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Industrial water pollution, water environment treatment, and health risks in China☆

Qing Wang [b,*,1], Zhiming Yang [a,1]

[a] Donlinks School of Economics and Management, University of Science and Technology Beijing, Beijing, 100083, China
[b] School of Business, Dalian University of Technology, Panjin, 124221, Liaoning, China

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ABSTRACT

The negative health effects of water pollution remain a major source of morbidity and mortality in China. The Chinese government is making great efforts to strengthen water environment treatment; however, no studies have evaluated the effects of water treatment on human health by water pollution in China. This study evaluated the association between water pollution and health outcomes, and determined the extent to which environmental regulations on water pollution may lead to health benefits. Data were extracted from the 2011 and 2013 China Health and Retirement Longitudinal Study (CHARLS). Random effects model and random effects Logit model were applied to study the relationship between health and water pollution, while a Mediator model was used to estimate the effects of environmental water treatment on health outcomes by the intensity of water pollution. Unsurprisingly, water pollution was negatively associated with health outcomes, and the common pollutants in industrial wastewater had differential impacts on health outcomes. The effects were stronger for low-income respondents. Water environment treatment led to improved health outcomes among Chinese people. Reduced water pollution mediated the associations between water environment treatment and health outcomes. The results of this study offer compelling evidence to support treatment of water pollution in China.

1. Introduction

Since the 1970s, China has experienced dramatic environmental degradation, including water pollution, as a by-product of rapid economic development and industrialization (Ministry of Environmental Protection, 2015). Pollutant discharge causes widespread organic pollution, toxic pollution, and eutrophication, along with severe ecological destruction (Miao et al., 2012). For example, the latest review showed that the Tonghui River and Guanting Reservoir of Beijing, Minjiang River Estuary and Wuchuan River in China had comparatively higher ranges and mean values of dichlorodiphenyltrichloroethanes (DDTs) and hexachlorocyclohexanes (HCHs) in water (Ahmed et al., 2015). Concurrent with the water pollution, the country has also experienced an increase in health risks (Lu et al., 2015). Approximately 190 million people fall ill and 60,000 people die from a range of other diseases and injuries associated with water pollution each year (Tao and Xin, 2014).

The health impacts of water pollution are of increasing concern for Chinese citizens and policymakers, and the unaddressed health consequences at regional and global levels pose major policy challenges (Lu et al., 2008; Miao et al., 2015). Over 70 percent of Chinese people feel threatened by water pollution (China Youth Daily, 2013). The country has stepped up its efforts to tackle the problem (Zhang et al., 2012, 2013). Generally, increasing environmental awareness coupled with more stringent regulation standards has triggered various industries to challenge themselves in seeking appropriate wastewater treatment technologies (Teh et al., 2016a).

Researchers have reported connections between water pollution and acute water-borne diseases which include hepatitis, cholera, dysentery, cryptosporidiosis, giardiasis, diarrhea and typhoid (WB-SCEA, 2006; Cutler and Miller, 2005; Jalan and Ravallion, 2003; Roushdy et al., 2012), and also, the increasing negative effects of water pollution have put more people at risk of carcinogenic diseases, potentially contributing to cancer villages (Lu et al., 2015; Lin et al., 2000; Morales-Suarez-Varela et al., 1995;

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* Corresponding author.
E-mail address: wangqing1984@126.com (Q. Wang).
[1] Joint first authors.

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Ebenstein, 2012). Much of what we know about the marginal effects of pollution on health is derived from data reported in developed countries, where pollution levels are relatively low. Compared to developed countries, health risks related to water pollution in developing countries are more serious. About 2.3 billion peoples in the whole world are suffering from water related diseases. Among them, 2.2 billion people live in developing countries (e.g. India, Pakistan) (Jalan and Ravallion, 2003; Azizullah et al., 2011). Given the low levels of water pollution in developed countries, these estimates may not be valid in developing countries if there is a nonlinear dose relationship between pollution and health. Moreover, to our best knowledge, no other study has analyzed the health effects of environmental treatment in China.

Using nationally representative data, this study examined the effects of industrial water pollution and related environmental regulations pertaining to water pollution on individual health outcomes in China. To be specific, this study makes three major contributions to the existing literature. First, by exploiting treatment-induced changes in water pollution, it addresses a policy-relevant question: to what extent does environmental treatment in developing countries lead to improved health outcomes? This is the first study to evaluate the effects of water pollution treatment on human health in China. Second, this study contributes to our understanding of the relationship between water pollution and health outcomes in a developing country with high water pollution levels using nationally representative individual data. According to the 2012 Environmental Performance Index from Yale University, China is one of the worst performers (ranked 116th of 132 countries). Thus, findings in China provide compelling evidence applicable to the unique context of developing countries where water pollution levels are relatively high. Third, although previous research in other countries has linked health disparities to socioeconomic status, much less is known about differences in health outcomes due to exposure to water pollution (Zhang et al., 2010). Diseases related to pollution remain a major source of health problems, especially among people of low socioeconomic status in China; the significant income-related health disparities in China may partly result from different exposures to polluted water (Zhang et al., 2010). Thus, the present study aims to identify vulnerable populations, which may be useful for policy design.

2. Data and methods

2.1. Water pollution data

This study investigated 51 sample cities that (a) were distributed nationwide and representative of China's various geographical locations and climatic conditions; (b) varied in population and economic scales; and (c) were part of China's collection of environmental protection pilot cities, from which data on environmental pollution is collected yearly by the Chinese Ministry of Environment Protection; thus the data from these 51 cities have strong reliability and robustness.

Pollution intensity refers to the indicator of pollution emission per industrial gross domestic product. Per industrial gross domestic product represents industrial economic output and eliminates the effects of population scale. In accordance with previous environmental research, pollution intensity was selected as a pollution indicator to measure the effects of pollution on health outcomes (Tang and Mudd, 2015). Concentrations of lead (Pb), arsenic (As), mercury (Hg), chemical oxygen demand (COD), ammonia nitrogen (NH_3-N), and volatile phenol (Fn) per industrial gross domestic product were also used to measure water pollution. These indicators of the liquid phases of pollutants can be used to map a city's industrial water pollution. Moreover, these types of pollutants are consistent with official statistical indicators. Sequential data on the emissions of such pollutants in 51 cities were obtained from the 2011 and 2013 China Environment Yearbook. Industrial gross domestic product and populations within the same time sequence were obtained from the China City Statistical Yearbook.

According to the method described by Managi and Kaneko (2009), the efficiency in terms of water pollution treatment at the city level was calculated as:

$$TFP(L) = TFP_B(L) - TFP_A(L) \tag{1}$$

Where $TFP(L)$ is the environmental management productivity, $TFP_A(L)$ is calculated based on the Luenberger productivity index (the Luenberger productivity index is $TFP(L) = (1/2) \times \{[D^t{}_i(t) - D^t{}_i(t+1)] + [D^{t+1}{}_i(t) - D^{t+1}{}_i(t+1)]\}$, where $D^t{}_i(t)$ denotes the total factor productivity measured by a sequential slack-based directional distance function (SSDDF)), which includes only market inputs and outputs,[2] and $TFP_B(L)$ is calculated based on the Luenberger productivity index, which includes environmental inputs and outputs in addition to the market inputs and outputs.[3] $TFP(L) > 0$ represents productivity progress in terms of environmental management. The environmental management productivity, which describes the relationship between the outputs and inputs of environmental management, is widely considered to be cost-effective environmental economic instrument for pollution control (Lannelongue et al., 2015). Such a continuous measure could capture the difference in intensity of water pollution treatment among cities.

2.2. Health outcomes and demographic data

This study used data from the 2011 and 2013 China Health and Retirement Longitudinal Study (CHARLS). The CHARLS is a nationally representative sample of Chinese residents aged 45 years and above. The baseline national wave of CHARLS was fielded in 2011 and contained approximately 10,000 households in 150 counties/districts (a total of 450 villages/resident communities). The overall response rate was 85%. These individuals will be followed up every two years. The CHARLS uses a multi-stage stratified probability-proportionate-to-size (PPS) sampling framework. The CHARLS is similar to the Health and Retirement Study (HRS) in the United States, the English Longitudinal Study of Aging (ELSA) in the United Kingdom, and the Survey of Health, Aging and Retirement in Europe (SHARE). The CHARLS questionnaire includes the following modules: demographics, family structure/transfer, health status and functioning, biomarkers, health care and insurance, work, retirement and pension, income and consumption, assets (individual and household), and community-level information. More information about the CHARLS data can be found at http://charls.ccer.edu.cn/en.

2.2.1. Mental health

Mental health was measured by a seven-item modification of

[2] Labor, physical capital and water withdraw as inputs, and gross industrial output value as desirable output. The gross industrial output is deflated by producer price index in 2011, and the value of physical capital is deflated by price index of investment in fixed assets.

[3] Labor, physical capital and water withdraw, costs of waste water treatment facilities as input indicators. Gross industrial output value as desirable output; industrial waste water discharged, COD in industrial waste water, and NH_3-N discharge in industrial waste water were added as a set of undesirable outputs. The gross industrial output is deflated by producer price index in 2011, and the value of physical capital is deflated by price index of investment in fixed assets.

the Center for Epidemiologic Studies Depression (CES-D) scale (Mirowsky and Ross, 2003). Respondents were directly interviewed about their frequencies of experiencing the following seven depressive symptoms during the previous week: (1) was bothered by things, (2) had trouble keeping mind on tasks, (3) felt depressed, (4) felt everything he/she did was an effort, (5) felt fearful, (6) restless sleep, and (7) felt lonely. This shortened seven-item CES-D scale is commonly used for general populations (Lee, 2009; Maximova and Quesnel-Vallee, 2009) and the validity, reliability and cultural equivalence of the Chinese version have been established (Lam et al., 2005). A summed score of the responses to these seven items was used to indicate mental health, with lower scores indicating fewer depressive disorders and thus better mental health status. This study used the continuous score to indicate mental health rather than adopting a cut-off point to dichotomously distinguish "good" from "poor" mental health with the following considerations: First, the current literature varies on the optimal threshold-point to separate "good" from "poor" mental health in self-reported responses (Cole and Tembo, 2011). Second, symptom burden is a better measure of the functional impairment of mental health than a threshold between "good" and "poor" (Rucci et al., 2003), and it warrants caution when attaching pathological labels to self-reported symptoms. A dimensional scale with higher scores indicating more symptoms is likely to be more accurate and better describe common mental disorders (Hanlon et al., 2008), particularly in the Chinese cultural setting, where mental illness is highly stigmatized and people prefer to acknowledge the somatic disorder related to depression instead of the psychological symptoms (Kleinman, 1977; Liang et al., 1992).

2.2.2. Self-reported physical health

Self-reported physical health status is based on the question: "Would you say your health is excellent, very good, good, fair, or poor?" We construct a binary variable of "bad physical health" that equals 1 if the respondents reported their health as "fair" or "poor", and 0 otherwise.

2.2.3. Individual and family characteristics

Household yearly income per capita, education level, employment status, and rural/urban residence were used to characterize the respondents' socioeconomic status. The education levels were grouped into four categories: no education, no education but can read/write, primary school, and junior high school and above. There were also four types of employment status: unemployed or retired, farmer, informal, and formal employment. Current smoker and/or frequent drinker (Drink more than 2–3 times a week) were included as indicators of the respondents' current health behaviors. The demographic variables included gender (reference group: female), marital status (reference group: married with spouse present (common-law marriage was considered married)), and age.

2.3. Estimation strategy

To estimate the effects of water pollution on health status, the basic regression model was defined as follows:

$$Y_{ijt} = X_{ijt}a + T_{jt}b + u_j + v_i + e_{ijt}, \tag{2}$$

where Y_{ijt} is the health measure of person i in city j in year t.

X_{ijt} represents individuals' characteristics such as age, sex, education,
T_{jt} is a variable indicating the intensity of water pollution,
u_j and v_i are the region and year dummy variables, respectively, and e_{ijt} is the idiosyncratic error term. All standard errors were clustered at the city level.

A mediator model was used to estimate the effects of water environment treatment on health outcomes by water pollution intensity. Water pollution intensity was considered a mediator as it reflected the influence of a given water environment treatment on the health outcomes assessed in this study. Generally speaking, mediation occurred when (1) water environment treatment significantly affected water pollution intensity[4] $T_{jt} = X_{ijt}a + E_{jt}c + u_j + v_i + e_{ijt}$, (2) water environment treatment significantly improved health outcomes in the absence of the water pollution intensity $Y_{ijt} = X_{ijt}a + E_{jt}c + u_j + v_i + e_{ijt}$, (3) water pollution intensity had a significantly and independent effect on health outcomes $Y_{ijt} = X_{ijt}a + T_{jt}b + u_j + v_i + e_{ijt}$, and (4) the coefficients of water environment treatment on health outcomes decreased upon the addition of water pollution intensity to the model. $Y_{ijt} = X_{ijt}a + T_{jt}b + E_{jt}c + u_j + v_i + e_{ijt}$, where E_{jt} is the efficiency in terms of water pollution treatment. Bootstrap case resampling was used to calculate the standard error of the indirect effect.

Since health risks related to water pollution are heterogeneous, rather than fixed effect model, random effects model which hypothesize random individual effects was more properly used to estimate the effects of water pollution and treatment on mental health, in which the coefficient and std. Error were presented (Brainerd and Menon, 2015); because self-reported physical health was a category variable, random effects logit model was applied to estimate the association of water pollution, treatment and physical health, Odds ratios (ORs) with 95% confidence intervals (CIs) were reported.

Stata version 12 was used for all statistical analyses.

3. Results

3.1. Statistical description

Participant characteristics and average water pollutant concentrations across income levels are shown in Table 1. The total study population consisted of 14,487 participants with a mean age of 59 years; 52% were male, 88.08% were married or cohabiting, and 31.84% were retired or unemployed. A minority (18.37%) of participants had no formal education, 15.51% had no formal education but could read and write, and 23.31% had primary school education. A total of 29.88% reported having smoked and 24.86% reported that they drank alcohol frequently. The respondents earned an average of 10,435 Chinese Yuan per year per capita. Among all respondents, 48.73% reported they were in bad physical health (fair, poor), and the average mental health score was 11.68. Compared to participants with low income, those with higher income were slightly less likely to report bad physical health (52.76% vs. 41.58%) and mental health (12.21 vs. 10.77).

Discharged polluted water accounted for 73.4 thousand tons per billion industrial gross domestic product, including 11.16 tons chemical oxygen demand (COD), 0.93 tons ammonia nitrogen, 0.11 tons Fn and other trace heavy metal (including Pb, As, Hg).

[4] Fixed effect model and Random effects model were all applied to estimate the effects of treatment on water pollution intensity. Results from the two models were very similar.

Table 1
Statistical description.

Variable	All sample		High income group		Low income group	
	Mean or n	Std. Dev. or %	Mean or n	Std. Dev. or %	Mean or n	Std. Dev. or %
	N = 14487		N = 5232		N = 9255	
Health outcomes						
Mental health	11.68	4.48	10.77	3.84	12.21	4.74
Self-reported bad physical health	7060	48.73	2170	41.58	4890	52.76
Water pollution intensity (Industrial waste water: 10000 ton/billion Yuan; Pb, As, Hg, COD, NH_3-N, Fn: ton/billion Yuan)						
Industrial waste water	7.336	5.588	6.513	4.767	7.800	5.950
Pb	0.005	0.020	0.005	0.020	0.005	0.019
As	0.012	0.053	0.011	0.052	0.013	0.053
Hg	0.0000289	0.000124	0.0000195	0.0001052	0.0000326	0.0001331
COD	11.155	11.414	9.652	9.789	12.001	12.152
NH_3-N	0.930	1.364	0.861	1.427	0.969	1.325
Fn	0.107	0.325	0.089	0.294	0.118	0.340
Environmental treatment						
Efficiency in terms of water pollution treatment	−0.512	2.010	−0.683	1.926	−0.415	2.050
Individual characteristics						
Age	59.41	10.09	58.69	9.96	59.82	10.14
Male	7523	52.00	2648	50.82	4875	52.67
Married	1723	11.92	438	8.42	1285	13.89
Household income per capita	10434.62	17501.55	22422.65	24528.73	3816.30	4487.44
Education						
No education	2654	18.37	462	8.89	2192	23.69
No education but can read/write	2242	15.51	562	10.81	1680	18.16
Primary school	3368	23.31	972	18.70	2396	25.90
Junior high school and above	6186	42.81	3202	61.60	2984	32.25
Employment status						
Farmer	5460	38.00	2371	46.19	3089	33.44
Unemployed or retired	4576	31.84	667	12.99	3909	42.32
Informal employed	1402	9.76	545	10.62	857	9.28
Formal employed	2932	20.40	1550	30.20	1382	14.96
Health behavior						
Current smoker	4290	29.88	1428	27.73	2862	31.08
Frequent drinker	3555	24.86	1446	28.19	2109	22.99

Table 2
Associations between water pollution intensity and health outcomes.

Variables	Mental health		Self-reported bad physical health	
	Coef.	Std. Err.	Adjusted OR	95% CI
Industrial water pollution intensity	0.047***	0.008	1.014***	0.006,0.022
Log of age	−0.647*	0.346	1.296	−0.095,0.614
Male	0.993***	0.118	0.942	−0.185,0.065
Married	1.103***	0.161	0.892	−0.269,0.041
Log of household income per capita	−0.253***	0.027	0.911***	−0.121,−0.064
Education				
No education but can read/write	0.263	0.183	1.142	−0.032,0.298
Primary school	−0.292*	0.161	1.028	−0.125,0.181
Junior high school and above	−0.738***	0.156	0.794***	−0.381,−0.081
Employment status				
Unemployed or retired	0.020	0.116	0.720***	−0.448,−0.210
Informal employed	−0.284*	0.152	0.576***	−0.722,−0.382
Formal employed	−0.675***	0.122	0.496***	−0.843,−0.561
Current smoker	−0.078	0.109	1.016	−0.107,0.139
Frequent drinker	−0.154	0.102	0.633***	−0.577,−0.339

Notes: Coef. and Robust standard errors were reported for mental health; Odd ratio and CI were reported for physical health.
***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.
Year and region dummy variables were included.

3.2. Associations between water pollution and health outcomes

The associations between exposure to water pollution and health outcomes after adjusting for multiple covariates in China are shown in Table 2. Water pollution was significantly positively associated with health outcomes measures. As water pollution intensity increased, the mental health increased by 0.047 and bad physical health was more likely to be reported by 1.4 percent (CI: 0.006, 0.022), respectively.

The results remained consistent after the analyses were stratified by income (see Table 3). Compared to high-income participants, water pollution more significantly influenced mental and physical health among low-income participants. More precisely, for each water pollution intensity, participants with lower income showed lower mental health than those with higher socioeconomic status (0.036 vs. 0.045 for high and low-income participants, respectively); and respondents with low income were significantly associated with bad physical health, while higher one were not.

Table 3
Associations between water pollution intensity and health outcomes: High income group and Low income group.

Variables	Mental health				Self-reported bad physical health			
	High income group		Low income group		High income group		Low income group	
	Coef.	Std. Err.	Coef.	Std. Err.	Adjusted OR	95% CI	Adjusted OR	95% CI
Industrial water pollution intensity	0.036***	0.013	0.045***	0.010	1.012	−0.003,0.028	1.012**	0.002,0.022
Log of age	−0.440	0.503	−0.530	0.469	1.865**	0.036,1.211	1.256	−0.222,0.678
Male	1.033***	0.163	1.008***	0.163	1.134	−0.074,0.326	0.861*	−0.311,0.010
Married	0.697***	0.250	1.272***	0.207	0.632***	−0.738,−0.179	1.018	−0.171,0.206
Log of household income per capita	−0.239***	0.068	−0.192***	0.034	0.879***	−0.216,−0.042	0.962**	−0.073,−0.003
Education								
No education but can read/write	0.349	0.343	0.280	0.219	1.072	−0.269,0.408	1.202*	−0.007,0.375
Primary school	−0.297	0.304	−0.206	0.193	0.906	−0.408,0.210	1.120	−0.066,0.293
Junior high school and above	−0.794***	0.282	−0.448**	0.202	0.753*	−0.569,0.001	0.921	−0.269,0.105
Employment status								
Unemployed or retired	−0.009	0.202	−0.110	0.149	0.758**	−0.518,−0.037	0.647***	−0.579,−0.292
Informal employed	−0.032	0.221	−0.537**	0.210	0.622***	−0.743,−0.206	0.527***	−0.862,−0.419
Formal employed	−0.643***	0.164	−0.695***	0.183	0.588***	−0.740,−0.323	0.425***	−1.052,−0.659
Current smoker	−0.131	0.154	−0.079	0.148	1.118	−0.089,0.311	0.932	−0.227,0.085
Frequent drinker	−0.015	0.139	−0.233*	0.141	0.738***	−0.493,−0.115	0.589***	−0.682,−0.376

Notes: Coef. and Robust standard errors were reported for mental health; Odd ratio and CI were reported for physical health.
***p < 0.01, **p < 0.05, *p < 0.1.
Year and region dummy variables were included.

Table 4
Associations between the common pollutants in industrial wastewater and health outcomes.

Variable	Mental health		Self-reported bad physical health	
	Coef.	Std. Err.	Adjusted OR	95% CI
Heavy metals				
Pb	6.277***	2.086	1.478	−1.876,2.658
As	3.740***	0.804	1.361	−0.535,1.152
Hg	745.556**	322.590	6.7e + 141*	−57.647,710.771
Other pollutants				
COD	0.014***	0.004	1.008***	0.003,0.012
NH_3-N	0.108***	0.029	1.049***	0.014,0.081
Fn	0.249*	0.130	1.014	−0.130,0.157

Notes: Coef. and Robust standard errors were reported for mental health; Odd ratio and CI were reported for physical health.
***p < 0.01, **p < 0.05, *p < 0.1.
Individual characteristics, education, employment status, health behavior, year and region dummy variables were included.

3.3. *Associations between the common pollutants in industrial wastewater and health outcomes*

The associations between the common pollutants in industrial wastewater and health outcomes after adjusting for multiple covariates are shown in Table 4. The common elements in industrial wastewater resulted in poor health outcomes. Pb, As, Hg, COD, NH_3-N and Fn were all significantly associated with mental health, while only Hg, COD and NH_3-N were significantly associated with physical health.

3.4. *Effects of water environment treatment on health outcomes*

Table 5 shows the effects of water environment treatment on health outcomes according to decreasing intensity of water pollution. Water environment treatment significantly affected water pollution intensity, which was available from author at request. Table 2 shows that water pollution intensity had a significant and independent effect on health outcomes. As expected, the effects of water environment treatment on health outcomes were favorable. Water treatment lead to improved mental health by 0.07 and decreased likelihood of bad physical health by 0.8 percent in the absence of water pollution (available at request). The coefficients decreased with the addition of water pollution. After controlling water pollution, increased water environment treatment resulted in mental and physical health improvements by 0.12 and 2 percent, respectively. Water pollution treatment may directly and indirectly influence health. The efficiency of water pollution treatment was associated with improved health outcomes by decreasing the intensity of water pollution in China.

4. Discussion

4.1. *Health effects of water pollution and water environment treatment*

This study explored the relationships between water pollution intensity, treatment efficiency, and health outcomes in China. Our results revealed a significant negative relationship between water pollution and health outcomes, a finding similar to results reported by previous studies (Cutler and Miller, 2005; Jalan and Ravallion, 2003; Roushdy et al., 2012; Lin et al., 2000; Morales-Suarez-Varela et al., 1995; Ebenstein, 2012; Zhang, 2012).

Although the common pollutants in industrial wastewater led to increased health risks, the health effects varied among the elements found in water pollution. Compared to other elements, heavy metals had greater effects on mental health but not on physical health instantly. One possible explanation for this difference may be that although the negative impacts of heavy metal are well known, heavy metal contaminants may not instantly negative influence physical health until heavy metal accumulates in the human body to a threshold and has long-term effects on physical health, while non-metallic pollutants may be gradually detoxified in vivo (Cheng, 2003).

Our results revealed water pollution-associated disparities in health outcomes related to income, with a greater relative risk for low-income individuals. High-income individuals were more capable of compensating for increased pollution by reducing their exposure to protect their health, which likely contributed to the observation that their health outcomes was less influenced by water pollution. The rich have the greater chance to live in areas with better water quality and make other health capital investments (Lavaine, 2015). Similarly, Chakraborty and Zandbergen (2007) observed that children from low-income household are more likely to attend schools near hazardous facilities or busy

Table 5
Health effects of water environment treatment.

Variables	Mental health		Self-reported bad physical health	
	Coef.	Std. Err.	Adjusted OR	95% CI
Industrial water pollution intensity	0.062***	0.008	1.016***	0.007,0.025
Efficiency in terms of water pollution treatment	−0.120***	0.020	0.980*	−0.044,0.002
Log of age	−0.657*	0.345	1.295	−0.096,0.612
Male	0.999***	0.118	0.942	−0.184,0.065
Married	1.112***	0.161	0.894	−0.268,0.043
Log of household income per capita	−0.252***	0.027	0.911***	−0.121,−0.064
Education				
No education but can read/write	0.262	0.183	1.141	−0.033,0.297
Primary school	−0.298*	0.161	1.026	−0.127,0.179
Junior high school and above	−0.748***	0.156	0.792***	−0.383,−0.084
Employment status				
Unemployed or retired	0.030	0.116	0.721***	−0.446,−0.208
Informal employed	−0.264*	0.153	0.578***	−0.718,−0.378
Formal employed	−0.668***	0.122	0.496***	−0.842,−0.559
Current smoker	−0.068	0.109	1.017	−0.106,0.140
Frequent drinker	−0.154	0.102	0.633***	−0.577,−0.390

Notes: Coef. and Robust standard errors were reported for mental health; Odd ratio and CI were reported for physical health.
***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.
Year and region dummy variables were included.

roads, and are disproportionately exposed to airborne toxic hazards at school locations, for example.

Relative to demographic characteristic such as marital status, water pollution might have a minor effect on mental health, which may be due to the fact that the two variables have different dimension. Moreover, water pollution results from people's behavior such as overexploiting natural resources, which can be controlled and reversed. A great number of governments and international organizations have launched water-related programs and interventions to improve people's health and welfare. Investment in water pollution management could ameliorate the negative influence of water pollution on health outcomes in China. By reducing the intensity of water pollution, water pollution management could alleviate the negative impact of water pollution in China. The results of the current study showed that water environment treatment indirectly influenced health by decreasing water pollution, in addition to directly affecting participant health.

4.2. Limitations

This paper has certain limitations. The selected pollution compounds are restricted due to the data constrain. Other contaminates, such as polycyclic aromatic hydrocarbon, Endocrine Disrupting Chemicals, may also be related to health outcomes. More data need to be collected and analyzed in the future. Besides, our work on physical health in CHARLS relied on a retrospective self-evaluation using a standard five-point scale (excellent, very good, good, fair, or poor) of the general state of health. Self-reported health status may lead to measure error (Johnston et al., 2009). However, self-report health is a widely-used variable to measure health outcome and has been validated as providing a good summary measure of overall health in the context of China (Smith et al., 2012).

Furthermore, a pervasive problem in the literature on the health costs of pollution is that individuals may compensate for increases in pollution by reducing their exposure to protect their health. For example, individuals with higher preferences for clean water may take more attentions to avoid exposure to water pollution (Moretti and Neidell, 2011). This concern is quite pertinent since those who are most vulnerable to pollution are also the most driven to take protective measures (Zhang et al., 2010). The findings suggest that the overall welfare effects of pollution may be greatly underestimated when evaluating the health effects of pollution. To solve the simultaneity issue, panel data model has been widely used, which controls for time-invariant differences across locations and overall trends. We have also applied this technique in the current study (Gómez et al., 2012). Besides, limiting free migration and distributing social welfare are the most notable characteristics of the functions of Chinese existing household registration system, which somehow reduced the problem. The results of the current study were largely consistent with previous reports. To some extent, our results reflect the impacts of water pollution intensity and treatment on health.

4.3. Policy implications

The findings in this study have important implications for policy. First, the question of whether, and to what extent, water pollution treatment in developing countries can lead to improved health outcomes remains unanswered. This study highlights a significant improvement in health correlated to reducing water pollution. Our results offer compelling evidence to support water pollution treatment in developing countries with high levels of water pollution.

Second, our findings indicate that health outcomes among respondents with low socioeconomic status were particularly susceptible to fluctuations in water quality. Although all individuals are potentially exposed to ambient pollution, the evidence suggests that socioeconomic status cushions the health effects of water pollution. Rich individuals are able to engage in behaviors that counteract some of the negative health consequences through exposure to pollution water (Brainerd and Menon, 2015). As such, our findings provide justification for interventions that target low-income households, including those that provide technology on avoiding exposure to water pollution and improve the access/affordability to social resource.

Third, given the facts that the common pollutants in industrial wastewater had differential impacts on health outcomes, more precisely measures should be figured out and implemented according to the characteristic of such pollutants. The concentrations of As, COD, Fn and NH_3-N were 0.73, 790, 7.8 and 69 mg/L, respectively, higher than their respective permissible limits (standard level of As: 0.5; Grade II limits of COD: 300; Grade II limits of Fn: 0.5 mg/L; Grade II limits of NH_3-N: 50 mg/L). Indicators of organic pollution, which exceeded their safe levels, should be more strictly controlled by properly implementing existing protection standards. In addition, although the Chinese government targeted COD and NH_3-N in the first Environmental five-year plans (FYPs), their emissions remain over the national standard. Goals of the first FYPs for National Environmental Protection should be clear (Deng et al., 2015). On the other side, water pollutants such as Hg and Pb may meet national standard criterion, some water pollutants may still negatively impact health. The Chinese government may need to adjust the national standard criterion of such pollutants and take pollutants' health effects into consideration when determining national emission standards. The risk-based approach adopted by Thailand to determine weather any detected contamination has the potential of causing unacceptable human health risks may be worth learning. Furthermore, although there is no recent complete guideline for risk assessment in Thailand, the government has started a good effort towards environmental protection and will provide information with good quality to help owners, developers, potential purchasers and regulators to identify the risks of potential contaminations to the environment and human health from potential contaminations (Teh et al., 2016b).

5. Conclusion

To our knowledge, this is one of the most comprehensive epidemiological studies to be conducted in a large cohort in China, and also the first to assess the effects of water pollution treatment in China. Water pollution resulted in worse physical and mental health outcomes in China. Fortunately, water environment treatment could partially ameliorate the negative health effects of water pollution, both directly and indirectly. Water-related programs and interventions should be launched as an effective way to improve physical and mental health, particularly people of low socioeconomic status.

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Conflicts of interest

The authors have no conflicts to declare.

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