = \rho W y_{it} + X_{it}\beta + W X_{it}\theta + f_i + \mu_{it}, \tag{2}$$

where W denotes the non-negative $N \times N$ spatial weight matrix, reflecting the spatial interdependent relationship between different cross-sections. Wy denotes the spatial lag terms of the dependent variable, while WX represents the spatial lag term of the independent variables. The introduction of such spatial lag terms allows us to analyze the spillover effects of the neighboring regions to certain region.

One of the main differences between the spatial econometric method and the traditional ones is the introduction of spatial weight matrix. There are two standards for constructing the spatial weight matrix: neighboring and distance standards. In this paper, we take the non-bordering regions into consideration, since such regions are close to our concerned regions geographically and they are apt to be mutually influenced by the non-bordering ones. Thus, we do not use the simple binary geographic unit matrix as our weight matrix, but the reciprocal of the distances among cities as the elements in our distance weight matrix as follows:

$$w_{ij} = \begin{cases} \dfrac{1}{d_{ij}} & i \neq j \\ 0 & i = j \end{cases}, \tag{3}$$

Spatial Durbin model has jointly considered the impacts of spatial lag dependent variable and spatial lag independent variables. Under certain assumption restriction on the spatial Durbin model, it can be reduced to a spatial autoregressive model or spatial error model. According to Eq. (2), we consider two following assumptions: (i) $H_0^1: \theta = 0$; and (ii) $H_0^2: \theta + \beta\rho = 0$. If H_0^1 holds, then the SDM can be reduced as a spatial autoregressive model (SAR). If H_0^2 holds, then the SDM can be reduced as a spatial error model (SEM). While both conditions are satisfied, the SDM is equivalent to a non-spatial panel model. Therefore, the SDM is a more generalized form comparing with other spatial models. Whereas, related statistical test is needed to carry out to judge whether the SDM is applicable to the specific regression analysis.

With respect to the regression results of the SDM, LeSage and Pace (2009) pointed out that, due to the spatial correlation in the spatial panel model, the coefficients of the independent variables in the regression model cannot accurately reflect the marginal effect. The marginal effect should be divided into two categories: direct and indirect effects, which can be used to provide the informative explanation of the model. Referring to the method proposed by Elhorst (2010), the spatial panel Durbin model can be transferred as the following form:

$$y_{it} = (\mathbf{I} - \rho W)^{-1}(X_{it}\beta + WX_{it}\theta + f_i + \mu_{it}), \tag{4}$$

where $\mathbf{I}$ is an N × 1 unit matrix, with N being the number of cross sections (i.e. sample cities). The spatial Leontief inverse matrix can be spread as follows:

$$(\mathbf{I} - \rho W)^{-1} = \mathrm{I} + \rho \mathrm{W} + \rho^2 W^2 + \cdots, \tag{5}$$

The first term of the right of Eq. (4) is the direct effect, while the remaining part is the indirect effect. The first partial derivative of the dependent variable to the independent ones is as follows:

$$\frac{\partial y_i}{\partial x_{ir}} = S_r(W)_{ii} \quad \text{for all } i \text{ and } r, \tag{6}$$

$$\frac{\partial y_i}{\partial x_{jr}} = S_r(W)_{ij} \quad \text{for all } i \neq j \text{ and for all } r, \tag{7}$$

$$S_r(W) = (\mathbf{I}_N - \rho W)^{-1}(\mathbf{I}_N\beta_r - \omega_r W), \tag{8}$$

where β_r represents the coefficient for the rth independent variable, ω_r denotes the coefficient of the spatial lag term of the rth independent variable, $S_r(W)_{ii}$ is the element in the diagonal line, indicating the impact of the independent variable in the ith region on the dependent variable in the ith region, which refers to the direct effect. The simple average of the elements in the diagonal line is the average direct effect. The off-diagonal elements, which reflects the impact of the independent variable of the jth region on the dependent variable of the ith region, refers to the indirect effect or the spillover effect. The simple average of all the off-diagonal elements is the average indirect effect. The summation of the average direct and indirect effect is the average total effect, which is also the average of all the elements.

Based on the above analysis, we improve Eq. (1) into the following spatial panel Durbin model to investigate the air pollution and its spillover effect on public health:

$$\ln M_{it} = \rho \sum_{j=1}^{N} w_{ij} \ln M_{jt} + \beta \ln AP_{it} + \theta \sum_{j=1}^{N} w_{ij} \ln AP_{jt} + X_{it}\gamma + \varphi \sum_{j=1}^{N} X_{jt} + \alpha_i + \mu_{it}, \tag{9}$$

Because the spatial lag term of the dependent variable is introduced into the model, such a spatial interdependence contributes to the endogeneity problem while using the ordinary least square (OLS) method. Hence, the OLS estimation may lead to biased and non-consistent parameter estimation in the spatial regression model. One of the feasible methods is to use the most likelihood estimation (MLE) method (LeSage and Pace, 2009). Elhorst (2014) elaborated the MLE for the spatial lag and the spatial error model and argued that since the spatial Durbin model can be transferred to the SEM and SAR model, the MLE is still applicable to the estimation of Eq. (9).

2.2. Variables and their measured indices

We employ a panel dataset covering 116 prefecture-level cities in China over 2006–2012. The dependent variables are measured by two indices: the respiratory diseases mortality in a ten thousand population and the lung cancer mortality in a ten thousand population in a city. To construct the two indices, we first get the numbers for certain death cause in 161 sites of mortality censoring spots in China, covering a certain district or a subordinate county in a city, and then divide the numbers by the population of the corresponding spot to get the mortality of the specific death cause. Since 161 sites are not one to one correspondence with the prefecture-level cities, some cities occupy more than one site. Therefore, the number of sample cities is less than 161. However, as shown in Fig. 1, our sample cities cover all the provinces, autonomous regions, and municipalities in China except Hong Kong, Macao, Taiwan, and Tibet, including 44 cities in Eastern China, 41 cities in Central China, and 31 cities in Western China. Therefore, the sample cities are sufficiently representative for the whole country.

The reason for choosing the lung cancer and respiratory diseases mortalities is the strong causality between air pollution and both diseases. The air pollution has been ranked the fourth death cause to China's citizens (Wang et al., 2013), while the most related indices related to air pollution are upper and lower respiratory system illnesses. Moreover, the lung cancer can be the long term result of exposure to the serious polluted air conditions, and the mortality of lung cancer is the highest in all kinds of cancers.[3] The air pollution not only affects the public health in a long term and chronical manner, but also presents some short-term and acute effects. Therefore, we also select the mortality of respiratory diseases to capture such a short-term effect. The combination of such two indices would be more comprehensive and accurate for identifying the causality of air pollution and public health.

With respect to air pollution indices, we select the industrial sulfur dioxide (SO_2) emissions and the industrial soot emissions as our main concerns, since the industrial source is the main cause of air pollution in most regions in China. Furthermore, such two air pollutants are the major components constituting the smog and haze in China, while the majority of China's cities censored and reported the data of standard small particulate (PM2.5) after 2013. During our sample period, the soot emissions could be a good proxy for small particulate suspended in the air. A perfect example to justify the rationality of choosing such two indices is the famous London smog incident in 1952. Due to the environmental disaster, more than 12,000 persons were killed within a week in the shroud of heavy smog. The major components of the smog are the sulfur dioxide and the soot. London used coal as its primary source of heating system back then, which highly resembles the energy consumption structure of China in the past decades. Medical literature had also confirmed that one of the leading causes of respiratory system illness (including lung cancer) is the concentration of sulfur dioxide and small particulates (Peel et al., 2005; Shiraiwa et al., 2012).

According to the existing literature and the data availability, we select the following indices as the control variables to better explain the mortality induced by air pollution.

(1) Population density. Levy and Herzog (1974) argued that high density crowding in residential settings is associated with

[3] See CDC stands for Chinese Center for Disease Control and Prevention.

Fig. 1. Geographical distribution of sample cities.

higher all-cause mortality, especially with the higher mortalities from cancer and stroke. Therefore, the expected sign for the coefficient of population density should be positive.

(2) Economic development level. GDP per capita is generally used as a proxy to represent the economic development level in certain region. Marmot (2005) confirmed that social and economic development factors are the root of the inequalities in public health. The people in a much more developed region tend to have more access to public sanitary facilities and the public awareness of health. Hence, we need to consider the effect of the economic development level on public health, and GDP per capita is the most well-received and authentic index. Its expected sign could be negative.

(3) Public medical condition. According to many previous studies (e.g., Crémieux et al., 2005), the public medical condition is crucial to explain the diseases and mortality in certain region. Based on the data availability, we choose the number of hospital beds per ten thousand persons to reflect the public sanitary and medical condition in a region. Such an index can help to control an overall medical condition in a city for curing the diseases related to air pollution. Hence, its expected sign could be negative.

2.3. Data source and descriptive statistics

All the used variables and their indices in our econometric model are summarized and listed in Table 1.

This work focuses on the regional air pollutions and their spillover effects on the public health using the dataset of 116 prefecture-level cities in China from 2006 to 2012, i.e. 812 observations, and the sample cities cover all the provinces, autonomous regions, and municipalities in China except Hong Kong, Macao, Taiwan, and Tibet. To our knowledge, our dataset is the largest in related studies. Therefore, from the perspective of the scale and scope of dataset, our data sample can be regarded as a big data sample in the fields of environmental and health economics compared with the existing studies. The used data are from *Death Surveillance Database of Chinese Center for Disease Control and Prevention*, *China City Statistical Yearbook*, *County Level Population Statistical Yearbook of China*, and *China Environmental Yearbook*.

The basic descriptive statistics of the used data are shown in Table 2.

Fig. 2 shows the fitting relationship between two types of air pollutants and two types of public health indices. We can find the deterministic positive correlations among industrial sulfur dioxide, soot, and the mortalities of lung cancer and respiratory diseases. Intuitively, the more serious air pollutions are, the heavier toll the corresponding cities have to bear, which is consistent with our expectations. However, the real impacts of the two pollutants on the public health must be examined through rigorous spatial econometric analysis in the next section.

3. Results and discussion

3.1. Spatial autocorrelation test

Before conducting spatial econometric analysis, a spatial autocorrelation test should be carried out. We use the most common Moran's I index to test the spatial autocorrelation of air pollution and public health. The calculation formula of Moran's I index is as follow:

$$I = n\sum_i \sum_{j\neq i} w_{ij}(y_i-\bar{y})\left(y_j-\bar{y}\right) \Bigg/ \left(\sum_i \sum_{j\neq i} w_{ij}\right) \sum_i (y_i-\bar{y})^2, \tag{10}$$

where w_{ij} is the element in the weights matrix corresponding to observation pair $i-j$, y_i and y_j are observations for regions i and j, n is the number of cross section. Moran's I index value is range of [−1, 1]. Moran's I index greater than zero means that there have positive spatial connection among the observations, and the adjacent space regions have similar properties. Moran's I index smaller than zero means that there have negative spatial connection among the observations, and the adjacent space regions have different properties. When Moran's I index is equal to zero, there is no spatial connection among the observations. We present the Moran's I

Table 1
Descriptions of variables in econometric model.

Variable	Definition	Unit	Data source	Expected sign
Cancer	Lung cancer mortality	Persons per ten thousand persons	*Death Surveillance Database of* Chinese Center for Disease Control and Prevention and *County Level Population Statistical Yearbook of China*	N. A.
Respiratory	Respiratory diseases mortality	Persons per ten thousand persons	*Death Surveillance Database of* Chinese Center for Disease Control and Prevention and *County Level Population Statistical Yearbook of China*	N. A.
SO_2	Industrial SO_2 emissions	Tonnes	*China Environmental Yearbook* and *China City Statistical Yearbook*	Positive
Soot	Industrial soot emissions	Tonnes	*China Environmental Yearbook* and *China City Statistical Yearbook*	Positive
Density	Population density	Persons per square kilometer	*China City Statistical Yearbook*	Positive
Y	GDP per capita	RMB per person	*China City Statistical Yearbook*	Negative
Beds	Number of hospital beds	Beds per ten thousand persons	*China City Statistical Yearbook*	Negative

Table 2
Descriptive statistics of variables in Econometric model.

Variable	Observation	Mean	Standard deviation	Maximum	Minimum
Cancer	812	3.83	2.10	24.85	0.24
Respiratory	812	8.15	5.20	62.71	0.70
SO_2	812	79,261.31	77,678.40	682,922	92
Soot	812	35,657.30	123,731.10	3,257,261	93
Density	812	0.04	0.03	0.23	0.0005
Y	812	33,544.67	27,005.29	185,422.2	4722.49
Beds	812	35.80	14.68	126.94	9.57

indices of lung cancer mortality, respiratory diseases mortality, industrial sulfur dioxide emissions, and industrial soot emissions in Table 3.

The results show that the Moran's I indices of the four indicators are all significantly greater than zero, indicating that both air pollution and public health present an obvious spatial agglomeration. The Moran's I indices of industrial sulfur dioxide emissions and industrial soot emissions present an overall upward trend in the sample period, indicating that the spatial agglomeration of air pollution is strengthened.

Moran's I index can test the spatial agglomeration of economic activities in global areas, but it is unable to reflect the spatial characteristics of the local areas. Anselin (1995) proposed that Moran's I scatter plot can be used to measure the local spatial autocorrelation. Figs. A1–A8 in Appendix are the Moran's I scatter plots of lung cancer mortality, respiratory diseases mortality,

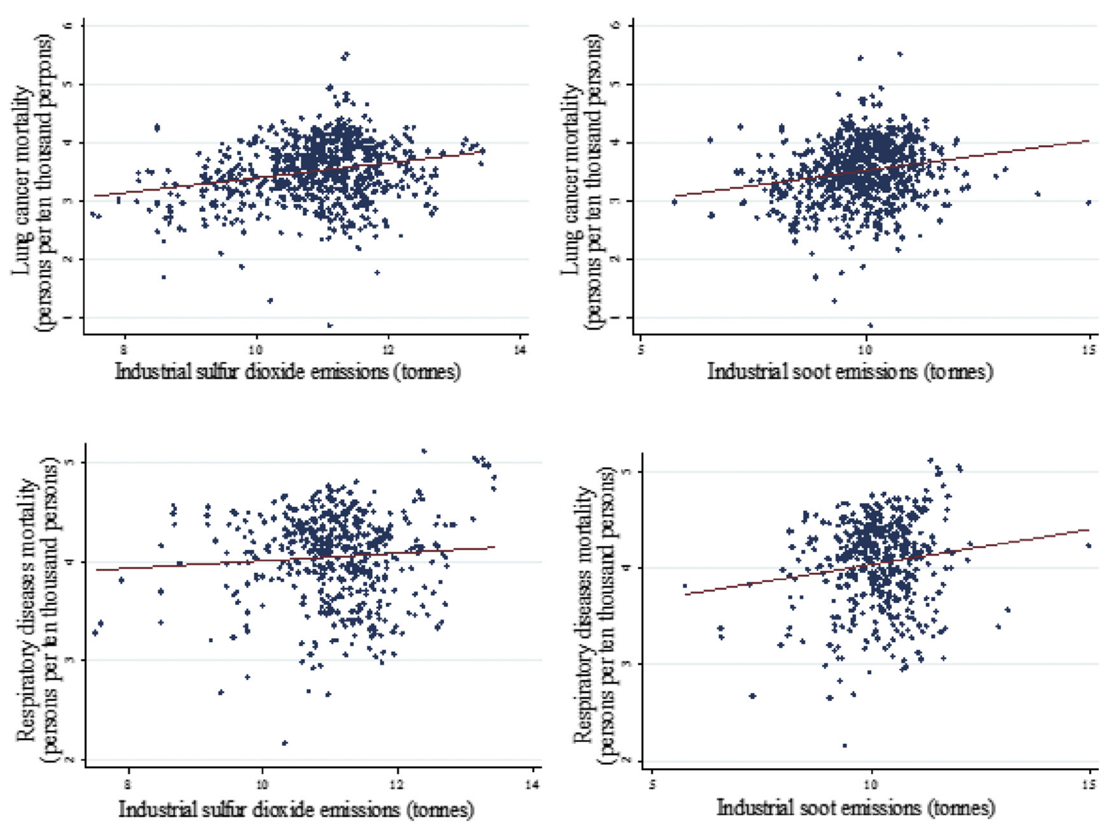

Fig. 2. Scatter plot of air pollution and health.

Table 3
Moran's I indices of air pollution and public health over 2006–2012.

	2006	2007	2008	2009	2010	2011	2012
Cancer	0.095***	0.075***	0.072***	0.073***	0.086***	0.073***	0.062***
Respiratory	0.044***	0.058***	0.058***	0.053***	0.079***	0.049***	0.069***
SO_2	0.026***	0.017**	0.014***	0.015**	0.017***	0.050***	0.046***
Soot	0.063***	0.056***	0.068***	0.040***	0.030***	0.059***	0.078***

Note: *, **, and *** represent the significances at 10%, 5%, and 1% levels, respectively.

industrial sulfur dioxide emissions, and industrial soot emissions in the beginning year (2006) and the end year (2012) of the sample period. The Moran's I scatter plots in these figures mostly locate in the first and third quadrant, indicating the high–high values to gather and low–low values to gather among the observations. Air pollution and public health among adjacent cities have an obvious spatial correlation. Hence, a spatial econometric analysis is necessary to investigate the impacts of air pollution on public health.

3.2. Overall discussion of estimated results

This section presents the estimated results of the spatial panel Durbin model and quantifies the impacts of air pollution on public health. Compared with the spatial Durbin model, we first estimate the non-spatial panel data model to further examine whether spatial autocorrelation exists. If the LM or the robust LM test rejects the null hypothesis that there is no spatial autocorrelation, then the spatial econometric model is appropriate.

Table 4 shows the results of the non-spatial panel data model through the OLS. The LM test rejects the null hypothesis at the significant level of 5% in the four groups of regression, indicating that the models have a significant spatial autocorrelation and that the spatial econometric model should be established. Industrial sulfur dioxide emissions and industrial soot emissions have a positive impact on lung cancer mortality in the non-spatial model. On the contrary, the impacts of industrial sulfur dioxide emissions and industrial soot emissions on respiratory diseases mortality are all negative, although the impact of industrial sulfur dioxide emissions is not significant. Such a result is not consistent with our expectations. We believe that one vital reason is that non-spatial model does not consider the spatial spillover effect of air pollution. Thus, we turn to focus on the analysis of the SDM.

Table 5 presents the estimated results of the SDM. The Wald test shows the SDM is more appropriate than the SAR and SEM in all the four groups of regression. The coefficients of industrial sulfur dioxide emissions and industrial soot emissions are significantly greater than zero. Such results are completely consistent with our expectations, implying that air pollution has a significant negative effect on public health.

Moreover, the coefficients of the spatial lags of industrial sulfur dioxide emissions are significantly greater than zero and even greater than the coefficients of the industrial sulfur dioxide emissions. Meanwhile, the coefficients of the spatial lags of industrial soot emissions are not significant negative and significant positive in the regressions of lung cancer mortality and respiratory diseases mortality, respectively. Overall, the spatial spillover effect of air pollution presents a significant negative impact on public health. Hence, the damage of air pollution to public health would be seriously underestimated if ignoring the spatial spillover effect of air pollution.

Due to the existence of spatial autocorrelation, the regression coefficients of the explanatory variables cannot be expressed as marginal effects, and the coefficients of the spatial lags of explanatory variables cannot accurately reflect the spatial spillover effect. However, we can use the direct, indirect, and total effects calculated based on regression coefficients of the SDM to quantify the impacts of air pollution and its spatial spillover effect on public health (Elhorst, 2014). Such works will be presented in the next section.

3.3. Direct and indirect effects

Table 6 shows the results of the direct, indirect, and total effects calculated based on Eqs. (6)–(8) and the regression coefficients of the SDM in Table 5. The direct effects of industrial sulfur dioxide emissions and industrial soot emissions on lung cancer mortality are 0.072 and 0.052 with a significant level of 1%, respectively, while the direct effects of industrial sulfur dioxide emissions and industrial soot emissions on respiratory diseases mortality are 0.029 and 0.030 with a weakly significant level of 20%, respectively. If transferring the above results into absolute magnitude, on average, an increase of ten thousand tonnes in industrial sulfur dioxide emissions leads to an increase of 0.035 and 0.03 per ten thousand persons in mortalities from lung cancer and respiratory diseases, respectively. Meanwhile, an increase of ten thousand tonnes in industrial soot emissions leads to an increase of 0.056 and 0.068 per ten thousand persons in mortalities from lung cancer and respiratory diseases, respectively. Therefore, air pollution presents a significant negative effect on public health.

Table 4
Results of non-spatial panel OLS regression.

	Cancer	*Cancer*	*Respiratory*	*Respiratory*
SO_2	0.073*** (4.39)		−0.016 (−0.67)	
Soot		0.066*** (4.09)		−0.052** (−2.31)
Density	0.086*** (4.44)	0.091*** (4.68)	−0.068** (−2.47)	−0.065** (−2.39)
Y	0.333*** (8.34)	0.350*** (8.90)	0.086 (1.52)	0.093* (1.69)
Beds	−0.188*** (−32.84)	−0.211*** (−3.19)	−0.339*** (−3.64)	−0.327*** (−3.52)
C	−1.942*** (−6.25)	−1.871*** (−6.07)	2.176*** (4.96)	2.407*** (5.56)
R^2	0.27	0.26	0.03	0.04
SAR-LM	123.545***	105.423***	72.978***	61.239***
SAR-RLM	39.867***	29.246***	31.678***	48.891***
SEM-LM	86.141***	77.041***	62.966***	46.891***
SEM-RLM	2.462	0.859	21.665***	33.961***

Note: *t*-statistics in parentheses; *, **, and *** represent the significances at 10%, 5%, and 1% levels, respectively.

Table 5
Results of SDM regression.

	Cancer	*Cancer*	*Respiratory*	*Respiratory*
SO_2	0.083*** (4.88)		0.045* (1.90)	
Soot		0.050*** (2.87)		0.045* (1.91)
Density	0.088*** (3.64)	0.088*** (3.61)	−0.107*** (−3.21)	−0.101*** (−3.03)
Y	0.190*** (4.05)	0.240*** (5.21)	0.149** (2.31)	0.145** (2.31)
Beds	−0.074 (−1.01)	−0.093 (−1.26)	−0.278*** (−2.75)	−0.295*** (−2.95)
ρ	−1.634*** (−3.49)	−1.698*** (−3.74)	−1.012* (−1.89)	−0.878* (−1.66)
W^*SO_2	1.148** (2.26)		2.602*** (3.48)	
*W*Soot*		−0.137 (−0.30)		2.903*** (4.36)
*W*Density*	−0.083 (−0.11)	0.958 (1.40)	−2.171** (−2.06)	−2.020** (−2.18)
*W*Y*	−1.678* (−1.69)	−1.881** (−1.96)	2.447** (1.81)	1.382 (1.12)
*W*Beds*	−0.075 (−0.03)	4.027 (1.55)	−6.743* (−1.87)	−8.825** (−2.51)
R^2	0.39	0.38	0.21	0.22
Log-L	−362.67	−369.89	−583.59	−580.49
Wald-SAR	11.23**	3.85**	18.13***	25.28***
Wald-SEM	14.93***	10.75**	16.36***	22.91***

Note: *t*-statistics in parentheses; *, **, and *** represent the significances at 10%, 5%, and 1% levels, respectively.

The indirect effect of industrial sulfur dioxide emissions on lung cancer mortality are 0.451 with a significant level of 10%, while that of industrial soot emissions on respiratory diseases mortality is not significant. In addition, the indirect effects of industrial sulfur dioxide emissions and industrial soot emissions on respiratory diseases mortality are 1.53 and 1.83 with a significant level of 5%, respectively. On average, an increase of ten thousand tonnes in industrial sulfur dioxide emissions in a city causes a total increase of 0.217 and 1.543 per ten thousand persons in the mortalities of all its neighboring cities from lung cancer and respiratory diseases, respectively. An increase of ten thousand tonnes in industrial soot emissions causes a total increase of 4.115 per ten thousand persons in the mortalities of all its neighboring cities from respiratory diseases. It is noteworthy that all the significant indirect effects are greater than their corresponding direct effects in Table 6, indicating that air pollution has a strong negative spatial spillover effect on public health.

Other explanatory variables control the effects of population density, economic development, and public medical condition on public health. The direct effect of population density on lung cancer mortality is greater than zero, but it is negative in respiratory diseases mortality regressions. A higher population density means there are more people in the unit area, increasing the likelihood of suffering from lung cancer as a long-term result of exposure to the serious polluted air conditions in a city. However, the incidence of respiratory diseases is shorter than the lung cancer. Moreover, the respiratory diseases are more controllable than lung cancer, since the public health system and the public could pay more attention to the prevention of respiratory diseases. Therefore, the respiratory diseases mortality may be relatively lower in a city with a higher population density.

The direct effects of per capita GDP on public health are all significantly positive in the four regressions. Generally, the higher level of economic development means higher energy consumption and more serious air pollution under the current growth mode of China, causing the prevalence of lung cancer and respiratory diseases. Moreover, the people aggregate to the region with the higher level of economic development may raise the total of potential victims. However, the indirect effect of per capita GDP on lung cancer mortality is significantly smaller than zero. This is consistent with our previous conclusion. The local population and pollution gather toward the neighboring regions with a higher level of economic development, resulting in a fall of lung cancer mortality in the local region.

At last, the direct effect of public medical condition on public health is smaller than zero, indicating that a good public health service condition plays a positive role in public health. The indirect effect of public medical condition on respiratory diseases mortality is significant smaller than zero. This means a good public health

Table 6
Direct, indirect, and total effects of SDM.

	Cancer	*Cancer*	*Respiratory*	*Respiratory*
Direct impact				
SO_2	0.072*** (4.82)		0.029# (1.37)	
Soot		0.052*** (3.50)		0.030# (1.38)
Density	0.091*** (3.55)	0.080*** (3.07)	−0.092** (−2.56)	−0.088** (−2.47)
Y	0.212*** (4.38)	0.267*** (5.58)	0.140** (2.06)	0.143** (2.16)
Beds	−0.079 (−0.99)	−0.142* (−1.75)	−0.244** (−2.24)	−0.255** (−2.33)
Indirect impact				
SO_2	0.451* (1.92)		1.529** (2.16)	
Soot		−0.049 (−0.28)		1.830** (2.15)
Density	−0.099 (−0.31)	0.321 (1.20)	−1.156* (−1.65)	−1.142 (−1.62)
Y	−0.833* (−1.88)	−0.945** (−2.22)	1.301 (1.35)	0.728 (0.83)
Beds	−0.050 (−0.05)	1.579 (1.51)	−3.629 (−1.60)	−5.179* (−1.86)
Total impact				
SO_2	0.523** (2.21)		1.558** (2.19)	
Soot		0.002 (0.01)		1.859** (2.16)
Density	−0.008 (−0.02)	0.401 (1.49)	−1.248* (−1.77)	−1.230* (−1.73)
Y	−0.622 (−1.41)	−0.677 (−1.54)	1.442 (1.49)	0.871 (0.99)
Beds	−0.129 (−0.12)	1.437 (1.40)	−3.873* (−1.71)	−5.434* (−1.95)

Note: *t*-statistics in parentheses; *, **, and *** represent the significances at 10%, 5%, and 1% levels, respectively; # denotes a weakly significance at 20% level.

Table 7
Death tolls and medical expenses caused by two types of air pollutants.

Year	SO_2 emissions (tonnes)	Soot emissions (tonnes)	Cancer death toll (persons)	Respiratory diseases death toll (persons)	Cancer medical expenses (hundred million RMB)	Respiratory diseases medical expenses (hundred million RMB)	Total medical expenses (hundred million RMB)
2006	7,131,412	2,805,730	22,868	63,600	19.06805	1827.302	1846.370
2007	7,068,368	2,478,525	27,374	67,965	22.82568	1952.727	1975.553
2008	6,605,843	2,170,478	30,191	72,929	25.17440	2095.352	2120.526
2009	6,122,687	1,981,924	30,225	69,172	25.20239	1987.404	2012.607
2010	6,218,452	1,979,032	31,774	70,333	26.49379	2020.741	2047.235
2011	6,616,941	6,874,638	32,307	68,890	26.93844	1979.284	2006.222
2012	6,118,556	3,432,404	34,294	72,126	28.59543	2072.280	2100.875
Average	6,554,608	3,103,247	29,862	69,288	24.89974	1990.727	2015.627

service condition in a city can present a positive spatial spillover effect on the public health of its neighbors.

3.4. Estimate of medical expenses

Although we have finished the investigation of the comprehensive impacts of air pollution and its spillover effect on public health, we still know nothing about the loss from the health damage caused by air pollution, which may be more concerned by economists and policy-makers. Table 7 evaluates the pollution and health nexus from such a perspective. Based on the above regression results, we further estimate the death toll and medical expenses resulted from air pollution. The average costs for treating the two diseases and the average mortality rate of the two diseases can be found in previous studies (Hou et al., 2010; Xia et al., 2012; Liu and Cai, 2012). Based on the above regression coefficients, we can calculate the death tolls caused by two types of air pollutants. The total death tolls of lung cancer and respiratory diseases are shown in the fourth and fifth column of Table 7. Next, through the average mortality rate of certain disease, we can reckon the actual number of victims suffering from this disease. Further, after multiplying the corresponding average treatment cost per person, we can get the overall cost for treating certain disease. The medical expenses of the two diseases and their total expenses are presented in the last three columns of Table 7.

We find that on an annual average, more than 200 billion RMB had been spent on the medical treatment for curing health damage induced by air pollution in 116 cities of China. Considering there are more than two thousand counties and county-level cities or districts in China and we only investigate parts of them, the total cost of health damage from air pollution for the whole nation could be several times higher than that reported in Table 7. In addition, according to the average total of the death tolls of two diseases, approximate hundred thousand lives (99,150 persons) were taken away every year due to air pollution.

4. Conclusions and policy implications

China is currently facing serious air pollution problems. It is beyond doubt that the probability for Chinese citizens giving exposure to ambient atmospheric environment is much greater than to other environmental conditions. Therefore, air pollution almost inevitably undermines the public health and social welfare in China. Air pollution accelerates the depreciation process of health human capital to impair the precious human capital in China. Meanwhile, a heavy public expenditure for curing health damage is unthinkable. Undoubtedly, the ongoing deteriorating air conditions will eventually damage the regional and national appearance and cast the negative impacts on long-term economic growth.

Regarding the influence of air pollution on public health, the existing literature mainly focused on the related issues at the individual level or from a pathological perspective. The study from the health economics aspect is rare. Moreover, the current studies mostly targeted at the sample at provincial level or took a certain city as a case. In addition, the spillover effect of air pollution is also neglected in the previous studies, causing serious bias and inconsistency in terms of air pollution and public health nexus. The main target of this paper is to investigate to what extent is the impact of air pollution on the public health in China. In particular, we examine whether there is significant spillover effect of air pollution in a city on the public health of its neighbors.

In detailed, one of the major contributions of this paper is our utilization of the environmental and public health big data sample. We use the survey data of lung cancer and respiratory disease mortalities at China's 116 prefecture-level city over 2006–2012 as the proxy of public health. Furthermore, the spatial panel Durbin model is established to estimate the specific damaging impacts of air pollution and its spillover effect on 116 prefecture-level cities in China. Our empirical results indicate that industrial sulfur dioxide and soot emissions present the significant positive impacts on the mortalities of both lung cancer and respiratory diseases. If industrial sulfur dioxide emissions in certain city increase by ten thousand tonnes, the mortalities of lung cancer and respiratory diseases will augment 0.035 and 0.030 per ten thousand persons, respectively. Meanwhile, air pollution has a strong spillover effect, i.e., the public health within a certain region is not only affected by the local air pollution, but also by that of its neighboring regions. If industrial sulfur dioxide emissions in a city increase by ten thousand tonnes, the mortalities of lung cancer and respiratory diseases will add 0.217 and 1.543 per ten thousand persons, respectively, in the neighboring cities. Astonishingly, the health damage brought out by the neighboring regions is more serious than that by the local one. Accordingly, the severe underestimation of the harm could be made if ignoring the spatial spillover effect of air pollutants.

Contemporary serious air pollution in China can be mainly attributed to the extensive economic growth mode with the distinct feature of high consumption, high emission, and low output. Hence, various policies and measures should be implemented, such as restructuring economic growth mode, promoting energy utilizing efficiency, increasing the proportion of clean energy in China's energy consumption structure, and upgrading the emission standard of industrial production for the sake of reducing pollutant emissions. With the joint efforts of the above measures, the air pollution can be reduced from its source, and its affirmative and benign impacts on the public health can be expected.

Meanwhile, in terms of the prophylaxis and treatment of air pollution, if we take the strong spillover effect of air pollution into consideration, the positive externality of curbing the air pollution will achieve in a region and its neighbors. Since it is hard to accurately identify the accountability and benefit in a certain region's environmental protection, the arising free riding problem will disturb the normal incentive and constrain mechanism in the regional management of environmental problems. Hence, comprehensive ecological improvement and management are urgently needed. We call for a series of more well-rounded plans as a whole for interregional effective management system. The regional joint prevention and control mechanism for air pollution could effectively internalize the externality generated by the spillover effect, in order to enhance the efficiency of curbing pollution and improve the environmental quality.

Moreover, our results also show that a sound medical and sanitary condition could play an active role in promoting the public health and benefiting neighboring regions through a positive spillover effect. Hence, increasing funding to public health facilities and perfecting public sanitary service system will alleviate the health damage from air pollution.

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Appendix

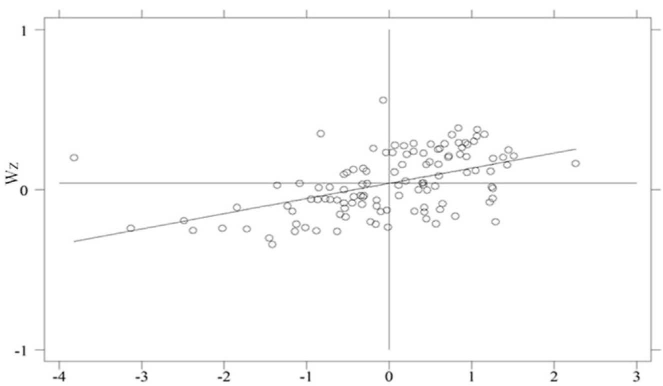

Fig. A1. Moran's I scatter plot of *Cancer* in 2006 (Moran's I = 0.095).

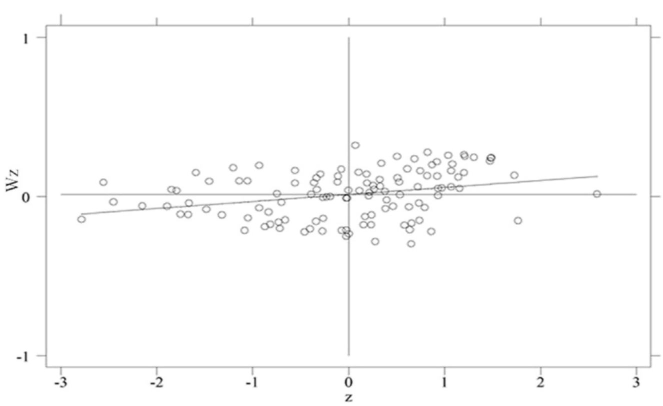

Fig. A2. Moran's I scatter plot of *Respiratory* in 2006 (Moran's I = 0.044).

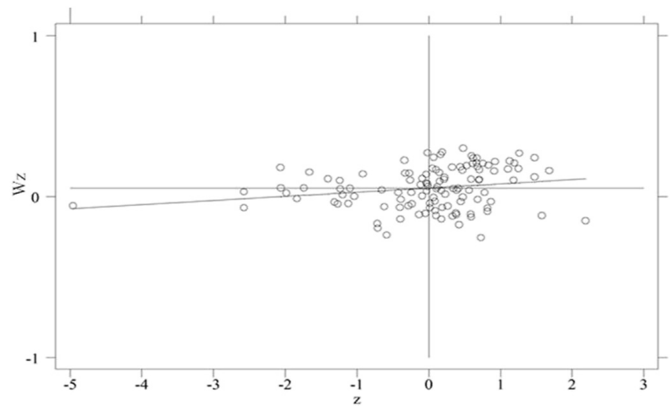

Fig. A3. Moran's I scatter plot of SO_2 in 2006 (Moran's I = 0.026).

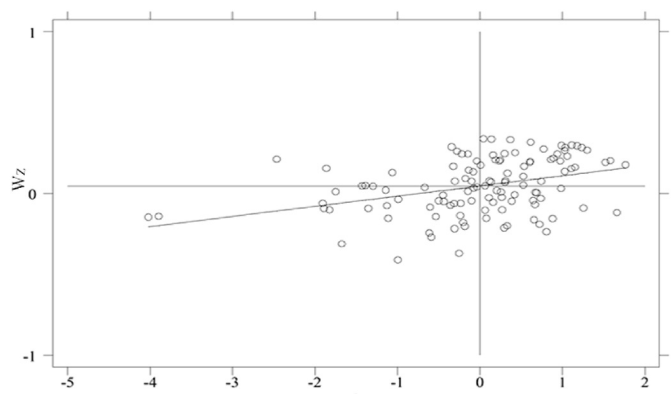

Fig. A4. Moran's I scatter plot of *Soot* in 2006 (Moran's I = 0.063).

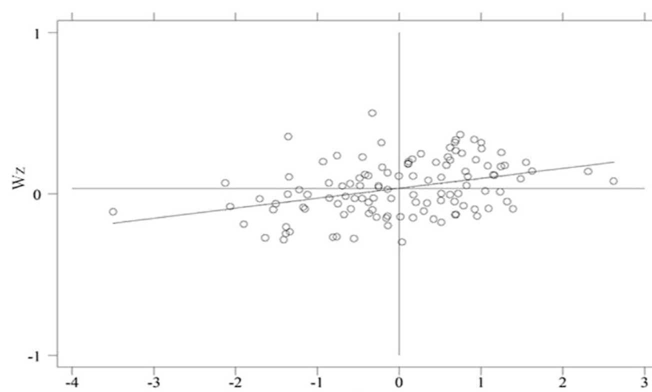

Fig. A5. Moran's I scatter plot of *Cancer* in 2012 (Moran's I = 0.062).

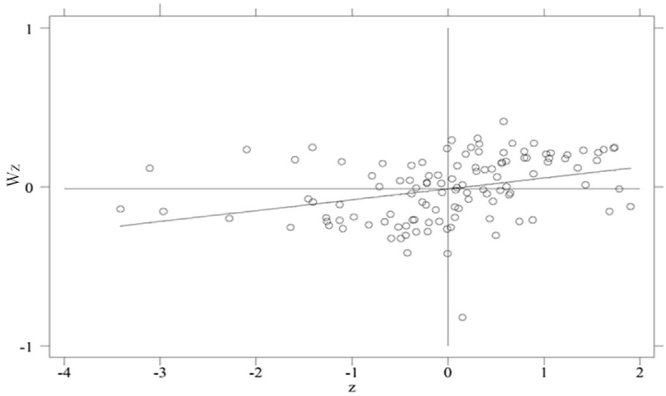

Fig. A6. Moran's I scatter plot of *Respiratory* in 2012 (Moran's I = 0.069).

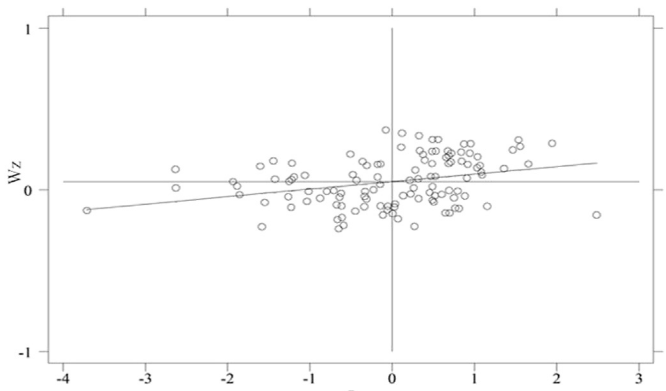

Fig. A7. Moran's I scatter plot of SO_2 in 2012 (Moran's I = 0.046).

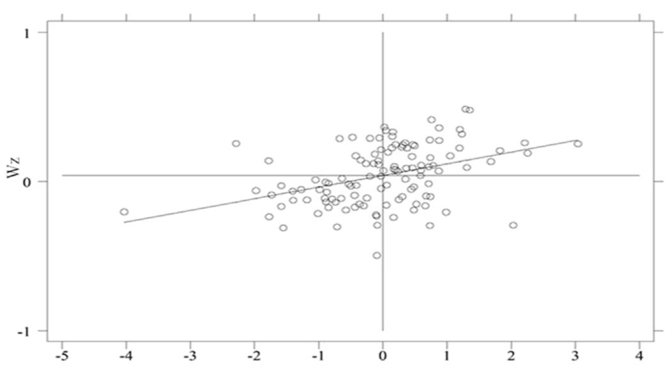

Fig. A8. Moran's I scatter plot of *Soot* in 2012 (Moran's I = 0.078).

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