Health Environ, 2021, 2(1): 68-83
DOI: 10.25082/HE.2021.01.002

RESEARCH ARTICLE

The short-term and long-term effects of industrial pollution on human health in China

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Received: May 20, 2021;
Accepted: June 18, 2021;
Published: June 21, 2021

Citation: Xiang H, Yang J and Zhang Y. The short-term and long-term effects of industrial pollution on human health in China. *Health Environ*, 2021, **2**(1): 68-83. https://doi.org/10.25082/HE.2021.01.002

Abstract: The impact of environmental pollution on human health has become a consensus. Based on the provincial panel data of China from 2002 to 2017, this paper analyzes the impact of industrial wastes on human health. With respect to human health, average annual frequency of physician visits per capita (AAFPV) is used as a measure for the short-term human health; all-cause mortality is used to illustrate the long-term human health. The results show that in the short term, with the level of industrial smoke dust increasing every 1 percentage, AAFPV would increase by 0.24 percentage. This effect is significant in East China and West China. Central China is affected by industrial waste water, with a rate of increasing AAFPV by 0.12 percent for every 1 percent increase of chemical oxygen demand per unit area. In the long term, water pollution is the main influencing factor of all-cause mortality.

Keywords: health production function, econometric analysis, human health, industrial pollution

1 Introduction

Since China adopted the economic reform and opening-up polices about 40 years ago, China's economy has maintained a rapid pace of growth, creating a "Chinese-style miracle". That fast economic growth inevitably led to excessive consumption of resources and environmental pollution. According to Global Burden of Disease Study 2015 (GBD2015), China's multiple health indicators scored low, ranked only 92 in 188 countries and regions. The report by World Health Organization in 2016 on "Preventing Disease through Healthy Environments: A global assessment of the burden of disease from environmental risks" stated that there were 12.6 million deaths worldwide due to living in unhealthy environments in 2012 (An estimated 12.6 million deaths each year were attributable to unhealthy environments, 15 March 2016). The deaths from non-communicable diseases were estimated to be up to 8.2 million that were mainly caused by air pollution (including exposure to second-hand smoke). There is now a large body of medical literature that suggests environmental pollution having a direct relationship with human health.

The diseases, such as cardio-cerebral vascular diseases, respiratory diseases, and lung cancer, are caused by air pollution, and they have become the main causes of deaths in China. Both cancer morbidity and mortality have surged along with economic growth [1]. Lung cancer is now a leading cause of cancer deaths in China [2]. According to the data from monitoring the causes of death as released by the Chinese Center for Disease Control and Prevention, lung cancers were ranked at the top among all causes of deaths in 2018 (53.40%). China's increasingly serious problems of environmental pollution pose a huge medical burden while seriously threatening public health [3]. The rapid industrialization, resource and environmental constraints, the population agglomeration due to urbanization and the deepening of aging population have worsen the environmental health situation in China.

Worldwide, environmental pollution poses a great threat to human health. The Chinese government has begun paying special attention to environmental governance to improve citizen health. Considering these two realistic backgrounds, the topic of this article has very important practical significance.

The existing literature on the relationship between environmental pollution and health from the perspective of natural sciences [4], focuses on the impacts on public health by specific environmental pollutants [5–7]. Those studies established the connection between specific pollutants to the environment and certain diseases. Most studies with a focus on economic issues examined the interactions between environmental pollution and economic development [8, 9]. However,These literature do not build empirical models based on theory, so the choice of independent variables in the model does not have theoretical basis. Based on the theory of health production function, this paper constructs the model, which has strong theoretical significance.

Based on the realistic and theoretical background discussed above, the objective of this article is to construct a regional health production function, quantitatively analyze the impact of three major industrial pollution on average annual frequency of physician visits and all-cause mortality(these two variables are regarded as proxy variables of short-term human health and long-term human health), build an intermediary between environmental pollution and economic development, and provide empirical support for further research on economic losses caused by environmental pollution.

Since China joined the World Trade Organization in 2001, relevant provisions and rules have prompted China to improve and upgrade its production systems and controls of environmental pollution. Based on this, we chose 2002 as the starting year for our study. Since the implementation of the Western Development Policy, the government-led industrial transfers from eastern coastal regions to inner regions have been implemented. Such transfers have made substantial progresses in the construction of major infrastructure such as transportation, water conservancy, energy, and communications in the west.

With the progress of China's market economy, the costs of land, labor, water, electricity and other factors in China's east have risen sharply. The east now has an urgent need for industrial transformation and upgrading. With the policies (such as "encouraging the eastern region to transfer industries to the central and western regions", "continuing to promote infrastructure and ecological construction in the western region", and "increasing investment in the development of the western region"), the industrial transfers are listed as the main task of national economic work in 2007. Under that, every Chinese sector has been actively exploring ways to accelerate the pace of industrial transfer between the eastern and the western regions. Since 2017, Chinese economy has shifted from pursuing quantity to pursuing quality to enter the industrial transfer based on market economy. Therefore, the ending time for this research was set to 2017.

The main contributions of this paper are as follows: firstly, based on the quantitative research method, the impact of industrial pollution on human health is analyzed; The second is to analyze the difference of the impact of industrial pollution on human health from the perspective of space; Thirdly, it expands the micro level health production function from the regional macro perspective.

In the subsequent sections, Section 2 reviews relevant literature on human health, and factors that may influence human health and regional health production function. Section 3 discusses how to select variables, including dependent variables and independent variables to be included in the regional health production model. Section 4 descriptively analyzes the main variables both spatially and temporally. Section 5 reports findings from statistically building an econometric model for human health, regional production function, and environment pollution. Section 6 analyzes results from the econometric model. The final section concludes the study and offers recommendations for policy makers and future researchers.

2 Literature review

2.1 Health capital and human health

Different disciplines understand and define health capital differently. Relevant theories can be divided into three categories. The first category is what Schultz [10] put forward from the perspective of development economics. Schulz suggested that human capital (including healthy capital) was the quality and ability of people. The expenditure on health is a form of human capital investment, including health care expenditures. Based on this notion, Fogel's healthy human capital [11] was proposed, which is also known as healthy human capital when considering food consumption and nutrient intake. Most research believe that Fogel's healthy human capital points us to a way for improving healthy human capital. However, Wang (2012) [12] found that Fogel's healthy human capital cannot become an endogenous driving force for economic growth. It can only accelerate the pace of economic growth when a region's economic growth is also powered by other auxiliary forces.

The second theory of health capital is what Sen (1999) [13] proposed from the perspective of welfare economics. He suggested that health is a viable ability and a prerequisite for human subjectivity (Subjectivity refers to the ability, role, and status that people display in the course of engaging or practicing activities in live). Losing health loses the possibility of participating in other activities, which in turn loses the opportunities for freedom and choice. In that regard, health is an important dimension of human well-being. It promotes the realization of a viable ability and is also an important component of happiness.

The third theory of health capital is one that was first put forward by Folland, Goodeman, & Stano (2001) [14] from the perspective of health economics. It postulates that health is a good thing that can bring utility and can be used as a type of capital. As a reserve capital, health is a consumer product that can be purchased through health care.

Health can be influenced by environmental and economic factors. Moreover, input factors for health production may include health care and non-health care factors. Non-health care factors mainly refer to lifestyles that affect health, social environment, and income status. The human health in this article is the regional health human considered from the perspective of Grossman's (1972) [15] micro-health production function, which represents the health quality and level of a regional population as a whole.

2.2 Influencing factors of human health

Empirical research on the influencing factors of human health is an important topic of interdisciplinary research. The factors used in research include economic factors, social factors, cultural factors, family genetic factors, and environmental factors.

Economic factors are important factors affecting human health, and the impact of income on human health is crucial. Kitawaga & Hauser (1973) [16] conducted a study on mortality in various states in the United States and found that differences in absolute income often lead to health-income stratification. That is, income is directly proportional to health. Preston (1975) [17], based on data from more than 40 countries in 1930-1960, found that income can explain 10-25% of rising life expectancy. Public health services can also be an important factor affecting human health.

According to sub-Saharan Africa Demographic and Health Survey Data Analysis (DHS), Fortson (2011) [18] found that public health improvement and epidemiological control have a direct impact on the accumulation of healthy human capital investments. In addition, Chen (2010) [19], based on the analysis of health structure data of 30 provinces in China from 1993 to 2008, found that differences in regional health care structure have a significant impact on regional health human capital accumulation.

Insufficient early nutritional intake in infants and young children can have a negative impact on their health status in adulthood. Through a survey conducted in United Kingdom, Wadsworth, & Kuh (1997) [20] found that insufficient nutritional intake in infants and young children tends to increase the incidences of cardiovascular disease, coronary heart disease, *etc*. during their middle age. Ravelli *et al*. (1998) [21], based on data from Amsterdam in 1944-1945, found that Infant babies have insufficient nutrient intake due to famine in the third trimester of pregnancy, thereby increasing the incidence of diabetes when they are adults.

In addition, inter-generational transmission also has an impact on health. A mother's unhealthy body may be passed on to her children through birth. Environmental pollution is also another important factor affecting human health. Qi & Lu (2015) [22] found that environmental pollution, according to the 1990-2010 world pollution data, explained 24% of global diseases and 23% of premature deaths. They found a negative relationship between health status and PM_{10}. Miao and Chen (2010) [23], based on data from a survey conducted in Shanxi Province in 2008, found that major air pollutants PM_{10} and SO_2 have negative impacts on residents' health demands (Thinking of health as a commodity of consumption,"health demand" refers to the demand for that commodity.), and for every 1% increase of the concentrations of two inhalable particulate matters, the health demands of residents were reduced by 0.199% and 0.127% respectively. Peng, Tian & Liang (2002) [24] used the field survey data of a municipal hospital in Shanghai in a study on the correlation between air pollutants and the daily outpatient volume of hospital respiratory diseases. Peng found that there is a significant correlation between the two. According to Health Impact Assessment (HIA) of the World Health Organization (WHO), the determinants of health include the social and economic environment, the physical environment, and the person's individual characteristics and behaviors.

2.3 Regional health production function

The Grossman health production function is a model constructed from a microscopic perspective. Many scholars use it as a theoretical basis for constructing a macroscopic health production function [25, 26]. Puig-Junoy evaluated the health production effectiveness of OECD countries based on the Grossman micro-health production function. Since then, a large body of literature has been built up based the macroscopic approach, such as those studying health care [27], health system [28], and medical services [29].

Wang & Chang (2007) [30] constructed a regional macro-health production function. This function links economic, social, and educational and health variables for describing the overall health level of a region. In presenting their work, they pointed out that, since the reform and opening up of China, the health influencing factors have been changed. Economic factors and educational factors tend to promote health gradually, while living factors have shown a certain negative contribution to health. Feng *et al*. (2019) [31] used the function to analyze spatial effects of air pollution on public health in China based on spatial econometrics method.

From the macroscopic point of view, this article focuses on the impact of regional environmental pollution on health status. The macro health production function is that, for a region, health is a product of environmental, social, health, educational and economic variables, or:

H = F (environment, society, health, education, economy)

The overall health status of the region is seen as the result of a combination of environmental, social, health, education, and economic variables in the region.

3 Selection of model variables

3.1 Human health variables

All-cause mortality has been used widely as a measure for residents' health status when studying the impact of environmental pollution on human health [22, 30]. Obviously, a model that uses all-cause mortality as a dependent variable needs to consider selecting a lag period. This is because, in general, the current environmental pollution would only impact future mortality. Some scholars use self-assessment health data as the dependent variable as a workaround to avoid the problem of lag period selection [24].

From the macro level, this article examines the short- and long-term impacts of environmental pollution on human health. Specifically, average annual frequency of physician visits per capita (AAFPV)(The calculation method is the total number of physician visits in the region divided by the total population at the end of the year.) by the local residents is used as a measure for the short-term health status of the region. As opposed to that, all-cause mortality is used to illustrate the long-term health status of the region. Therefore, there are two dependent variables in this study, which are the AAFPV to measure short-term health status and regional mortality to measure long-term health status.

3.2 Independent variables

In order to examine the impact of environmental pollution on human health, a set of variables were carefully selected as independent variables that are related to environmental pollution. Moreover, other factors affecting human health are used as control variables. These selected variables are discussed below.

3.2.1 Environment variables

Literature on the health effects of environmental pollution has focused on the health effects of air pollution. For example, Peng, Tian & Liang (2002) [24] used content of NO_X and SO_2 in the air as independent variables to measure the impact of air pollution on respiratory diseases and the resulting losses. Miao & Chen (2010) [23] used the Grossman model to analyze the effects of two air pollutants, PM_{10} and SO_2 on residents' health demands. Most existing studies focus on air pollution. On the one hand, the effects of air pollution on health are easy to observe, especially on respiratory diseases. On the other hand, the time lag effect of air pollution on health is relatively short and the deterioration of air pollution in the current period would significantly affect the health of current residents. However, in China, emissions of three industrial wastes are the main source of environmental pollution. Our study uses pollutant emissions indicators per unit area (PEIPA) as the measurement for environmental pollution rather than per capita pollutant emission indicators (PCPEI). Using PEIPA has two advantages. First, as a density indicator, it reflects the intensity of pollution emissions. The environment itself has limits on the containment of pollution, and the density indicator can reflect the level of pollution emissions in a certain region. The second advantage is that PEIPA overcomes the disadvantages of per capita indicators. In the case of per capita indicators, the more people there are in a region, the lower the per capita pollution emissions there may be. PEIPA denotes the lower the level of pollution emissions, which is not in line with experience and facts. At the same time, for reasons of data availability, the environmental pollution in a region is measured here by industrial smoke dust emissions per unit area, chemical oxygen demand discharge per unit area of industrial wastewater, and industrial solid waste discharge per unit area.

3.2.2 Control variables

This article uses environmental protection, population structure, education level, public health supply, income status as control variables. These factors have different effects on human health.

(1) Environmental protection: environmental pollution would have an impact on the health of residents in a region. Proper environmental protection practices can eliminate and reduce the effect that environmental pollution would impact on health. The degree to which environmental pollution control directly affects residents' health in the polluted areas. Taking into account the availability of data for successive years, we use the proportion of industrial pollution control investment to GDP of the region as the indicator for environmental protection in this study.

(2) Population structure: most studies in the current literature indicate that there exist significant differences in the health status between those for men and those for women. Zhao & Hou (2005) [32] used the Grossman model to analyze the health demands of urban residents in China from the perspective of human capital. Existing studies found that the educational level of women has a positive impact on their health, while the educational level of men has no significant effect on their health. In addition, age has a greater impact on men's health than women. Wang & Chang (2007) [30] constructed a Chinese health production function from a macro perspective and found that the increase in the proportion of women reduces the health level. This study selected the proportion of women to total population as an indicator to measure the population structure.

(3) Education level: One of the important factors affecting health is the level of education. Compared with people with higher education level, people with lower education level have many disadvantages. They tend to lack effective ways to obtain real health information, which often lead to less healthy lifestyles. There is also a lack of ability to choose jobs with lower health risks. This study selects the proportion of illiterate and semi-literate people over the age of 15 as an indicator as the educational level of a region.

(4) Medical supply level: Health care improves the health of residents through the treatments and prevention of diseases. The level of medical supply in a region is important for the health of residents in the region. In this study, we choose three indicators as the level of medical supply in a region, such as health expenditures, the number of doctors per 1,000 people, and the number of hospital beds per 1,000 people.

(5) Income level: Income level determines the living standards of residents and the ability and access to medical services. The increase in income can improve the health of residents by improving their daily diets and nutritional levels, housing and living environments, the quantity and quality of health care services, and increasing investments in education to accumulate educational human capital. Due to the differences in those aspects between regions, the selection of per capita indicators can more accurately reflect the impact of changes in income levels on population health. When combined with other available data, the regional per capita disposable income of residents is selected to reflect changes in income levels.

On the other hand, according to previous research, in the initial stage of industrialization, economic development tends to bring a series of health problems. The increase of personal income likely causes some damage to health. For example, environmental pollution would threaten individual's health, but as the economy continues to grow, the accumulation of personal wealth may improve a person's health as she/he becomes better able to find ways to shield off negative effects by environmental pollutions. Therefore, the squared value of per capita disposable income of residents is introduced to verify this problem in this paper.

3.3 Data sources

The data selected in this study are the inter-provincial data of 30 provinces (excluding Tibet because its data is not available, the same below) in China from 2002 to 2017. The data are all from the China Statistical Yearbooks and the China Environmental Yearbooks (China Yearbooks Full-text Database). To adjust for inflation, environmental protection expenditures and health fiscal expenditures, per capita disposable incomes of residents of the region were recalculated using the price of 2000 as a base period. The absolute amounts of industrial pollution control investment and health fiscal expenditure were converted into proportions of these expenditures. The variables selected for this study are summarized in Table 1.

Table 1 Variable description

Type	Variable	Indicator	Name	Unit
Dependent variable	Frequency of physician visits	Average annual frequency of physician visits per capita	AAFPV	frequency
	Mortality	All-cause mortality	MORT	‰
Independent variable	Air pollution	Industrial smoke dust emissions per unit area	ISDEPA	ton/km^2
	Water pollution	Chemical oxygen demand discharge per unit area of industrial wastewater	CODPA	ton/km^2
	Solid waste pollution	Industrial solid waste discharge per unit area	ISWPA	10^4ton/km^2
Control variable	Environmental protection	The proportion of industrial pollution control investment to GDP of the region	PIPCI	%
	Population structure	The proportion of women	FEMALE	%
	Education level	The proportion of illiterate and semi-literate people over the age of 15	PIP	%
	Medical supply level	The proportion of health expenditures	PHE	%
		The number of doctors per 1000 people	DOCTOR	person
		The number of hospital beds per 1000 people	BED	bed
	Income level	Logarithm of per capita disposable income of residents	LPCDI	—
		The square of LPCDI	LPCDI2	—

Notes: To some variables, such as AAFPV, MORT, ISDEPA, CODPA and ISWPA, natural logarithmic processing was carried out before the econometrics analysis due to the varying numerical ranges of the data.

4 Summary of Data

4.1 Spatial distribution of main variables

Figure 1 shows spatial distributions of main variables in 2017. Figure 1a and Figure 1b denote spatial distributions of AAFPV and Mortality. AAFPV and Mortality in the west of Hu line [33](Chinese geographer Hu Huanyong proposed a population spatial distribution line. There are sparse population and broad land in the west side of the line, and there are dense population and narrow land in the east side of the line.) are lower than that of the national average, and ones in the east of Hu line are the opposite. Most of the industrial pollution is concentrated in the east of Hu line, so this data has shown that industrial pollution has a significant impact on human health.

The spatial distribution of CODPA in Figure 1c shows that CODPA in some regions, such as Shanghai, Tianjin, Jiangsu, and Guangdong, are higher than that of the national average. Figure 1d denotes spatial distribution of ISDEPA, which shows that ISDEPA in some regions, such as Hebei, Liaoning, Shandong, Inner Mongolia, Xinjiang, Shanxi, Heilongjiang, and Jiangsu, are higher than that of the national average. Figure 1e denotes spatial distribution of ISWPA, which shows that ISWPA in some regions (such as Shanghai, Shanxi, Liaoning, Hebei, Shandong, Tianjin and Jiangsu) are higher than that of the national average. From these spatial distribution maps, industries that emit large amounts of industrial wastewater are concentrated in coastal areas such as Shanghai, Jiangsu, and Guangdong. Industries with large emissions of smoke and dust are concentrated in the northern margin of China. Industries with mass solid waste output are concentrated in central coastal area such as Shanghai, Jiangsu, Hebei, and Tianjin.

4.2 Changes in the main variables over time

For study areas, we chose Beijing, Shanghai in the east, Chongqing in the west, and Hubei in the middle as the typical regions for analysis. From Figure 2a, Mortality fluctuated year by year, but the mortality rate in Chongqing was significantly higher than that in other regions with Guangdong having the lowest mortality rate. Figure 2b shows that AAFPV was increasing year by year, but Beijing and Shanghai had sudden decreases in 2016 and 2017 when Guangdong Province had a sudden increase. Figure 2c shows that ISWPA has an inverted U-shaped relationship, especially in Shanghai. It reached its highest emission in 2010 and then began to decrease after that. Figure 2d shows a downward trend of CODPA in Shanghai. Other regions had shown volatility in their CODPA trends, though they had been decreasing in recent years.

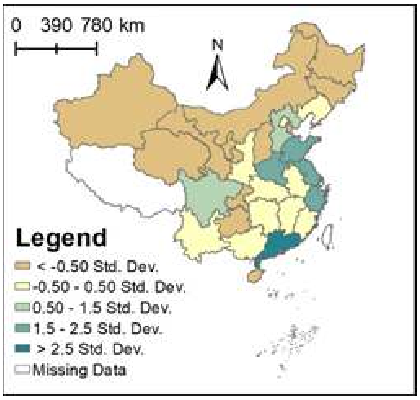

Figure 1a AAFPV

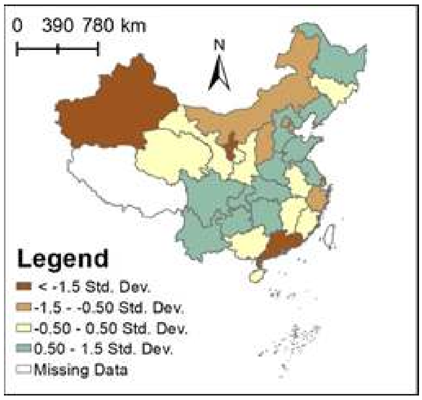

Figure 1b MORTALITY

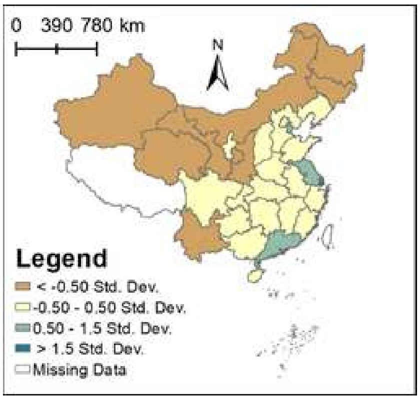

Figure 1c CODPA

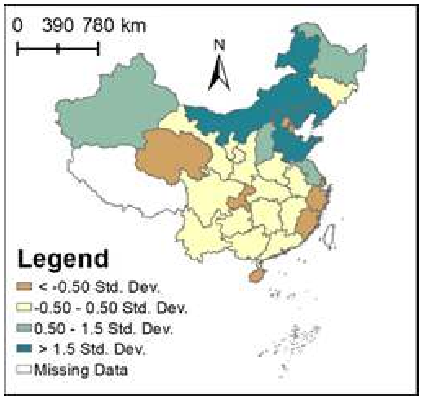

Figure 1d ISDEPA

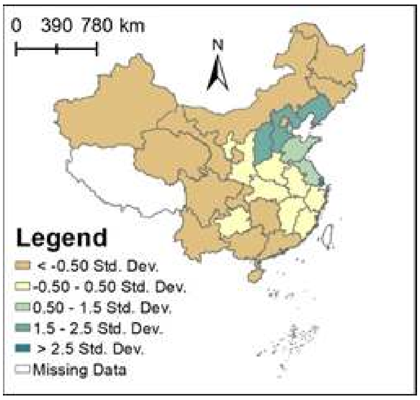

Figure 1e ISDEPA

Figure 1 Spatial distributions of main variables in 2017

Figure 2e shows that Guangdong Province had the highest ISDEPA.

AAFPV in 2017 compared with one in 2002, the results show that AAFPV declined in only Beijing, Shanghai, Tianjin, Ningxia, Qinghai, Hainan, Xinjiang and Jilin but increased in other regions. AAFPV in Guangdong Province increased the most. Mortality had fluctuated year by year. Mortality rates in 2017, when compared with those in 2002, show that there were declines in Tianjin, Xinjiang, Shanxi, Zhejiang, Yunnan, Guangdong, Beijing, Guizhou, Inner Mongolia, Qinghai, Shaanxi, Ningxia and Guangxi. For ISWPA, only Beijing showed a decline from 2002 to 2017. In terms of CODPA, the largest reduction from 2002 to 2017 occurred in Shanghai. In the meantime, the largest reduction in ISDEPA was in Guangdong Province. Since the 13th Five-Year Plan of China, the implementation of environmental protection policies has been stricter, which has led to industrial transfers, along with improvements in environmental governance technologies. It is worth mentioning that Beijing has been dealing with sandstorms and “great urban disease”, resulting in a large number of industrial enterprises moving out and floating population flowing out. This explains the above data characteristics to a certain extent.

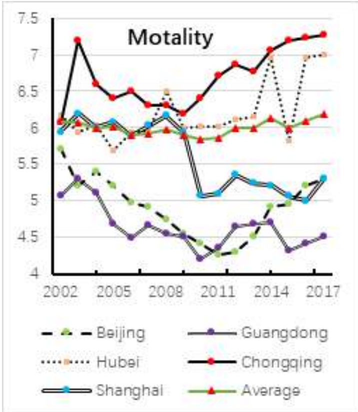

Figure 2a Mortality from 2002 to 2017

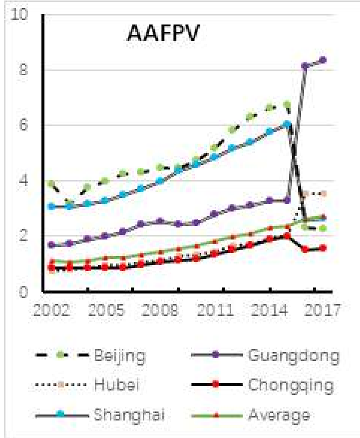

Figure 2b AAFPV from 2002 to 2017

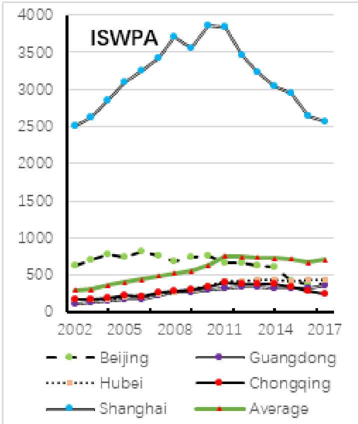

Figure 2c ISWPA from 2002 to 2017

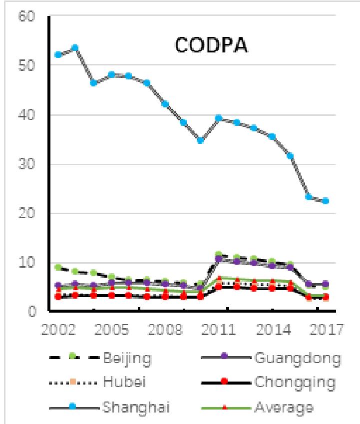

Figure 2d CODPA from 2002 to 2017

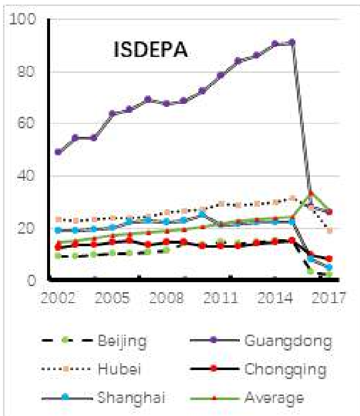

Figure 2e ISDEPA from 2002 to 2017

Figure 2 Changes in the main variables over time

5 Econometric strategy

5.1 Unit root test

For time series data, some non-stationary time series may have the same trend over time, but there may be no relationship between them. If these data are used directly, a phenomenon of "pseudo-regression" will happen based on econometric theory. This will lead to no practical significance in the research done with this empirical method. For the panel data, the "pseudo-regression" phenomenon can be effectively avoided by testing the stationarity of each time series. The commonly used testing methods are LLC test and Fisher-ADF test. In this paper, the unit root tests of panel data was performed by LLC test, Im-Pesaran-Skin test, Fisher-ADF test and Fisher-PP test. Table 2 shows that each variable is instability according to the level value of these tests. But the first-order difference of each variable is stable, so we consider the variables to be first-order single series.

Table 2 Unit Root Tests for variables

	Endogenous Variable	LLC	Im-Pesaran-Skin	Fisher-ADF	Fisher-PP
Level value	AAFPV	4.50979	10.246	12.438	24.6542
	MORT	-4.33365	-2.30259	94.35173	98.06809
	ISDEPA	-7.8056***	-3.90117	107.88	134.135
	CODPA	-1.4485	1.781483	30.21457	35.40574
	ISWPA	-7.11953	-0.23922	58.93296	95.1102
	PHE	2.7911	6.126781	18.00258	14.91887
	NOEDU	-2.5977***	0.076259	47.41306	43.72865
	DOCTOR	12.12224	14.20805	30.95317	30.76681
	PIPCI	-6.26567	-3.41027	117.8986	135.9287
	FEMALE	-8.6127	-6.59805	146.366	165.9778
	BED	11.38525	15.04586	6.43796	4.44607
	LPCDI	6.1494	10.7093	9.07599	1.41969
	LPCDI2	11.87018	11.66987	19.3622	0.334223
First-order difference	AAFPV	-19.717***	-15.6702***	299.087***	385.321***
	MORT	-21.6466***	-17.5003***	327.284***	395.056***
	ISDEPA	-17.180***	-12.8861***	251.045***	247.493***
	CODPA	-17.7075***	-11.0855***	219.1804***	241.1887***
	ISWPA	-10.6491***	-6.79064***	145.8039***	174.7807***
	PHE	-14.2884***	-12.4377***	243.8218***	239.163***
	NOEDU	-6.66336***	-3.67734***	96.326***	109.88***
	DOCTOR	-5.42181***	-6.37298***	162.4213***	262.7724***
	PIPCI	-23.0244***	-17.5826***	337.9296***	486.0781***
	FEMALE	-19.7757***	-16.3471***	316.4328***	460.4098***
	BED	-11.329***	-6.00986***	135.386***	132.5032***
	LPCDI	-6.66336***	-3.67734***	96.3265***	109.887***
	LPCDI2	-2.35426***	0.98432*	39.0535	35.7363

Notes: *, **, *** represents the significance level of 10%, 5%, 1% respectively. The following is the same as it.

5.2 Cointegration test

From the unit root tests of the variable, the selected variables are all first-order single series, which meet the preconditions of the cointegration test. The test results show that value of t-Statistic is -7.558 and p-value is less than 0.001. These suggest that there is a long-term cointegration relationship between dependent variables and explanatory variables.

5.3 Modeling human health and environmental pollution

Since this paper focuses on comparing the differences between regions, in order to simplify the analysis, it is assumed that the structural differences within the region are not considered, that is, the slope terms within each region are equal, and only the individual effects are considered, and the time effect is not considered. Therefore, it is only necessary to test whether the model is a hybrid estimation model, an individual fixed effect model, or an individual random effects model. According to the different constraints of the intercept term, the model may be a hybrid estimation model (no individual influence and the explanatory variable coefficient is unchanged), a variable intercept model (there is individual influence and the explanatory variable coefficient is unchanged); Depending on whether the individual effect is related to the explanatory variable, the variable intercept model may be an individual fixed effect model or an individual random effects model. The F-test and Hausman test are usually used to decide the model form, and the panel data of the eastern, central and western regions are used for model test. The results are shown in Table 3.

It can be seen from Table 3 that the F-test statistic of Average annual number of physician visits per capita in the country, the eastern and western regions is significant at the significance level of 1%, so the null hypothesis is rejected that the intercept term is unchanged. For the eastern, central and western regions, the model should be set to the variable intercept model. At the same time, further from the results of the Hausman test of the three models, it can be seen that the test statistic H is significant at the significance level of 1%, thus rejecting the null hypothesis that the individual effect is independent of the explanatory variable. For the national, eastern and western models, the model should be set to the individual fixed effect model. Because the number of the central provinces too small to carry out the Hausman test, in order to compare the eastern, central and western regions, the individual fixed effect model is still adopted for the central regions.

Table 3 F test and Hausman test

Region	F test		Hausman test	
	Statistic	P value	Statistic	P value
Nationwide	148.338	0.000	50.605	0.000
Eastern region	56.828	0.000	120.206	0.000
Central region	-	-	-	-
Western region	209.032	0.000	579.343	0.000

Notes: There are only 8 provinces in the central region, and the number of independent variables is larger than the number of cross-section samples, so the Hausman test cannot be performed.

6 Empirical results

6.1 Short-term effects

When Qi & Lu (2015) [22] examined the impact of environmental pollution on life expectancy, mortality, labor supply and labor productivity, they pointed out that there could be a certain lag period for the impact of environmental pollution on economic growth. In other words, the environmental pollution produced in the current economic development process would not immediately affect the economic growth right away.

While examining the impact of environmental pollution on human capital (life expectancy and mortality), most studies did not consider the problem of lag period. However, there is often a significant lag period in the impact of environmental pollution on health. This is especially the case when variables are less sensitive to short-term environmental pollution, such as life expectancy and mortality. Wang & Chang (2007) [30] found that the impact of regional GDP on mortality reached the maximum when the lag period is set the 8th one in the analysis of the healthy production function as a single influencing factor. Since AAFPV was used as one measure for human capital, this variable itself was more sensitive to environmental pollution than mortality and life expectancy, especially to air pollution. Therefore, we set the impact of industrial smoke dust emissions on AAFPV as the current effect, while industrial wastewater discharge and industrial solid waste emissions as having a lag effect behind the first phase. This was to analyze the impact by the previous phase of industrial wastewater and solid waste on AAFPV.

This article builds a short-term health production function as follows.

$$\begin{aligned} Inaafpv_{it} = &\beta_0 + \beta_1 Inisdepa_{it} + \beta_2 Incodpa_{it-1} + \beta_3 Iniswpa_{it-1} + \beta_4 phe_{it} + \\ &\beta_5 noedu_{it} + \beta_6 doctor_{it} + \beta_7 pipci_{it} + \beta_8 female_{it} + \beta_9 bed_{it} + \\ &\beta_{10} Ipcdi_{it} + \beta_{11} Ipcdi2_{it} + \varepsilon_{it} \end{aligned} \tag{1}$$

where

i = 1, 2. . .30 represents the provinces, municipalities or autonomous regions of China,

t =1, 2. . .16 indicates the number of periods, 1 indicates 2002 year, and 16 indicates 2017 year.

The data of 30 provinces in China will be estimated in 2002-2017. Due to the large differences between regions, when these data are used for regression analysis, there will be biased results. Hence the data were divided into three parts that is Eastern, Central and Western respectively. The coefficient estimates of the model are shown in Table 4.

An R^2 of 0.9 or higher indicates that the regression model has a good fit describing the association between independent and dependent variables. The F-statistic of the regression model also passes the significance test and the **DW** statistic value is between 1.7 and 2.4, which indicates that there is no sequence autocorrelation between independent variables.

From the nationwide model, ISDEPA shows a significant impact on AAFPV. CODPA and ISWPA have not passed the significant test. With every 1 percent increase in ISDEPA, AAFPV would increase by 0.24 percentages. This is in line with the fact that the effect of air pollution on health has a short time lag [34]. The proportions of health expenditure to total fiscal expenditure and to the number of beds per thousand people (BED) have significant impacts on AAFPV. Every 1 percent increase of the proportion of health expenditure (PHE) would likely increase

Table 4 Coefficient estimation of all factor analysis model

	Nationwide	Eastern	Central	Western
Intercept term	-4.053***	-5.465*	-1.811*	-3.026***
ISDEPA	0.24***	0.46**	-0.084	0.173***
CODPA [-1]	-0.007	-0.041	0.12***	0.039
ISWPA [-1]	0.022	-0.132	0.062*	-0.002
PHE	0.05***	0.055**	0.045***	0.031***
NOEDU	0.006***	0.011	0.002	0.004**
DOCTOR	0.014	-0.013	0.068***	0.046*
PIPCI	0.016	0.043	0.013	-0.007
FEMALE	0.012	0.01	0.03***	0.007
BED	0.046***	0.007	0.02	0.073***
LPCDI	0.07	0.15*	0.157***	0.165***
LPCDI2	0.001	-0.004	-0.017***	-0.015***
F statistic	149.1***	56.7***	265.3***	181.6***
R square	0.945	0.907	0.982	0.969
DW statistic	1.978	2.4	1.98	1.7

Notes: [-1] indicates a period of lag, the following is the same as it.

AAFPV by 4.7 percentage. Also, a 1% increase in PHE is associated with a 5.1 percent increase in AAFPV. When PIP is increased by 1 percentage, AAFPV is likely increase by 0.6 percentage. The proportion of female population to total population does not have a significant impact on AAFPV. Although from a genetic point of view, women's life expectancy is indeed longer than that of men, there is not yet a consensus on how different genders differ in health status.

In terms of geography, ISDEPA in both the eastern and western regions have showed significant negative impacts on residents' health. For every 1% increase in ISDEPA, AAFPV increases by 0.46 and 0.173 percentage points respectively. CODPA in the central regions has become the main source of pollution. Due to the time lag, a 1% increase in CODPA is likely to cause 0.12% increase in AAFPV in the central regions in the subsequent year. Most studies on spatial aggregation of water pollution suggest that water pollution in the eastern coastal regions are significantly more severe and concentrated than those in the central and western regions [35, 36].

Shi *et al*. (2017) [37] suggests that the spatial pattern and evolutional structure of the discharge of industrial water pollution found that the reduction of CODPA in China from 2005 to 2010 can be attributed mainly to the adoption of new technology that purification treatment waste water before releasing it by the industries of paper and paper products. Among them, the papermaking and paper products industries in the western region contributed prominently, followed by the eastern region. The central region contributed only slightly to water pollution while the northeast region actually helps to bring down the national average level of water pollution.

Recently water pollution-intensive industries have moved into the central regions, but the technical effect of adopting new technology for emission reduction is not obvious. The wastewater pollution in the central regions have a greater impact on the health of residents than that in other regions. The increase in health expenditures in the eastern, central, and western regions would increase AAFPV, but such increase is the highest in the eastern region, followed by that in the central region, and lastly in the west region. The number of hospital beds and the number of physicians per 1,000 people both have significant positive impacts on AAFPV in the western region. There is a significant "U"-shape trend of the relationship between per capita disposable income of residents and AAFPV of the central and western regions. That is, as the per capita income level increases, AAFPV increases first, then decreases with time.

6.2 Long-term effects

This article constructs a long-term healthy production function with mortality as a dependent variable as follows.

$$\begin{aligned} Inmort_{it} = \beta_0 &+ \sum \beta_{1,a} Inisdepa_{it-a} + \sum \beta_{2,b} Incodpa_{it-b} \\ &+ \sum \beta_{3,c} Iniswpa_{it-c} + \sum \beta_{4,d} pipci_{it-d} + \sum \beta_{5,e} phe_{it-e} \\ &+ \sum \beta_{6,f} doctor_{it-f} + \sum \beta_{7,g} noedu_{it-g} + \beta_8 bed_{it} \\ &+ \sum \beta_{9,h} female_{it-h} + \beta_{10} Ipcdi_{it} + \beta_{11} Ipcdi2_{it} + \varepsilon_{it} \end{aligned} \tag{2}$$

where

i=1, 2. . .30 indicates the provinces/regions,
t =1, 2. . .16 indicates the number of periods, and
a, b, . . ., h indicates the lag periods.

According to the long-term health production function model, the data of the provinces in 2002-2017 are used in the regression analysis to obtain estimated regression coefficients of the independent variables. To account for the significant lag period of the independent variables on mortality, the lag periods were introduced into the regression model. Estimated regression coefficients of the model are shown in Table 5.

Table 5 Regression results of Long-term healthy production function

	coefficient	Standard deviation	T statistic	P value
Intercept term	-0.295	1.208	-0.244	0.807
ISDEPA	0.002	0.040	0.054	0.957
ISDEPA [-1]	-0.072	0.048	-1.488	0.138
ISDEPA [-2]	-0.059	0.042	-1.428	0.154
CODPA	0.019	0.015	1.248	0.213
CODPA [-1]	0.033	0.017	1.950	0.052
CODPA [-2]	0.036	0.017	2.040	0.042
CODPA [-3]	0.020	0.015	1.354	0.177
ISWPA	-0.012	0.018	-0.639	0.524
ISWPA [-1]	0.003	0.022	0.147	0.883
ISWPA [-2]	-0.029	0.022	-1.324	0.187
ISWPA [-3]	-0.024	0.019	-1.216	0.225
PHE	0.002	0.005	0.309	0.758
PHE [-1]	0.001	0.005	0.049	0.961
NOEDU	0.001	0.001	0.007	0.995
DOCTOR	-0.012	0.006	-2.137	0.034
BED	0.014	0.008	1.692	0.092
PIPCI	-0.006	0.007	-0.864	0.389
PIPCI [-1]	-0.003	0.007	-0.495	0.621
FEMALE	0.504	0.214	2.362	0.019
FEMALE [-1]	0.455	0.228	2.000	0.047
LPCDI	0.039	0.016	2.403	0.017
LPCDI2	-0.002	0.001	-2.004	0.046
F statistic	44.5			0.000
R square	0.893			
DW statistic	1.52			

ISDEPA and ISWPA of the current period show no significant impact on the current mortality. That is the same with ISDEPA of one-year time lag period and of two-year period and with ISWPA of lag period. On the other hand, CODPA shows a significant impact on mortality. At the 5% significance level, CODPA with one-year time lag shows the greatest impact on mortality. However, there is no effect on the mortality rate when the lag period is three years. When considering the regression coefficients, each 1% increase in CODPA with a time lag of one year and two years is associated with 0.033% and 0.036% increases in the mortality rate, respectively.

The impact of changes in health care services on mortality is also different. The impact of health expenditure on mortality is not significant. The number of physicians per 1,000 persons shows a significant impact on mortality. Specifically, given the number of physicians per 1,000 persons increases by 1 percentage, mortality would decrease by 0.012 percentage. At the 10% significance level, an increase in the number of hospital beds per 1,000 persons will cause an increase in mortality.

The lag period of the impact of education on mortality is long. The illiteracy rate in current period has no significant effect on mortality. The illiteracy rate of the three-year time lag does show a significantly positive impact on mortality. When the illiteracy rate increases by one percentage, the mortality would increase by 0.2 percentage.

The long-term impact of gender difference on health capital is more significant than that of the short-term impact. At the 5% significance level, the proportion of female population in the current period with one-year time lag has a significantly positive impact on mortality. The proportion of female population in the current period not only affects the current mortality rate, but also affects the mortality rate of the future period. However, based on the estimated regression coefficient, the result seems to contradict with those concluded in existing studies that suggested "women's life expectancy is higher than men". To that end, we wish to point out that Brettingham (2005) [38] suggested that, as more modern women accepting the concept of "work hard, more entertainment", the long-standing differences in life expectancy between men and women may disappear eventually. In addition, Brettingham predicted that there may be similar life expectancy between men and women in 2010.

Wang & Chang (2007) [30] used the data of 1952-1984 and 1985-2003 to construct China's macro-health production function, respectively. The results showed that the female population had a completely opposite effect on mortality during the two time periods. In the early days, the proportion of the female population effectively reduced the mortality rate. With the development of the economy and society, Chinese women have been facing more social pressures, some female-specific diseases have seen increases in numbers. These included cervical cancer and breast cancer, and the like [38, 39]. In addition, after the 1990s, Chinese women's postpartum depression and suicide rate were also increasing year by year [40, 41]. These studies have all reflected that the impact of the increase in proportion female in population on mortality has changed significantly from a significant reduction in mortality to an increase in mortality.

As LPPCDI increased, the mortality rate rose firstly and then decreased. Both LPPCDI and its squared values passed the significance test. With the increase in LPPCDI, the mortality rate showed a U-shape trend, first decreased then increased. When the per capita income level was low, the increase of income could harm the level of health. There is a positive correlation between LPPCDI and mortality. With the accumulation of personal wealth, people could pay more attention to the input of human health capital. The increase in income level likely result in better medical services and more time for physical exercises. At this time, the increase in income could effectively reduce the mortality rate. Liang (1994) [42] proposed that there was a certain relationship between the level of economic development and mortality at the regional scale. However, such relationship between economic development and population mortality is not a linear relationship, but a curve of approximate logarithm.

7 Discussion and conclusion

This article divides the impact of industrial pollution on human health into short-term effects and long-term effects. In the short-term, the impact of the industrial pollution on human health is reflected in the increase in AAFPV. In the long-term, the industrial pollution is linked to the increase in all-cause mortality. In the estimation of the regression coefficients of short-term and long-term healthy production functions, there is a difference in how significant the pollution variables might have on human health. In the short-term, ISDEPA has a significant impact on AAFPV but CODPA and ISWPA have no significant impact on AAFPV. In the long-term. CODPA has a significant impact on all-cause mortality while ISDEPA and ISWPA have no significant impact on all-cause mortality.

In terms of regional differences, AAFPV in the eastern and western regions are greatly affected by ISDEPA but is less affected by CODPA and ISWPA. The central region is opposite to the eastern and western regions. The central region's CODPA and ISWPA show to have a high impact on AAFPV but less by ISDEPA. In addition, among the control variables, health fiscal expenditure and illiteracy rate show no significant impact on regional all-cause mortality, but it is associated with increases in AAFPC in the short term. The increase in LPCDI would cause the all-cause mortality to follow a U-shape trend of increasing initially then decreases. AAFPV of residents in central and western regions in the short term also show to follow similar U-shape growth trends with an increase in LPCDI.

In order to comprehensively improve the overall healthy level of Chinese residents, we propose the following policy recommendations:

(1) As the eastern, central, and western regions are shown to be sensitive to different types of industrial pollution, and the eastern and western regions should pay more attention to air pollution control. The central region should pay attention to the treatment of water pollution and solid waste pollution.

(2) We should pay attention to women's health issues, especially the prevention and treatment of diseases of high incidences such as cervical cancer and breast cancer to improve the level of women's mental health and health investment.

(3) We should improve the education level of residents, promote widespread knowledge in health care and raise awareness of medical and health knowledge among residents.

(4) We should further reform the system of public health care to improve its operational efficiency with better government's supervision of the health sector.

(5) We might further develop the market economy to play a leading role in promoting the adoption of new and efficient pollution-reduction technology in developed regions and in promoting the construction of infrastructure in backward regions to support the transfer/upgrade of industries in developed regions.

Measuring the long-term health of a region, life expectancy is a relatively stable indicator. But this indicator can only be obtained at the time of the census. Therefore, this article chose to use all-cause mortality indicators. All-cause mortality in a region often shows great volatility over time. From the descriptive analysis discussed earlier, all-cause mortality in developed regions (such as Guangdong, Beijing, and Shanghai) are much lower than those in the central and western regions (such as Hubei and Chongqing). Therefore, all-cause mortality can still reflect the health of a region in the long run. The increase in AAFPV, in the case of same medical service levels and income levels, can reflect levels of people's health in different regions. We considered two indicators (BED, LPCDI) as control variables in our analysis. Although the analysis in this article was somewhat abstract and macroscopic, this type of analysis is necessary, and it offers important baseline understanding. Based on the analysis discussed here, the next step can quantitatively measure the loss of human health caused by various industrial pollutions.

In the analysis of long-term influencing factors, the effect has hysteresis, and the lag period is difficult to grasp. In addition, it is difficult to separate other influencing factors and avoid endogenous problems. This is a problem that we need to study further in the later period.

Funding

This study was financially supported by Major Program of National Fund of Philosophy and Social Science of China (No. 18ZDA132).

Conflicts of Interest

The authors declare no conflict of interest.

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