

The Impact of Environmental Pollution on the Health of Middle-Aged and Older Adults in China

Hongli Fan (✉ 20177686@sdufe.edu.cn)

Shandong University of Finance and Economics <https://orcid.org/0000-0001-8675-2438>

Yingcheng Wang

Shandong University of Finance and Economics

Ying Wang

Shandong University of Finance and Economics

Peter C Coyte

University of Toronto

Research Article

Keywords: Environmental pollution, Chronic diseases, Middle-aged and older people, China

Posted Date: March 22nd, 2021

DOI: <https://doi.org/10.21203/rs.3.rs-301066/v1>

License: © ⓘ This work is licensed under a Creative Commons Attribution 4.0 International License.

[Read Full License](#)

Version of Record: A version of this preprint was published at Environmental Science and Pollution Research on August 17th, 2021. See the published version at <https://doi.org/10.1007/s11356-021-15832-z>.

Abstract

While several studies have demonstrated the negative impacts of environmental pollution on population health, in general, few studies have examined the potential differential effects on the health of middle-aged and older populations, i.e. 45 years and older. Given the twin concerns of environmental pollution and population aging in China, this article employed a fixed effects model to infer the impact of environmental pollution on public health with a particular focus on middle-aged and older adults. The analyses were based on data from the 2011–2018 waves of the CHARLS and pollutant data from prefecture-level cities. The results showed that environmental pollution significantly increased the risk of chronic diseases and negatively impacted the health of middle-aged and older adults. Environmental pollution had its greatest negative effect on the health of the elderly, women, urban residents and those with lower incomes than for their counterparts. We further found that the main channels of effect were through reduced physical exercise and an increase in depressive symptoms, and the pollution prevention actions alleviated the health deterioration of environmental pollution for the middle-aged and elderly. It is imperative for the government to urgently reinforce policy's enforcement to decrease air and water pollution, and enhance the ability to circumvent pollution for the lower socioeconomic groups.

Introduction

The growing prevalence of chronic conditions over the last 20 years has become a serious health problem and the main cause of premature mortality (Zhong and Xiang, 2010; Li and Ping, 2016). It is widely recognized that non-communicable chronic diseases have become more prevalent than acute infectious diseases in China and in the rest of the world. Estimates suggest that chronic diseases in China accounted for 86.6% of deaths and 70% of the total burden of disease (Xiong, 2019). Chronic illnesses not only seriously affect the quality of life of individuals and their families, but also have a huge impact on health systems and the economy. Health systems around the world face a daunting task in managing the quality of health service provision for chronic conditions and their long-term consequences (Epping-Jordan et al., 2004).

An extensive review of the literature reveals that the prevalence of chronic conditions is associated with lower social and economic status (Xia and Li, 2018; NoorUIHuda, 2020). For example, studies from China have shown a link between urbanization and the prevalence of diabetes (Attard et al., 2012; Li et al., 2017). Similarly, the development of chronic illnesses is closely correlated with the increasing prevalence of obesity and unhealthy behaviors (e.g., tobacco use, poor nutrition, and the lack of physical activity) and worsening environmental conditions (Siavash et al., 2008; Protani et al., 2010; Cai et al., 2013); recently, concerns in China have been expressed about the impact of pollution on population health (Shan et al. 2016).

Rapid industrial growth has led to an increase in waste emissions in China. The range of health effects stemming from environmental pollution have been well documented. Air pollution has been shown to be associated with the birth of underweight babies (Gong et al., 2018), a growth in infant mortality (Lelieveld

et al., 2015; Nihit et al., 2019; Fotourehchi, 2016), and a greater incidence of otitis media infections in early childhood (Deng et al., 2017). Studies have also found that adults' health has been impacted. For instance, industrial air pollution has been shown to elevate mortality rates, shorten life expectancy, and reduce disability-adjusted life years (Ahmad et al., 2020; Pope et al., 2013; Peng et al., 2020; Huang et al., 2018). These effects have tended to result in increased hospitalizations and higher health expenditures (Cui et al., 2016; Zeng and He, 2016). Water pollution has been linked to water-borne diseases and chemical poisoning (Han and Yan, 2014), and negatively associated with mental and self-reported health outcomes (Wang and Yang, 2016). However, there is a paucity of studies on the impact of environmental pollution on the prevalence of chronic diseases, in general, rather than on specific chronic diseases, such as asthma and other related respiratory problems in children (Sram et al., 2013; Ranci re et al., 2017), hypertension, and cardiovascular and cerebrovascular diseases (Shan et al., 2016; Shanley et al., 2016). Chinese research examining the total number of chronic diseases as an indicator of the effects of pollution, particularly on middle-aged and older people, is lacking.

The present study attempts to address this gap in the literature. It assesses and explains the impact of environmental pollution on the prevalence of chronic disease in China. It focuses on air and water pollution at the prefecture level, because this poses a major threat to population health (Shan et al., 2016; Deng et al., 2017; Pope et al., 2013; Peng et al., 2020; Huang et al., 2018; Wang and Yang, 2016). We limit our attention to middle-aged and older adults in China, since they are more susceptible to environmental pollution and are likely to suffer from multiple chronic diseases (Freedman and Martin, 2000; Wolff et al., 2002). It is hoped that the insights from our study will inform policy decision making on a range of pollution measures and mechanisms and thereby have a positive impact on the health of Chinese residents.

To shed light on this important issue, we highlight the general effects of environmental pollution on chronic diseases using data drawn from the China Health and Retirement Longitudinal Survey (CHARLS). The potential differential effects of environmental pollution on the health of different age groups are assessed. We also examine the channels through which the prevalence of chronic conditions are indirectly affected by environmental pollution using a mediation model. Finally, we consider whether pollution control policies alleviate the negative consequences of environmental pollution using a moderation effects model.

The study is organized as follows. The next section introduces the data and the empirical strategy employed. The empirical results are presented in Sect. 3. Section 4 discusses the findings in the context of the literature and identifies policy implications, and Sect. 5 offers a brief set of conclusions.

Data And Methods

Data

Information on the health status of individuals as well as their age-sex and family structure were derived from the China Health and Retirement Longitudinal Survey (CHARLS). This is a longitudinal survey based on nationally representative samples of Chinese residents aged 45 and over. Four waves of this survey have been conducted from 2011 to 2018 through use of a multistage random cluster design (Shan et al. 2016; Zhao et al., 2014). The CHARLS contains information on 17,500 individuals and 10,000 households in 150 counties/districts and 450 villages/resident committees in 28 provinces and municipal cities. These areas vary substantially in geography, economic development, public resources, and health indicators. By 2018, the 28 sample units included in the CHARLS constituted 98.59% of China's population. The survey provides detailed information on respondents' health, demographics, socioeconomic status, and other related information both at the individual and household level. It presents a rich array of information on chronic illnesses that makes it ideal for analyzing the effect of environmental pollution on the physical health of middle-aged and older people.

Environmental pollution data on sulfur dioxide, air particulate matter, and wastewater were obtained from the 2011–2018 China Urban Statistical Yearbook (Zeng and He, 2016; Tao et al., 2019). Information on atmospheric temperatures were acquired from the national meteorological information center of the China Meteorological Administration (Dong and He, 2019). Person-level health data and social-economic status from the CHARLS were linked to corresponding prefecture-level pollution and air temperature data based on the primary sampling units (PSUs) in the CHARLS. We obtained unbalanced panel data for the 2011–2018 waves of the CHARLS to take advantage of the sample and we omitted observations with incomplete information. The final sample contained a total of 57,891 observations of 13,083, 14,183, 15,604, and 15,021 individuals from the 2011, 2013, 2015, and 2018 surveys, respectively.

Measures

We examined the effect of environmental pollution on health, similar to the previous literature, but with a special focus on those aged 45 years and older. For the dependent variable, we relied on information on chronic illnesses documented in the CHARLS to define the health status of middle-aged and older people. The information derives from physical examinations or diagnoses by doctors (Shan et al., 2016). Thus, the diagnosed chronic disease data represents an objective measure of ill health and therefore may be free of “justification bias” (Ning et al., 2016; Fan et al., 2019). We created a continuous variable to represent the “number of chronic diseases,” including hypertension, dyslipidemia, diabetes or high blood sugar, malignant tumor, chronic lung diseases, liver disease, heart attack, stroke, kidney disease, and asthma.

Independent variables were the air and water pollution indicators. Secondary industry is the primary source of pollution emissions, and sulfur dioxide (SO₂) and air particulate matter (PM)—the waste products of fossil fuel combustion—are the major air pollutants (Wang, 2019; Fayomi et al., 2019). Moreover, water waste is another industrial pollutant related with chronic disease (Han and Yan, 2014). In line with existing studies, we used SO₂, PM, and wastewater emissions from prefecture-level cities to measure the severity of air and water pollution, because they are the main contributing factors to

deteriorating air and water quality and public health generally (Gong et al., 2018; Lelieveld et al., 2015; Nihit et al., 2019; Fotourehchi, 2016; Deng et al., 2017; Pope et al., 2013; Zeng and He, 2016). We did not consider inhalable PM such as PM_{2.5} and PM₁₀ specially, because data availability was restricted to the prefecture-level. We evaluated SO₂, PM, and water pollution emissions measured in per unit area (ten thousand tons per square kilometers) in each prefecture to map the prefecture-level cities' precise environmental pollution level (Tao et al., 2019).

We also controlled for a series of individual-level, household-level, and other environmental characteristics. The individual-related variables included age, gender, marital status, educational attainment, health behaviors (smoking, alcohol consumption, and social activities), medical insurance coverage, and individual income. Household-related variables included the residential area and whether the respondent was living with their children. We also controlled for the prefecture level annual average air temperature, because this can also affect health status (Cui et al., 2016).

Statistical Analyses

We examined the effects of air and water pollution on chronic disease status for adults aged 45 years and older using multiple Poisson regression analysis. The number of chronic diseases was measured on count data. Poisson regression has the advantage of fitting nonlinear models over the linear regression models, because it deals with situations in which the dependent variable is a count (Fagbamigbe and Adebowale, 2014). Additionally, there were large individual variations in ill health, so we used a fixed-effect model to control for time-invariant unobserved factors in the unbalanced panel data. We also used standard errors clustered at the individual level to account for the multilevel, multistage sampling issues, and controlled for potential individual heteroscedasticity to obtain consistent parameter estimates (Cui et al., 2016; Stock and Watson, 2008). The fixed-effect Poisson regression model was specified as follows:

$$E(\text{ill-health}_{it} | \text{Pollutant}_{it}, X_{it}, \mu_i, \varepsilon_{it}) = \exp(\alpha + \beta_1 \text{Pollutant}_{it} + \varphi X_{it} + \mu_i + \varepsilon_{it}) \quad (1)$$

where the outcome, *ill-health*_{it}, stands for the number of chronic diseases for individual *i* at time *t*. The key explanatory variable *Pollutant*_{it} indicates the air and water pollutants, that is, the SO₂ and PM, and wastewater emissions per unit area of each prefecture. *X*_{it} is a vector of individual and household observable characteristics and environmental variables, such as age, gender, educational levels, health behaviors, individual income, cohabitants, annual temperature. The term μ_i represents individual-related fixed-effects accounting for all time-invariant factors that may affect health, and ε_{it} is a random error term. Because the Poisson regression is a nonlinear model, we calculated the marginal effects of environmental pollution on individuals' ill health to obtain more intuitive and practical results.

Results

Statistical description

Table 1 reports the descriptive statistics used in the analysis and defines each variable. The average number of chronic diseases was 0.684. The annual average industrial emissions were 74.67 thousand tons of SO₂ /km², 27.85 thousand tons of PM/km², and 7.74 thousand tons of wastewater/km², respectively. More than half of the respondents were between 45 and 60 years of age, and most had a primary school level of education. Most (86.5%) were married, and around 60% lived in rural areas.

Table 1
Variable definition and descriptive statistics.

Variable	Definition	Mean	S.D.
Dependent variables			
Number of chronic diseases		0.684	1.029
Independent variables			
SO ₂	Industrial sulfur dioxide emission (10 ⁴ tons/km ²)	7.467	11.565
PM	Industrial particulate matter emission (10 ⁴ tons/km ²)	2.785	3.125
Wastewater	Industrial wastewater emission (10 ⁴ tons/km ²)	0.774	1.149
Age	Continuous variable	60.535	10.103
Gender	1 = Male, 0 = Female	0.476	0.499
Married	1 = Married, 0 = Otherwise (divorced, widowed and others)	0.865	0.342
Education			
Primary or less※	1 = Primary school or less	0.661	0.473
Junior school	1 = Middle school	0.211	0.408
High school	1 = High school	0.103	0.304
College or more	1 = College or more	0.024	0.153
Smoke	1 = Smoke cigarettes	0.311	0.463
Drink	1 = Drink alcohol	0.330	0.470
Social activity	1 = Social active in the past month	0.586	0.493
Insurance	1 = Enrolling in medical insurance	0.832	0.374
Urban	1 = Urban, 0 = Rural	0.407	0.491
Cohabitants	1 = Co-resident with children	0.673	0.469
Ln (Income)	Logarithm of annual income (RMB)	8.004	3.499
Temperature	Annual average temperature in each city	15.276	4.214
Physical exercise	1 = Have physical exercise in a usual week	0.460	0.498
Depressive symptoms	CES-10 Score (0–10)	2.197	2.342

Note: ※ refers to the base group.

Variable	Definition	Mean	S.D.
Observations		57, 891	
Note: ※ refers to the base group.			

Full analysis

Table 2 reports the marginal effects of pollution on ill-health from the fixed-effect Poisson regression model. Model 1 reports the determinants of number of chronic illnesses. Columns 1–3 correspond to the health effects for the three key independent variables: SO₂, PM, and wastewater. We found evidence of a significant positive effect of environmental pollution on ill health when controlling for the estimate bias. As indicated in Columns 1–2, the SO₂ and PM emission per unit area significantly increased the number of chronic diseases by 0.66% and 3.24%, respectively, which indicated air pollutants had significant negative effect on the health of middle-aged and older people. The results for water pollution exhibit the same general pattern; the number of chronic diseases increased 8.29 percentage points because of the industrial wastewater emissions increase (see Column 3).

Table 2
Effect of environmental pollution on the prevalence of chorionic diseases.

Variables	Model 1: Number of Chronic diseases			Model 2: Having any Chronic diseases		
	FE-Poisson (dydx)			FE (dydx)		
	(1)	(2)	(3)	(4)	(5)	(6)
SO ₂	0.0066 ^{***}			0.0017 ^{***}		
	(0.0004)			(0.0002)		
PM		0.0324 ^{***}			0.0078 ^{***}	
		(0.0024)			(0.0009)	
Wastewater			0.0829 ^{***}			0.0156 ^{***}
			(0.0156)			(0.0045)
Age	0.1044 ^{***}	0.1064 ^{***}	0.0889 ^{***}	0.0384 ^{***}	0.0391 ^{***}	0.0349 ^{***}
	(0.0166)	(0.0165)	(0.0153)	(0.0056)	(0.0056)	(0.0056)
Age ²	-0.0010 ^{***}	-0.0010 ^{***}	-0.0008 ^{***}	-0.0003 ^{***}	-0.0003 ^{***}	-0.0003 ^{***}
	(0.0001)	(0.0001)	(0.0001)	(0.0000)	(0.0000)	(0.0000)
Married	-0.0364	-0.0318	-0.0416	-0.0093	-0.0083	-0.0099
	(0.0400)	(0.0395)	(0.0344)	(0.0154)	(0.0154)	(0.0134)
Junior school	-0.1633 ^{***}	-0.1633 ^{***}	-0.1220 ^{**}	-0.0480 ^{**}	-0.0491 ^{***}	-0.0411 ^{**}
	(0.0616)	(0.0610)	(0.0537)	(0.0187)	(0.0186)	(0.0172)
High school	-0.2068 ^{**}	-0.2063 ^{**}	-0.2100 ^{**}	-0.0817 ^{**}	-0.0824 ^{**}	-0.0851 ^{***}
	(0.0951)	(0.0946)	(0.0871)	(0.0335)	(0.0333)	(0.0316)
College or more	0.0460	0.0391	0.0115	0.0235	0.0203	0.0100
	(0.1405)	(0.1401)	(0.1275)	(0.0559)	(0.0559)	(0.0519)
Smoke	0.1421 ^{***}	0.1510 ^{***}	0.2420 ^{***}	0.0232 ^{**}	0.0262 ^{**}	0.0487 ^{***}
	(0.0309)	(0.0307)	(0.0273)	(0.0103)	(0.0103)	(0.0093)
Drink	0.0093	0.0106	0.0158	0.0008	0.0009	0.0017
	(0.0175)	(0.0174)	(0.0152)	(0.0067)	(0.0067)	(0.0059)

Note: *** P < 0.01, ** P < 0.05, * P < 0.1. Clustered-robust standard errors are in parentheses.

Variables	Model 1: Number of Chronic diseases			Model 2: Having any Chronic diseases		
	FE-Poisson (dydx)			FE (dydx)		
	(1)	(2)	(3)	(4)	(5)	(6)
Social activity	0.0172 (0.0112)	0.0159 (0.0112)	0.0163 (0.0101)	0.0127 ^{***} (0.0043)	0.0123 ^{***} (0.0043)	0.0106 ^{***} (0.0038)
Insurance	-0.0496 ^{***} (0.0133)	-0.0539 ^{***} (0.0132)	-0.0896 ^{***} (0.0115)	-0.0119 ^{**} (0.0050)	-0.0134 ^{***} (0.0050)	-0.0201 ^{***} (0.0044)
Cohabitants	-0.0204 ^{**} (0.0118)	-0.0241 ^{**} (0.0117)	-0.0280 ^{***} (0.0106)	-0.0088 (0.0045)	-0.0099 ^{**} (0.0045)	-0.0092 ^{**} (0.0040)
Ln(income)	0.0012 (0.0026)	0.0023 (0.0025)	0.0067 ^{***} (0.0021)	0.0007 (0.0008)	0.0009 (0.0008)	0.0017 ^{**} (0.0007)
Temperature	0.0061 (0.0074)	0.0128 (0.0072)	0.0116 (0.0067)	-0.0008 (0.0029)	0.0019 (0.0028)	0.0006 (0.0026)
Hausman test	246.25 ^{***} (p = 0.000)	254.54 ^{***} (p = 0.000)	301.17 ^{***} (p = 0.000)	395.84 ^{***} (p = 0.000)	395.84 ^{***} (p = 0.000)	406.78 ^{***} (p = 0.000)
Wald /F test	588.52 ^{***} (p = 0.000)	473.01 ^{***} (p = 0.000)	335.39 ^{***} (p = 0.000)	19.27 ^{***} (p = 0.000)	16.27 ^{***} (p = 0.000)	11.66 ^{***} (p = 0.000)
N	57,891	57,891	57,891	57,891	57,891	57,891
Note: ^{***} P < 0.01, ^{**} P < 0.05, [*] P < 0.1. Clustered-robust standard errors are in parentheses.						

Model 2 (Table 2) presents estimates of a robustness test, to assess how sensitive the findings were to alternative measure of ill health. Specifically, we defined a dichotomous variable *presence or absence of chronic disease*, which was coded as 1 if a respondent had been diagnosed with any chronic disease in the last year otherwise zero. This variable was used to examine the robustness of the health effects of environmental pollution. The marginal effects from the fixed-effect model are showed in Columns 4–6 of Table 2. The probability of having any diagnosed chronic disease increased 0.16%, 0.78%, and 1.56% with higher emissions of SO₂, PM, and wastewater, respectively. These findings confirmed the robustness of the central conclusion.

Table 2 also indicates that age, education, health behaviors, insurance all played an important role in the determination of ill health. The effect of age on the number of chronic diseases was captured by an inverse U-shaped relationship. The health of middle-aged and older adults improved in line with

educational attainment, but deteriorated with smoking behaviors. Medical insurance significantly improved health status.

Subsample analysis

We further explored the extent to which the effects of environmental pollutants on the number of chronic diseases varied within different subgroups. We used the fixed-effect Poisson model, and presented the marginal effects (Fig. 1). We examined the health effects by individual-level characteristics, that is, by age and sex. In particular, we analyzed 3 age groups: 45 to 59 years old, 60 to 74 years old, and 75 years and above. These reflected the fact that the body and immunity status may differ for those who are middle-aged, those who are elderly, and finally, those who are even older (Zhong and Xiang, 2010). The negative effects of environmental pollution on health appeared to be greater among the elderly between 60 to 74 (see Fig. 1A). This may be attributed to the fact that middle-aged adults have higher levels of protective immunity to, while the very elderly are more likely to stay indoors (and so are less likely to be exposed to environmental pollution) (Lü et al., 2015; Huang et al 2020). Also, the results in Fig. 1B show a larger negative impact of air and water pollution on health among women. We also investigated the differential effects of household income and residential area. We classified the sample into low and high-income groups using the 50th percentile of household income. We found that SO₂, PM, and wastewater emissions per unit area significantly increased the number of chronic diseases by 0.60%, 2.67%, and 15.51%, respectively in the low-income group, but the effects were insignificant for those in the high-income group (see Fig. 1C). This may be due to the fact that poor individuals are more likely to be exposed to pollution as they have no means of staying away from environmental pollution, for instance by migrating or purchasing air purification equipment. (Lü et al., 2015). Additionally, air and water pollutants have a stronger negative impact on people living in urban areas (see Fig. 1D). This may be attributed to the fact that pollution is worse in urban areas than it is elsewhere (Li et al., 2020).

Mechanism analysis

In this section, we reveal the mechanisms behind the negative effects of environmental pollution on health. According to previous studies, environmental pollution can pose a barrier to involvement in outdoor physical activities (Lü et al., 2015; Huang et al., 2020), increase depressive symptoms in middle-aged and older people (Dong and He, 2019; Wang et al., 2018), and elevate the risk of chronic illnesses of depression (Ning et al., 2016; Chen et al., 2020; He, 2019; Susan et al., 2014). We considered physical activities and symptoms of depression as possible channels through which health might be affected. In the first instance, we established whether those in the sample had engaged in high intense physical exercise during an ordinary week. If the answer was yes, the variable was coded as 1, and 0 otherwise. We used a ten-item modification of the Center for Epidemiologic Studies Depression scale (CES-D) to evaluate the depression status of middle-aged and old people. This has been widely used in previous studies (Dong and He, 2019; Wang et al., 2018; Adjaye-Gbewonyo et al., 2018). The variable was based on ten questions posed in the CHARLS. Responses included "I was bothered by things that don't usually bother me," "I had trouble keeping my mind on what I was doing," "I felt depressed," "I felt fearful," "I felt lonely," and so on. The value 1 was assigned if the participants stated that they felt depressed or very

depressed in answers to each question, and 0 otherwise. A summed score of the responses to these ten items was used to indicate depression, with higher scores meaning a greater degree of depression.

We estimated the mechanisms through the use of a mediation model. In particular, we first calculated the effect of environmental pollutants on the mediators for “physical exercise” and “depressive symptoms” (see Panel A in Table 3). Models 1 and 2 in Panel A revealed that air and water pollutants emission per unit area significantly reduced the probability of physical exercise participation and increased the CESD scores. Consequently, we used physical exercise and depression symptoms as the mediator variables in the next step.

Table 3
Mediation effects of environmental pollution.

Panel A: The effect of environmental pollution on mediators						
	Model 1: Physical exercise			Model 2: Depressive symptoms		
SO ₂	-0.0040 ^{***}			0.0013		
	(0.0003)			(0.0008)		
PM	-0.0182 ^{***}			0.0092 ^{**}		
	(0.0012)			(0.0044)		
Wastewater	-0.0459 ^{***}			-0.0181		
	(0.0055)			(0.0174)		
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Hausman test	5347.54 ^{***}	5183.93 ^{***}	5332.24 ^{***}	567.38 ^{***}	526.38 ^{***}	445.05 ^{***}
	(p = 0.000)	(p = 0.000)	(p = 0.000)	(p = 0.000)	(p = 0.000)	(p = 0.000)
R ²	0.2040	0.2546	0.2575	0.0289	0.0273	0.0266
N	57,891	57,891	57,891	57,891	57,891	57,891
Panel B: Physical exercise and depressive symptom as the mediators						
	Model 3: Physical exercise as mediator			Model 4: Depressive symptoms as mediator		
SO ₂	0.0064 ^{***}			0.0065 ^{***}		
	(0.0004)			(0.0004)		
PM	0.0316 ^{***}			0.0321 ^{***}		
	(0.0023)			(0.0023)		
Wastewater	0.0791 ^{***}			0.0831 ^{***}		
	(0.0155)			(0.0156)		
Physical exercise	-0.0431 ^{***}	-0.0441 ^{***}	-0.0564 ^{***}			
	(0.0133)	(0.0131)	(0.0109)			
Depressive symptoms				0.0151 ^{***}	0.0150 ^{***}	0.0142 ^{***}

Note: ^{***} P < 0.01, ^{**} P < 0.05, ^{*} P < 0.1. Clustered-robust standard errors are in parentheses. The other control variables were the same as shown in Table 2.

Panel A: The effect of environmental pollution on mediators						
				(0.0026)	(0.0026)	(0.0024)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Hausman test	246.25 ^{***}	254.54 ^{***}	301.17 ^{***}	497.03 ^{***}	507.84 ^{***}	610.30 ^{***}
	(p = 0.000)	(p = 0.000)	(p = 0.000)	(p = 0.000)	(p = 0.000)	(p = 0.000)
Wald test	593.16 ^{***}	478.56 ^{***}	366.60 ^{***}	619.85 ^{***}	513.40 ^{***}	375.69 ^{***}
	(p = 0.000)	(p = 0.000)	(p = 0.000)	(p = 0.000)	(p = 0.000)	(p = 0.000)
N	57,891	57,891	57,891	57,891	57,891	57,891
Note: ^{***} P < 0.01, ^{**} P < 0.05, [*] P < 0.1. Clustered-robust standard errors are in parentheses. The other control variables were the same as shown in Table 2.						

Panel B in Table 3 presents the results for the mediation effect, and marks the second step of our mechanism analysis. Statistical mediation was demonstrated by a fall in or loss of significance of the coefficient on the environmental pollution variables when controlling for the mediating indicator (Baron and Kenny, 1986; Wen and Ye, 2014). As is shown in Panel B, the effects of three pollutants on the number of chronic diseases fell after adding the mediating effect of physical exercise and depression. The negative effect of SO₂, PM, and wastewater on health was significantly reduced by 1.54%, 2.47%, and 4.52%, respectively. The negative effect of PM was reduced by 0.93% through the mediator “depression.” These findings support the view that environmental pollution indeed limited middle-aged and older people’s capacity to engage in intense physical exercise and increased their levels of depression. They highlight possible mechanisms through which the risk of chronic illnesses is increased by environmental pollution in China.

Moderation analysis

The adverse impact of air and water pollution on individuals’ health has become an increasingly serious problem. The Chinese government has repeatedly stressed the importance of environmental protection, which may alleviate the negative effect of exposure to industrial pollution on citizens’ physical health. A moderator is a variable that alters the strength or direction of the relationship between the environmental pollution and health (Holmbeck, 1997). We discovered that air and water pollutants emissions fell after 2013, which can be explained by the fact that the Chinese central government under Mr Xi took greater efforts to reduce pollution (Gao et al., 2016). We therefore used the pollution control policies issued in 2013 as the moderator. Because environmental improvement policies become more influential over time, we created the variable “policy” coded as the number of years since these policies were implemented in 2011, 2013, 2015, and 2018, which ranged from 0 to 6. We added the interaction term to the health equation, which was created by multiplying the environmental pollutants emissions and the moderator

(Gao et al., 2016; Kamimura et al., 2017). We further examined the role of pollution control policies with the moderation model.

We used the interaction term created by multiplying the SO₂, PM and wastewater emissions and the moderator separately (Holmbeck, 1997; Kenny and Judd, 1984), to examine the role of pollution control policies in reducing the negative effect of environmental pollution. The results in Model 3 of Table 4 show that the negative effect of SO₂, PM, and wastewater reduced by 0.17%, 0.38%, and 0.69%, respectively, through the pollution control policies indicator. Therefore, the pollution control policies did significantly reduce the negative relationship between environmental pollution and chronic diseases among middle-aged and older people.

Table 4
Moderate effect of environmental pollution.

Model 1: SO ₂		Model 2: PM		Model 3: Wastewater	
SO ₂	0.0056 ^{***} (0.0012)	PM	0.0150 ^{***} (0.0043)	Wastewater	0.0268 ^{**} (0.0145)
Policy	-0.0441 ^{***} (0.0075)	Policy	-0.0425 ^{***} (0.0077)	Policy	-0.0454 ^{***} (0.0063)
SO ₂ *Policy	-0.0017 ^{***} (0.0004)	PM*Policy	-0.0038 ^{***} (0.0011)	Wastewater*Policy	-0.0069 ^{**} (0.0027)
Control variables	Yes	Control variables	Yes	Control variables	Yes
Hausman test	136.28 ^{***} (p = 0.000)	Hausman test	138.06 ^{***} (p = 0.018)	Hausman test	249.50 ^{***} (p = 0.000)
Wald test	601.97 ^{***} (p = 0.000)	Wald test	601.97 ^{***} (p = 0.000)	Wald test	779.87 ^{***} (p = 0.000)
N	57,891	N	57,891	N	57,891

Note: ^{***} P < 0.01, ^{**} P < 0.05, ^{*} P < 0.1. Clustered-robust standard errors are in parentheses. The other control variables were the same as shown in Table 2.

Discussion

The present study considered how the air and water pollution affected the health of adults aged 45 years and older in China. We found clear evidence that environmental pollution was associated with poorer

health status. In particular, air and water pollutants significantly increased both the risk of chronic diseases as well as the number of chronic diseases. These findings were consistent with other studies. Brook et al. (2010) and Shanley et al. (2016) used the US data set and found that long-term exposure to PM is associated with increased cardiovascular disease. Shan et al. (2016) found that SO₂ had a significant negative effect on the self-report health of patients with heart disease and ischemic stroke in China. Yang et al. (2018) found that air pollution increased the risk of diabetes in Liaoning province in China.

We discovered that the effects of environmental pollution varied according to age, sex, household income, and residential area. In particular, the greatest negative effect of air and water pollution on health was found among 60–74-year-olds, females, adults of lower income, and urban residents. Furthermore, we revealed two possible channels through which the air and water pollutants reduced middle-aged and old people's physical activities and increased their depression levels, ultimately leading to worse chronic conditions. Finally, we found pollution control policies did alleviate the negative impact of environmental pollution on the health of the middle-aged and the elderly.

Our findings have a number of implications for public policies designed to reduce environmental pollution and its health costs and to improve the health of the elderly. The moderator effect of pollution control policies suggests the need for developing, testing, and implementing an appropriate mix of policy instruments to prevent, control, or dramatically reduce environmental pollution, as well as the for monitoring the efficacy of air and water pollution prevention efforts. For example, investment to increase green space is essential. This can benefit residents' psychological well-being, encourage middle-aged and old people to undertake more physical activity, and reduce air pollution (Gascon et al., 2016; Liu et al., 2017). In addition, adults of lower income can be plunged into poverty and poorer health because of environmental pollution. A vicious circle is thus created. A comprehensive plan for environmental protection, health reform, and poverty alleviation programs should be tailored to the low-income elderly to dissipate the negative effect of environmental hazards on health.

The present study has several limitations. First, because of a lack of operational data at the prefecture level, we were unable to use other air pollution indicators, such as respirable PM (PM_{2.5} and PM₁₀). We were also unable to establish concentrations of air pollution. Second, we were limited to industrial air and water pollutants again because of a lack of (access to) data. Future studies could evaluate the effect of other environmental pollutants to which people are exposed in their daily lives, for instance localized, traffic, and domestic pollutants. Third, it would be helpful to identify the spatial spillover effects of pollution, because pollution is apt to diffuse and migrate across different regions. In particular, it would be valuable to do this at provincial rather than prefecture level. The spatial spillover effects are not apparent in our study because most of the counties/districts surveyed in CHARLS are not adjacent to each other. Finally, we focused on physical chronic diseases because they are the most common cause of death among elderly Chinese people. Future researchers could examine in detail the subjective health damage caused to the elderly by environmental pollution.

Conclusions

This is the first study to assess the effects of air and water pollution at the prefecture level on the chronic disease risk of the middle-aged and elderly in China. It has found quite robust evidence that SO₂, PM, and wastewater emissions per unit area significantly increased the number of chronic diseases, indicating that they have a corrosive effect on health status. Among all the subgroups, the elderly aged between 60–74, females, adults of lower income, and urban residents faced the greatest risk of chronic disease from environmental pollution. The study further disentangled the channels of physical activity and symptoms of depression through which health is comprised by pollution. Finally, pollution control policies did reduce the negative impact of environmental pollution on the health status of the middle-aged and elderly in China.

Declarations

Ethics approval and consent to participate: Not applicable.

Consent for publication: Not applicable.

Availability of data and materials: The datasets used during the current study are available from the corresponding author on reasonable request.

Conflict of interest: The authors declare that they have no competing interests.

Funding: This study was supported by the National Social Science Foundation of China (No.19CSH073).

Acknowledgments: We would like to acknowledge the China Health and Retirement Longitudinal Study (CHARLS) team for providing data.

Author Contributions:

Hongli Fan: Conceptualization, Methodology, Data Curation, Formal analysis, Writing - Original Draft, Supervision, Funding acquisition, Project administration.

Yingcheng Wang: Methodology, Software, Formal analysis, Data Curation, Writing - Original Draft.

Ying Wang: Data Curation, Verification.

Peter C. Coyte: Methodology, Formal analysis, Writing - Review & Editing.

References

1. Adjaye-Gbewonyo K, Kawachi I, Subramanian SV, Avendano M (2018) High social trust associated with increased depressive symptoms in a longitudinal South African sample. *Soc Sci Med* 197: 127-135 <http://dxdoiorg/101016/jsocscimed201712003>

2. Ahmad N A, Ismail N W, Sidique SFA, et al. (2020) Air pollution effects on adult mortality rate in developing countries. *Environ. Sci. Pollut Res* 28(2): 1-13 <http://dxdoiorg/10.1007/s11356-020-11191-3>
3. Attard SM, Herring AH, Mayer-Davis EJ, Popkin BM, Meigs JB, Gordon-Larsen P (2012) Multilevel examination of diabetes in modernising China: What elements of urbanisation are most associated with diabetes? *Diabetologia* 55(12): 3182-3192 <http://dxdoiorg/101007/s00125-012-2697-8>
4. Baron RM, Kenny DA (1986) The moderator-mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations. *J Pers Soc Psychol* 51(6): 1173-1182 <http://dxdoiorg/101037//0022-35145161173>
5. Brook RD, Rajagopalan S, et al. (2010) Particulate matter air pollution and cardiovascular disease: An update to the scientific statement from the American Heart Association *Circulation* 121: 2331–2378 <http://dxdoiorg/101161/CIR0b013e3181dbee1>
6. Cai L, He J, Song Y, Zhao K, Cui W (2013) Association of obesity with socio-economic factors and obesity-related chronic diseases in rural southwest. *China Public Health* 127(3): 247-251 <http://dxdoiorg/101016/jpuhe201212027>
7. Chen L, Fan HL, Chu et al. (2020) The double-burden effect: does the combination of informal care and work cause adverse health outcomes among females in China. *J Aging Health* 32(9): 1222-1232 <http://dxdoiorg/101177/0898264320910916>
8. Cui EH, Jiang SZ, Jia SB (2016) Research on the impact of environmental pollution, commercial health insurance to health costs: Based on the empirical analysis of provincial panel data. *Nankai Econ Stud* (6): 140-150 <http://dxdoiorg/1014116/jnkes201606009>
9. Deng QH, Lu C, Li YG, Chen L, He YR, Sundell J, Norbäck D, (2017) Association between prenatal exposure to industrial air pollution and onset of early childhood ear infection in China. *Atmos Environ* 157: 18-26 <http://dxdoiorg/101016/jatmosenv201703005>
10. Dong XY, He QH, (2019) Study on the relationship between air pollution and mental health of middle-aged and old people. *China Econ Stud* (05): 50-61 <http://dxdoiorg/1019365/jissn1000-418120190504>
11. Epping-Jordan JE, Pruitt SD, Bengoa R, Wagner EH (2004) Improving the quality of health care for chronic conditions. *Qual Safety Health Care* 13(4): 295-305 <http://dxdoiorg/101136/qhc134299>
12. Fagbamigbe, A, Adebowale, AS, 2014 Current and predicted fertility using Poisson regression model: Evidence from 2008 Nigerian Demographic Health Survey *Afr J Reprod Health* 18(1), 71-83 <https://www.jstor.org/stable/24362495>
13. Fan HL, Yan QY, Peter CC, Yu WG (2019) Does public health insurance coverage lead to better health outcomes? Evidence from Chinese adults. *J Health Care Organ ProvFinanc* 56:46958019842000 <http://dxdoiorg/101177/0046958019842000>
14. Fayomi GU, Mini SE, Fayomi OSI, et al (2019) Overview of industrial pollution activities and its curbing mechanisms. *IOP Confer Series Mater Sci Eng* 640: 012097 <http://dxdoiorg/101088/1757-899X/640/1/012097>

15. Fotourehchi Z (2016) Health effects of air pollution: An empirical analysis for developing countries. *Atmos Pollut Res* 7(1): 201-206 <http://dxdoiorg/101016/japr201508011>
16. Freedman VA, Martin LG (2000) Contribution of chronic conditions to aggregate changes in old-age functioning. *Am J Public Health* 90(11): 1755-1760 <http://dxdoiorg/102105/AJPH90111755>
17. Gascon M, Triguero-Mas M, Martinez D, et al. (2016) Residential green spaces and mortality: A systematic review. *Environ Int* 86: 60-67 <http://dxdoiorg/101016/jenvint201510013>
18. Gao J, Yuan Z, Liu X, Xia X, Huang X, Dong Z (2016) Improving air pollution control policy in China: a perspective based on cost-benefit analysis *Sci Total Environ* 543: 307-314 <http://dxdoiorg/101016/jscitotenv201511037>
19. Gong X, Lin Y, Benjamin ZF (2018) Industrial air pollution and low birth weight: A case-control study in Texas. *Environ Sci Pollut Res Int* 25(30): 30375-30389 <http://dxdoiorg/101007/s11356-018-2941-y>
20. Han Y, Yan W (2014) Bimetallic nickel-iron nanoparticles for groundwater decontamination: Effect of groundwater constituents on surface deactivation. *Water Res* 66: 149-159 <http://dxdoiorg/101016/jwatres201408001>
21. He MF (2019) Prevalence and impact of depression symptoms among middle-aged and older Chinese adults with chronic disease. Jilin University <http://cdmdcnkicomcn/Article/CDMD-10183-1019159182htm>
22. Holmbeck GN (1997) Toward terminological, conceptual, and statistical clarity in the study of mediators and moderators: Examples from the child-clinical and pediatric psychology literatures. *J Consult Clin Psychol* 65: 599-610 <http://dxdoiorg/101037//0022-006X654599>
23. Huang CY, Zhao XY, Lu Y, Wang LC, Hu YH, Zhang J, Huang QL, Chen G (2018) Changes in life expectancy from 2006 to 2015 in Suzhou, east China: Contributions of age-and cause-specific mortality. *Asia-Pac J Public Health* 30(1): 75-84 <http://dxdoiorg/101177/1010539517752429>
24. Huang JZ, Ma YX, Hu GY (2020) A review of research on travel behaviors of the elderly from a health perspective. *Sci Technol Rev* 38(07): 69-75 <http://dxdoiorg/103981/jissn1000-7857202007009>
25. Kamimura A, Armenta B, Nourian M, Assasnik N, Nourian K, Chernenko A (2017) Perceived environmental pollution and its impact on health in China, Japan, and South Korea. *J Prev Med Public Health* 50: 188-194 <http://dxdoiorg/103961/jpmph17044>
26. Kenny DA, Judd CM, Estimating the linear and interactive effects of latent variables. *Psychol Bull* 1984, 96(1): 201-210 <http://dxdoiorg/101037/0033-2909961201>
27. Lelieveld J, Evans J S, Fnais M, Giannadaki D, Pozzer A 2015 The contribution of outdoor air pollution sources to premature mortality on a global scale. *Nature: Int Weekly J Sci* 525(3): 367-371 <http://dxdoiorg/101038/nature15371>
28. Li H, Ping G (2016) Power law for the rates of different numbers of chronic diseases among elderly Chinese people. *Open J Stat* 6(6):1155-1165 <http://dxdoiorg/104236/ojs201666093>
29. Liu X, Liang X, Li X, Xu X, Ou J, Chen Y, Li S, Wang S, Pei F (2017) A future land use simulation model (FLUS) for simulating multiple land use scenarios by coupling human and natural effects. *Landsc Urban Plan* 168: 94-116 <http://dxdoiorg/101016/jlandurbplan201709019>

30. Li X, Wang C, Zhang G, Xiao L, Dixon J (2017) Urbanisation, inequality and non-communicable disease risk. *Ann Nutr Metab* 5(5): 313 [http://dxdoiorg/101016/S2213-8587\(17\)30116-X](http://dxdoiorg/101016/S2213-8587(17)30116-X)
31. Li Y, Wu H, Shen K, et al. (2020) Is environmental pressure distributed equally in China? Empirical evidence from provincial and industrial panel data analysis. *Sci Total Environ* 718: 1373631-13736315 <http://dxdoiorg/101016/jscitotenv2020137363>
32. Lü JJ, Liang L, Feng Y, Li R, Liu Y (2015) Air pollution exposure and physical activity in China: Current knowledge, public health implications, and future research needs. *Int J Environ Res Public Health* 12: 14887-14897 <http://dxdoiorg/103390/ijerph121114887>
33. Nihit G, Mahesh K, David C (2019) Early-life exposure to ambient fine particulate air pollution and infant mortality: pooled evidence from 43 low- and middle-income countries. *Int J Epidemiol* 48(4), 1125-1141 <http://dxdoiorg/101093/ije/dyz090>
34. Ning MN, Gong JQ, Zheng XH, Zhuang J (2016) Does new rural pension scheme decrease elderly labor supply? Evidence from CHARLS. *China Econ Rev* 41: 315-330 <http://dxdoiorg/101016/jchieco201604006>
35. NoorUlHuda S, (2020) Do we need a new perspective on chronic diseases? The combined effects of workplace stress and socioeconomic status as non-traditional disease risk factors in Canada. University of Waterloo <https://uwspaceuwaterlooca/handle/10012/15526>
36. Peng L, Xiao ST, Gao W, Zhou Y, Zhou J, Yang DD, Ye XF (2020) Short-term associations between size-fractionated particulate air pollution and COPD mortality in Shanghai. *Environ Pollut* 257: 113483 <http://dxdoiorg/10.1016/j.envpol.2019.113483>
37. Pope CA, Dockery DW (2013) Air pollution and life expectancy in China and beyond. *Proc Natl Acad Sci U S A* 110(32): 12861-12862 <http://dxdoiorg/10.1073/pnas.1310925110>
38. Protani M, Coory M, Martin JH (2010) Effect of obesity on survival of women with breast cancer: Systematic review and meta-analysis. *Breast Cancer Res Treat* 123(3): 627-635 <http://dxdoiorg/101007/s10549-010-0990-0>
39. Ranci re F, Bougas N, Viola M, Momas I (2017) Early exposure to traffic-related air pollution, respiratory symptoms at 4 years of age, and potential effect modification by parental allergy, stressful family events, and sex: A prospective follow-up study of the PARIS birth cohort. *Environ Health Perspect* 125(4): 737-745. <http://dxdoiorg/101289/EHP239>
40. Shan J, Li HY, Liu GF, Yang X, Dong W, Jian WY, Deng FR, Guo XB (2016) Effect of air pollution on health service demand of the elderly and middle-age patients with hypertension, cardiovascular and cerebrovascular diseases: based on analysis of data from CHARLS. *J Peking Univ (Health Sci)* 48(03): 460-464. <http://dxdoiorg/103969/jissn1671-167X201603015>
41. Shanley RP, Hayes RB, Cromar KR, Ito K, Gordon T, Ahn J (2016) Particulate air pollution and clinical cardiovascular disease risk factors. *Epidemiology* 27(2): 291-298 <http://dxdoiorg/101097/EDE000000000000426>
42. Siavash M, Sadeghi M, Salarifar F, Amini M, Shojaee-Moradie F (2008) Comparison of body mass index and waist/height ratio in predicting definite coronary artery disease. *Ann Nutr Metab* 53(3-4),

- 162-166 PMID: 19011279 <http://dxdoiorg/101159/000172977>
43. Sram RJ, Binkova B, Dostal M, et al. (2013) Health impact of air pollution to children. *Int J Hyg Environ Health*, 216(5), 533-540 <http://dxdoiorg/101016/jijheh201212001>
44. Stock JH, Watson MW (2008) Heteroskedasticity: Robust standard errors for fixed effects panel data regression. *Econometrica* 76(1), 155-174 <http://dxdoiorg/101111/j0012-9682200800821x>
45. Susan A, Everson-Rose et al. (2014) Chronic stress, depressive symptoms, anger, hostility, and risk of stroke and transient ischemic attack in the multi-ethnic study of atherosclerosis. *Stroke* 45(8), 2318-2323 PMID: 25013018 <http://dxdoiorg/101161/STROKEAHA114004815>
46. Tao Y, Li F, Crittenden J, Lu ZM, Ou WX, Song YS (2019) Measuring urban environmental sustainability performance in China: A multi-scale comparison among different cities, urban clusters, and geographic regions. *Cities* 94: 200-210 <http://dxdoiorg/101016/j.cities201906014>
47. Wang Q, Yang Z (2016) Industrial water pollution, water environment treatment, and health risks in China. *Environ Pollut* 218: 358-365 <http://dxdoiorg/101016/j.envpol201607011>
48. Wang RY, Xue DS, Liu Y, Liu PH, Chen HS (2018) The relationship between air pollution and depression in China: is neighbourhood social capital protective. *Int J Environ Res Public Health* 15(6): 1160 <http://dxdoiorg/103390/ijerph15061160>
49. Wang YY (2019) Research on current situation and countermeasures of coal-fired air pollutants control in China. *Coal Econ Res* 39(08): 66-70 <http://dxdoiorg/1013202/jcnkicer201908004>
50. Wen ZL, Ye BJ (2014) Analyses of mediating effects: the development of methods and models. *Adv Psychol Sci* 22(5): 731-745 <http://dxdoiorg/103724/SPJ1042201400731>
51. Wolff JL, Starfield B, Anderson G (2002) Prevalence expenditures and complications of multiple chronic conditions in the elderly. *Arch Int Med* 162: 2269-2276 PMID: 12418941 <http://dxdoiorg/101001/archinte162202269>
52. Xia CC, Li JX (2018) Influence of socioeconomic status on the middle aged and elderly's chronic non-infectious disease in China: the case of cardiovascular disease and chronic respiratory disease. *Popul J* 40(03): 82-92 <http://dxdoiorg/1016405/jcnki1004-129X201803008>
53. Xiong Z (2019) Challenges and countermeasures of chronic diseases prevention and control in China. *Chin J Prev Control Chronic Dis*, 27(09):720-721 <http://dxdoiorg/1016386/jcjpccdissn1004-6194201909021>
54. Yang BY, Qian Z, Li S, et al. (2018) Ambient air pollution in relation to diabetes and glucose-homoeostasis markers in China: a cross-sectional study with findings from the 33 Communities Chinese Health Study. *Lancet* 2(2): e64-e73 [http://dxdoiorg/101016/S2542-5196\(18\)30001-9](http://dxdoiorg/101016/S2542-5196(18)30001-9)
55. Zeng JY, He QQ (2016) Does industrial air pollution drive health care expenditures? Spatial evidence from China. *J Clean Prod* 218: 400-408 <http://dxdoiorg/101016/j.jclepro201901288>
56. Zhao YH, Hu YS, Smith JP, Strauss J, Yang GH (2014) Cohort profile: The China Health and Retirement Longitudinal Study (CHARLS). *Int J Epidemiol* 43(1): 61-68 <http://dxdoiorg/101093/ije/dys203>

Figures

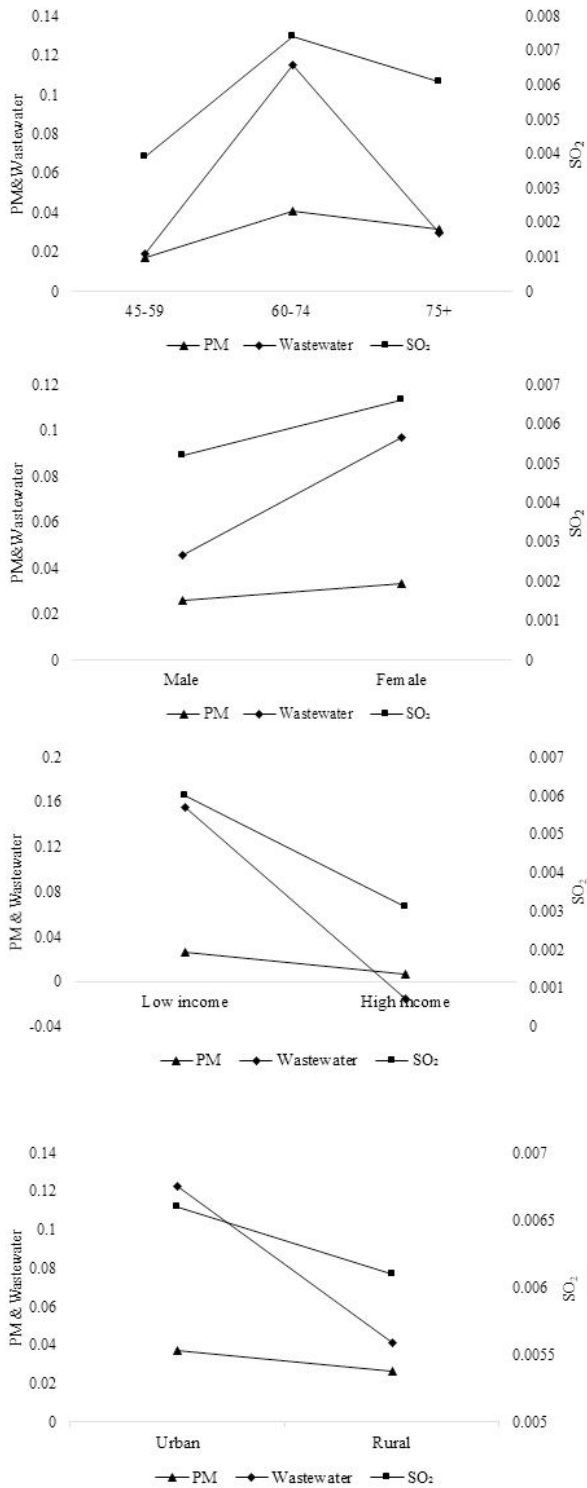


Figure 1

A The effect of environmental pollution by age group. B The effect of environmental pollution by sex group. C The effect of environmental pollution by household income group. D The effect of environmental pollution by residential area group.

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- [Appendix.docx](#)