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Original Article

Spatial Analysis of China Province-level Perinatal Mortality

***Kun XIANG, Deyong SONG**

The Research Center of Population, Resources and Environment, School of Economics, Huazhong University of Science and Technology, Wuhan, China

***Corresponding Author:** Email: Kwanxiang@gmail.com

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Abstract

Background: Using spatial analysis tools to determine the spatial patterns of China province-level perinatal mortality and using spatial econometric model to examine the impacts of health care resources and different socio-economic factors on perinatal mortality.

Methods: The Global Moran's I index is used to examine whether the spatial autocorrelation exists in selected regions and Moran's I scatter plot to examine the spatial clustering among regions. Spatial econometric models are used to investigate the spatial relationships between perinatal mortality and contributing factors.

Results: The overall Moran's I index indicates that perinatal mortality displays positive spatial autocorrelation. Moran's I scatter plot analysis implies that there is a significant clustering of mortality in both high-rate regions and low-rate regions. The spatial econometric models analyses confirm the existence of a direct link between perinatal mortality and health care resources, socio-economic factors.

Conclusions: Since a positive spatial autocorrelation has been detected in China province-level perinatal mortality, the upgrading of regional economic development and medical service level will affect the mortality not only in region itself but also its adjacent regions.

Keywords: Perinatal mortality, Spatial data, Spatial autocorrelation

Introduction

As an important parameter of health, perinatal mortality serves as a crucial indicator of maternal care, maternal health and nutrition. Besides, it is also a reflection of socio-economic development. To improve the health status of pregnant women, new mothers and newborns, most of the governments have set the reduction of perinatal mortality as their key development goal. As a key indicator, perinatal mortality provides information necessary for decision-makers to identify problems, track temporal, geographical trends and disparities, assess changes in public health policy and practice (1, 2).

There is an annual perinatal death of over 6.3 million across the world, among which the developing countries account for the largest share, with 27% in the least developed countries alone. "In developing countries, only about 40% of deliveries occur in health facilities and little more than one in two takes place with the assistance of a doctor, midwife or qualified nurse" (3). As the largest developing country, China's perinatal mortality rate dropped from 1247(per 100000) in 2003 to 589 (per 100000) in 2013. On the national level, China has witnessed a significant decrease in its perinatal mortality rate (4). However, it is reported that the mortality rate is unevenly distributed across the nation, with some provinces extremely higher than the national average while others extremely lower. For example, in 2013, the perinatal

mortality rate of Tibet is 2404 (per 100000); 5 times higher than the national average.

Since the statistical data show that there are regional differences in perinatal mortality, further researches should be conducted to examine what factors have contributed to the regional differences. Recently, as tools for analyzing spatial data improved, spatial analysis has been wildly used in projects of public health and epidemiology, such as infant mortality rates, associations between birth defects and exposures, socio-economic status and neural tube defects (5, 6). Compared with traditional methods, spatial analysis is more instrumental in decision-making, planning, information management and dissemination in epidemiological research. With spatial analysis, the regional variation in health problems, spatial distribution and transmission route of epidemic and regional difference in disease outbreak can be easily modeled.

In investigating China province-level perinatal mortality rates in 31 regions during the period 2003-2013, this study offers a unique contribution to the relevant literature. Its objectives are: 1) using novel spatial analysis to examine whether regional differences existed in perinatal mortality and clarify the spatial pattern of perinatal mortality. 2) using spatial econometrics models to determine how the relative socio-economic factors and health care resources affected perinatal mortality.

Materials and Methods

Data source

This research is the study of risk-modifying factors on health based on populations defined spatially, risk-modifying factors is averaged for the populations in each spatial unit and then compared using spatial statistical method, therefore, we categorized this research into Ecological study. Data are obtained from *Statistical Yearbooks of China* and *Statistical Yearbooks of China Health*. In order to avoid the aggregation bias, there are two approaches can be applied into research. The first uses box plot to confirm the outliers, once all outliers are determined, they will be deleted from raw data. The second is enlarging the sample size, the larger sample size will result more precise estimation. Although the two approaches can be applied to eliminate the aggregation bias, the spatial analysis only supports balanced panel data, if the first approach is adopted, the whole data structure would be unbalanced. Therefore, the decade from 1996 to 2013 is selected as the observation period and the 31 province-level regions as the subject for analysis, which include 22 provinces, 4 municipalities and 5 autonomous regions.

Spatial autocorrelation analysis

Compared with the traditional analysis method, spatial analysis method makes different assumptions on the sample data collected with reference to locations measured as points in space. Traditional method assumes that the locations measured as points are fixed, but spatial method assumes that the spatial dependence existed between the observations. Spatial dependence means that observations at location i depend on other observations at location j, and $j \neq i$. Formally, it has been stated as:

$Y_i = f(Y_j),\ i=1,\ldots,nj \neq i$

The dependence to be allowed among several observations, the index i can take on any value from $i=1,\ldots,n$. There are two reasons why we expect the sample data we observed at different points in space to be dependent on values each other. First, we usually use zip codes, counties, states, and census tracts to collect data of observations associated with spatial units, but measurement errors might occur thereof, this might reflect measurement error. Secondly and more importantly, if we want to construct a model which fits the data accurately, we must understand the spatial dimension of socio-demographic, economic or regional activity (7, 8). To clarify the spatial distribution of perinatal mortality in 31 province-level regions, we introduced a standard spatial weight matrix W to consider how geographic distance affected perinatal mortality. Spatial weight matrix W is a positive matrix where the rows and columns correspond to the cross-sectional observations, and w_{ij} expresses the element of the weighting matrix. There are so many specifications for weighting matrix, but the most commonly used are the bi-

nary contiguity and the distance function matrix. In this study, we choose the specification of binary contiguity to create the spatial weight matrix W. The elements of W are defined as $w_{ij}=1$ when location *i* is adjacent to location *j*, and $w_{ij}=0$ when location *i* is not adjacent to location *j*. After we created the spatial weight matrix W, the Moran's I index can be used to measure the spatial autocorrelation of perinatal mortality. The formula for calculating Moran's I index is

$$I=\frac{n\sum_{i=1}^{n}\sum_{j=1}^{n}w_{ij}(x_i-\bar{x})(x_j-\bar{x})}{\sum_{i=1}^{n}\sum_{j=1}^{n}w_{ij}\sum_{i=1}^{n}(x_i-\bar{x})^2}=\frac{n\sum_{i=1}^{n}\sum_{j=1}^{n}w_{ij}(x_i-\bar{x})(x_j-\bar{x})}{S^2\sum_{i=1}^{n}\sum_{j=1}^{n}w_{ij}}$$

$$\bar{x}=\frac{1}{n}\sum_{i=1}^{n}x_i$$

$$S^2=\frac{1}{n}\sum_i(x_i-\bar{x})^2$$

Where x_i and x_j represent perinatal mortality rates of regional *i* and *j* respectively. The terms $\bar{x}$ and S^2 denote means and variance. The value of Moran's I index is defined between -1 and 1. Positive values of Moran's I index imply positive spatial autocorrelation and negative values imply negative spatial autocorrelation. The perfect correlations and perfect dispersion appear when the valve of Moran's I index equal to 1 and -1 respectively. A zero value indicates a random spatial pattern (9, 10).

Spatial econometrics model analysis

In the literature, there are a large number of spatial econometrics models, but the most commonly used in applied research are the spatial lag model (SLM), the spatial error model(SEM) and spatial Durbin model (SDM). The SLM model assumes that the values of the dependent variables at one location and neighboring locations affected each other. According to the spatial weighting matrix W, perinatal mortality rate in region *i* is partially determined by perinatal mortality rate in neighboring region *j*. The SLM model is specified as

$$y=\rho Wy+X\beta+\varepsilon$$

Where y denotes the dependent variable, i.e. China province-level perinatal mortality rates, ϱ is the spatial autoregressive parameter and *a* column vector of regression coefficients. W denotes spatial weighting matrix. *X* is a matrix of explanatory variables, ε is the error term.

Unlike the spatial lag model, spatial error model incorporates spatial autocorrelation in disturbance term. This suggests that the perinatal mortality rate in region *i* is affected by unobserved shocks in neighboring regions. The SEM model is specified as $y=X\beta+\varepsilon \quad \varepsilon=\lambda W\varepsilon+\epsilon$

Where λ is the spatial autocorrelation coefficient on the error term.

The SDM model is specified as

$$y=\rho Wy+X\beta+\theta WX+\varepsilon$$

Where the parameters are the same as before but the parameter θ now indicates a spatial autocorrelation coefficient on the explanatory variables (11-13).

Before we use the spatial model to analyze China province-level perinatal mortality rates, we adopted a non-spatial model and other tests to determine whether spatial model is more appropriate. We first employ classic LM tests and Robust LM tests to determine the two null hypothesis of no spatially lag dependent variable and no spatially auto correlated term (14). Secondly, the likelihood ratio (LR) test is used to investigate the null hypothesis that the individual fixed effects and time-period fixed effects are jointly insignificant. Both hypotheses must be rejected at 5% as well as 1% significance.

The spatial econometrics literature is divided about whether to apply the specific-to-general approach or the general-to-specific approach (15, 16). When we use classic LM tests and Robust LM tests to determine whether the non-spatial model or the spatial model is more appropriate, it is the specific-to-general approach. In case the spatial Durbin model is employed, the general-to-specific approach test whether it can be simplified to spatial lag model or spatial error model. The likelihood Ratio (LR) test and Wald test are performed to test this hypothesis. The two null hypothesis tests for determining the correct spatial model are: H_0:$\theta=0$ and H_0: $\theta+\rho\cdot\beta=0$. The first hypothesis determines if the spatial Durbin can be simplified to the spatial lag model and the

second determines if it can be simplified to the spatial error model (17).

Data Description

This paper adopts China province-level perinatal mortality rates as the dependent variable, which includes 22 provinces, 4 municipalities and 5 autonomous regions. Due to the unavailability of certain data, Hong Kong, Macao and Taiwan are excluded. The explanatory variables include province-level per-capita GDP and urbanization rate, the total provincial number of health agencies and health staffs. The specific definition of each variable is as follows:

1. Province-level perinatal mortality rates: measured as number of stillbirths and deaths in the first of life per 1,000 live births of selected region.
2. Province-level per-capita GDP (PGDP): measured by the province-level gross domestic product divided by the population of selected region.
3. Province-level urbanization rate (URB): is measured as the urban population dived by the total population of selected region.
4. The total number of health agencies (HA): represent the health agencies of selected region, such as hospitals, community-level medical institutions and public health institutions.
5. The total number of health staffs in province-level (HS): denotes the health staffs of selected region.

All variables are expressed in natural logs, therefore, the empirical model is specified as follows

$$ln(y_{it}) = \beta_0 + \beta_1 lnPGDP + \beta_2 lnURB + \beta_3 lnHA + \beta_4 lnHS + \mu_i + \eta_t + u$$
$$i=1,\ldots,N \; t=1,\ldots,T$$

Results

Global spatial autocorrelation

Issues associated with spatial dependence have been largely ignored in health economics literature. Firstly, spatial tools are used to analyze the spatial correlation of province-level maternal mortality in China.

Table 1 display the Global Moran's I index of China province-level perinatal mortality rates and its *P*-valve in period from 1996 to 2013. All Moran's I of selected years are positive, which indicates a positive spatial correlation in China province-level perinatal mortality rates. However, the Moran's I of each year shows tremendous variations, which indicates the different clustering tendency of perinatal mortality in selected regions.

Since tremendous variations are found in Moran's I index, we will employ Moran's I scatter plot to examine the latest clustering distribution among selected regions. Fig. 1 shows the results. In this scatter plot, the horizontal axis denotes the deviation of regional perinatal mortality rate in 2013 while the vertical axis denotes the spatial lags of the deviation of the regional perinatal mortality rate.

Table 1: Moran's I index of China province-level perinatal mortality rates

Year	Moran's I	*P*-value
1996	0.512	0.001
1997	0.544	0.001
1998	0.489	0.001
1999	0.522	0.001
2000	0.601	0.001
2001	0.566	0.001
2002	0.489	0.001
2003	0.434	0.001
2004	0.459	0.001
2005	0.567	0.001
2006	0.612	0.001
2007	0.603	0.001
2008	0.552	0.001
2009	0.465	0.001
2010	0.382	0.004
2011	0.401	0.006
2012	0.471	0.003
2013	0.344	0.009

The scatter plot has four quadrants and the specification of each is as follows:

1. Quadrant Ⅰ: HH clustering, it denotes regions with high perinatal mortality rates are associated with neighboring regions with high perinatal mortality rates.
2. Quadrant Ⅱ: LH clustering, it denotes regions with low perinatal mortality rates are associated with neighboring regions with high perinatal mortality rates.

3. Quadrant Ⅲ: LL clustering, it denotes regions with low perinatal mortality rates are associated with neighboring regions with low perinatal mortality rates.

4. Quadrant Ⅳ: HL clustering, it denotes regions with high perinatal mortality rates are associated with neighboring regions with low perinatal mortality rate.

According to Fig. 1, there are 8 regions in quadrant Ⅰ and 17 regions in quadrant Ⅲ, accounting for 25.8% and 54.84% respectively and these regions show similar characteristics of spatial autocorrelation. On the other side, there are 2 regions in quadrant Ⅱ and 4 regions in quadrant Ⅳ, accounting for 6.4% and 12.9% respectively and these regions demonstrate different characteristics of spatial autocorrelation.

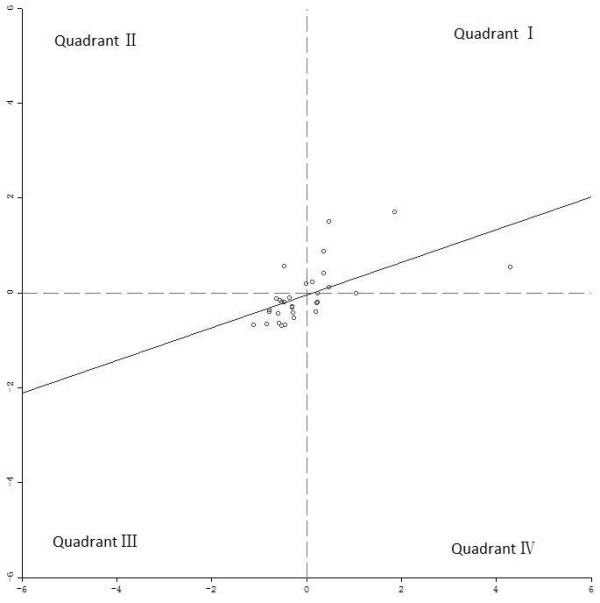

Fig. 1: Moran scatter plot of perinatal mortality rate of 2013

According to the result of scatter plot, Fig. 2 displays the spatial distribution of perinatal mortality rate in 2013, the number zero in the legend denotes the regions where are not included in the analysis, the number one to four denote the regions where distribute in quadrant Ⅰ to quadrant Ⅳ respectively. The details of Fig. 2 consist of the following:

1. Eight regions in quadrant Ⅰ: Jinin, Heilongjiang, Yunnan, Tibet, Gansu, Qinghai, Ningxia, Xinjiang.

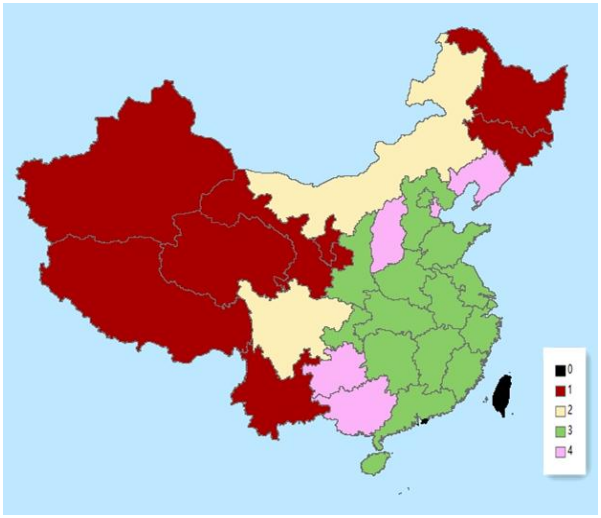

Fig. 2: Spatial distribution of perinatal mortality rate in 2013

2. Two regions in quadrant: Inner Mongolia, Sichuan.

3. Seventeen regions in quadrant Ⅲ:Beijing, Hebei, Shanghai, Jiangsu, Zhejiang, Anhui,Fujian,Jiangxi,Shandong,Henan,Hubei,Hunan,Guangdong,Hainan,Chongqing,Shanxi.

4. Four regions in quadrant Ⅳ: Tianjin, Shanxi, Liaoning, Guangxi, Guizhou.

The positive spatial autocorrelation of China province-level perinatal mortality rates is found through globe Moran's I test, and the spatial autocorrelation and dispersion among selected regions through Moran scatter plot, which these suggest the different clustering effects exist in China perinatal mortality. The statistically significant, positive spatial autocorrelation implies that standard OLS regressions of the drivers of mortality may lead to estimation bias in the regression results. Therefore, to further analyze the drivers of perinatal mortality, we need to apply the spatial panel model to describe the data.

Empirical results of spatial econometric models

To determine which type of model is more appropriate, firstly we adopted several non-spatial panel

models for investigation. Table 2 shows the estimation results of non-spatial panel models. Columns 1-4 represent the different specifications we used: pooled OLS, fixed effects only, time-period effects only and both fixed effects and time-period effects, respectively.

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To investigate the null hypothesis that the individual fixed effects and time-period fixed effects are jointly insignificant, the likelihood ratio (LR) test was performed. According to the test results, we reject the hypothesis that the individual fixed effects are insignificant at LR-test=356.784, with 31 degrees of freedom, $P<0.001$, and we also reject the hypothesis that the time-period fixed effects are insignificant at LR-test=33.530, with 18 degrees of freedom, $P<0.01$. When we use non-spatial panel models to determine which type of model is more appropriate, the classic LM and robust LM test were conducted to investigate the null hypothesizes of no spatially lagged dependent variable and no spatially auto correlated error term. Recalled the results of LR test, we focus on the estimation in Column 4 of Table 2. The results show that when using classic LM tests, both hypothesizes of no spatially lagged dependent variable and no spatially auto correlated error term are accepted. However when using robust LM tests, both hypothesizes of no spatially lagged dependent variable and no spatially auto correlated error term are strongly rejected at 1% significance level. These results point to spatial panel model best fits the data; however, the results also imply that the non-spatial models are rejected in favor of the spatial lag model or the spatial error model.

Since the results of (robust) LM test imply that the spatial model is more appropriate, we use spatial Durbin model for further estimation. The results for spatial Durbin model are reported in Table 3, the results of LR test and Wald test are listed in the bottom. The column 1 is the estimation result of the spatial Durbin model without bias correction, while the column 2 is with bias correction (18, 19).

Table 2: Estimation results of non-spatial panel data models

Determinants	Pooled OLS	Individual fixed effects	Time-period fixed effects	Individual and time-period fixed effects
Intercept	7.235 ** (27.125)	NA	NA	NA
LNPGDP	-0.201*** (-15.522)	-0.301*** (-9.102)	-0.455*** (-9.325)	-0.566*** (-7.358)
LNURB	0.203* (1.550)	-0.221 (-2.033)	0.201 (2.366)	-0.066 (-0.669)
LNHA	0.188*** (5.366)	0.077* (3.014)	0.425** (8.366)	0.102 (3.022)
LNHS	-0.396*** (-9.866)	-0.682** (-6.322)	-0.560*** (-12.022)	-0.966*** (-8.011)
σ^2	0.079	0.022	0.069	0.022
R^2	0.711	0.766	0.577	0.356
LM spatial lag	63.258***	0.152	55.322***	0.122
Robust LM spatial lag	88.336***	3.255*	75.223**	16.322***
LM spatial error	9.322***	0.455	4.326*	3.236
Robust LM spatial error	18.232***	3.124*	22.033***	15.665***

Note: All variables are measured as natural logs. Numbers in the parentheses represent t-stat values. * Denotes $P<0.1$. ** Denotes $P<0.5$. *** Denotes $P< 0.01$.

Table 3: Estimation results with spatial Durbin model and a comparison of cumulative impacts from spatial Durbin model

Determinants	Individual and time-period fixed effects	Individual and time-period fixed effects(bias-corrected)	Direct effects	Indirect effects	Total effects
LNPGDP	-0.632*** (-6.322)	-0.622*** (-8.321)	-0.601*** (-9.322)	0.401** (3.014)	-0.301* (-2.366)
LNURB	0.033 (0.633)	0.032 (0.699)	0.040 (0.455)	-0.886** (-4.332)	-0.833*** (-4.355)
LNHA	0.022* (1.366)	0.020 (1.699)	0.033 (0.655)	-0.166 (-2.355)	-0.165 (-2.066)
LNHS	-0.603*** (-6.337)	-0.599*** (-6.102)	-0.430** (-4.366)	-0.896*** (-6.322)	-1.405** (-8.236)
W*LNPGDP	0.311** (2.033)	0.303** (2.669)	-	-	-
W*LNURB	-1.033** (-6.325)	-0.902** (-6.988)	-	-	-
W*LNHA	-0.093 (-3.022)	-0.089 (-3.669)	-	-	-
W*LNHS	-0.865*** (-9.322)	-0.833*** (-9.655)			
W*dep.var	-0.203** (-4.322)	-0.183* (-5.336)	-	-	-
σ^2	0.018	0.017	-	-	-
R^2	0.912	0.912	-	-	-
Wald test spatial lag	69.325***	50.355***	-	-	-
LR test spatial lag	57.122***	57.232***	-	-	-
Wald test spatial lag	69.321***	46.322***	-	-	-
LR test spatial lag	50.221***	50.321***	-	-	-

Note: All variables are measured as natural logs. Numbers in the parentheses represent t-stat values. * Denotes $P<0.1$. ** Denotes $P<0.5$. *** Denotes $P< 0.01$.

According to the test, both hypothesizes of $H0:\theta = 0$ and $H0:\theta + \rho \cdot \beta = 0$ are rejected at one percent level. These LR and Wald test results indicate that the spatial Durbin model best describes the data.

Discussion

We focus on the spatial Durbin model coefficients estimation with bias corrected. An interpretation of the coefficient on per-capita GDP is that a 10% increase of per-capita GDP is associated with 6.22% decrease of perinatal mortality. An interpretation of the coefficient on total number of health staffs is that 10% increase will lead to a 5.99% decrease of perinatal mortality. These results imply that the level of per-capita GDP and the total number of health staffs are critical factor contributing to the decrease of perinatal mortality. However, we do not find a significant relationship between urbanization rates, the total number of health agencies and perinatal mortality.

In the two-way fixed effects non-spatial model, a 10% increase of per-capita GDP is associated with 5.66% decrease of perinatal mortality and a 10% increase in the total number of health staffs will lead to 9.66% decrease of perinatal mortality. However, as the spatial Durbin model was found to best fit the data, we identify these coefficient estimates as biased. To investigate the difference estimation results, we compared the coefficient estimates and their counterparts between the two different models, but this comparison is invalid because the parameter estimates in the non-spatial model denote the marginal effect but in the spatial Durbin model do not. Therefore, we used the direct and indirect effects to investigate

the spatial spillover (20). Table 3 also shows all these effects.

According to Table 3, we found per-capita GDP and the total number of health staffs are significant at 1% and 5% level among the direct effects. The indirect effects of per-capita GDP, urbanization rate and the total number of health staffs are significant at 5%, 1% and 1% level respectively. Since the spatial autocorrelation coefficient is positive and statistically significant in estimation results of spatial Durbin model, in order to test the existence of spatial spillovers, several studies use these results to explain it, but the best way to interpret spatial spillovers is cumulative impacts estimation. The difference between the results with spatial Durbin model and the results of cumulative impacts are partially due to the estimated coefficient of the spatially lagged dependent variable and partially due to the estimated coefficients on the independent variables. These coefficients imply that the changes of per-capita GDP, urbanization rate and the total number of health staffs lead to the feedback effects that causing impacts passing through neighboring regions and back to the regions themselves. The total effects of per-capita GDP, urbanization rate and the total number of health staffs are significant at 10%, 1% and 5% level respectively, these imply that the increases of them will decrease the perinatal mortality. However, the direct effect of per-capita GDP is negative and indirect effect of it is positive, which implies that an increase in per-capita GDP in one region will lead to a perinatal mortality decrease in this region but an increase in its neighboring regions. The indirect effects of urbanization rate and the total number of health staffs are negative, which means an increase in the urbanization rate and the total number of health staffs in one region will reduce the perinatal mortality of neighboring regions.

Conclusion

The results of the Moran test confirm the positive spatial autocorrelation in China province-level perinatal mortality, which in turn indicates that the perinatal mortality tends to cluster together. Besides, by using Moran's I scatter plot, we find that China has significant clustering of perinatal mortality in high-rate regions and significant clustering of perinatal mortality in low-rate regions. The regression results suggest that the increase of per-capita GDP and health staffs decreases the perinatal mortality, but the increase of urbanization rate and the total number of health agencies have no significant effect on perinatal mortality.

Ethical considerations

Ethical issues (Including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication and/or submission, redundancy, etc.) have been completely observed by the authors.

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The authors declare that there is no conflict of interests.

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