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Spatial Effects of Air Pollution on Public Health in China

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Abstract Increasingly serious air pollution poses a great threat to public health and daily life. Based on the Grossman China health production function, this paper examines the effects of the spatial agglomeration of Chinese public health and the spatial effects of air pollution and other factors on public health considering three aspects. This study employed Chinese macro data on public health and air pollution from 2004 to 2013 to conduct an empirical analysis using a spatial econometrics technique. The main conclusions are as follows. Due to extensive and persistent air pollution, there was a significant spatial agglomeration impact on public health, regional public health presented a convergence effect, and effects of air pollution's negative externalities on public health were significant. Compared with the estimation results obtained when spatial dependence was not considered, the negative effect of the concentration of PM2.5 on public health was higher, implying that the traditional approaches tend to create biases when spatial correlation is ignored; from a regional perspective, the regional differences in the effects of air pollution on public health were significant. Adopting differentiated environmental policies for different regions is the future direction towards which China's environmental governance will develop.

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1 Introduction

Given the rapid development of industrialization and urbanization, China's economy continues to grow at a high speed. However, attendant environmental pollution has become a serious problem. The *China National Environmental Analysis* (2012) reported that three cities in China were listed among the world's top ten most polluted cities in 2012. It also showed that the economic losses caused by air pollution in China accounted for 1.2–3.8% of the gross national product. In 2013, Beijing and the vast area of Central East China experienced sustained and continuous fog and haze, and China even received a new name: "Haze China". Environmental pollution, especially air pollution, has been a serious threat to the daily life and health of residents. According to *China's Environmental Development Report* (2014), various kinds of diseases caused by air pollution exhibit rising trends in China. The damage to public health caused by air pollution is becoming prominent and increasingly serious. The *Global Burden of Disease Report* (2010) showed that outdoor $PM_{2.5}$ pollution had already caused 1.2 million premature deaths and 25 million disabilities in China. Fang et al. (2016) noted that $PM_{2.5}$ pollution in China has incurred great health risks that are even worse than those of tobacco smoking. The Chinese Academy of Environmental Sciences (2011) noted that 21% of the burden of disease was caused by air pollution factors in China, eight percent higher than in the United States. The declining environmental quality and public health hazards caused by air pollution are becoming the key factors restricting China's sustained economic growth and social development (Lu and Qi 2013).

The environment is an important determinant of health. Environmental impacts on health depend on pollutant concentrations, exposure response coefficients and other aspects. Air pollutants reach certain levels of concentrations, and after long periods of exposure, the harmful effects to human respiratory health become visible, and coughing due to colds, sputum, asthma, bronchitis, asthma, and respiratory disease hospitalization rates increase significantly. With the aggravation of environmental pollution, the public health problem caused by air pollution cannot be ignored. The Eighteenth Report of the People's Republic Party noted that we should continuously improve environmental air quality and improve people's health. However, air pollution often has a strong regional correlation. The negative externalities of air pollution and regional disharmonies in allocations of public health resources induce a spatial effect on public health. In view of this, this paper will construct a spatial econometric model on the public health of air pollution, which is based on the expanding Grossman health production function, with a comprehensive consideration of social, economic, medical, educational, and other factors. It will then be used to explore the effects of air pollution on public health and spatial interaction.

When Grossman pioneered the theory of healthy production function theory in 1972, studies on air pollution and health began citation. The health production function describes the relationship between health production input and output. Grossman introduced health into the consumer utility function as a kind of consumer good that can bring utility and an investment product that can gain income. Cropper (1981) established the health of an air pollution analysis framework with air pollutant variables based on the theoretical model of Grossman and concluded that air pollution is an important factor affecting health. Gerking and Stanley (1986) directly introduced air pollutant concentration into the health production function to study residents' willingness to pay for improving air quality.

In a life cycle, air pollution affects the health of the depreciation rate. Residents living in areas with severe air pollution face the impacts of the accelerated depreciation of health capital stocks (Alberini et al. 1997). Dockery et al. (1993) found that the rise in the concentration of particulates (PM_{10}) was closely related to respiratory system disease and incidence of heart disease. Studies of Chay and Greenstone (2003) showed that the PM_{10} and $PM_{2.5}$ concentrations in air increased by one percentage point and that infant mortality rate would increase by 0.35 percentage points at the same time. These studies were mainly from the perspective of biological science; however, the factors considered in the analysis were not that comprehensive. The study of Chen et al. (2013b) showed that the average life expectancy of residents in Northern China would be reduced by approximately 5.5 years because of air pollution, while increasing risks of stroke, lung cancer, heart disease and other diseases. Chen et al. (2013a) also claimed that in the 1990s, air pollution had caused the lifespans of residents in Northern China to be reduced by 25 years, which was equivalent to 12.5% of the North's labour force. All of these studies have shown that air pollution has had an important impact on the health of the residents. However, the analysis of air pollution was mainly from a macro perspective, and there is little literature that considers regional differences in air pollution.

The impact of air pollution on public health was too obvious, and how to develop effective environmental policy to improve the environmental health effects had become the focus of researchers. Wong et al. (1998) found that SO_2 emissions decreased by approximately 80% after the implementation of the policy when studying environmental policies for sulphur fuels in Hong Kong. The numbers of children suffering from respiratory diseases had decreased by approximately 16–29%. In addition, because of the implementation of environmental regulations on transport and related industries in Beijing during the Olympic Games, the average value of $PM_{2.5}$ decreased by 32.1 mg m^{-3}, the average value of PM_{10} decreased by 46%, and the cost of environmental health dropped by approximately 38% (Li et al. 2010). Environmental regulation was used mainly to control and reduce the level of pollution to improve environmental health effects, but the effect on this study was that the structural effects, i.e., the impact of air pollution on the health of residents with heterogeneity, could not be ignored. The heterogeneity was mainly due to two aspects: micro individual differences and differences in the distributions of public resources such as education, environment, health and other public resources (Wang 2007). Compared to adults, children and lower income families faced greater health risks and were also more vulnerable to the impacts of air pollution (Currie et al. 2008; Neidell 2004). Brooks and Sethi (1997) noted in their study that the people who are most exposed to air pollutants, including tenants, have low incomes and poor education. Ebenstein (2012) showed that the risks of cancer and other diseases of families with tap water or clean water resources were significantly lower than for other families. Lu and Qi (2013) claimed that there were differences between the environmental health effects in countries or areas, and environmental health risk depended on different levels of education, environment and health and other public services. Although those studies analysed the impacts of air pollution on public health from several perspectives, there have been few studies on the spatial spillover of air pollution and the spatial effect on public health.

Air pollution not only affects local area but also impacts adjacent areas (Ma et al. 2014). Because of the spatial dependence of the air pollution problem, a single regional effort is insufficient to improve air quality. Due to regional differences in economic, social, environmental, medical and other aspects, the factors that cause air pollution in different regions produce significant spatial differences on public health (Yang et al. 2013). In particular, the differences in the medical situations of different regions, can produce spatial attributes in the data on the numbers of people receiving treatment and health examinations in hospitals (Broome et al. 2015; Wu et al. 2015). Most of the world's research on environment and

health can be summarized via two aspects. One is mainly concentrated in the fields of environmental science and medicine, and most of the studies are based on using individual or non-random samples to inquire into the effects of environmental health economic loss (Larson and Rosen 2002; Tarricone 2006; Xie 2013). The other mainly uses panel data to analyse relationships between air pollution and public health using spatial econometrics. Chen et al. (2017) employed a spatial Durbin model to investigate air pollution health impacts employing survey data on mortality from China's 116 cities. Wang et al. (2015) studied the spatial and temporal effects of $PM_{2.5}$ in the Yangtze River Delta. Liu et al. (2016) found that areas of high population density exhibited the highest health risks attributable to air pollution. In our study, we used the concentrations of three main air pollutants ($PM_{2.5}$, PM_{10}, and SO_2) to characterize air pollution and undertake a study from the perspective of provincial level. In a traditional panel regression, it is assumed that all areas of public health are independent of each other, which is an obvious deviation from reality. For example, air pollution, as an area of public health, will inevitably be affected by adjacent areas of pollutant discharge, and if we ignore that influence, model estimations will be biased or falsely validated (Anselin and Griffith 2010). Therefore, it is more important and meaningful to analyse the spatial effects of air pollutants on public health while considering the spillover effects of air pollution and health.

## 2 Materials and Methods

2.1 Theoretical Model

Many factors affect the health of residents and disease (Fig. 1), mainly including the environment, personal behaviour and lifestyle, genetics, and health care. Grossman first established the micro health production function to analyse the health needs of residents in 1972. The function included income, health, education, environment, and other factors. It showed that the health statuses of residents were not only affected by the environment but were also influenced by other factors. The health level of residents would have a certain degree of improvement with good health services, and governmental investment in health care would indirectly affect the health of residents. In the complete Grossman model, the expression of the determinants of health can be formulized as Eq. (1):

$$h = f(x) = f \left(\begin{matrix} Life, Income, Pub\_Goods, EDu, \\ Inp\_Time, P\_E, Envi \dots \end{matrix} \right) \tag{1}$$

where h is the individual health condition, and x is a group of vectors that affect the health of the residents. These vectors include lifestyle (*Life*), income levels (*Income*), public goods consumption (*Pub_Goods*), education (*Edu*), input time (*Inp_Time*), individual endowments (*P_E*), and environmental endowments (*Envi*).

The health production function constructed by Grossman studies the factors of residents' health from a microcosmic point of view. The study of Nejat et al. (2004) analysed the factors from the perspective of traditional medicine. Considering the study of the two at the same time, referencing Lu and Qi (2013), Wang (2007) and Zhong (2006), we selected factors that affect the health of residents such as economy, society, education, health care, and environment. Thus, the health production function of this paper can be expressed as

$$H = F(X) = F(Eco, Soc, Edu, Mc, Envi) \tag{2}$$
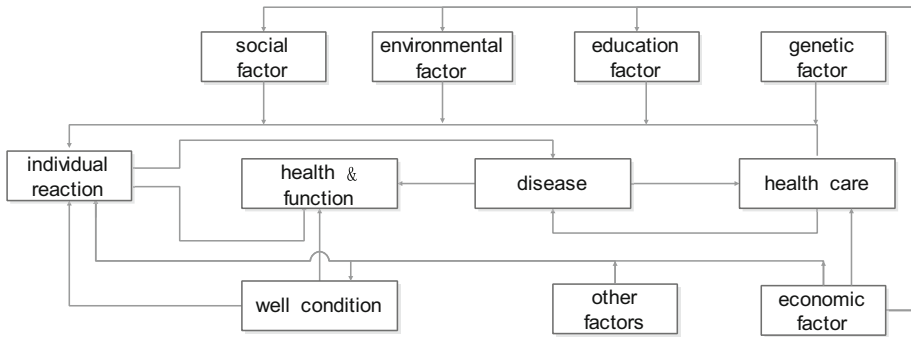
Fig. 1 Multi-factor decision model of health (see Nejat et al. 2004)

where H represents the health level, Eco, Soc, Edu, Mc, and $Envi$ represent economic, social, educational, health, and environmental variables.

On the basis of Eq. (2), we can obtain the expression for the China macro health function.

$$LnH = Ln\Omega + \alpha LnEnvi + \beta_1 LnEco + \beta_2 LnSoc + \beta_3 LnEdu + \beta_4 LnMc \qquad (3)$$

where α represents the elastic coefficient of the core explanatory variables β_1, β_2, β_3, and β_4, represent the elastic coefficients of other control variables, and Ω represents estimates of initial health status (Grossman 1972).

An individual's health has a close relationship with his living environment ($Envi$). Environmental impacts on health depend on the concentrations of pollutants, exposure response coefficients, and other aspects. Air pollutants reach a certain level of concentration, and after a long period of exposure, the harmful effects to human respiratory health become visible; coughs due to colds, sputum, asthma, bronchitis, asthma and respiratory disease hospitalization rates increase significantly. For this paper, we chose the concentrations of three main air pollutants ($PM_{2.5}$, PM_{10}, and SO_2) to characterize the air pollution.

Health is also closely related to the economic level of residents (Eco). The economic level of residents is generally expressed by income, and we chose per capita GDP to characterize economic level. Many studies have indicated that high income and good health are closely related. Ma et al. (2016) claimed that $PM_{2.5}$ pollution has significant spatial aggregation and diffusion effects that are significantly influenced by regional economic association in China. However, whether good health results in high income or high income leads to good health level has been a significant controversy. At the same time, some studies have claimed that residents with high incomes must suffer high work time intensities, high social pressures, unhealthy lifestyles, and other issues, and this will surely result in declines in their health. Therefore, the relationships between health and the economic level of residents in empirical studies differ.

Social factors (Soc) and the health of residents have a great degree of correlation. With increases in public expenditure and investment in public facilities, residents receive more opportunities for physical exercise and leisure activities, which will improve residents' health.

Health and education (Edu) are also inseparable. Grossman (1972) noted that well-educated people can be more effective in improving their health, and that conclusion has been confirmed by many empirical studies. Improvements to medical factors (Mc) is very important for improving the health of residents.

2.2 Spatial Econometric Model

2.2.1 Spatial Correlation Test

Global spatial correlation test Taking into account the existence of Tobler's First Law, researchers began to pay attention to spatial correlations between regions. In present studies, the Moran's I value is generally used to test spatial correlations, the equation for which is

$$Moran's\ I = \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} W_{ij}(Y_i - \bar{Y})(Y_j - \bar{Y})}{S^2 \sum_{i=1}^{n} \sum_{j=1}^{n} W_{ij}} \tag{4}$$

where $S^2 = \frac{1}{n} \sum_{i=1}^{n} (Y_i - \bar{Y})^2$, $\bar{Y} = \frac{1}{n} \sum_{i=1}^{n} Y_i$ and Y_i represent the observed values of region i, n represents the number of regions, and W represents the binary spatial weight matrix. In this paper, the setting of the spatial weight matrix W is based on the distance-based weight matrix, that is, the geographical adjacency weight matrix. Its assignment rule is that 1 means that regions i and j are spatially adjacent, and 0 means that regions i and j are not spatially adjacent.

$$W_{ij} = \begin{cases} 1, & i\ is\ adjacent\ to\ j; \\ 0, & i\ isn't\ adjacent\ to\ j. \end{cases} \quad (i \neq j) \tag{5}$$

Local spatial correlation test The value of global Moran's I reflects the spatial correlation of the entirety, but that evaluation may ignore atypical local area features. Anselin (1995) proposed the local s' I Moran value (or LISA) to test the local spatial correlation. Its formula is

$$Moran'\ I_i = \frac{(Y_i - \bar{Y})}{S^2} \sum_{j=1}^{n} W_{ij}(Y_j - \bar{Y}) \tag{6}$$

2.2.2 Spatial Econometric Model

The general spatial econometric model can be divided into a spatial lag model (SLM, which is also called a spatial autoregressive model, SAR) and spatial error model (SEM). Elhorst (2003) divided the spatial panel data model into four categories, a spatial fixed effect model, spatial random effect model, spatial fixed coefficients model, and spatial random coefficient model, provided the log likelihood function of each model and analysed the asymptotic properties of the ML estimators. In this study, we used a spatial fixed effect model. Usually, when regression analysis is limited to specific individuals, a fixed effect model is a better choice; in addition, in the spatial panel research literature, fixed effect models are generally chosen. The spatial econometric model of the panel data is expressed as follows:

Spatial autoregressive model (SAR):

$$Y_{it} = \delta \sum_{j=1}^{N} w_{ij} y_{it} + x_{it}\beta + \mu_i + \varepsilon_{it} \tag{7}$$

Spatial error model (SEM):

$$Y_{it} = x_{it}\beta + \mu_i + u_{it}$$

$$u_{it} = \lambda \sum_{j=1}^{N} w_{ij} u_{it} + \varepsilon_{it} \tag{8}$$

The δ and λ in Eqs. (7) and (8) represent the spatial regression coefficient and the spatial error coefficient, respectively. δ reflects the spatial dependence of the observed value of the sample, and λ represents the spatial autocorrelation coefficients of the explained variable, which reflect the degree of influence of the residual term of the neighbouring region on the residual term of the local area. Y_{it} represents the $N \times 1$ dependent variables of the observed value of the explanatory variables in time $t(t = 1, \ldots, T)$ of each space unit $(i = 1, \ldots, N)$. represents the elements of the $N \times K$ order explanatory variable matrix. W_{ij} represents the elements of the $N \times N$ order non-negative spatial weight matrix.

2.3 Variables and Data

The analysis in this paper of the impact of environmental and other factors on public health is based on Eq. (3). Thus, we need to define the variables for each factor.

Explained variable: Public health It is difficult to directly measure health. Current studies have mainly selected population mortality, the mortality of children under 5 years old, and healthy life index at birth to measure public health. It is not appropriate to measure the effects of air environment on public health through population mortality, however, because the impact of air pollution on health is relatively slow, and the causes of death in populations are usually various and complex. Mortality of children under 5 years old and healthy life index at birth lack corresponding provincial and time series data. Aggravation due to air pollution can easily cause residents' immune systems to experience increased incidences of disease, especially original chronic cardiovascular and respiratory diseases that are more likely to cause patients to get sick or be hospitalized. At the same time, air pollution, especially fog and haze, causes residents to be more concerned about their own health, and increasing numbers of people will visit hospitals for examinations. Therefore, considering the variety of ways air pollution can impact public health and data availability, the health statuses of residents were measured along three dimensions for this paper: passive medical diagnoses, active health examinations, and health state. (In this paper, we first consider respiratory system disease mortality, lung disease mortality and other data to characterize the level of public health. However, due to the lack of provincial data and the short time periods of data, it is difficult to undertake effective spatial panel measurement analyses, and we therefore used alternative indicators.) The specific indicators were selected with respect to the number of people receiving treatment in hospitals per ten thousand (Y1_RT), the number of health examinations in hospitals per ten thousand (Y2_HE), and the number of in-patient stays per ten thousand (Y3_HN).

Core explanatory variables: Air pollution We know that exposures to PM_{10}, $PM_{2.5}$, SO_2, NO_2, O_3, and CO are significantly associated with increased all-cause and cardio-respiratory mortality risks in the Chinese population (Shang et al. 2013). In this paper, we use the concentrations of three main air pollutants ($PM_{2.5}$, PM_{10}, and SO_2) to characterize air pollution. Those three kinds of air pollutants are more harmful to public health than others air pollutants. $PM_{2.5}$ is the main pollutant, which caused a large area of fog and haze in Northern China in early 2013, and increased concentrations of $PM_{2.5}$ and PM_{10} increase the probabilities of occurrence of respiratory system and circulatory system disease (Chen et al. 2010). Increased emissions of SO_2 also increase the number of patients with respiratory disease and lung cancer (Chen and Chen 2014).

The other control variables were primarily obtained from economic, medical, education, and social dimensions, and the specific indicators are per capita GDP, the number of physicians per ten thousand, junior high school enrolment rate, and the proportion of public finance expenditures. Herein, the proportion of public finance expenditures is with respect to the ratio

of government spending on public services, the establishment of the social medical security system, and disease prevention and control systems to GDP.

For this paper, the data were mainly obtained from the China Statistical Yearbook (2005–2014), China Health Statistical Yearbook (2005–2013), China Health and Family Planning Statistical Yearbook (2014), China National Bureau of Statistics, and other sources. The $PM_{2.5}$ concentration data (2004–2012) for each province in Chinese reference the annual global mean (2004–2012), which was measured by the International Earth Science Information Network Center of Columbia University (Battelle Memorial Institute, CIESIN, 2013). The $PM_{2.5}$ concentration data (2004–2010) were obtained from Battelle Memorial Institute and the Center for International Earth Science Information Network (CIESIN) at Columbia University. The remaining provincial $PM_{2.5}$ panel data (2011–2012) were calculated based on $PM_{2.5}$ data compiled by the Chinese Environmental Monitoring Center (CNEMC). The $PM_{2.5}$ panel data (2013) were obtained from the National Bureau of Statistics of the People's Republic of China. The data and China's haze situation were basically consistent.

3 Results and Discussion

3.1 Spatial Autocorrelation Test

3.1.1 Global Spatial Autocorrelation Test

The values calculated using the function for Moran's I for the three dimensions of the public health during 2004–2013 in China are shown in Table 1.

From Table 1, we can see that the spatial autocorrelations of the Moran's I values along the three dimensions of public health in the 10 years showed a growing trend, the values were positive, and the results were significant. This was due to the sharp increase in China's GDP during the past decade and the high pollution caused by the extensive economic growth mode. Highly polluting industries also gathered in conjunction with economic development in all places. Public health also faces a more concentrated threat due to the development of polluting industrial clusters. It also shows that PM2.5 and PM10 had strong autocorrelations, whereas that for SO_2 was not obvious. In addition, the spatial autocorrelation of public health showed a significant growing trend, but the PM2.5 and PM10 spatial autocorrelations did not exhibit that trend. This means that the autocorrelation of public health was not entirely due to the spillover effect of air pollution. Further, we can see that the global spatial autocorrelation of the number of people receiving treatment in hospitals per ten thousand (Y1_RT) was the most significant and was followed by the number of health examinations in hospitals per ten thousand (Y2_HE) and the number of in-patient stays per ten thousand (Y3_HN). The results show that public health in China had a strong positive spatial correlation during 2004–2013, which means that the spatial distributions of public health in China were not independent of each other but that there was rather a spatial spillover or diffusion effect between the regions, and the index values of the three dimensions of public health had obvious spatial agglomerations.

China public health has significant spatial convergence and consistency. With the development of economy and society, this kind of agglomeration effect is increasing, which is closely related to the agglomerations of regions' social, economic, educational, and other resources in China.

Table 1 Moran's I values of public health and air pollution in China during 2004–2013

Year	Y1_RT	Y2_HE	Y3_HN	PM2.5	PM10	SO$_2$
2004	0.231***	0.173**	0.158*	0.438***	0.061	−0.048
	(2.442)	(2.013)	(1.632)	(4.094)	(0.820)	(−0.899)
2005	0.240**	0.189**	0.170**	0.509***	0.190**	−0.047
	(2.351)	(2.113)	(1.749)	(4.721)	(2.065	(−0.941)
2006	0.244***	0.213**	0.182**	0.480***	0.239***	−0.048
	(2.482)	(2.109)	(1.975)	(4.450)	(2.575)	(−0.836)
2007	0.242***	0.177**	0.163**	0.535***	0.163***	−0.046
	(2.584)	(1.883)	(1.753)	(4.997)	(1.878)	(−0.935)
2008	0.248**	0.220**	0.171**	0.535***	0.127*	−0.049
	(2.584)	(2.286)	(1.864)	(5.026)	(1.455)	(−0.874)
2009	0.261***	0.204**	0.190**	0.543***	0.223**	−0.048
	(2.596)	(2.130)	(2.090)	(4.771)	(2.140)	(−0.861)
2010	0.273***	0.229**	0.166**	0.545***	0.218**	−0.048
	(2.672)	(2.351)	(1.800)	(4.724)	(2.212)	(−0.927)
2011	0.280***	0.221***	0.167**	0.509***	0.179**	−0.047
	(2.791)	(2.332)	(1.839)	(4.673)	(1.856)	(−0.821)
2012	0.270***	0.208**	0.163**	0.437***	0.211**	−0.048
	(2.847)	(2.204)	(1.737)	(4.110)	(2.190)	(−0.893)
2013	0.277***	0.203**	0.164**	0.380***	0.321***	−0.049
	(2.975)	(2.146)	(1.741)	(3.444)	(3.391)	(−0.967)

*, **, and *** represent significance at the 10, 5, and 1% levels, respectively; the Z statistic values are shown in brackets

3.1.2 Local Spatial Autocorrelation Test

The Moran's I public health values show that public health had a global spatial correlation. To investigate the public health of the local characteristics, this paper presents local Moran's I scatterplots along the three dimensions of public health (Figs. 2, 3, 4, 5). The scatterplots can be divided into four parts that correspond to the local spatial correlations between the regions. The first and the third quadrants represent positive spatial correlations, and the second and the fourth quadrants represent negative spatial correlations. The first quadrant represents high observation units surrounded by high value regions (H-H), the second quadrant represents low observation units surrounded by high value regions (L-H), the third quadrant represents low observation units surrounded by low value regions (L-L), and the fourth quadrant represents high observation units surrounded by low value regions (H-L).

Among the figures, Figs. 2 and 3 show the local Moran's I scatterplots of Y1_RT in 2004 and 2013, which were selected to reflect the trends in the local spatial correlations of the explained variables over time. Figures 3, 4 and 5 show the local Moran's I scatterplots for Y1_RT, Y2_HE, and Y3_HN in 2013, which were used to analyse the local correlations of the explained variables in three dimensions. In the figures, the horizontal coordinate is the index value, and the vertical coordinate is the spatial lag term of the index. Each point in the figures represents a province, and the distances between the points and curves represent the differences between the provinces and other regions. A larger distance between a point and a curve indicates greater differences between the province and other regions.

As seen from Figs. 2 and 3, Moran's I increased from 0.231 to 0.277 during 2004–2013, which indicates that the local autocorrelation of Y1_RT had been enhanced in China. Fig-

Fig. 2 Local Moran's I
scatterplot of Y1_RT in 2004.
Note: due to the length of the
paper, we only show a part of the
local Moran's I scatterplots
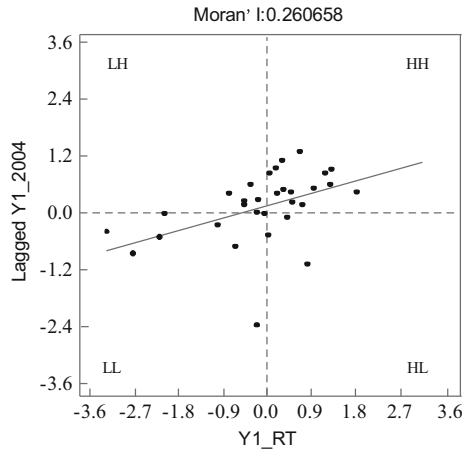
Fig. 3 Local Moran's I
scatterplot of Y1_RT in 2013.
Note: due to the length of the
paper, we only show a part of the
local Moran's I scatterplots
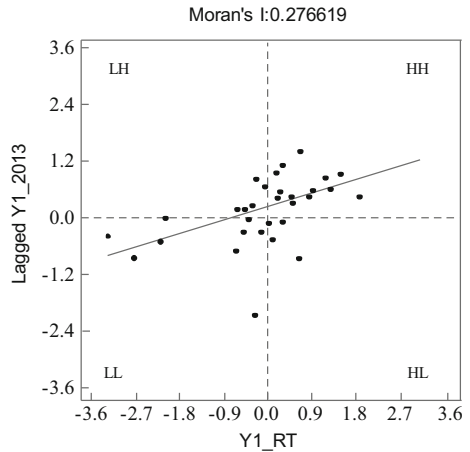
Fig. 4 Local Moran's I
scatterplot of Y2_HE in 2013.
Note: due to the length of the
paper, we only show a part of the
local Moran's I scatterplots

Fig. 5 Local Moran's I scatterplot of Y3_HN in 2013. Note: due to the length of the paper, we only show a part of the local Moran's I scatterplots

ures 3, 4 and 5 indicate that the three-dimensional Chinese public health indicators were mainly concentrated in the first and the third quadrants i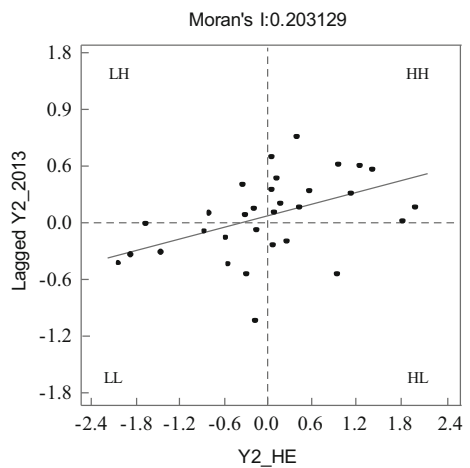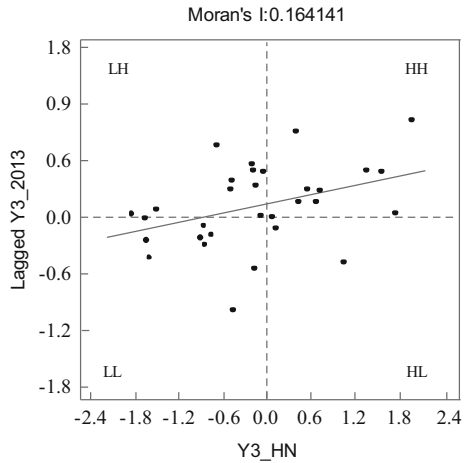n 2013. Figure 3 shows that the number of H-H agglomeration provinces along dimension Y1_RT was 14 and included, among others, Zhejiang, Shandong, Hunan, Hubei, Beijing, Tianjin, Anhui, and Guangdong. There were 8 provinces agglomerated in L-L, which included Xinjiang, Tibet, Qinghai, Ningxia, and Jilin. Figure 4 shows that there were 14 H-H agglomeration provinces along dimension Y2_HE, which included Zhejiang, Shaanxi, Shanxi, Shandong, Hunan, Hubei, Jiangsu, Guangdong, and Hebei. Yunnan, Xinjiang, Tibet, Qinghai, Heilongjiang, and Jilin, were among the 10 L-L agglomeration provinces. Figure 5 shows that the number of H-H agglomeration provinces along dimension Y3_HN was 8 and included Shandong, Hunan, Hubei, Anhui, Jiangsu, and Guangdong, and there were 8 L-L agglomeration provinces, among which were Xinjiang, Qinghai, Inner Mongolia, Jilin, and Gansu. Combined with the analysis of the three dimension indicators of public health, we can see that although each indicator's concentration differed slightly, the regional effect was consistent and significant. Overall, (1) the H-H agglomeration provinces of China's public health were mainly concentrated in Shanxi, Shaanxi, Beijing, Tianjin, Hubei, Hunan, Henan, Anhui, Jiangsu, Guangdong, Shanghai and other parts of North China, Central China, and the eastern coastal areas; the economies of those provinces are better economic developed, and their populations and education and health care resources are more concentrated. (2) The L-L agglomeration provinces of China's public health were mainly concentrated in Xinjiang, Tibet, Qinghai, Jilin, Heilongjiang, and other Northwest and Northeast China areas; the environments of those provinces are relatively poor, and their public service resources are also relatively scarce.

Thus, it can be seen that Chinese public health has characteristics of spatial heterogeneity as well as spatial dependency.

3.2 Spatial Panel Regression Analysis

The spatial effect of public health is significant, and the spatial econometric models in the three dimensions were determined as fixed effect models employing the Hausman Test. Generally, when a study sample is randomly obtained from a population, a random effect model is more appropriate, but when regression analysis is aimed at specific individuals, it

is more appropriate to choose a fixed effect model. This paper is based on the 31 provinces of China employed as the research object, and the fixed effect is therefore more appropriate.

3.2.1 Full Sample Estimation without Spatial Factors

From Table 2, we can see that the full sample estimates of the three dimensions of public health indicators were all significant, and the R2 value for each model exceeded 0.7. The DW value was close to 2, which indicates that the serial correlation was not significant. In addition to several indicators that showed that the number of people receiving treatment in hospitals per ten thousand (Y1_RT) was not significant, the remaining explanatory variables were highly significant.

Additionally, we know that as the concentrations of $PM_{2.5}$, PM_{10}, and SO_2 increase, the number of people receiving treatment in hospitals, the number of health examinations in hospitals, and the number of in-patients significantly increase. The other influence is the consequent reduction in public health levels. The results of the coefficient show that PM_{10} indicator had the greatest impact on public health, followed by SO_2 and $PM_{2.5}$. The concentrations of PM_{10} rose 1%, and the number of people receiving treatment in hospitals, the number of health examinations in hospitals, and the number of in-patients increased by 0.706, 0.954, and 0.878%, respectively. The estimated control variable results showed that increased inputs to education (junior high school enrolment rate), medicine (the number of physicians per ten thousand), and social services (proportion of public finance expenditure) can significantly improve the level of public health, and the effect of the increased proportion of public finance expenditures on improving public health is relatively high. Economic growth (per capita GDP) increased the number of people receiving treatment in hospitals and the number of health examinations in hospitals but reduced the number of in-patients. This indicates that the impacts of economic conditions on public health may be multifaceted. On the one hand, improvements in economics cause public diets, lifestyles, health, and other conditions to improve, and thereby the incidence of major diseases and number of in-patients is reduced. On the other hand, the growth in per capita GDP is costlier, in that there are increased public works that operate over longer hours. This means that the public is exposed to air pollution over a longer time and that the incidence of various types of respiratory diseases will generally increase, thus increasing the number of people receiving treatment in hospitals and the number of health examinations in hospitals.

However, due to the spatial spillover effect of the explanatory variables, the general panel regression may be biased. The existence of spatial effects on public health was verified in the front part of this paper. Therefore, it is necessary to establish a spatial panel regression model to analyse the spatial effects of air pollution on public health. Table 2 shows the two Lagrange multipliers and their robust test results, and we can see that LMlag was statistically significant compared to LMerr, and the robust R-LMlag was more significant than R-LMerr. According to Anselin et al., with respect to the discriminant rule and spatial correlation, the spatial lag model (SAR) was selected for this paper.

3.2.2 Full Sample Estimation with Spatial Factors

Due to the existence of the spatial effect, a full sample estimation with spatial factors was performed for this paper. Table 3 shows the results of the full sample estimates for public health when considering spatial factors. It can be seen from the table that the regression estimation with spatial factors was more significant. The R^2 values of the two models along

Table 2 Full sample estimate of public health without considering spatial factors

Variables	Y1_RT			Y2_HE			Y3_HN		
PM2.5	0.316*** (5.872)			0.366*** (5.506)			0.303*** (5.276)		
PM10		0.706*** (7.074)			0.954*** (7.916)			0.878*** (8.601)	
SO$_2$			0.356*** (7.430)			0.458*** (7.850)			0.435*** (8.877)
Eco	0.534*** (5.387)	0.627*** (6.271)	0.613*** (6.260)	0.292*** (2.383)	0.456*** (3.768)	0.418*** (3.506)	−0.447*** (−4.222)	−0.276*** (−2.697)	−0.300*** (−2.987)
Edu	−0.591*** (−3.694)	−0.761*** (−4.692)	−0.675*** (−4.315)	−0.549*** (−2.772)	−0.828*** (−4.226)	−0.689*** (−3.617)	−0.309* (−1.810)	−0.594*** (−3.581)	−0.480*** (−2.996)
Mc	−0.517*** (−3.126)	−0.759*** (−4.476)	−0.699*** (−4.235)	−0.578*** (−2.824)	−0.938*** (−4.576)	−0.834*** (−4.144)	−0.055 (−0.314)	−0.404** (−2.330)	−0.322* (−1.908)
Soc	−1.100*** (−10.344)	−1.427*** (−20.178)	−1.364*** (−18.725)	−1.240*** (−9.426)	−1.592*** (−18.622)	−1.520*** (−17.115)	−1.458*** (−12.843)	−1.730*** (−23.906)	−1.656*** (−22.195)
R^2	0.861	0.772	0.775	0.699	0.725	0.715	0.735	0.767	0.770
Sigma^2	0.198	0.189	0.187	0.303	0.276	0.277	0.226	0.198	0.196
DW	1.832	1.754	1.883	1.849	1.726	1.907	1.769	1.580	1.792
LogL	−186.230	−179.284	−177.046	−252.206	−237.928	−238.369	−206.527	−186.406	−184.442
LM spatial lag	80.097***	34.786***	31.026***	69.130***	28.924***	26.974***	48.126***	18.404***	16.030***
Robust LM spatial lag	67.796***	26.997***	18.018***	54.839***	20.694***	12.997***	59.265***	23.974***	18.333***
LM spatial error	15.979***	8.319***	18.197***	17.767***	8.600***	14.381***	2.495	0.357	0.859
Robust LM spatial error	3.679*	0.531	3.475*	3.475*	0.371*	0.404*	13.634***	5.927**	3.162*

*, **, and *** represent significance at the 10, 5, and 1% levels, respectively; the Z statistic values are in brackets

the dimension of the number of people receiving treatment in hospitals were 0.78, and the R^2 values of the other models exceeded 0.8, which were higher than that for the model without considering the spatial factors. At the same time, the LogL value was higher than that for the model without spatial factors, and the explanatory variables in the model were more significant. Therefore, the public health regression model considering spatial factors was more effective.

In comparison with the estimated results in Table 2, we can see that the negative effect of $PM_{2.5}$ concentration on public health was higher than that without considering the spatial factor. The negative effects of PM_{10} and SO_2 on the three dimensions of public health were weakened after taking into account the spatial factor. It appears that the impact of air pollution on public health is biased if spatial factors are not considered. It will underestimate the impact of $PM_{2.5}$ concentrations on public health, while overestimating the impact of PM_{10} concentrations and SO_2 concentrations on public health. After considering spatial factors, the negative impact of PM_{10} concentration on public health remained the largest, followed by that of $PM_{2.5}$ concentration. When PM_{10} concentration increased by one percent, the number of people receiving treatment in hospitals per ten thousand (Y1_RT), the number of health examinations in hospitals per ten thousand (Y2_HE), and the number of in-patient stays per ten thousand (Y3_HN) increased by 0.490, 0.722, and 0.737%, respectively. When PM2.5 concentration increased by one percent, the number of people receiving treatment in hospitals per ten thousand (Y1_RT), the number of health examinations in hospitals per ten thousand (Y2_HE), and the number of in-patient stays per ten thousand (Y3_HN) increased by 0.398, 0.466, and 0.380%, respectively. Air pollution is the main cause of the incidence of various types of diseases. Public health after long exposures to air pollution are bound to be seriously affected. A research report by Peking University and the international environmental organization Greenpeace noted that the excess mortality due to PM2.5 in Chinese urban residents is close to 1‰. Lu and Qi (2013) also noted that air pollution causes a rise in the mortality rate of children under 5 years of age and a decrease in the life expectancy of the nation.

The growth of the economy (per capita GDP) continues to exert multiple influences on public health after considering spatial factors. However, compared to the regression estimation without considering the spatial factors, the negative influence of the growth in per capita GDP on the number of people receiving treatment in hospitals per ten thousand (Y1_RT) and the number of health examinations in hospitals per ten thousand (Y2_HE) correspondingly increased, and the positive influence of the growth of per capita GDP on the number of in-patients correspondingly decreased. This shows that the impact of economic factors on public health has a spatial effect. The negative effect is becoming enhanced, the positive effect is weakening, and the effects of per capita GDP growth in improving public health are gradually weakening.

Ignoring the estimation of spatial factors may lead to underestimates in the influences of education (junior high school enrolment rate) and medical (number of physicians per ten thousand people) factors on public health, and the positive influences of education and medical factors on public health were significantly enhanced after considering the spatial factors. In the model of $PM_{2.5}$ concentration, we can see that the enrolment rate of junior high school students increased by 1%, and the number of people receiving treatment in hospitals per ten thousand (Y1_RT), the number of health examinations in hospitals per ten thousand (Y2_HE), and the number of in-patient stays per ten thousand (Y3_HN) were reduced by 0.866, 0.814, and 0.455%, respectively. The number of physicians per ten thousand people increased by 1%, and the number of people receiving treatment in hospitals per ten thousand (Y1_RT), the number of health examinations in hospitals per ten thousand (Y2_HE), and the number

Table 3 Full sample estimates of public health considering spatial factors

Variables	Y1_RT			Y2_HE			Y3_HN		
PM2.5	0.398*** (8.661)			0.466*** (8.072)			0.380*** (7.233)		
PM10		0.490*** (5.233)			0.722*** (6.336)			0.737*** (7.443)	
SO$_2$			0.240*** (5.136)			0.339*** (5.937)			0.365*** (7.458)
Eco	1.040*** (11.137)	0.852*** (8.689)	0.828*** (8.672)	0.792*** (6.936)	0.647*** (5.483)	0.606*** (5.251)	−0.169* (−1.685)	−0.188* (−1.875)	−0.218** (−2.227)
Edu	−0.866*** (−6.442)	−0.773*** (−5.151)	−0.702*** (−4.816)	−0.814*** (−4.822)	−0.807*** (−4.405)	−0.691*** (−3.864)	−0.455*** (−2.966)	−0.561*** (−3.512)	−0.460*** (−2.972)
Mc	−1.232*** (−8.436)	−1.094*** (−6.828)	−1.032*** (−6.592)	−1.376*** (−7.557)	−1.288*** (−6.595)	−1.190*** (−6.207)	−0.581*** (−3.542)	−0.626*** (−3.704)	−0.537*** (−3.251)
Soc	−1.140*** (−12.930)	−1.585*** (−23.263)	−1.542*** (−21.349)	−1.279*** (−11.538)	−1.763*** (−21.262)	−1.710*** (−19.395)	−1.490*** (−14.745)	−1.853*** (−25.487)	−1.785*** (−23.262)
ρ	−0.504*** (−11.772)	−0.346*** (−7.449)	−0.336*** (−7.166)	−0.529*** (−10.979)	−0.345*** (−6.773)	−0.337*** (−6.574)	−0.430*** (−8.843)	−0.270*** (−5.520)	−0.252*** (−5.191)
R^2	0.849	0.820	0.820	0.811	0.788	0.785	0.825	0.821	0.821
Sigma^2	0.134	0.162	0.162	0.215	0.241	0.244	0.179	0.183	0.183
LogL	−136.017	−157.201	−157.158	−208.298	−219.494	−221.045	−176.496	−175.172	−174.456

*, **, and *** represent significance at the 10, 5, and 1% levels, respectively; the Z statistic values are in brackets

of in-patient stays per ten thousand (Y3_HN) were reduced by 1.232, 1.376, and 0.581%, respectively. The impact of medical factors on health was positive, the growth in the number of physicians per ten thousand people caused the coverage of medical services in China to become wider, and the public was healthier because of timelier scientific treatment. The overall impact of education on the improvement of public health was positive, and the growth rate in junior high school enrolment will increase the public's demand for personal health. After considering the spatial factors, the impact of social factors (proportion of public finance expenditure) on public health changed little but was also very important. The proportion of public finance expenditure increased by 1%, and the number of people receiving treatment in hospitals per ten thousand (Y1_RT), the number of health examinations in hospitals per ten thousand (Y2_HE), and the number of in-patient stays per ten thousand (Y3_HN) were reduced by 1.140, 1.279, and 1.490%, respectively. The growth in the proportion of public finance expenditure will help the government provide more public services to improve the overall level of public health and increase public health services, which may improve public health.

3.2.3 Sub-sample Estimation in Three Regions

Taking into account the vast territory of China, there are significant differences between the levels of regional economic and social resource endowments, population, education, science and technology. This section studies the impacts of air pollution on public health in China's eastern, central, and western regions from the perspective of regional differences in China. Limited by the length of this paper, this section will only present sub-sample estimates of three kinds of important air pollutants on the number of people receiving treatment in hospitals per ten thousand (Y1_RT) in the three regions.

The division of the three regions corresponds to the divisions presented on China's National Bureau of Statistics website. The eastern region includes Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, and Hainan, the central region includes Shanxi, Jilin, Heilongjiang, Anhui, Jiangxi, Henan, Hubei, and Hunan, and the western region includes Sichuan, Chongqing, Guizhou, Yunnan, Tibet, Shaanxi, Gansu, Qinghai, Ningxia, Xinjiang, Guangxi, and Inner Mongolia. The results of the sub-sample estimates of air pollution in the three regions are shown in Table 4.

From Table 4, we can see that there was a significant difference between regions in terms of the impact of air pollution on public health. The negative impact on public health due to the three kinds of air pollutants in the central region was significant. The negative impact of PM_{10} and SO_2 concentrations on public health in the eastern region was significant, and the effect of $PM_{2.5}$ concentration was not significant. The impact of air pollution on local public health was not significant in the western region. As seen, the central region was most affected by the impact of air pollution on public health. Many central provinces, including Shanxi and Henan, are coal provinces, and the direct combustion of large amounts of coal produces significant amounts of air pollution. The eastern region was slightly better than the central region, where the negative impact on public health due to SO_2 concentrations was lower than in the central region. The eastern region's economic level is higher, and the environmental protection industry is relatively complete, resulting in superior exhaust emission purification compared to other parts of China. Moreover, most of the eastern region is located in coastal areas, and the natural capacity to purify air pollution is higher than in the central and western regions. In the western area, the effects on public health from air pollution are, at this stage, not that serious. The primary reason is that economic development in the western region is slower than that for Central and Eastern China. Therefore, industrial waste gas emissions are

Table 4 Sub-sample estimation of Y1_RT considering spatial factors

Variables	Eastern region			Central region			Western region		
PM2.5	0.061 (0.605)			0.302*** (3.306)			0.055 (0.945)		
PM10		0.643*** (3.733)			0.539*** (5.330)			0.161 (1.644)	
SO$_2$			0.166** (2.047)			0.539*** (5.330)			0.123 (2.490)
Eco	1.097*** (6.508)	1.384*** (7.893)	1.138*** (6.888)	0.539* (1.654)	0.151 (0.551)	0.151 (0.551)	−0.615*** (−2.904)	−0.850*** (−4.363)	−0.830*** (−4.583)
Edu	−0.480* (−1.608)	−1.014*** (−3.220)	−0.673** (−2.161)	−0.636*** (−5.125)	−0.604*** (−5.349)	−0.604*** (−5.349)	−0.718*** (−4.669)	−0.525*** (−3.444)	−0.597*** (−4.499)
Mc	−0.620** (−2.127)	−1.215*** (−4.088)	−0.699*** (−2.696)	−0.415** (−2.093)	−0.431** (−2.300)	−0.431** (−2.300)	−0.988*** (−4.301)	−0.852*** (−3.745)	−0.868*** (−3.934)
Soc	−1.517*** (−7.661)	−1.085*** (−5.371)	−1.420*** (−8.024)	−1.129*** (−4.769)	−1.628*** (−11.323)	−1.628*** (−11.323)	−1.973*** (−16.505)	−2.094*** (−36.318)	−2.192*** (−29.877)
ρ	−0.437*** (−6.798)	−0.438*** (−7.459)	−0.419*** (−6.561)	−0.296*** (−4.918)	−0.236*** (−4.957)	−0.236*** (−4.957)	−0.720*** (−11.693)	−0.758*** (−11.335)	−0.759*** (−12.411)
R^2	0.812	0.834	0.817	0.918	0.932	0.931	0.940	0.942	0.943
Sigma^2	0.144	0.127	0.139	0.015	0.013	0.012	0.058	0.056	0.055
LogL	−51.510	−44.836	−49.239	55.051	56.231	56.123	−5.515	−5.040	−3.526

*, **, and *** represent significance at the 10, 5, and 1% levels, respectively; the Z statistic values are in brackets

relatively low, and in some provinces, clean energy, which accounted for a relatively large proportion of their energy consumption structures, lessened environmental pollution.

From the perspective of the economy, the promotion of per capita GDP was not significant to public health in the central region; the increase of per capita GDP in the eastern region had a negative impact on public health, but the increase in per capita GDP in the western region will contribute to improved public health. The health care condition in the eastern region is better than those in the central and western regions, and the increase in per capita GDP may raise health care conditions, although they will be smaller than the negative impacts on people's health. Health care conditions in the western region are relatively backward, and increases in per capita GDP can improve the lives of local people, significantly improving public health. Other control variables such as education, medical and social factors all contribute to the improvement of public health, which was most obvious in the western region.

In the model of $PM_{2.5}$ concentrations, the number of physicians per ten thousand, junior high school enrolment rate, and the proportion of public finance expenditure increased by 1%, and the numbers of people receiving treatment in hospitals per ten thousand (Y1_RT) in the western, eastern and central regions were reduced by 0.718, 0.988, and 1.973%, respectively. This shows that the gaps in education, medical treatment, and other aspects between the western region and the other regions of China remain large. Increasing investments in education, medical and other aspects will significantly improve public health in the western region.

3.3 Robustness Test

To test the robustness of the effects of air pollution on public health, this study re-examined the empirical results by constructing an economic spatial weight matrix instead of the geographic distance space weight matrix. The formula for the economic spatial weight matrix is

$$W_{ij}^e = W_d \times diag\left(\bar{X}_1/\bar{X}, \bar{X}_2/\bar{X}, K, \bar{X}_n/\bar{X}\right)$$

$$\bar{X}_i = \sum_{t_0}^{t_1} X_{it}/(t_1 - t_0 + 1), \quad \bar{X} = \sum_{i=1}^{n} \sum_{t_0}^{t_1} X_{it}/n(t_1 - t_0 + 1) \tag{9}$$

where W_d is the geographical distance spatial weight matrix. $\bar{X}_i$ represents the mean value GDP of regional i during the period t_0 to t_1. $\bar{X}$ represents the mean value of the GDPs of all regions during the investigation period.

The greatest difference between the robustness test results and the empirical results above is that some of the variable coefficients, spatial spillover coefficients and their significances were improved or decreased (Table 5). However, the estimation results of the core variables were basically consistent with the above conclusions. This shows that the impact of air pollution on public health effect is reliable and robust.

4 Conclusions and Recommendations

In this paper, we used the expansion of China's macro health production function based on the Grossman health production function and spatial panel data analysis method and employed provincial panel data on China's public health and air pollution during 2004–2013 to analyse the spatial agglomeration of Chinese public health, air pollution and other factors on the spatial effects of the three dimensions of public health. The main conclusions from the empirical research are as follows.

Table 5 Results of the robustness test

Variables	Y1_RT			Y2_HE			Y3_HN		
PM2.5	0.326*** (6.787)			0.375*** (6.207)			0.298*** (5.486)		
PM10		0.578*** (6.291)			0.809*** (7.181)			0.775*** (7.726)	
SO$_2$			0.269*** (5.859)			0.365*** (6.465)			0.384*** (7.753)
Eco	0.624*** (6.999)	0.656*** (7.170)	0.630*** (6.930)	0.398*** (3.533)	0.497*** (4.408)	0.447*** (3.992)	−0.353*** (−3.467)	−0.250** (−2.491)	−0.281*** (−2.840)
Edu	−0.646*** (−4.390)	−0.808*** (−5.195)	−0.737*** (−4.797)	−0.753*** (−4.052)	−1.023*** (−5.372)	−0.912*** (−4.824)	−0.222 (−1.328)	−0.462** (−2.723)	−0.373** (−2.239)
Mc	−0.695*** (−4.864)	−0.779*** (−5.234)	−0.687*** (−4.732)	−0.659*** (−3.656)	−0.843*** (−4.624)	−0.703*** (−3.926)	−0.403** (−2.484)	−0.560*** (−3.695)	−0.489*** (−3.093)
Soc	−1.231*** (−12.887)	−1.600*** (−23.240)	−1.561*** (−21.243)	−1.365*** (−11.364)	−1.761*** (−21.174)	−1.713*** (−19.270)	−1.575*** (−14.599)	−1.827*** (−24.922)	−1.752*** (−22.714)
ρ	−1.000*** (−6.568)	−0.999*** (−6.677)	−0.999*** (−6.443)	−1.000*** (−5.858)	−1.000*** (−6.085)	−0.999*** (−5.868)	−0.999*** (−5.806)	−0.688*** (−4.356)	−0.597*** (−3.743)
R^2	0.827	0.823	0.822	0.782	0.790	0.785	0.804	0.815	0.814
Sigma^2	0.156	0.159	0.161	0.248	0.2410	0.244	0.201	0.189	0.190
LogL	−160.442	−163.295	−164.702	−230.311	−224.571	−227.859	−197.047	−182.361	−181.493

*, **, and *** represent significance at the 10, 5, and 1% levels, respectively; the Z statistic values are presented in brackets

1. Public health had a significant effect on spatial agglomeration, and the agglomeration increased year by year. North China, Central China, and the eastern coastal areas showed H–H agglomeration, and Northwest China, Northeast China, and other places showed L–L agglomeration. This also supports the conclusions of predecessors and scholars. Due to the wide diversity and persistence of air pollution, the spatial agglomeration effect of public health has become increasingly significant. This shows that regional public health has a convergence effect, which is closely related to the spatial agglomeration of social, economic, educational, and other resources and supports the research of Lu and Qi (2013). Given the spatial correlations, China's public health has characteristics of spatial heterogeneity and spatial dependence.

2. The negative externalities of air pollution on public health are significant. The increases in the concentrations of air pollutants significantly increased the number of people receiving treatment in hospitals per ten thousand (Y1_RT), the number of health examinations in hospitals per ten thousand (Y2_HE), and the number of in-patient stays per ten thousand (Y3_HN) and reduced the level of public health. Compared with traditional econometric models that do not consider spatial correlations, the $PM_{2.5}$ concentrations in this study had a higher negative effect on public health. This means that ignoring the existence of spatial autocorrelations can lead to biases in estimations of public health. This also coincides with the argument we mentioned earlier. We should pay attention to the problem of air pollution in the process of economic development, and the need to improve public health is imminent.

3. The influence of air pollution on public health is significant among regions. The influence of air pollution on public health in the central region was the most significant, followed by the eastern region. The eastern and central regions of China belong to the more developed areas of industry, and the extensive development in the earlier period has produced serious environmental pollution. Therefore, at this stage, we need to continue to increase environmental protection efforts to improve public health in the eastern and central regions. Regarding the western region, the government needs to increase investment in education, medical, and other aspects to gradually improve the health of the public. Thus, the implementation of a differentiated environmental policy is the development direction of China's environmental governance in the future.

4. This study shows that the environmental pollution in a region and its geographical location are also closely related to economic, educational and other factors in surrounding areas. The spillover effect of air pollution should arouse sufficient attention of government departments. Therefore, governments at all levels should not only control the discharge of pollutants at their sources but also should break the administrative monopolies of their own arrays and achieve cross-regional environmental cooperation. All provinces need to achieve common governance across regions, share resources and technologies, and actively respond to various unexpected cross-border environmental pollution.

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