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Does industrial air pollution drive health care expenditures? Spatial evidence from China

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ABSTRACT

The severe health damage and massive health costs associated with industrial air pollution have attracted global concern. A spatial lag model with decomposed direct and indirect spatial effects was used to estimate the impact of industrial air pollution on health care expenditures in Chinese provinces from 2002 to 2014. The control variables of health reform, GDP per capita, urbanization, aging, education level, and hospital supplies were considered. Moran's I index was applied to investigate the spatial agglomeration of health care expenditures. The spatial lag model with fixed effects provided the best fit to measure the effect of industrial air pollution on health care expenditures. The global Moran's I of provincial health care expenditures increased from 0.3988 in 2002 to 0.4554 in 2014. The estimated spatial lag coefficient of provincial health care expenditures was 0.188. The estimated direct and indirect effects of industrial air pollution on provincial health care expenditures were 0.032 and 0.0072, respectively. The direct effect of health reform on health care expenditures was −0.006. The results indicate that the strengthening spatial agglomeration of provincial health care expenditures is caused by the joint effect of industrial air pollution, health reform, and other socioeconomic factors. Industrial air pollution increases health care expenditures in the local and neighboring provinces. Most importantly, the effect of industrial air pollution outweighs the reduction effect of health reform on health care expenditures. The final remarks of this paper suggest three main measures to reduce industrial air pollution and its health costs.

1. Introduction

Manufacturing industries are the primary sources of pollution because of the chemical waste and toxic fumes they discharge into the environment (Dillinger, 2017; Ritchie and Roser, 2017), causing poor air quality and health problems. The rapid growth of industry has led to waste emission increases in China in recent decades. For example, the levels of industrial dust in China, which causes severe air pollution, increased from 17.53 to 69.42 trillion m^3 between 2002 and 2014 (Xu et al., 2014; Yang et al., 2018).

The manifold effects of this air pollution on human health have been well documented (e.g., World Health Organization, 2016). For example, industrial air pollution may cause childhood-onset asthma (Buteau et al., 2018), low birth weights of babies born to women living near industrial areas (Gong et al., 2018), and otitis media infection in early childhood (Deng et al., 2017). Moreover, industrial air pollution is positively linked to the incidence of related cancers. Simpson et al. (2013) indicated that the incidence of male hematopoietic cancers (leukemia and non-Hodgkin lymphoma) was much higher in industrial areas of Alberta, Canada, based on a 13-year record (1994–2006). Fernández-Navarro et al. (2017) found that cancer mortality rates in Spanish regions that were exposed to industrial pollution were around 17% higher than in unexposed regions. The comprehensive health impacts of industrial air pollution are summarized in Table 1. These include premature death, infant mortality (Dockery et al., 1993; Ma et al., 2017; Lelieveld et al., 2015; Fotourehchi, 2016), reduced life expectancy (Correia et al., 2013), disability-adjusted life years (Pope et al., 2015; Tong et al., 2018; Huang et al., 2018), and increase in hospitalization and emergency department visits (Lagravinese et al., 2014; Fotourehchi, 2016; Li et al., 2016).

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Table 1
Health impacts of industrial air pollution.

Health impact category	Literature
Premature death and infant mortality	Dockery et al. (1993); Ma et al. (2017); Lelieveld et al. (2015); Fotourehchi (2016)
Life expectancy decrease	Correia et al. (2013)
Disability-adjusted life years (DALYs)	Pope et al. (2015); Tong et al. (2018); Huang et al. (2018)
Risk of polycyclic aromatic hydrocarbons	Xu et al. (2016)
Frequent hospitalization and ER visits	Lagravinese et al. (2014); Fotourehchi (2016); Li et al. (2016)
Subjective well-being	Li et al., (2016); Zhang et al. (2017)

Studies have examined the health care costs associated with air pollution (Landrigan, 2012; Preker et al., 2016). According to estimates by the OECD (2016), outdoor air pollution will gradually lead to an increase in global economic costs equivalent to 1% of global GDP by 2060, with costs related to additional health care expenditures dominating in the long run. Jerrett et al. (2003) conducted exploratory analysis using cross-sectional data from 49 counties in Ontario, Canada. They found that counties with higher pollution had higher per capita health care expenditures, whereas those that spent more on environmental quality had lower health care expenditures. Khoshnevis Yazdi et al. (2014) used an autoregressive distributed lag approach to examine the relationship between environmental quality, income, and health care expenditure between 1967 and 2010 in Iran. Both short- and long-run income elasticities showed that the emissions of sulfur oxide and carbon monoxide exerted a statistically significant positive effect on health spending. Khoshnevis Yazdi and Khanalizadeh (2017) applied the autoregressive distributed lag method to estimate the effect of economic growth and environmental quality on health care expenditures in the Middle East and North Africa (MENA) between 1995 and 2014. They concluded that CO_2 and PM_{10} emissions had statistically significant positive effects on long-term health care expenditures.

The growing literature on industrial air pollution in China extensively discusses its adverse health effects, which range from minor restrictions in activity to emergency room (ER) visits for asthma, otitis media infection in early childhood, hospitalizations for respiratory and cardiovascular problems, premature mortality, lung cancer mortality, and respiratory disease mortality (Lu et al., 2016; He et al., 2016; Deng et al., 2017; Chen et al., 2017; Shen et al., 2017; Jiang et al., 2018). However, few studies have explored the relationship between air pollution and health care expenditures (Jerrett et al., 2003; Maryam et al., 2015; Khoshnevis Yazdi and Khanalizadeh, 2017), and little is known about the impact of industrial air pollution on health care expenditures, which represent a major economic burden for China.

Studies have shown that air pollution has significant spatial aggregation and diffusion effects and that geographically neighboring cities influence each other through spatial dependence and spatial spillovers (Xu and Lin, 2016; Wang and Nie, 2016; Ma et al., 2016; Zhang et al., 2018; Hao and Liu, 2016; Liu et al., 2017). The Chinese government has sought to control unreasonable increases in health care expenditures since 2009 by initiating a new health reform. The literature provides evidence that income per capita, urbanization, the population aged over 65 years, government health spending per capita, education level, and number of physicians could determine health care expenditures in different countries (Gerdtham et al., 1992; Lin and Shu, 2007; Wang and Zhang, 2013). However, it remains unclear whether, together with health reform and the socioeconomic indicators of income per capita, urbanization, aging, education level, and hospital supplies, industrial air pollution increases health care expenditures with spatial spillover effects across Chinese provinces.

To shed light on this important issue, we address the following research questions: (1) Does industrial air pollution have a spatial spillover effect on health care expenditures in other Chinese regions? (2) What is the impact of industrial air pollution on health care expenditures in local and neighboring regions? (3) Considering other socioeconomic factors as control indicators, is a reduction in health care expenditures due to health reform outweighed by the adverse impact of industrial air pollution? We used ArcGIS10.2 and R software to establish the spatial lag model (SLM) and the spatial error model (SEM), and to analyze the spatial spillover effect of industrial air pollution on health care expenditures for 31 provinces for the period 2002 to 2014. We also considered other socioeconomic indicators.

This paper is organized as follows. Section 2 describes the spatial measurement methodology and presents the research data. Section 3 presents the results of the spatial measurement analysis of industrial air pollution's effect on health care expenditures for 31 Chinese provinces. Section 4 discusses the results. Section 5 presents the conclusions and implications of the study.

2. Methodology

2.1. Spatial measurement

This section establishes the spatial econometric model of industrial air pollution and health care expenditures for 31 Chinese provinces. The recent health reform and other socioeconomic indicators are also considered in the model.

2.1.1. Spatial autocorrelation test

Moran's I test and scatter plots were employed to determine whether there was similar spatial agglomeration for health care expenditures across Chinese provinces. Equations (1) and (2) present the estimations of the global and standardized Moran's I:

$$Moran's \quad I = \frac{\sum_{i=1}^{n}\sum_{j\neq i}^{n} W_{ij}(y_i - \bar{y})\left(y_j - \bar{y}\right)}{S^2 \sum_{i=1}^{n}\sum_{j\neq i}^{n} W_{ij}} \tag{1}$$

Where n is the number of regions; y_i and y_j are the health care expenditures of spatial locations i and j, respectively; S denotes the standard deviation of the samples; and W_{ij} is a non-negative $n \times n$ spatial weight matrix reflecting the spatial relevance relationship of the observations in the neighborhood set for each location.

The value of the global Moran's I is located at [-1, 1]. To further investigate the spatial spillover and aggregation effect of health care expenditures in neighboring provinces, the local spatial correlation Moran's I index is given by:

$$Moran's \quad I_i = \frac{(y_i - \bar{y})}{S^2} \sum_{j \neq i}^{n} w_{ij}\left(y_j - \bar{y}\right) \tag{2}$$

2.1.2. Spatial econometric model

In spatial econometric models, it is assumed that the dependent variable for each region depends on the data for that region and neighboring regions. In our study, health care expenditure (the dependent variable) in one province might interact with health care expenditures in neighboring provinces. Regarding the exposure-response relationship (Samoli et al., 2005), we assumed that industrial air pollution in a given province increased health care expenditures in that province. Industrial air pollution (the independent variable), represented by industrial waste gas emissions, spreads easily across geographically close regions (Wang and Nie, 2016). Other independent variables (including health reform and the socioeconomic indicators of income, aging, urbanization, supply of hospital beds, supply of doctors, government health care spending, and education level) associated with neighboring regions might also interact with each other.

In our study, if the health care expenditure of one province is determined by the health care expenditures, industrial air pollution, and other socioeconomic indicators in that province and neighboring provinces, the SLM can be expressed by:

$$\begin{aligned} y_{it} = {} & \rho \sum_{j=1}^{n} w_{ij} y_{ij} + \beta_1 \ln \mathrm{Gas}_{it} + \beta_2 D_{it} + \beta_3 \ln Inc_{it} + \beta_4 \ln Aged_{it} \\ & + \beta_5 \ln Urb_{it} + \beta_6 \ln Bed_{it} + \beta_7 \ln Doc_{it} + \beta_8 \ln Gov_{it} \\ & + \beta_9 \ln Edu_{it} + \mu_i + \varphi_t + \varepsilon_{it} \end{aligned} \tag{3}$$

where y_{it} is the logarithm of health care expenditure; $\ln \mathrm{Gas}_{it}$is the logarithm of industrial air pollution; D_{it} is the dummy variable of health reform; $\ln Inc_{it}$, $\ln Aged_{it}$, $\ln Urb_{it}$, $\ln Bed_{it}$, $\ln Doc_{it}$, $\ln Gov_{it}$, and $\ln Edu_{it}$, are, respectively, the logarithms of income, aging, urbanization, supply of hospital beds, supply of doctors, government health care spending, and education level for province $i$at time $t(i = 1, 2, \cdots n;\ t = 1, 2, \cdots T)$; ρ is the spatial autoregressive coefficient, which weights the effect of the independent variable in adjacent regions; $\beta_1,\ \beta_2, \cdots, \beta_9$ are the estimation coefficients for variables $\ln Inc$, $\ln Aged$, $\ln Urb$, $\ln Bed$, $\ln Doc$, $\ln Gov$, and $\ln Edu$, respectively; W is the $n \times n$ spatial-weights matrix; $\sum_{j=1}^{n} w_{ij} y_{ij}$ denotes the endogenous interaction effects among dependent variables; μ_i is the i^{th}individual effect; φ_t is the time effect; and $\varepsilon_{it}$is the normally distributed random error term.

The error terms in the spatial model are likely to interact due to issues such as missing variables (Liu et al., 2017). If spatial interaction effects exist among the error terms (ε_{it}), the spatial error model (SEM) is expressed by:

$$\begin{aligned} y_{it} = {} & \lambda \sum_{j=1}^{n} w_{ij} \phi_{it} + \beta_1 \ln \mathrm{Gas}_{it} + \beta_2 D_{it} + \beta_3 \ln Inc_{it} + \beta_4 \ln Aged_{it} \\ & + \beta_5 \ln Urb_{it} + \beta_6 \ln Bed_{it} + \beta_7 \ln Doc_{it} + \beta_8 \ln Gov_{it} \\ & + \beta_9 \ln Edu_{it} + \mu_i + \varepsilon_{it} \end{aligned} \tag{4}$$

where λrefers to the spatial autocorrelation coefficient; and ϕ_{it} are the error terms with spatial autocorrelation for province i at time t.

Anselin's k-nearest neighbor spatial weight matrix W (Anselin, 1995) was also used to examine and measure possible interaction effects. Specifically, we set region i as the central province and then selected K as the nearest provinces j to the central region and defined their spatial weights $w_{ij} = 1$. Otherwise, spatial weights were defined as $w_{ij} = 0$. We considered non-bordering provinces because industrial air pollution in some provinces affects others greatly even if they are not adjacent. We also determined four K values.

R was employed to perform Moran's I test and the spatial regression modeling. First, parameter estimates were obtained using the maximum likelihood (ML) method. Then, we used a traditional ordinary least squares (OLS) regression model, the Lagrange multiplier test (LM), and the Hausman test to determine which model best fit the sample data. Third, goodness-of-fit tests and the likelihood ratio (LR) test based on the log-likelihood function values of the different models were used for different models.

2.1.3. Direct and indirect spatial effect decomposition

Independent variables usually exert indirect effects (spatial spillovers) on the dependent variables for surrounding non-local areas in a spatial econometric model. We estimated the direct, indirect, and total spatial effects based on estimated spatial regression coefficients (Elhorst, 2014; Pace and Lesage, 2009) to further quantify the spatial spillover effects of industrial air pollution, health reform, and other socioeconomic indicators on health care expenditures. Both direct and indirect spatial effects were determined based on the identified spatial correlation coefficient, ρ, shown below:

$$(I_{\mathrm{n}} - \rho W) y = X\beta + \tau_n \alpha + \varepsilon \tag{5}$$

where X represents the dependent variables of ($\ln GasD$, $\ln Inc$, $\ln Aged$, $\ln Urb$, $\ln Bed$, $\ln Doc$, $\ln Gov$, and $\ln Edu$), τ_n is the constant vector and α is the parameter of intercept term.

Eq. (5) can be rewritten as Eq. (6):

$$y = \sum_{r=1}^{k} S_r(W) x_r + V(W)\tau_n \alpha + V(W)\varepsilon \tag{6}$$

where $S_r(W) = V(W) I_n \beta_r, V(W) = (I_{\mathrm{n}} - \rho W)^{-1} = I_n + \rho W + \rho^2 W^2 + \rho^3 W^3 + \cdots$, W is the spatial weights matrix, ρ is the spatial autoregressive coefficient, and $\beta_r,\ r = 1, 2, \cdots, 9$ are the estimation coefficients for dependent variables in Eq. (3).

Eq. (6) can be further transformed into:

$$\begin{aligned} \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix} = {} & \sum_{r=1}^{9} \begin{bmatrix} S_r(W)_{11} S_r(W)_{12} \cdots S_r(W)_{1n} \\ S_r(W)_{21} \ S_r(W)_{21} \cdots S_r(W)_{2n} \\ \vdots \qquad \vdots \qquad \vdots \\ S_r(W)_{n1} S_r(W)_{n2} \cdots S_r(W)_{nn} \end{bmatrix} \begin{bmatrix} x_{1r} \\ x_{2r} \\ \vdots \\ x_{nr} \end{bmatrix} + V(W)\tau_n \alpha \\ & + V(W)\varepsilon \end{aligned} \tag{7}$$

Denoting $S_r(W)_{ij}$ and $V(W)_{ij}$as the ij^{th} element in $S_r(W)$ and the i^{th} row of $V(W)$, Eq. (7) can be written as:

$$\begin{aligned} y_i = {} & \sum_{r=1}^{k} \left[S_r(W)_{i1} x_{1r} + S_r(W)_{i2} x_{2r} +, \cdots, + S_r(W)_{in} x_{nr} \right] \\ & + V(W)_i \tau_n \alpha + V(W)_i \varepsilon \end{aligned} \tag{8}$$

The overall spatial effect of the independent variable x_{it} on y_i can be obtained by the average of row i. The direct spatial effect of the independent variable x_{it} on y_i can be obtained by the average of the diagonal elements of matrix $S_r(W)$. Moreover, the indirect spatial spillover effect of the independent variable x_{it} on y_i is the average value of the diagonal elements of matrix $S_r(W)$, which is the difference between the overall and direct effects and indicates the effects of the independent variable in one province on y_i in a neighboring province.

Direct spatial effects indicate how the independent variables (industrial air pollution and health reform) for a given province affect health care expenditure in that province. The indirect spatial spillover effects measure the effects of the independent variables for a given province on health care expenditures in neighboring provinces.

2.2. Data

We collected panel data on all indicators for 31 Chinese provinces (excluding Hong Kong, Macao, and Taiwan) for the period 2002 to 2014. Various sources were used to collect the data on indicators, including provincial health care expenditures, industrial waste gas emissions, health reform dummy variables, and other control indicators (income, urbanization, hospital supply, population aging, government health care spending, education level, etc.). The dependent variable *provincial health care expenditure* was proxied by provincial health care expenditure per capita for urban and rural citizens according to the China Health Statistical Yearbook (2003–2015). Table 2 shows the data sources for the explanatory variables.

Province-level disposable income per capita, government health care spending, and health care expenditure per capita for urban and rural citizens were deflated by the consumer price index with base year 2002 to account for the influence of population growth and changing prices. Except for the health reform dummy variable, all deflated indicators were taken as the logarithm of the current value to account for the influence of dimensional change and heteroscedasticity.

Figs. 1 and 2 show the spatial distributions of provincial health care expenditures and industrial air pollution in 2014, respectively. These figures show spatial dependence and agglomeration for both provincial health care expenditures and industrial air pollution. Provinces with more serious air pollution generally had higher health care expenditures. This observation validates our initial assumption that industrial air pollution increases provincial health care expenditures. The spatial spillover of air pollution may affect health care expenditures in other provinces.

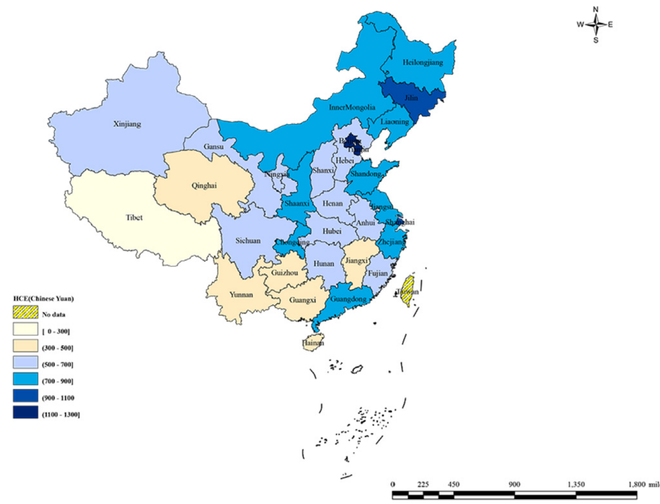

Fig. 1. Spatial distribution of provincial health care expenditures in 2014.

3. Spatial measurement results

3.1. Spatial autocorrelation of industrial air pollution and health care expenditures

The global Moran's index of industrial air pollution varied from 0.2648 to 0.1946 from 2002 to 2014. Global Moran's I index (Table A1 in Appendix A) and Moran's I scatter plots of the industrial air pollution in 2002 and 2014 (Fig. 3) show that industrial air pollution followed high-high and low-low positive spatial agglomeration patterns across Chinese provinces between 2002 and 2014.

Health care expenditures were characterized by the spatial

Table 2
Explanatory variables.

Explanatory variables	Nomenclature	Brief description; Unit	Data source
Industrial air pollution	Gas	The provincial industrial waste gas discharge volume (standard cubic meters per person)	China Environmental Yearbook 2003–2015
Health reform	D	$D_{it} = \begin{cases} 0, \text{ if } t < 2009, \text{ for } i = 1, 2, \cdots N \\ 1, \text{ if } t \geq 2009, \text{ for } i = 1, 2, \cdots N \end{cases}$	China Statistical Yearbook 2003–2015
Income level	Inc	The provincial income per capita = (provincial urban population × disposable income per capita for urban citizen + provincial rural population × disposable income per capita for rural citizen)/ provincial total population (percent)	China Statistical Yearbook 2003–2015
Aging process of population	Aged	The provincial proportion of population aged 60 (65) and above to total population (percent)	Statistical Yearbook for each province 2003–2015
Urbanization level	Urb	The provincial proportion of urban population to total population (percent)	Statistical Yearbook for each province 2003–2015
Hospital supply-beds	Bed	Beds per 1000 people for each province (beds)	China's Health and Family Planning Statistical Yearbook 2003–2015
Hospital Supply-Doctors	Doc	The technical health personnel per 1000 people for each province	China's Health and Family Planning Statistical Yearbook 2003–2015
Governmental health care spending	Gov	Provincial governmental health care spending per capita (10,000 Chinese Yuan)	China Fiscal Statistics Yearbook 2003–2015
Education level	Edu	The illiterate population older than 15 years as a proportion of total population of each province (percent)	Educational Statistical Yearbook of China 2003–2015

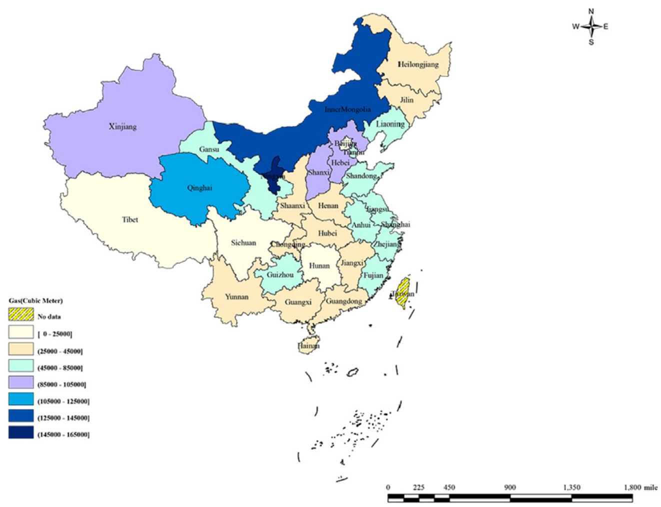

Fig. 2. Spatial distribution of provincial industrial air pollution in 2014.

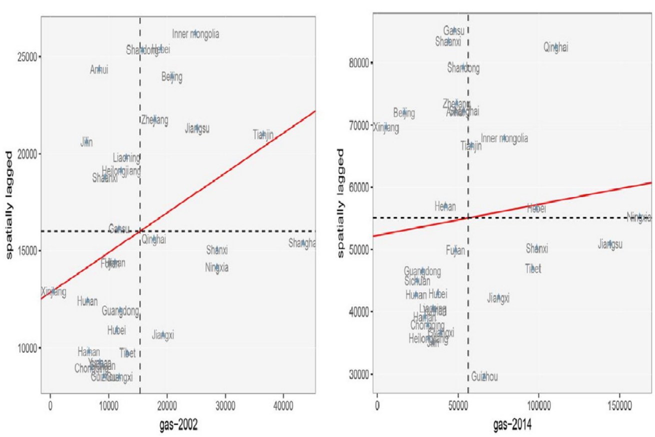

Fig. 3. Local Moran's I scatter plots of industrial air pollution in 2002 and 2014.

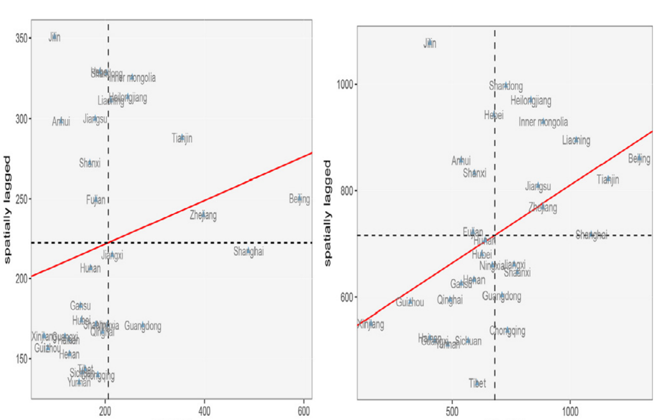

Fig. 4. Local Moran I's scatter plots of health care expenditures in 2002 and 2014.

agglomeration effect. The global Moran's I of provincial health care expenditures in China increased from 0.3988 in 2002 to 0.4554 in 2014 (Table A2 in Appendix A). Together with Moran's I scatter plots of health care expenditures (Fig. 4), the spatial dependence and agglomeration effects for provincial health care expenditures strengthened over time.

According to the results of the global Moran's I index and Moran's I scatter plots for industrial air pollution and health care expenditures, the spatial dependence and aggregation for provincial health care expenditures were stronger than for industrial air pollution. This is probably because health care expenditures were affected by health reform and other socioeconomic indicators.

3.2. Spatial estimation results

We built the spatial model using the following steps. First, we built an OLS regression model and tested whether there was spatial correlation between provinces. Second, we conducted a Lagrange multiplier test (LM) to determine whether the SLM or SEM was more appropriate. In the LM, if neither the LM-error nor the LM-lag passes the significance test, the sample data fit the OLS regression model. If the LM-error passes the significance test and the LM-lag does not, the sample data fit the spatial error model. If the LM-error does not pass the significance test and the LM-lag does, the sample data fit the SLM. If both the LM-error and LM-lag pass the significance test, the robust LM must be conducted. If the robust LM-error passes the significance test, the sample data fit the spatial error model. If the robust LM-lag passes the significance test, the sample data fit the SLM. If both the robust LM-error and the robust LM-lag pass the significance test, the log likelihood (LogL), likelihood ratio (LR), Akaike information criterion (AIC), and Schwartz criterion (SC) must be calculated. Finally, the Hausman test was used to determine whether the spatial model with a fixed effects or spatial model with random effects was more appropriate in our study.

Table 3 provides the estimated results for the spatial models with LM tests. The LM-lag was 319.9, leading to the rejection of the null hypothesis of not fitting the spatial lag model at a significance level of 5%. The LM-error was 0.31, leading to the acceptance of the null hypothesis of not fitting a spatial error model at a significance level of 5%. These results are consistent with a situation where the LM-error did not pass the significance test and the LM-lag did. Therefore, the sample data fit the SLM. Furthermore, the results show that $\chi^2 = 32.524$, so we rejected the null hypothesis at a significance level of 5% based on the Hausman test. This result indicates that the SLM with fixed effects should be adopted (Model 3 in Table 3).

The spatial lag coefficient ρ was 0.188 at a significance level of 5%. In addition to the effects of other explanatory variables, a 1% increase in health care expenditures in one province caused 0.188% growth in expenditures in each neighboring province.

The elasticity coefficient of industrial air pollution on health care expenditures was 0.032 at a significance level of 10%. A 1% increase in industrial air pollution caused a 0.032% increase in health care expenditures. The health reform dummy variable D had a small negative impact (−0.006) on provincial health care expenditures at a significance level of 10%.

The socioeconomic indicators of disposable income per capita, population aging, urbanization, beds per 1000 people, and government health spending per capita all exerted significant positive effects on provincial health care expenditures. At the 1% level, the estimated effects of disposable income per capita, population aging, urbanization, and beds per 1000 people were 0.493, 0.221, 0.571, and 0.052, respectively. At the 10% level, the estimated effect of government health spending was 0.043.

However, the proxy indicators of health personnel per 1000 people, and the illiterate population older than 15 years as a proportion of the total population had negative effects on provincial health care expenditures. At the 1% level, the estimated effect of health personnel per 1000 people was −0.237. At the 5% level, the estimated effect of the illiterate population older than 15 years as a

Table 3
Parameter summary of spatial regression model estimates.

	Regular panel model		Spatial lag model		Spatial error model	
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
	fixed effects	random effects	fixed effects	random effects	random effects	fixed effects
C		−1.693*** (0.453)		−1.759*** (0.456)		−1.019** (0.477)
Ln(Gas)	0.037* (0.020)	0.053** (0.018)	0.032* (0.019)	0.042** (0.018)	0.039** (0.018)	0.054*** (0.017)
D	−0.002 (0.022)	−0.007 (0.028)	−0.006* (0.004)	−0.009* (0.005)	−0.035* (0.021)	−0.035* (0.022)
Ln(Inc)	0.549*** (0.051)	0.493*** (0.049)	0.429*** (0.055)	0.404*** (0.047)	0.487*** (0.054)	0.451*** (0.053)
Ln(Aged)	0.246*** (0.053)	0.221*** (0.051)	0.257*** (0.050)	0.236*** (0.050)	0.227*** (0.051)	0.221*** (0.050)
Ln(Urb)	0.445*** (0.147)	0.571*** (0.104)	0.376*** (0.137)	0.564*** (0.106)	0.292** (0.127)	0.479*** (0.103)
Ln(Bed)	0.258*** (0.066)	0.238*** (0.064)	0.262*** (0.061)	0.234*** (0.062)	0.274*** (0.059)	0.255*** (0.06)
Ln(Doc)	−0.293*** (0.061)	−0.237*** (0.059)	−0.257*** (0.057)	−0.215*** (0.057)	−0.237*** (0.056)	−0.203*** (0.057)
Ln(Gov)	0.057** (0.029)	0.052** (0.026)	0.043* (0.024)	0.037 (0.025)	0.104*** (0.029)	0.082*** (0.027)
Ln(Edu)	−0.050** (0.021)	−0.063** (0.021)	−0.042** (0.020)	−0.052** (0.020)	−0.060** (0.025)	−0.080*** (0.024)
ρ			0.188*** (0.049)	0.157*** (0.046)		
λ					0.479*** (0.054)	0.478*** (0.057)
Adjusted R^2	0.852	0.918	0.912	0.915	0.886	0.897
LM Test			LM-lag = 319.9 (0.000)		LM-error = 0.31 (0.578)	
Fixed/Random Effect Hausman Test	$\chi^2 = 20.673$ (0.014)		$\chi^2 = 32.524$ (0.000)		$\chi^2 = 39.326$ (0.000)	

Note: ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 4
Decomposed estimates of the direct, indirect, and total effects on health care expenditures.

Variable	direct	P-value	indirect	P-value	total	P-value
Ln(Gas)	0.0320*	0.0845	0.0072*	0.0904	0.0394*	0.0863
D	−0.0060*	0.0723	−0.0013	0.1259	−0.0073*	0.0801
Ln(Inc)	0.4315***	0.0000	0.0966***	0.0055	0.5282***	0.0000
Ln(Aged)	0.2584***	0.0000	0.0579***	0.0044	0.3163***	0.0000
Ln(Urb)	0.3781***	0.0061	0.0847**	0.0278	0.4628*	0.0058
Ln(Bed)	0.2635***	0.0000	0.0590**	0.0240	0.3225***	0.0001
Ln(Doc)	−0.2583***	0.0000	−0.0578**	0.0170	−0.3161***	0.0000
Ln(Gov)	0.0432*	0.0855	0.0097	0.1508	0.0529*	0.0896
Ln(Edu)	−0.0425**	0.020	−0.0095*	0.0978	−0.0520**	0.0450

Note: ***, **, and *indicate significance at the 1%, 5%, and 10% levels, respectively.

proportion of the total population was −0.063.

3.3. Direct and indirect spatial effects

Table 4 shows the decomposed coefficients of direct, indirect, and total spatial effects on health care expenditures based on the SLM to further quantify the spatial spillover effects of industrial air pollution, health reform, and other socioeconomic indicators on health care expenditures.

The direct spatial effects, indirect spatial spillover effects, and total spatial effects of industrial air pollution on provincial health care expenditures were 0.0320, 0.0072, and 0.0394, respectively, at a significance level of 10%. The direct spatial and total spatial effects of health reform on provincial health care expenditures were −0.0060 and −0.0073, respectively, at a significance level of 10%. The indirect spatial spillover effect was non-significant at the 10% level.

Considering the other socioeconomic indicators, the direct and total spatial effects of government health spending on provincial health care expenditures were 0.0432 and 0.0529, respectively, at a significance level of 10%. The indirect spatial spillover effect was non-significant at the 10% level.

The direct spatial effects (0.4315, 0.3781, 0.2635, and 0.2584) and indirect spatial spillover effects (0.0966, 0.0847, 0.059, and 0.0579) of Ln(Inc), Ln(Aged), Ln(Urb), and Ln(Bed) on the logarithm of health care expenditures in a given province indicate that the socioeconomic factors considered in this study increased health care expenditures in that province and neighboring provinces. However, the supply of doctors and education level in a given province were found to exert significant negative direct spatial effects (−0.258, −0.0425) and indirect spatial effects (−0.0578, −0.009) on health care expenditures in that province and neighboring provinces.

4. Discussion

The results of the global Moran's I index and Moran's I scatter plots of provincial health care expenditures in 2002 and 2014 and the spatial lag coefficient of provincial health care expenditures in SLM with fixed effects provide evidence of the spatial agglomeration effects of provincial health care expenditures across provinces. The results indicate that the spatial dependence of provincial health care expenditures strengthens over time. Overall, provincial health care expenditures are subject to the spatial spillover effects of industrial air pollution and other socioeconomic factors.

Industrial air pollution was found to have a significant positive effect on health care expenditures. The results imply that the negative impact of industrial air pollution on health care expenditures is significantly underestimated if the spatial spillover effects of air pollution are ignored. The results of the direct and indirect spatial estimates indicate that industrial air pollution in one province not only increases local health care expenditure but is also responsible for similar increases in health care expenditures in neighboring provinces.

China began a new health care reform in 2009. Since then, remarkable progress has been made in increasing life expectancy, reducing maternal and child mortality, and improving health insurance. Each province can set its own measures under the pilot reform. The health reform measures in one province may differ from those in other provinces. Consistent with the health reform across provinces, the spatial measurement results indicate that health reform in a given province results in a slight decrease in health care expenditure in that province. This decrease is exclusive and not shared with neighboring provinces. However, the direct and total spatial effects of health reform on reducing health care expenditures were observed to be weaker than the corresponding effects of industrial air pollution. This finding provides convincing evidence that the reduction in health care expenditures due to the health reform is unfortunately outweighed by the effect of industrial air pollution.

The socioeconomic indicators of disposable income per capita, population aging, urbanization, and beds per 1000 people were observed to have regional interactions and diffusion in terms of their positive effects on health care expenditures. According to the estimated direct, indirect, and total spatial effects, the listed indicators increase health care expenditures in the local province and neighboring provinces.

A 1% increase in disposable income per capita in a given province caused a 0.2432% increase in health care expenditure in that province and a 0.097% increase in health care expenditures in neighboring provinces. This finding is consistent with Grossman's health demand theory that the increase in income promotes citizens' health investment and causes an increase in health care expenditures (Tian and Qu, 2015).

A 1% increase in population aging in a given province caused a 0.258% increase in health care expenditure in that province and a 0.058% increase in health care expenditures in neighboring provinces. The elderly population is more vulnerable to chronic disease and the degradation of physiological functions. Thus, the acceleration of population aging increases the demand for medical services and raises health care expenditures.

A 1% increase in a province's urbanization caused a 0.378% increase in health care expenditure in that province and a 0.085% increase in health care expenditures in neighboring provinces. Normally, the average health care expenditure of an urban citizen is 2–4 times the level of a rural citizen because of significant urban-rural differences in many aspects (income, education, environmental quality, etc.).

A 1% increase in hospital bed supply in a given province caused a 0.264% increase in health care expenditure in that province and a 0.024% increase in health care expenditures in neighboring provinces. This is because the greater supply of medical resources accelerates supplier-induced demand because of information asymmetry, thereby raising health care expenditures.

The increase in government health spending per capita in a given province slightly increased health care expenditures in that province but had no effect on health care expenditures in neighboring provinces. An increase in government health spending on new equipment and office buildings ultimately increases total operational costs and increases health care expenditures for citizens. This finding is consistent with those of Wang and Zhang (2013). However, each province implements its specific, exclusive, non-sharable government health spending strategy to allocate financial resources to health care.

Only an increase in the number of doctors improved overall welfare and reduced health care expenditures both locally and in neighboring provinces. A 1% increase in the number of doctors in a province caused a 0.258% decrease in health care expenditures in that province and a 0.058% decrease in neighboring provinces. The increase in the number of doctors may encourage competition to provide better health care services and ultimately reduce health care expenditures.

5. Conclusions and policy implications

5.1. Conclusions

We systematically combined interdisciplinary perspectives to build a single research framework and measure how industrial air pollution transferred its spatial spillover effects to health care expenditures across Chinese provinces. We also considered health reform and other socioeconomic indicators. Regarding the exposure-response relationship between industrial air pollution and health risks, a spatial lag model with decomposed direct and indirect spatial effects was used to estimate the impact of industrial air pollution on health care expenditures in Chinese provinces from 2002 to 2014. Our main findings and conclusions are as follows.

With the results of Moran's I test, we found a significant and strongly positive spatial autocorrelation with respect to industrial air pollution and health care expenditures at the provincial level. Spatial dependence and agglomeration effects for provincial health care expenditures were found to strengthen between 2001 and 2014. The spatial dependence of provincial health care expenditures was observed to be stronger than the spatial dependence of industrial air pollution.

In our study, SLM with fixed effects provided the best fit to the sample data. Concerning research questions (1) and (2), the spatial estimate indicates that industrial air pollution has a positive spatial spillover effect on provincial health care expenditures. A 1% increase in industrial air pollution in a given province significantly increased health care expenditures by 0.032% and 0.0072% in that province and neighboring provinces, respectively.

Health reform in a province caused a slight decrease in health care expenditure in that province, with the fact that the direct effect of health reform on health care expenditures was −0.006. However, this decrease was not shared with neighboring provinces, and the spatial spillover effect was non-significant. Concerning research question (3), the reduction in health care expenditure due to health reform appears to be outweighed by the effect of industrial air pollution on provincial health care expenditures together with the joint effects of other socioeconomic indicators.

The spatial direct, indirect, and total effects of the socioeconomic indicators of disposable income per capita, population aging process, urbanization, and beds per 1000 people all increased health care expenditures in the local province and neighboring provinces. Only an increase in the number of doctors reduced health care expenditures in both local and neighboring provinces, thereby improving citizens' welfare.

This study contributes to the literature in two ways. First, it presents a systematic interdisciplinary framework to establish spatial estimates of how industrial air pollution increases health care expenditures in local and neighboring provinces. The spatial estimation provides a more precise estimate of health care expenditures due to industrial air pollution. Second, the study empirically validates that the reduction in health care expenditures due to health reform is outweighed by the effect of industrial air pollution on provincial health care expenditures together with the joint effects of other socioeconomic factors. The health costs are considerable and highlight a profound need to enhance environmental efforts to reduce industrial air pollution.

Further research is needed to measure the detailed health costs and health damage to individuals caused by industrial air pollution. Besides spatial autocorrelation, there is also spatial heterogeneity of health care expenditures. Further research could adopt combined spatially constant coefficient models and varying coefficient models to improve the accuracy of the estimates (Liu et al., 2017).

5.2. Policy implications

We offer three main measures to reduce industrial air pollution and its health costs. The mutual effect of industrial air pollutants on adjacent regions suggests the need for greater cooperation between local governments to control and prevent industrial air pollution. Complementary measures should be adopted by neighboring cities and provinces, especially at the urban agglomeration level (Liu et al., 2017). Shandong, Tianjin, Zhejiang, Gansu, and Shanxi could cooperate and collectively monitor their industrial waste gas emissions. Guangdong, Sichuan, Hunan, Hubei, Liaoning, Chongqing, Heilongjiang, and Jilin could take unified measures. This type of cooperation would involve common legislation and coordinated action to monitor, supervise, evaluate, and implement policies aimed at preventing and controlling industrial air pollution at the regional level.

The fact that industrial air pollution in a given province affects provincial health care expenditures in that province and neighboring provinces suggests that greater efforts should be made to improve industrial structure. Most enterprises encounter a technology bottleneck and have little room to decrease their waste gas emissions. Raising the barriers to entry to highly polluting industries, increasing investment in the environmental protection equipment industry, encouraging the development of the environmental equipment industry, reducing China's dependence on coal, and increasing the number of renewable and clean energy sources will stimulate technological innovation and accelerate the optimization of the industrial structure in China.

A comprehensive plan for environmental protection, health reform, and subsidy programs for outpatients and inpatients with haze-related diseases should be designed. Health costs, including increases in health care expenditures, should be measured periodically and in detail. Publishing such costs would raise society's awareness of the damage caused by industrial air pollution, leading people to work toward healthier, more balanced growth for society.

Declarations of interest

The authors report no conflicts of interest. The authors alone are responsible for the content and writing of this article.

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Appendix A. Global Moran's I index

Table A.1
Global Moran's I of industrial air pollution in China

Year	Moran's I	Year	Moran's I
2002	0.2648	2009	0.1786
2003	0.2845	2010	0.2329
2004	0.219	2011	0.2126
2005	0.2121	2012	0.1818
2006	0.1978	2013	0.2202
2007	0.1326	2014	0.1946
2008	0.1315	–	–

Table A.2
Global Moran's I of provincial health care expenditures in China

Year	Moran's I	Sd(I)	Z-value	P-value
2002	0.3989	0.1606	2.7303	0.015
2003	0.3832	0.1620	2.5631	0.017
2004	0.3635	0.1582	2.5366	0.013
2005	0.3655	0.1566	2.5629	0.016
2006	0.3729	0.1634	2.5164	0.015
2007	0.4171	0.1613	2.7783	0.006
2008	0.4284	0.1690	2.7033	0.009
2009	0.3928	0.1586	2.7247	0.008
2010	0.4724	0.1762	2.8770	0.001
2011	0.4982	0.1730	2.9896	0.001
2012	0.4322	0.1824	2.5611	0.005
2013	0.4111	0.1719	2.5331	0.007
2014	0.4557	0.1827	2.6553	0.003

Note: Sd(I) is the variance of I; Z-value is the standardized normal z test of I; P-value refers to the probability of I obtained by 999 Monte Carlo simulations.

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