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The spatial impacts of air pollution and socio-economic status on public health: Empirical evidence from China

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ABSTRACT

The impact of air pollution or socio-economic status on public health is a lively topic for social economists and environmental researchers across the world. Despite a lot of research, there is still a lack of clear understanding of the spatial heterogeneous impacts related to public health. In this study, we use the spatial econometric model with panel data to investigate the direct and interactive effects of air pollution and socio-economic status on public health and further explore the regional heterogeneity among different regions. The research results show that there is strong spatial agglomeration in air pollution, socio-economic status, and public health. Aggravation of air pollution significantly damages local public health status, leading to increased infant mortality rate and lower average life expectancy. Aggravated air pollution in one province significantly increases infant mortality in neighboring provinces. The increase in per capita income significantly leads to a significant positive effect on public health. As air pollution continues to increase, the impact of per capita income on improving public health has diminished gradually. Improving the level of education per capita significantly improves public health. As per capita education level increases, the impact of increased air pollution on public health damage has diminished gradually. The effects of air pollution and socio-economic status on infant mortality in the eastern, central, and western regions are heterogeneous.

1. Introduction

World Health Organization (WHO) estimates that in 2016, air pollution caused the premature deaths of 4.2 million people worldwide [1], and about 91% occurred in low-income and middle-income countries, especially in the Western Pacific. Since the reform and opening up, major achievements in economic development have made China one of the most polluted countries with sulfur dioxide (SO_2) and particulate matter (PM). China's current air pollution status is eight times that of the United States (US) [2]. China Environmental Development Report (2016–2017) pointed out that various diseases caused by air pollution have shown a clear upward trend in China. Besides, among the many factors affecting health, socio-economic status has always been one of the focuses of society. The health status of groups with higher socio-economic status is significantly better than that with lower SES. This trend has not changed with the changes in time and space [3]. Therefore, it has become a top priority to investigate the mechanism of how China's air pollution and socio-economic status affect health.

Most empirical studies on health effects have analyzed the direct effects of air pollution on health [4], and the direct effects of socio-economic status on health [5], ignoring the possible interaction effects of air pollution and socio-economic status on public health. In recent years, studies have noted that China's public health and its influencing factors have strong spatial dependence characteristics [6]. However, more evidence that is empirical needs to further support the spatial dependence of public health and its influencing factors in China.

To further advance the previous studies, the research motivation of this paper is reflected through the following four research questions. (1) What are the spatial dependence characteristics of air pollution, socio-economic status, and public health? (2) What are the spatial effects of air pollution and socio-economic status on public health, respectively? (3) How do the interactive effects of air pollution and socio-economic status affect public health? (4) What are the heterogeneous spatial effects of air pollution and socioeconomic status on public health from the

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perspective of regional differences in China?

The novelty of this paper is mainly reflected in three aspects. First, we explore the spatial dependence of public health and its influencing factors in various Chinese provinces. The use of spatial econometric models avoids the estimated bias resulted from neglecting the spatial correlation of public health and its influencing factors. Second, considering the spatial dependence of public health and its influencing factors, we study the direct effects of air pollution and socio-economic status on public health in the context of China, and the possible interaction effects of air pollution and socio-economic status on public health. China is the largest developing country in the world, which can play a "demonstration role" for other developing countries. Third, we further study the spatial effects of air pollution and socio-economic status on public health in eastern China, central China, and western China. The results of sub-regional studies might help policymakers to formulate more targeted policy designs.

The rest of this paper organizes as follows. Section 2 provides a literature review. Section 3 introduces the research design. Section 4 gives data and variables. Section 5 analyzes the estimation results of the empirical model and gives the results of the robustness test. Section 6 summarizes the main findings and proposes policy recommendations.

2. Literature review

According to the existing literature, the effects of air pollution and socio-economic status on health have been widely concerned by the academic community. This section reviews the studies analyzing the effects of air pollution on health, the effects of socio-economic status on health, and interaction effects on public health.

2.1. Effects of air pollution on health

There are two types of literature on the direct effects of air pollution on health. The first type of literature mainly studies the relationship between "air pollution and health" from the fields of environmental science and medicine. By using PM exposure data in Germany [7] and air pollution data in Shanghai [8], some studies explain the effects of different air pollutants on health risks. These health risks include infant mortality, cardiovascular disease, lung cancer, and asthma hospitalization rates [9,10].

The second type of literature mainly studies the relationship between "air pollution and health" from the social and economic fields. Because neonatal vulnerability helps to avoid endogenous risks, many social and economic studies have explored the effects of air pollution on infant health [4,11,12]. Some social and economic studies explore the relationship between air pollution and health from the perspective of total mortality in the US and life expectancy in China [13,14].

2.2. Effects of socio-economic status on health

Based on summarizing the existing definitions, Ref. [15] defines socio-economic status as income, education, and other resources for the acquisition of socially valuable things (in this case, health status), offers advantages for individuals, groups, or collections over other individuals, groups, or collections. In social science research, the positive correlation (gradient) between socio-economic status and health (such as mortality and morbidity) is well known [5].

Many studies explore the influence mechanism of socio-economic status on health from the perspective of income and education. These studies use data from the National Youth Longitudinal Survey [16], Vietnam National Health Survey [17], and China Health and Nutrition Survey [18] to illustrate the heterogeneity of the impact of different income levels on children's health [15]. Ref. [19] mentions that children who have mothers with lower education are generally in poor health and the gradient becomes steeper with age. However, some studies find that SES, represented by income, has a weaker relationship with health [20, 21]. Table 1 lists the influencing mechanism of air pollution and socio-economic status on public health.

2.3. Interaction effects of air pollution and socio-economic status on public health

The interaction of socio-economic status and air pollution may have important effects on public health. The health effects of air pollution depend on the probability of exposure to pollution risks to a large extent [22]. Socio-economic status determines the probability of exposure to air pollution to a certain extent [23–25].

Most relevant studies in the US have shown that low-income groups and ethnic minorities face higher pollution risks due to lower socio-economic status [26]. Furthermore, many studies have attempted to prove that, under other conditions stay unchanged, the higher the exposure status to air pollution from SES, the greater the loss of environmental health [27–30]. Some other studies find little evidence that the interaction of socio-economic status and air pollution affects public health [31].

2.4. Comments

There are certain defects of existing research from the environmental science and medical fields. Most of these studies explore the mechanisms of air pollution affecting health at the individual aspect [7–10]. However, air pollution often goes beyond the individual and belongs to the public domain [30]. Many studies do not consider the impact of population density, economic development, living standards, health condition, or other important macro-impact factors on public health status, which may lead to estimated results that are inconsistent with the reality in the estimation process [32].

Some studies in the social and economic fields explore the relationship between air pollution and public health [4,11–13] or the relationship between socio-economic status and public health [15–17,19] at a macro aspect. However, these studies paid less attention to the possible spatial dependence effects of public health and its influencing factors. Because of the spatial effects of air pollution [33], air pollution in one region is partially dependent on other regions. While economic development has made different regions in China more and more connected, public health conditions are also widely linked especially for the closer the provinces. If we ignore the effects of the possible spatial dependence, the model estimates would produce significant biases or false verification [34].

In recent years, some papers have focused on the spatial effects of air pollution on public health in China [6,32]. Most of these studies use specific pollutant emission intensity to characterize the state of air

Table 1
Influencing mechanism of air pollution and socio-economic status on public health.

Influencing factors	Direction	Influencing mechanism	Public health	Source
Air pollution	↑	Causing cardiovascular disease.	↓	[7]
Air pollution	↑	Causing acute asthma.	↓	[8]
Air pollution	↑	Bringing more risk of lung cancer.	↓	[10]
Socio-economic status - Income	↓	Insufficient nutrition costs of poor families → poor health of children.	↓	[17]
Socio-economic status - Income	↓	Unable to pay for treatment of chronic diseases in children.	↓	[18]
Socio-economic status - Education	↓	Mother's low level of education → less attention to children's health problems such as chronic diseases and nutritional deficiencies.	↓	[19]

pollution. In the process of reflecting air pollutant emission indicators into the ambient air quality monitoring indicators, there may be inconsistencies in the statistical results of different emission indicators and monitoring indicators due to the external influence of different natural environmental factors (such as air pressure, wind, outdoor temperature, and humidity) [14]. Moreover, compared with comparative experiments in the micro area, it is more difficult to effectively distinguish the impact of specific pollutant emission intensity on health in the macro field. The use of ambient air quality monitoring indicators can reflect the status of air pollution affecting public health truly. Therefore, it still requires more empirical evidence based on ambient air quality monitoring indicators to support the spatial dependence of public health and its influencing factors in China further.

Moreover, these studies considering the effects of spatial dependence ignore the possible interaction effects of socio-economic status and air pollution on public health. This is not conducive to exploring the heterogeneity of the spatial effects of air pollution on public health [22–24, 26–29]. Therefore, based on considering the effects of spatial spillovers, it is of great practical significance to explore the spatial effects of air pollution and socio-economic status on public health, especially the interaction effects of air pollution and socio-economic status on public health.

This paper has the following theoretical and methodological contributions. First, this paper explores the spatial dependence characteristics of air pollution, socio-economic status, and public health based on data from Chinese provinces. Second, this paper mainly studies the spatial impact of air pollution and socio-economic status and their interaction on public health based on Chinese experience, which is different from previous studies in developed countries. Third, this paper also studies the spatial heterogeneous impact of air pollution and socio-economic status on public health in three regions of China, respectively. Furthermore, the global Moran's Index and local Moran's Index scatter plots are used to perform the spatial autocorrelation test, which not only considers the overall spatial correlation, but also considers the atypical characteristics in local areas. Next, spatial econometric models, such as SEM (Spatial Error Model) and SDM (Spatial Durbin Model), are used to reflect the spatial effects in regression, which could avoid the estimation bias caused by ignoring the spatial correlation of public health and its influencing factors. Finally, the explanatory variables lagged 1 period as instrumental variables, and using an alternative spatial weight matrix, are used to test the robustness of the research results.

3. Research design

We propose the conceptual relationship below based on the theoretical analysis above. Fig. 1 shows the main conceptual relationship among air pollution, socio-economic status, and public health according to the existing literature [8,15,22].

3.1. Non-spatial econometric model

The Grossman health production function is the basic theoretical framework for explaining the factors affecting public health [35]. We build a basic model based on this theoretical framework. We first explore the correlation among air pollution, socio-economic status, and public health in China by applying Ordinary Least Squares (OLS), without considering the spatial correlation between adjacent provinces.

$$\begin{aligned}\ln Y_{it} = {} & \alpha_i + \beta_1 \ln AMI_{i,t} + \beta_2 \ln PDI_{i,t} + \beta_3 \ln AMI_{i,t} \times \ln PDI_{i,t} \\ & + \beta_4 \ln EDU_{i,t} + \beta_5 \ln AMI_{i,t} \times \ln EDU_{i,t} + \sum_{k=1}^{h} \gamma_k \ln C_{ik,t} + \varepsilon_{it}\end{aligned} \tag{1}$$

All variables in equation (1) are natural logarithms. i (i = 1, …, N) indicates the province, and t (t = 1, …, T) indicates time. γ represents the total number of control variables. Y_{it} is the dependent variable, representing the public health status expressed by infant mortality rate (*IMR*) and average life expectancy (*ALE*). *AMI*, *PDI*, and *EDU* indicate the average ambient air quality monitoring indicators, per capita disposable income, and per capita education level, respectively. $C_{ik,t}$ is the collection of control variables including population density [36], public medical care [37], and fiscal expenditure [32]. The details of the variables are shown in Section 4 "Data and variables" below. ε_{it} is the random disturbance term.

3.2. Spatial correlation test

The public health status in one place may be affected by various factors in neighboring areas, resulting in spatial dependence of space or time bringing invalid OLS estimation results. Before establishing a spatial econometric model, we need to test the existence of spatial effects first. Previous studies test the existence of spatial correlation by calculating Moran's Index [32]. We calculate the global and local Moran's Index by a spatial weight matrix based on geographic distance. To test the global spatial correlation, the calculation formula of the global Moran's Index is:

$$Moran's I = \frac{n \sum_{i=1}^{n} \sum_{j=1}^{n} \omega_{ij} \left(Y_i - \overline{Y}\right)\left(Y_j - \overline{Y}\right)}{\left(\sum_{i=1}^{n} \sum_{j=1}^{n} \omega_{ij}\right) \sum_{i=1}^{n} \left(Y_i - \overline{Y}\right)^2} \tag{2}$$

Among them, Y_i represents the observation value of area i; n indicates the number of areas; and ω_{ij} indicates the spatial weight matrix based on geographic distance.

The global Moran's Index reflects the overall spatial correlation, but the assessment might neglect atypical features in local areas. To test the local spatial correlation, we draw Moran's Index scatter plot by calculating the local Moran Index [38]. The calculation formula of the Local Moran's Index is:

$$Moran's\, I_i = \frac{n \sum_{j=1}^{n} \omega_{ij} \left(Y_i - \overline{Y}\right)\left(Y_j - \overline{Y}\right)}{\sum_{i=1}^{n} \left(Y_i - \overline{Y}\right)^2} \tag{3}$$

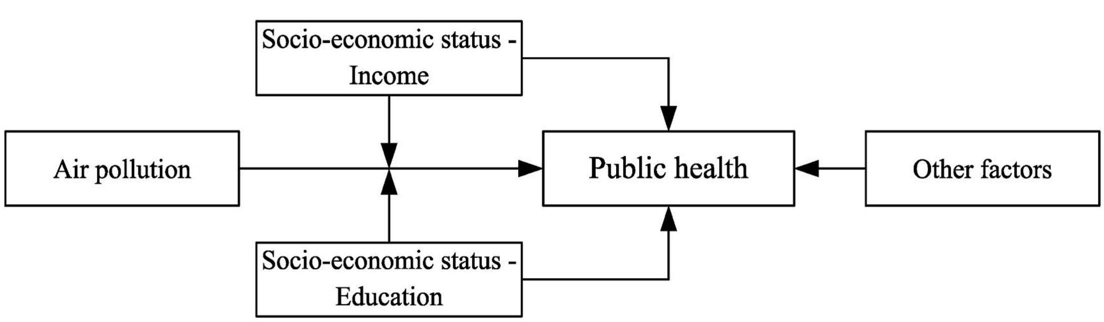

Fig. 1. The conceptual relationship between air pollution, socio-economic status, and public health.

3.3. Spatial estimation method

Before establishing a certain spatial econometric model, we need to test the form of spatial effects. In this paper, two Lagrange Multiplier (LM) tests and two robust LM tests based on residuals obtained from panel regression are applied to perform non-spatial OLS model regression and diagnose error or lag space dependence [39].

Then, we examine the relationship between air pollution, socio-economic status, and public health in China by considering spatial correlation. According to Ref. [40], three different spatial econometric models should be applied to test spatial correlation. The details of these models can be seen in Ref. [41], and the expression of these models is defined as follows.

Spatial Autoregressive Model (SAR):

$$\ln Y_{it} = \rho \sum_{j=1}^{n} W_{ij} \ln Y_{jt} + \sum_{k=1}^{f} \beta_k \ln X_{ik,t} + \mu_{it} + \lambda_{it} + \varepsilon_{it} \tag{4}$$

Spatial Error Model (SEM):

$$\ln Y_{it} = \alpha + \sum_{k=1}^{f} \beta_k \ln X_{ik,t} + \mu_{it} + \lambda_{it} + \varphi_{it} \tag{5}$$

$$\varphi_{it} = \delta \sum_{j=1}^{n} W_{ij} \varphi_{jt} + \varepsilon_{it} \tag{6}$$

Spatial Durbin Model (SDM):

$$\ln Y_{it} = \rho \sum_{j=1}^{n} W_{ij} \ln Y_{jt} + \sum_{k=1}^{f} \beta_k \ln X_{ik,t} + \sum_{k=1}^{f} \theta_k \sum_{j=1}^{n} W_{ij} \ln X_{ijk,t} + \mu_{it} + \lambda_{it} + \varepsilon_{it} \tag{7}$$

i or j means province i or j, respectively; and t indicates the year t. ρ, δor $\theta_k$indicates the spatial parameter which expresses the spatial correlation for different observations. $W_{ij}$is one element in the ($N \times N$) spatial weight matrix based on geographic distance [42]; n represents the number of provinces.μ_{it}indicates the time fixed effect of the spatial unit.λ_{it}indicates a spatial fixed effect.$\varepsilon_{it}$is a random disturbance term. $\varphi_{it}$is the spatial dependence error term.

We estimate the above spatial models by using the Maximum Likelihood Estimation (MLE) method for controlling the simultaneity caused by the introduction of equal space-weighted variables into the equation proposed by Ref. [40]. Spatial testing is performed according to the LM test method. If the LM-lag or LM-err test results are significant, the model will be estimated using SAR or SEM spatial form [43]. If both test results are significant, SDM should be used. We apply the spatial Hausman tests for testing whether random effects or fixed effects should be used in the estimations. In the condition of the fixed effect, we test whether time or spatial fixed effects should be included in the model by using the likelihood ratio (LR) test.

4. Data and variables

4.1. Data source

According to the principle of data availability, this paper uses the panel data of 30 provinces (excluding Tibet, Hong Kong, Macao, and Taiwan) in ten years to explore the spatial impact of air pollution and socio-economic status on public health empirically. The infant mortality rate and average life expectancy data representing public health status are from the China Disease Surveillance Point System, China Health Statistics Yearbook, and China Health and Family Planning Statistical Yearbook. The ambient air quality monitoring indicator (AMI) comes from the Information Center of the Ministry of Ecology and Environment. Other variables are sourced from the China Statistical Yearbook and the website of the National Bureau of Statistics.

4.2. Variables

The variables and data sources involved in this paper are shown in Table 2.

4.2.1. Public health variables

It is less likely to distinguish structural differences of macro data in public health compared with the health status measured in microdata. Due to this limitation, existing empirical studies have used indicators like infant mortality rate, average life expectancy, maternal mortality, and child mortality under 5 years old to quantify the health status of public groups [44]. Among the studies related to public health, the most commonly used indicators in the world are mainly focused on infant mortality rate [30] and average life expectancy [14]. Therefore, combined with previous research and China's demographics situation, this paper uses infant mortality rate and average life expectancy as variables to measure public health status.

4.2.2. Air pollution variable

At present, the indicators for measuring China's air pollution status mainly include two categories, namely, air pollutant emission indicators and ambient air quality monitoring indicators. Air pollutant emission indicators are the most commonly used variables to measure pollution reduction status [45]. Therefore, such indicators appear in many studies on the effects of environmental regulation policies [43]. Since ambient air quality monitoring indicators have the characteristics of more accurately describing the level of pollution exposure, such indicators are usually applied in the study about the relationship between environment and health [14,46]. Combined with the status of the research object, this paper uses the ambient air quality monitoring indicators that reflect the pollution exposure level as independent variables. Before the official implementation of the newly revised Ambient Air Quality Standards nationwide in 2016, ambient air quality monitoring indicator in China was calculated based on the concentrations of air pollutants like inhalable particulate matter (PM_{10}), SO_2 and nitrogen dioxide (NO_2) in the atmosphere. The pollutant with the highest index, which is called the main pollutant, determines the ambient air quality monitoring indicator of the day. Therefore, this paper selects the mean value of annual average ambient air quality monitoring indicators of different prefecture-level cities in each province as the air pollution index of the corresponding provinces affecting public health.

4.2.3. Socio-economic status variables

Income and education are the most commonly used indicators of socio-economic status [15]. According to the metrics of socio-economic status in the existing literature, this paper uses the two variables of per capita income level and per capita education level to describe the

Table 2
Variable definition table.

Type	Variable	Variable meaning	Data Source
Public health variables	*IMR*	Infant mortality rate	China Disease Surveillance Point System, China Health Statistics Yearbook, and China Health and Family Planning Statistical Yearbook
	ALE	Average life expectancy	
Air pollution variable	*AMI*	ambient air quality monitoring indicator	Information Center of the Ministry of Ecology and Environment
Socio-economic status variables	*PDI*	Per capita income level	China Statistical Yearbook
	EDU	Per capita education level	
Control variables	*PPOP*	Population density	China Statistical Yearbook and the website of National Bureau of Statistics
	PHT	Public medical care	
	PFE	Fiscal expenditure	

average socio-economic status of residents in different provinces.

We use per capita disposable income data in provinces to measure per capita income level [47]. The income data are at a constant price by taking the year 2006 as the base year. Besides, we use per capita education years' data in provinces to measure per capita education level. Per capita education years are calculated by the average years of education for primary school graduation (6 years), junior high school graduation (9 years), Senior high school graduation (12 years), bachelor's degree (16 years), and graduate degree (19 years).

4.2.4. Control variables

According to existing research, population density, public health care, and fiscal expenditure may all affect public health. Following existing research practices, we control them in the model to eliminate the effects of other variables.

(1) Population density. On one hand, the highly crowded residential environment is connected with a higher possibility of cancer and stroke mortality [48]. On the other hand, Ref. [36] argues that higher population density makes the public get limited public health services more easily. Based on the above two factors, the public health effect caused by population density will be determined by its net effect. Considering the large differences in administrative divisions and population size among provinces, the direct use of population absolute scale indicators is not scientifically comparable. Therefore, we use population density (PPOP), the population per unit area, to characterize the impact of population agglomeration on public health.
(2) Public medical care. Ref. [37] argues that public health conditions are critical to explaining disease and mortality in some places. According to the data availability, we select the number of health technicians per 10,000 (PHT) to reflect the public health status of a region.
(3) Fiscal expenditure. Providing public goods is one of the major contributions of fiscal expenditure to public health. The government's increased investment in recreational and public facilities can provide people with more opportunities for leisure and exercise, thereby improving public health [32]. Ref. [49] argues that more health spending from the government can increase health care facilities and further improve public health such as life expectancy. To eliminate the collinearity problem, we use the proportion of fiscal expenditure to GDP (PFE) to represent the fiscal expenditure status.

4.3. Summary statistics

Table 3 lists the summary statistics and correlation matrix for all variables in the 30 provinces during the study period. The correlation between the dependent variables IMR (ALE) and the independent variable AMI is negative (positive). The correlation between the dependent variables IMR (ALE) and the independent variable PDI is negative (positive). Moreover, the correlation between the dependent variables IMR (ALE) and the independent variable EDU is also negative (positive). We need to carefully explain these different correlations since they merely present contemporaneous effects without explaining the causal effects and spatial correlation contained in the model. Different from the spatial econometrics in this paper, the above correlation does not tell the time relationship and directionality among variables. The multicollinearity is tested by examining the correlation coefficient values among variables and calculating the Variance Inflation Factor (VIF). All of the values are in a reasonable range and the average VIF is 3.60.

5. Empirical results and discussion

5.1. Spatial correlation test

We mainly use the global spatial correlation test and local spatial correlation test to confirm the spatial dependence of the variables. First, the global Moran's Index can be used to test the global spatial autocorrelation [32], which can reflect the overall spatial agglomeration characteristics of air pollution, socioeconomic status, and public health. Besides, since the global Moran's Index may ignore the local spatial dependence characteristics of atypical regions, we use local Moran's Index scatter plot to test the local spatial autocorrelation [38].

5.1.1. Global spatial correlation test

Global Moran's Index value is in the range of [−1,1]. If the value is greater than 0, there is a positive spatial correlation among different observations, which means there are similar properties among adjacent spatial regions. If the value is less than 0, there is a negative spatial correlation among different observations and that adjacent spatial regions have different properties. If the value is equal to 0, it means no spatial relationship among different observations.

The results represent that Moran's Index value of the six indicators are all greater than 0 at the 5% or 1% significance level, indicating that there is strong spatial agglomeration in air pollution, socio-economic status, and public health (see Table 4).

5.1.2. Local spatial correlation test

To reflect the local spatial characteristics, we use the local Moran's Index scatter plot to examine local spatial correlation. The scatter plot is separated into four different parts. The first quadrant and the third quadrant indicate positive spatial correlation, while the second quadrant and the fourth quadrant indicate the negative spatial correlation.

In the local Moran's Index scatter plot (Fig. 2), the scatter points of each variable in 2015 are mainly located in the first quadrant and the third quadrant, indicating that the collected observations are mainly high-high values and low-low values. The eastern coastal line of China and north and central China are the areas with H–H clusters, while Northwest and Northeast regions are L-L clusters. Air pollution, socio-economic status, and public health of neighboring areas have a strong spatial correlation.

Therefore, air pollution, socio-economic status, and public health in China are characterized by spatial heterogeneity and spatial dependence. Spatial econometrics is needed to study the spatial influences of air pollution and socio-economic status on public health.

Table 3
Descriptive statistics and correlation matrix.

Variables	Mean	SD	1	2	3	4	5	6	7	8
1. IMR	0.111	0.074	–							
2. ALE	4.317	0.035	–	–						
3. AMI	4.283	0.230	−0.061	0.023	1.000					
4. PDI	9.237	0.452	−0.734	0.873	0.090	1.000				
5. EDU	2.151	0.108	−0.790	0.849	0.150	0.815	1.000			
6. PPOP	5.430	1.276	−0.489	0.705	−0.073	0.588	0.480	1.000		
7. PHT	3.826	0.338	−0.672	0.682	0.241	0.777	0.851	0.234	1.000	
8. PFE	2.965	0.393	0.444	−0.457	0.059	−0.301	−0.226	−0.607	−0.004	1.000

Table 4
Global Moran's Index for air pollution, socio-economic status and public health in China.

Year	AMI	PDI	EDU	IMR	ALE
2006	0.414***	0.361***	0.283***	0.207**	0.337***
	(4.180)	(3.607)	(2.924)	(2.219)	(3.380)
2007	0.403***	0.365***	0.255***	0.204**	0.332***
	(4.127)	(3.653)	(2.662)	(2.200)	(3.331)
2008	0.313***	0.361***	0.274***	0.204**	0.325***
	(3.280)	(3.603)	(2.836)	(2.195)	(3.276)
2009	0.333***	0.365***	0.283***	0.202**	0.318***
	(3.445)	(3.633)	(2.935)	(2.182)	(3.214)
2010	0.299***	0.362***	0.278***	0.201**	0.310***
	(3.213)	(3.593)	(2.879)	(2.172)	(3.144)
2011	0.273***	0.359***	0.245***	0.198**	0.302***
	(3.310)	(3.569)	(2.611)	(2.157)	(3.082)
2012	0.297***	0.356***	0.246***	0.194**	0.295***
	(3.619)	(3.534)	(2.616)	(2.124)	(3.016)
2013	0.308***	0.347***	0.268***	0.192**	0.286***
	(3.318)	(3.502)	(2.845)	(2.107)	(2.944)
2014	0.407***	0.345***	0.259***	0.190**	0.278***
	(3.986)	(3.480)	(2.773)	(2.093)	(2.866)
2015	0.392***	0.327***	0.265***	0.188**	0.268***
	(3.563)	(3.524)	(2.826)	(2.078)	(2.784)

Note: ** and *** indicate significance at the 5% and 1% levels, respectively.

5.2. Spatial regression and discussion

The regression results are reported in Table 5 and Table 7. We first use the linear OLS model to estimate equation (1) without space and fixed effects. To identify potential spatial effects, it is necessary to examine the form of spatial dependence before implementing spatial panel regression. The LM tests are reported in models (1) and (3) of Tables 5 and 7, respectively. In Table 5, when the LM tests are significant at the 5% significance level, we should not reject the SEM or SAR, which confirms that SDM can explain the results more appropriately. In Table 7, when the robust LM Lag does not pass the 10% significance test, the SEM is more explanatory for samples. Therefore, we need to apply the spatial panel model for exploring the issues examined in this paper. SDM and SEM are performed following Ref. [40] and Ref. [50], respectively.

Because the spatial Hausman test is significant in each model ($P < 0.05$), spatial fixed effects are used to control the characteristics of provinces with unobserved time and space. All results of the LR tests are significant at the significance level of 1% representing the joint significance for the spatial fixed effects in the OLS model. Since there are similar saliency results, the expansion of the spatial model should include time and spatial fixed effects. The R^2 values of each model are above 0.7 and higher than the OLS model without considering spatial factors, indicating that the SDM and SEM have a better interpretation of the dependent variables.

Because spatial correlation exists, coefficients of independent variables in SDM regression do not represent the direct marginal effects, and spatial lag coefficients of the independent variables do not represent the spatial effects accurately [51]. Based on SDM regression coefficients, we calculate the direct, indirect, and total effects to reflect the influences of air pollution and socio-economic status on infant mortality [40,50], which are shown in Table 6.

In models 2 and 4 of Tables 6 and 7, the increase of air pollution will significantly increase infant mortality rate and significantly reduce the average life expectancy, under the condition of considering the spatial dependence effect. Therefore, this paper demonstrates that air pollution has a significant detrimental effect on public health, which is consistent with some existing research results [14,30]. Moreover, in models 2 and 4 of Table 6, aggravation of air pollution in the local region increases infant mortality rate significantly in neighboring provinces, showing the spatial effect of air pollution on infant health in neighboring provinces. This result needs to be explained with the help of existing literature. Ref. [6] finds that local air pollution, represented by industrial SO_2 and soot emissions, has a significant negative impact on public health in neighboring areas because of the fluidity and space spillover of air pollutants. The results in this paper are the flexible extension of the conclusion applicability further compared with Ref. [6].

In models 2 and 4 of Tables 6 and 7, the increase of per capita income can significantly reduce infant mortality rate and significantly increase the average life expectancy. Therefore, this paper further demonstrates that per capita income level has a significant positive effect on public health, which is consistent with a series of existing research results [5, 18]. In models 2 and 4 of Tables 6 and 7, the per capita education level can significantly improve the public health level, which means reducing the infant mortality rate and increasing the average life expectancy. The results are consistent with the existing research. Ref. [19] finds out that a child who has a mother with a lower education level is generally in poorer health.

In this paper, two interaction variables, air pollution and per capita income (AMI*PDI) and air pollution and per capita education (AMI*EDU), are introduced in Model 4. The influence coefficient from the interaction term AMI*PDI on IMR is significantly positive, indicating that air pollution has a positive moderating effect on the negative relationship between per capita income level and infant mortality rate. As air pollution continues to increase, the impact of per capita income level on reducing infant mortality has gradually diminished. The influence coefficient of the interaction term AMI*PDI on ALE is significantly negative, indicating that air pollution has a negative moderating effect on the positive relationship between per capita income level and average life expectancy. As air pollution continues to increase, the impact of per capita income level on increasing average life expectancy has gradually weakened. In summary, the significant impact of the interaction term AMI*PDI on public health suggests that as air pollution continues to increase, the impact of per capita income level on improving public health has gradually diminished. This result complements existing research conclusions effectively [31].

The influence coefficient of the interaction term AMI*EDU on IMR is significantly positive, indicating that per capita education level has a negative moderating effect on the positive relationship between air pollution and infant mortality rate. With the increase of per capita education level, the effect of increased air pollution on the infant mortality rate has gradually weakened. The influence coefficient of the interaction term AMI*EDU on ALE is significantly positive, indicating that per capita education level has a positive moderating effect on the negative relationship between air pollution and average life expectancy. With the increase of per capita education level, the effect of increased air pollution on reducing average life expectancy has gradually weakened. In summary, the significant impact of the interaction term AMI*EDU on public health suggests that as per capita education level increases, the effect of increased air pollution on public health damage is diminished gradually. This result complements existing research effectively. A current study [30] has shown that families, where mothers are less educated, are more susceptible to air pollution, which results in increased health losses.

In terms of control variables, public medical care is significant in reducing the infant mortality rate of neighboring provinces in models 2 and 4 of Table 6, indicating the spatial effects of public medical care on infant health in neighboring provinces. Fiscal expenditure has a significant role in reducing the infant mortality rate, which is consistent with the studies by Ref. [32] and Ref. [49]. Besides, the spatial effect of the fiscal expenditure on the infant mortality rate of neighboring provinces is significantly negative, showing that fiscal expenditure reduces the infant mortality rate significantly in neighboring provinces.

5.3. Spatial regression in sub-samples of three regions

Considering China's vast territory, there are significant differences among regional economy, education, population, health care, fiscal

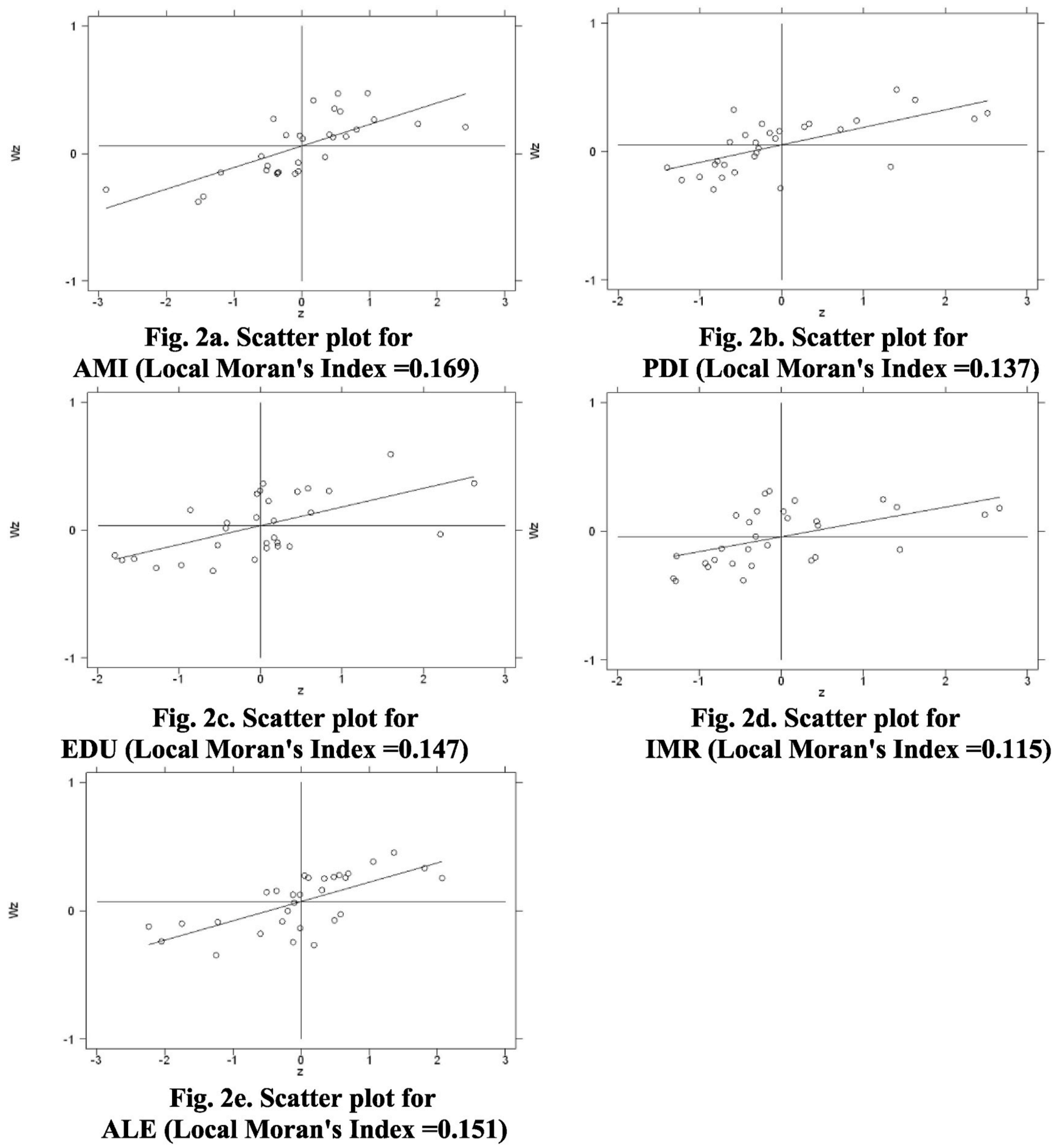

Fig. 2. Scatter plots of local Moran's Index for AMI, PDI, EDU, IMR, and ALE.

expenditure, and so on. We study the spatial influence of air pollution and socio-economic status on public health in the eastern region, central region, and western region of China. Considering the length of the paper, we only estimate the spatial influence of air pollution and socio-economic status on infant mortality rate in sub-samples of three regions. The division of these three regions corresponds to the division of the National Bureau of Statistics in China [52,53]. Table 8 lists the estimated results for the three regional subsamples. Table 9 shows the direct effects, indirect effects, and total effects of SDM for infant mortality rate in sub-samples of three regions.

Table 9 shows that there are significant differences among regions considering the influence of air pollution on infant mortality rate. On one hand, air pollution in central and western regions has a significant impact on improving infant mortality. Some provinces in the central region, such as Henan and Shanxi, are coal-producing. A large amount of coal combustion generates a large amount of air pollution. The economic development level in the western region of China is much lower than that in the central region and eastern region, and environmental regulation is even weaker. Therefore, the industrial transfer has made the western region undertake many heavily polluting industrial enterprises. On the other hand, the impact of air pollution in the eastern region on increasing infant mortality is not significant. The economic development level in the eastern region is relatively higher than in other regions, and the industry of environmental protection is intact to some extent. Compared with other regions in China, the effect of exhaust gas purification is better. Besides, the eastern region is near the coastal line, and its ability to clean up air pollution naturally is much higher than that of the central region and western region [32].

From the per capita income perspective, the increase of per capita income level in the eastern region has a significant effect on reducing infant mortality, but the increase of per capita income in the central and western regions has no significant impact on infant mortality. The increase of per capita income in the eastern region has a significant effect on reducing infant mortality in neighboring provinces, indicating the spatial effect of per capita income in the eastern region on infant health in the neighboring provinces. From an educational perspective, the increase in per capita education level has a significant effect on reducing the infant mortality rate in sub-samples of three regions. When per capita education level increases by 1%, infant mortality rates in the eastern region, central region, and western region decrease by 0.056%,

Table 5
Regression results of OLS model and time and spatial fixed effect model for infant mortality rate.

Variables	IMR-OLS (1)	IMR-SDM (2)	IMR-OLS (3)	IMR-SDM (4)
Intercept	0.962*** (0.100)		0.016(0.074)	
PPOP	0.005* (0.003)	0.088(0.054)	0.005(0.003)	0.097(0.063)
PHT	−0.029* (0.018)	0.010(0.013)	−0.033* (0.017)	0.008(0.013)
PFE	0.062*** (0.008)	−0.083*** (0.022)	0.066*** (0.008)	−0.076*** (0.024)
AMI	0.016(0.011)	0.031*** (0.011)	0.007(0.011)	0.036*** (0.010)
PDI	−0.028** (0.012)	−0.076** (0.036)	−0.028** (0.011)	−0.065** (0.028)
*AMI*PDI*			−0.172*** (0.047)	0.039** (0.017)
EDU	−0.356*** (0.052)	−0.144*** (0.053)	−0.360*** (0.051)	−0.154*** (0.051)
*AMI*EDU*			0.949*** (0.196)	−0.167** (0.071)
*W*PPOP*		−0.211 (0.291)		−0.339 (0.320)
*W*PHT*		−0.184*** (0.061)		−0.205*** (0.058)
*W*PFE*		−0.287*** (0.100)		−0.238** (0.099)
*W*AMI*		0.133** (0.057)		0.147** (0.059)
*W*PDI*		−0.300 (0.221)		−0.257 (0.275)
*W*AMI*PDI*				0.090(0.118)
*W*EDU*		−0.182 (0.350)		−0.315 (0.350)
*W*AMI*EDU*				−0.471 (0.522)
Rho		−0.229 (0.214)		−0.281 (0.223)
LM-LAG	152.121***		74.266***	
Robust LM-LAG	10.812***		5.139**	
LM-ERR	388.313***		231.852***	
Robust LM-ERR	247.005***		162.725***	
LR test spatial effect		667.400***		638.450***
Spatial Hausman tests		26.920***		22.780***
Spatial fixed effect	NO	YES	NO	YES
Time fixed effect	NO	YES	NO	YES
R2	0.613	0.716	0.636	0.719

Note: The regression coefficient is outside the brackets, and the robust standard error clustering at the provincial level is inside the brackets. *, **, and *** indicate statistically significant at 10%, 5%, and 1% levels, respectively. It is the same in the tables below.

0.164%, and 0.135%, respectively. It shows that there is still a large gap in education between the eastern region and other regions. Increased investment in education will significantly improve public health in the central and western regions.

The increase of fiscal expenditure in eastern, central, and western regions has a significant effect on reducing infant mortality. The increase of fiscal expenditure in the western region has a significant effect on reducing infant mortality in neighboring provinces, indicating the spatial effect of fiscal expenditure on infant health in neighboring provinces. Increased public health care in the eastern region and the central region has a significant effect on reducing infant mortality in neighboring provinces, indicating the spatial effect of public health care on infant health in neighboring provinces in eastern and central regions.

Table 7
Regression results of the OLS model and time and spatial fixed-effect model for average life expectancy.

Variables	ALE-OLS (3)	ALE-SEM (4)	ALE-OLS (3)	ALE-SEM (4)
Intercept	3.910*** (0.025)		4.298*** (0.022)	
PPOP	0.008*** (0.001)	0.026(0.017)	0.008*** (0.001)	0.028(0.016)
PHT	−0.005 (0.006)	0.001(0.002)	−0.002 (0.005)	0.002(0.002)
PFE	−0.005* (0.003)	0.015* (0.009)	−0.007** (0.003)	0.014(0.008)
AMI	−0.010*** (0.003)	−0.008*** (0.003)	−0.007** (0.003)	−0.010*** (0.002)
PDI	0.025*** (0.003)	0.029** (0.013)	0.024*** (0.003)	0.031** (0.013)
*AMI*PDI*			0.041*** (0.011)	−0.010** (0.005)
EDU	0.140*** (0.016)	0.030** (0.017)	0.136*** (0.016)	0.028** (0.011)
*AMI*EDU*			−0.190*** (0.053)	0.068*** (0.014)
Lambda		−0.339 (0.785)		−0.519 (0.811)
LM-LAG	48.028***		41.272***	
Robust LM-LAG	2.002		2.382	
LM-ERR	354.193***		296.572***	
Robust LM-ERR	308.167***		257.681***	
LR test spatial effect		212.570***		162.500***
Spatial Hausman tests		24.450***		23.600***
Spatial fixed effect	NO	YES	NO	YES
Time fixed effect	NO	YES	NO	YES
R2	0.881	0.944	0.887	0.946

Table 6
Direct effects, indirect effects, and total effects of SDM in infant mortality rate.

Variables	IMR-SDM (2)			IMR-SDM (4)		
	Direct effect	Indirect effect	Total effect	Direct effect	Indirect effect	Total effect
PPOP	0.089(0.054)	−0.197(0.260)	−0.107(0.216)	0.104(0.066)	−0.302(0.271)	−0.198(0.226)
PHT	0.012(0.014)	−0.157***(0.054)	−0.145***(0.046)	0.012(0.015)	−0.170***(0.052)	−0.158***(0.044)
PFE	−0.081***(0.021)	−0.231*(0.130)	−0.313**(0.129)	−0.074***(0.024)	−0.181*(0.100)	−0.255**(0.098)
AMI	0.030***(0.012)	0.108*(0.068)	0.138**(0.067)	0.035***(0.010)	0.115*(0.066)	0.149**(0.063)
PDI	−0.074**(0.032)	−0.227(0.167)	−0.301(0.189)	−0.064**(0.031)	−0.187(0.214)	−0.250(0.233)
*AMI*PDI*				0.039**(0.019)	0.059(0.090)	0.099(0.093)
EDU	−0.139***(0.050)	−0.089(0.295)	−0.228(0.308)	−0.153***(0.049)	−0.224(0.279)	−0.377(0.292)
*AMI*EDU*				−0.167**(0.069)	−0.346(0.433)	−0.513(0.389)

Table 8
SDM estimation results for infant mortality rate in sub-samples of three regions.

	Eastern region	Central region	Western region
PPOP	0.015(0.027)	0.082(0.103)	0.394(0.299)
PHT	−0.004(0.005)	0.043(0.033)	0.081(0.057)
PFE	−0.084*** (0.029)	−0.085*** (0.021)	−0.078**(0.032)
AMI	0.007(0.007)	0.042***(0.012)	0.037**(0.016)
PDI	−0.112*** (0.038)	−0.043(0.028)	0.023(0.044)
EDU	−0.046(0.032)	−0.176*** (0.058)	−0.143*(0.083)
*W*PPOP*	0.339(0.255)	−0.695(0.990)	1.448(1.003)
*W*PHT*	−0.082**(0.036)	−0.247*** (0.083)	−0.077(0.098)
*W*PFE*	−0.218*** (0.077)	−0.135(0.109)	−0.259**(0.100)
*W*AMI*	0.008(0.025)	−0.008(0.064)	−0.063(0.102)
*W*PDI*	−0.439*** (0.159)	−0.160(0.216)	0.667(0.473)
*W*EDU*	0.249(0.193)	−0.426(0.296)	−0.221(0.435)
Rho	−0.668**(0.277)	−0.340(0.213)	−0.665*** (0.180)
Spatial fixed effect	YES	YES	YES
Time fixed effect	YES	YES	YES
R2	0.748	0.838	0.766

Table 9
Direct effects, indirect effects, and total effects of SDM for infant mortality rate in sub-samples of three regions.

Variables	Eastern region	Central region	Western region
Direct impact			
PPOP	−0.003(0.035)	0.106(0.109)	0.328(0.207)
PHT	0.000(0.006)	0.049(0.033)	0.091(0.060)
PFE	−0.079***(0.03)	−0.083***(0.021)	−0.064**(0.030)
AMI	0.007(0.007)	0.044***(0.013)	0.044***(0.017)
PDI	−0.098***(0.031)	−0.041(0.030)	−0.018(0.047)
EDU	−0.056*(0.032)	−0.164***(0.057)	−0.135*(0.069)
Indirect impact			
PPOP	0.217(0.198)	−0.554(0.804)	0.828(0.658)
PHT	−0.052**(0.021)	−0.207***(0.067)	−0.091(0.067)
PFE	−0.107(0.077)	−0.090(0.107)	−0.145**(0.068)
AMI	0.003(0.019)	−0.018(0.054)	−0.056(0.069)
PDI	−0.244**(0.101)	−0.111(0.165)	0.459(0.289)
EDU	0.197(0.128)	−0.277(0.240)	−0.094(0.280)
Total impact			
PPOP	0.214(0.170)	−0.448(0.782)	1.156(0.782)
PHT	−0.053***(0.017)	−0.157***(0.056)	0.001(0.059)
PFE	−0.186***(0.064)	−0.173(0.109)	−0.209***(0.072)
AMI	0.010(0.016)	0.026(0.054)	−0.012(0.066)
PDI	−0.341***(0.127)	−0.152(0.152)	0.441(0.273)
EDU	0.141(0.138)	−0.441*(0.249)	−0.229(0.312)

5.4. Robustness test

The robustness test has important value for the generalizability and applicability of the research results [54,55]. To assess the regression results robustness of the spatial panel model, we perform two additional robustness tests. First, there may be endogenous problems with public health influencing factors such as air pollution [56,57]. Air pollution may have a certain incubation period for public health. According to the processing method of Ref. [58], we treat the lagged 1 phase of independent variables, moderating variables, and control variables as the instrument variables to alleviate the possible endogeneity problems in the model. Then we substitute the instrument variables into a spatial econometric model to study the influence of air pollution and socio-economic status on public health [59]. The study results in Table 10 show that the basic results remain unchanged.

Second, we use an alternative spatial weight matrix, the contiguity-based binary spatial weight matrix, instead of the spatial distance-based weight matrix [60] to reflect the spatial dependence of public health influencing factors in different provinces. The model regression in Table 11 shows that the overall regression results remain unchanged.

Table 10
Robust regression results of time and spatial fixed-effect model under the instrument variables.

	IMR	ALE
PPOP_1	0.096*(0.051)	0.027*(0.015)
PHT_1	0.010(0.013)	0.002(0.002)
PFE_1	−0.072***(0.022)	0.013*(0.008)
AMI_1	0.030***(0.009)	−0.010***(0.002)
PDI_1	−0.060*(0.035)	0.029**(0.012)
*AMI_1*PDI_1*	0.034*(0.019)	−0.010**(0.005)
EDU_1	−0.156***(0.051)	0.026*(0.014)
*AMI_1*EDU_1*	−0.147**(0.063)	0.065***(0.014)
*W*PPOP_1*	−0.305(0.310)	
*W*PHT_1*	−0.173***(0.054)	
*W*PFE_1*	−0.237**(0.098)	
*W*AMI_1*	0.116**(0.053)	
*W*PDI_1*	−0.264(0.258)	
*W*AMI_1*PDI_1*	0.042(0.103)	
*W*EDU_1*	−0.430(0.355)	
*W*AMI_1*EDU_1*	−0.248(0.457)	
Rho	−0.291(0.235)	
Lambda		−0.513(0.801)
Spatial fixed effect	YES	YES
Time fixed effect	YES	YES
R^2	0.730	0.944

6. Conclusions and policy implications

With rapid economic growth, China's provinces are facing serious air pollution problems currently. Effective control of air pollution to promote public health has become one of the priority objectives of all levels of government in China. Based on the spatial dependence effect of public health and its influencing factors, this paper studies the direct effect of air pollution and socio-economic status on public health and their possible interaction effects and further explores the regional heterogeneity between different regions by applying panel data in Chinese 30 provinces.

This paper draws the following conclusions. First, there is strong spatial agglomeration in air pollution, socio-economic status, and public health. The eastern coastal line of China and north and central China are the areas with H–H clusters, while Northwest and Northeast regions are L-L clusters. This conclusion fully demonstrates the importance of

Table 11
Robust regression results of time and spatial fixed-effect model under the contiguity-based binary spatial weight matrix.

	IMR	ALE
PPOP	0.069(0.073)	0.020(0.012)
PHT	0.010(0.013)	0.002(0.003)
PFE	−0.069***(0.025)	0.010(0.008)
AMI	0.040***(0.010)	−0.009***(0.003)
PDI	−0.071**(0.032)	0.023**(0.012)
*AMI*lnPDI*	0.066***(0.020)	−0.007*(0.003)
EDU	−0.159***(0.056)	0.026*(0.015)
*AMI*EDU*	−0.225**(0.091)	0.053**(0.021)
*W*PPOP_1*	−0.029(0.133)	
*W*PHT_1*	−0.049**(0.020)	
*W*PFE_1*	−0.078**(0.032)	
*W*AMI_1*	0.003(0.017)	
*W*PDI_1*	−0.058(0.046)	
*W*AMI_1*PDI_1*	−0.001(0.050)	
*W*EDU_1*	−0.197(0.126)	
*W*AMI_1*EDU_1*	−0.041(0.194)	
Rho	0.097(0.117)	
Lambda		0.193(0.268)
Spatial fixed effect	YES	YES
Time fixed effect	YES	YES
R^2	0.760	0.941

considering the spatial dependence and spatial heterogeneity of public health and its influencing factors. Second, increased air pollution can significantly damage local public health status, leading to increased infant mortality rate and lower average life expectancy. Aggravation of air pollution in the local region increases infant mortality rate significantly in neighboring provinces, showing the spatial effect of air pollution on infant health in neighboring provinces. Third, the increase of per capita income significantly reduces infant mortality rate and significantly increases average life expectancy, leading to a significant positive effect on public health. As air pollution continues to increase, the impact of per capita income on improving public health has gradually diminished. Fourth, the per capita education level can significantly improve public health, which means decreasing infant mortality rate and increasing average life expectancy. As per capita education level increases, the influence of increased air pollution on public health damage has diminished gradually. Finally, the effects of air pollution and socio-economic status on infant mortality in the eastern, central, and western regions are heterogeneous. Air pollution in central and western regions has a significant impact on improving the infant mortality rate. The increase in per capita income in the eastern region has a significant effect on reducing the infant mortality rate. The increase in per capita education level has a significant effect on reducing the infant mortality rate in three different regions.

Based on our empirical findings, we would propose the following policy recommendations.

- First, the central government should formulate a cross-regional public health policy based on actual conditions. Local governments should deepen inter-governmental medical and health cooperation and strengthen communication and cooperation in the fields of economy, culture and, education so that the public health of different provinces could be continuously improved.
- Second, governments at all levels should increase the intensity of pollution control from the source, and comprehensively use market mechanisms and macro-control measures to continuously reduce air pollution. Moreover, due to the existence of air pollution liquidity, local governments should fully realize that if they do not cooperate with other neighboring areas to control pollution, it is impossible to solve the problem of air pollution completely such as acid rain and haze in all provinces and to improve public health status fundamentally.
- Third, due to the important role of income in improving public health, all levels' governments in China should attach great importance to the issue of income distribution and focus on optimizing the reform of the income distribution. Governments should strive to increase the proportion of household income in the distribution of national income so that the development results will benefit all the people more fairly.
- Fourth, due to the important role of education in improving public health, Chinese governments at all levels should pay more attention to education and adhere to the path of rejuvenating the country through science and education. The government should increase funding for education at all stages and guide the role of social capital in promoting education rationally. By increasing the amount of human capital in the stock of labor resources, the Chinese government should turn the heavy population burden into a human resource advantage.
- Finally, implementing a differentiated regional air pollution control policy is an important environmental strategy. Governments need to keep on strengthening air pollution control and improving public health in the central and western regions. The government needs to increase investment towards education, medical care, etc., and increase public health level in the eastern, central, and western regions gradually by expanding fiscal expenditures.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

CRediT authorship contribution statement

Zhenhua Zhang: Data curation, Software, Writing – original draft. **Guoxing Zhang:** Conceptualization, Methodology. **Bin Su:** Validation, Writing – review & editing.

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