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The Association Between $PM_{2.5}$ and Depression in China

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Abstract

While China has been experiencing unprecedented economic growth, depression is becoming one of the most striking social and mental health problems in recent years. Such a paradox to progress may partially be due to the notoriously poor air quality of the country. To verify this argument, we constructed an index of the prevalence of depression (IPD) using internet search query volumes in Baidu to proxy the potential depression and examined how IPD is associated with $PM_{2.5}$, the major air pollutant in China. Our results from 2-way fixed effects models reveal that a 100 $\mu g \cdot m^{-3}$ increase in previous week's $PM_{2.5}$ in a city is significantly associated with 0.279 increase in its IPD, comparable to 7.34 hours decrease in weekly daylight, and such relationship is particularly pronounced in the spring and summer and in East and South areas. Our findings of large-scale pattern suggest that $PM_{2.5}$ at current levels in China poses serious mental health risks.

Keywords

$PM_{2.5}$, depression, China, internet search query volumes, Baidu index

Air pollution, as an environmental hazard, imposes a variety of adverse effects on individuals' health. Exposure to air pollution is positively associated with the incidence of stroke,[1] respiratory diseases,[2-4] and lung and cardiovascular dysfunction.[5-10] Long-term exposure to air pollution even leads to higher rates of mortality.[11-14]

As *Ambient Air Pollution*, a 2016 global health report published by the World Health Organization (WHO),[15] reported, in 2012 alone, ambient air pollution was complicit in 3 million deaths and 85 million disability-adjusted life years.[16] Foremost among the pollutants associated with these mortality and morbidity numbers were airborne particulate matter known as $PM_{2.5}$. As a mixture of fine particles and liquid droplets, $PM_{2.5}$ is a particular danger because it is easily sucked into the lungs, where it can create a devastating impact on an individual's health.

Aside from the role $PM_{2.5}$ plays in physical health, previous studies have touched on the potential relationship between $PM_{2.5}$ and individuals' mental health. Depression, one of the leading cause of the disability-adjusted life years, is closely associated with physical illness and decreased quality of life[17-19] and may also be associated with $PM_{2.5}$.[20-25] However, most of the existing studies focus on high-income countries, such as Canada, Europe, and United States; few have examined the situation in low-income countries, such as China (except 2 papers[24,26])

In the past 2 decades, China has experienced unprecedented economic growth. However, the health and longevity of the Chinese people have not improved as a result.[27] It is argued that economic growth has had the opposite effect as the suicide rate and the incidence of mental illness have rapidly increased.[28] This paradox of progress may be due, in part, to the country's notoriously poor air quality,[29] where $PM_{2.5}$ could

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be the culprit behind hazy skies. According to the latest $PM_{2.5}$ concentration data, on April 17, 2016, the annual average $PM_{2.5}$ concentration in 210 cities in China was in the range of 11 to 128 $\mu g \cdot m^{-3}$, around 99% of cities surpassed 15 $\mu g \cdot m^{-3}$, the maximum limits of annual average $PM_{2.5}$ concentration set by WHO.[30]

In this study, we attempt to examine the potential $PM_{2.5}$–depression link. We constructed a weekly index of the prevalence of depression (IPD) in 282 major cities in China using internet searches for depression-related terms on Baidu, the most widely used search engine in China. Note that there is unwarranted stigmatization associated with depression. Such stigma makes individuals embarrassed to confess their true feeling, and even avoid reaching out for help, leading to a high level of underreporting.[31,32] Internet search provides a way out, as internet searching is largely anonymous and confidential, without the presence of third party, and individuals are more likely to reflect the true feeling. Similar methods have been used in various studies to construct measures that cannot be captured in more traditional ways.[33-38]

Methods

Data

The data prepared for this analysis are from multiple sources. We constructed city-level IPD, and baseline web search index using search index extracted from Baidu, the most widely used internet search engine in China. We used Python 2.7.11 to gather search data from the web and chose "week" as the time unit.

City-level weekly $PM_{2.5}$ was collected from China's Air Quality Online Monitoring and Analysis Platform (https://www.aqistudy.cn/historydata). To rule out the potential confounding effect of weather, we collected the relevant meteorological information from the Chinese website Historical Weather (http://www.tianqihoubao.com/lishi) and the websites of Sunrise and Sunset in the website of Convenience Inquiry (https://richurimo.51240.com.zhongguo_richurimo).

Index of Prevalence of Depression

The dependent variable is the city-level IPD. To identify queries for depression, we searched for the 4 most common names for depressive disorders: depression (*yi yu zheng*), melancholia (*you yu zheng*), postpartum depression (*chan hou yi yu zheng*), and obsessive-compulsive disorder (OCD, *qiang po yi yu zheng*), as up to 75% of individuals with OCD have major depression.[39] We divided results into 52 weeks in 2017 and conducted a principal component analysis (PCA) to extract the largest component from the 4 items to serve as IPD (see Table 1). Similar results are shown when summing up the Z-score of the 4 time series as a proxy of IPD.

Table 1. Factor Loadings of Depression Search Index in Baidu.[a]

Variables	Factor	Uniqueness
Depression	0.92	0.16
Melancholia	0.83	0.30
Obsessive-compulsive disorder (OCD)	0.88	0.22
Postpartum depression	0.82	0.32
Eigenvalue	3.00	
Variance, %	74.98	
Cronbach α	0.79	

[a]Principal component factor analysis. KMO = 0.83. Bartlett's test of sphericity = 2.16e+05 (6), $P < .001$.

Table 2. Descriptive Statistics of Major Variables.

Variable	Description	Mean	SD
IPD	Index of the prevalence of depression measured by search frequency of major depression-related words in Baidu using PCA method (log value)	13.795	11.746
$PM_{2.5}$	Weekly averaged $PM_{2.5}$ 100 mcg/m^3	0.824	0.349
Internet	Internet usage measured by the frequency of surfing 11 major websites	0.018	1.009
Daylen	Weekly averaged day length multiplied by the weekly ratio of sunny day	3.298	3.038
Tem	Weekly averaged day mean temperature	16.113	10.509
Rain	Weekly ratio of rainy days	0.267	0.242
Wind	Weekly averaged wind speed	13.795	11.746

Control Variables

We control for several variables to take care of potential confounding effects and present the relevant descriptive statistics in Table 2. First, city-level internet usage. We average city-level weekly data from Baidu for 11 most popular portals (ie, *Baidu*, *We-chat*, *QQ*, *Taobao*, *Alipay*, *Sina*, *Sohu*, *Netease*, *Tencent*, *Chinese Central Television*, and *Bulliet strain*) and conducted a PCA to extract 1 factor from these items.

Second, city-level weather conditions. They are (1) weekly daylight (*Daylen*) (weekly averaged day length multiplied by the weekly ratio of sunny days), (2) weekly averaged day mean temperature (*Tem*), (3) weekly ratio of rainy days (*Rain*), and (4) weekly averaged wind speed (*Wind*). All the information were collected from the Chinese website Historical Weather (http://www.tianqihoubao.com/lishi) and the websites of Sunrise and Sunset in the website of Convenience Inquiry (https://richurimo.51240.com.zhongguo_richurimo).

To deal with the temporal effects, we also controlled for week number (centered) and its squared term to capture the potential nonlinearity.

Model

To examine how $PM_{2.5}$ might affect depression in China, we employed 2-way fixed effects model that is easy to rule out confounding effects rising from time-invariant, city-level

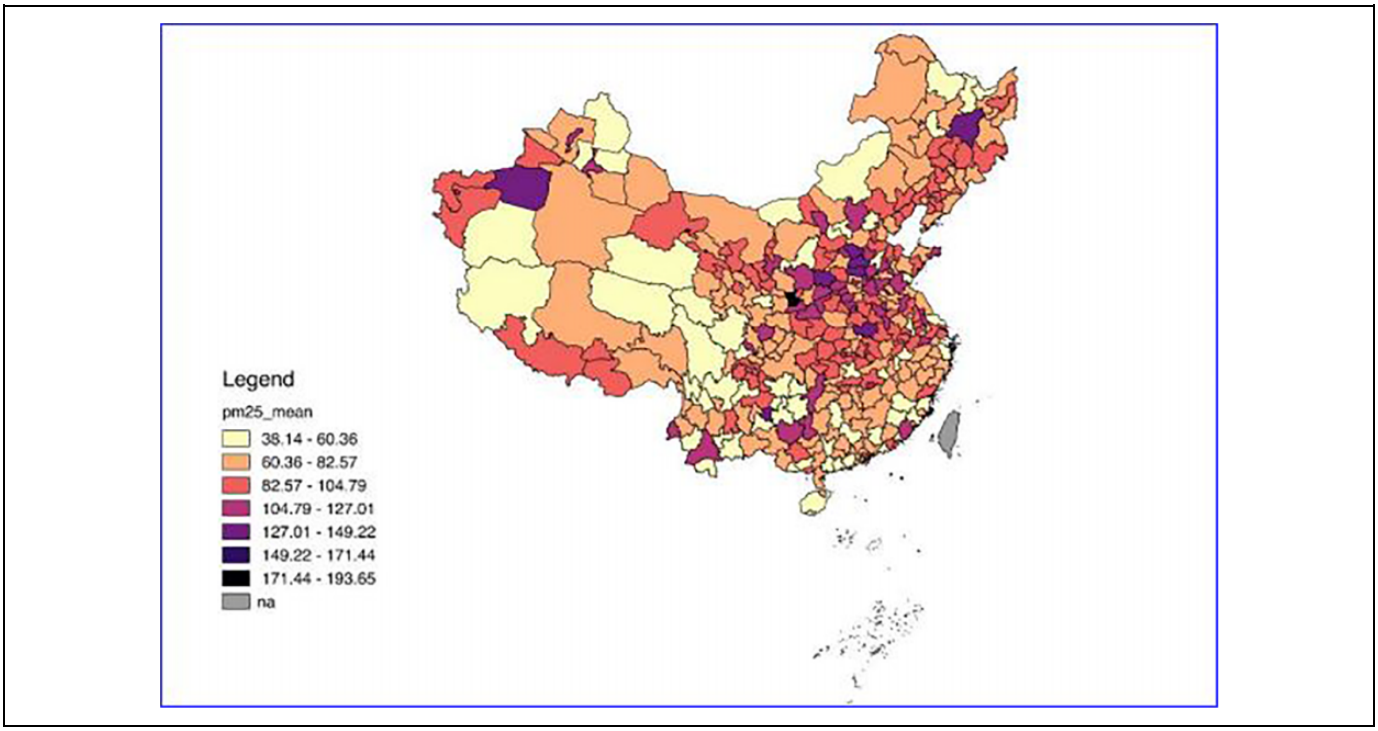

Figure 1. $PM_{2.5}$ level (weekly average) in 282 Chinese cities (2017).

factors. We use the lagged values ($t - 1$) of all explanatory variables to account for the potential time delay. The formula is written as follows:

$$IPD_{i_t} = \beta_1 PM2.5_{i_{t-1}} + \beta_2 Internet_{i_{t-1}} + \beta_3 Rain_{i_{t-1}} + \beta_4 Wind_{i_{t-1}} + \beta_5 Daylen_{i_{t-1}} + \beta_6 Week_i + \beta_7 Sqweek_i + c_i + \mu_{it} \quad (1)$$

In Equation 1, IPD_{i_t} is the dependent variable, denoting the level of prevalence of depression in city i week t, while $IPD_{i\_(t-1)}$ is its 1-week lagged value. Moreover, c_i is the city-level, time-constant error term, and μ_{it} is other city-level, time-varying error term.

Results

Distribution of Weekly $PM_{2.5}$ and IPD

Figure 1 presents the distribution of weekly average $PM_{2.5}$ in 282 cities in China. As shown, central China and some parts of northeast and northwest China with higher proportion of heavy industry are the most polluted areas as evidenced by the highest levels of $PM_{2.5}$. In contrast, western China, Inner Mongolia, and some parts of northeast and south China have relatively low levels of air pollution.

The distribution of IPD is visualized in Figure 2. As shown, individuals living in northwest China, especially Tibet, are the least likely to search for depression-related terms, followed by individuals from northern China, and then from the south and some parts of central China. Such distribution seems in line with the regional differences in socioeconomic development, internet accessibility, and air pollution.

Results From 2-Way Fixed Effects Model

Table 3 reports the results of a 2-way fixed-effects model. As Model 1 demonstrates, $PM_{2.5}$ is positively and significantly associated with IPD. Specifically, a 100 μg/m^3 increase in the previous week's $PM_{2.5}$ in a city is significantly associated with a 0.279 increase in its IPD ($P < .01$), suggesting a positive relationship between $PM_{2.5}$ and depression.[20-25] Consistent with previous research,[29,31] weekly daylight length ($P < .001$) and wind speed ($P < .001$) are significantly and negatively correlated with depression level. Specifically, a 1-unit increase in daylight length and wind speed level is associated with 0.038 and 0.378 increases of IPD, respectively.

As the contributions of particular components to particulate matter vary by season, we further conduct by-season analysis, presented in models 2 to 5. Results showed that $PM_{2.5}$ is positively associated with depression searches in all seasons but is more pronounced and statistically significant in spring ($P < .001$) and summer ($P < .01$), party of reason is higher temperatures are often associated with a faster dissipation of airborne particles.

China covers a massive amount of land area, and $PM_{2.5}$ patterns vary according to the region for reasons of geographical features, concentrations of industry, and regional idiosyncrasies; we further fitted models by region. As shown in Table 4, $PM_{2.5}$ is associated with depression searches in all Chinese regions except the west, where both $PM_{2.5}$ and depression

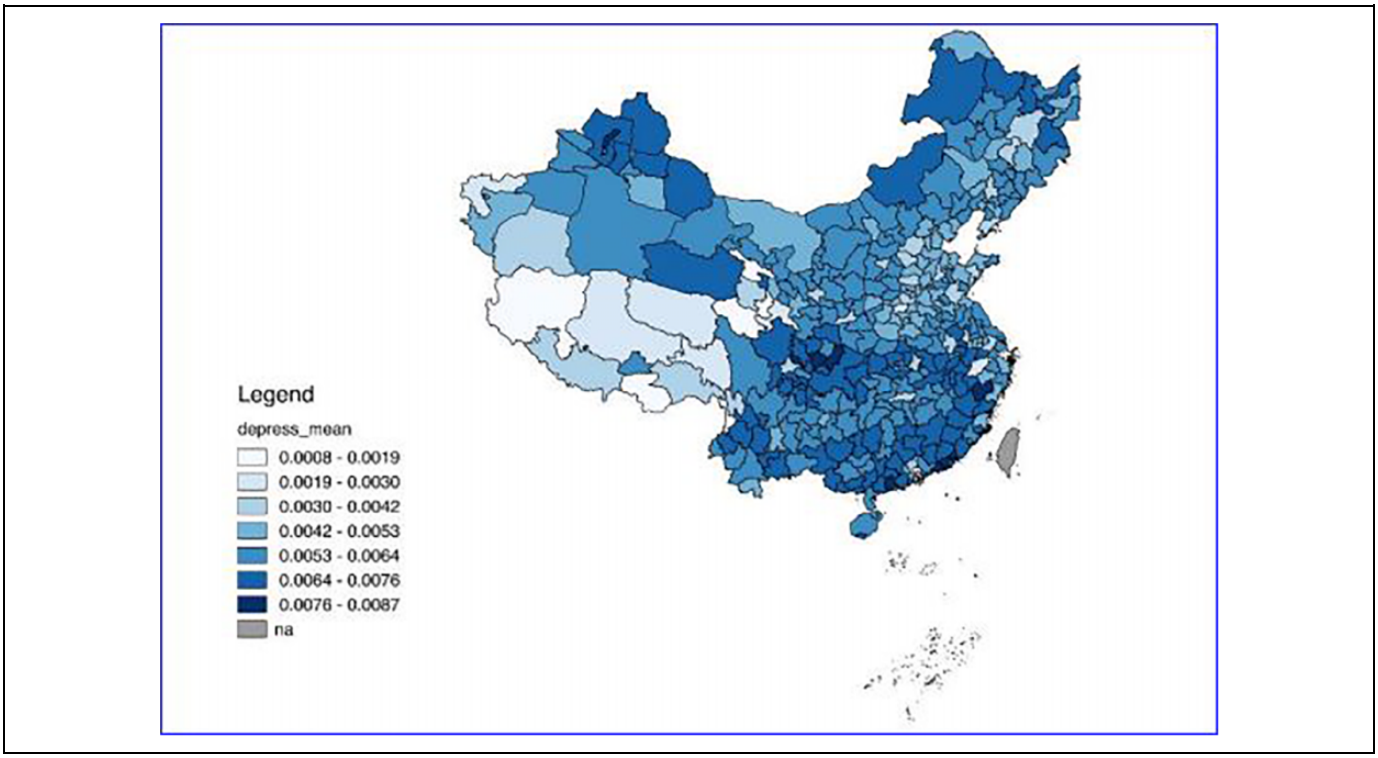

Figure 2. Depression-related online search volumes in 282 Chinese cities (2017).

Table 3. Two-Way, Fixed Effects Models Predicting Depression by Seasons.[a]

	(1) All	(2) Spring	(3) Summer	(4) Autumn	(5) Winter
Lagged $PM_{2.5}$	0.279[b]	0.520[c]	0.670[b]	0.310	0.036
	(0.089)	(0.129)	(0.239)	(0.184)	(0.190)
Lagged *Internet*	3.822[c]	2.520[b]	1.237[b]	0.719	4.142[c]
	(0.626)	(0.846)	(0.391)	(0.763)	(1.224)
Lagged *Tem*	−0.007	−0.022	−0.056[b]	−0.047[b]	0.159[c]
	(0.006)	(0.014)	(0.020)	(0.016)	(0.016)
Lagged *Rain*	0.172	−0.071	0.096	−0.052	1.564[c]
	(0.109)	(0.194)	(0.178)	(0.176)	(0.381)
Lagged *Wind*	−0.378[c]	−0.094	−0.414	0.030	−0.809
	(0.108)	(0.144)	(0.214)	(0.233)	(0.497)
Lagged *Daylen*	−0.038[c]	0.025	−0.033[d]	−0.020	−0.067[b]
	(0.008)	(0.014)	(0.013)	(0.018)	(0.024)
Week	0.042[c]	−0.239 [c]	0.195 [c]	0.113	0.038 [c]
	(0.003)	(0.051)	(0.026)	(0.071)	(0.004)
Week squared	−0.001[c]	−0.011[c]	−0.017[c]	−0.009[c]	0.007[c]
	(0.000)	(0.002)	(0.004)	(0.003)	(0.000)
Constant	15.140[c]	12.640[c]	16.354[c]	15.419[c]	12.021[c]
	(0.398)	(0.610)	(0.876)	(0.913)	(1.726)
Number of cities	282	277	277	282	282
Observations	14 066	3589	3587	3607	3283
R^2	.157	.022	.083	.071	.256

[a]Standard errors in parentheses.
[b]$P < .01$.
[c]$P < .001$.
[d]$P < .05$.

Table 4. Two-Way, Fixed Effects Models Predicting Depression by Regions.[a]

	(1) North	(2) East	(3) Central	(4) South	(5) West
Lagged $PM_{2.5}$	0.196	0.782[b]	0.278	1.470[c]	−0.220
	(0.117)	(0.291)	(0.260)	(0.322)	(0.154)
Lagged *Internet*	1.914	3.462[b]	6.476[d]	4.890[c]	3.918[c]
	(0.993)	(1.282)	(2.753)	(1.302)	(0.237)
Lagged *Tem*	0.031[b]	−0.016	−0.002	0.045[d]	0.003
	(0.011)	(0.024)	(0.017)	(0.020)	(0.013)
Lagged *Rain*	−0.190	1.041[b]	0.448	0.412[d]	0.056
	(0.252)	(0.304)	(0.403)	(0.199)	(0.193)
Lagged *Wind*	−0.467[d]	−0.357	−0.987[d]	−0.241	−0.573
	(0.184)	(0.240)	(0.459)	(0.234)	(0.338)
Lagged *Daylen*	−0.026	−0.019	−0.038	−0.124[c]	−0.031[d]
	(0.016)	(0.022)	(0.023)	(0.030)	(0.015)
Week	0.023[c]	0.054[c]	0.042[c]	0.044[c]	0.035[c]
	(0.006)	(0.010)	(0.008)	(0.007)	(0.005)
Week squared	0.002[b]	−0.002[d]	−0.002[d]	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Constant	13.262[c]	18.450[c]	16.750 [c]	14.326 [c]	12.599 [c]
	(0.714)	(0.928)	(1.501)	(0.912)	(1.271)
City number	64	58	52	46	62
Observations	3246	2912	2512	2282	3114
R^2	.085	.199	.161	.210	.211

[a]Standard errors in parentheses.
[b]$P < .01$.
[c]$P < .001$.
[d]$P < .05$.

searches are low. Specifically, the positive association between $PM_{2.5}$ and depression searches is statistically significant for the east ($P < .01$) and the south ($P < .001$), where socioeconomic development level is higher than the rest of the region. Such a pattern can also be taken as a manifestation of the paradox of progress in China. That is, regions enjoy the benefits of economic gain and, meanwhile, suffer from increased depression resulting from air pollution.

Discussion

While China's economy has boomed in the past 2 decades, the quality of life of Chinese people has not. On the contrary, there is an increased risk of depression. Such a paradox to progress might be partly attributable to air pollution. In this article, we examined whether $PM_{2.5}$, one of the most dangerous and heatedly discussed sources of air pollution, is associated with depression. We constructed a city-level weekly IPD using online query volume data from Baidu rather than self-reported depression to proximate the latent depression.

Our findings provide suggestive evidence on the source of China's paradox of progress that economic success has not translated into a better quality of life for all. We recommend that future studies identify the sources of depression and the associated mechanisms that lead to this paradox and that they inform policy with the aim of improving the quality of life for all Chinese citizens.

Limitations

This study had some limitations. First, the valid finding of this research is premised upon the fact that no short-term social, economic, or political changes influence the $PM_{2.5}$ level and searches for depression-related terms. We did not verify these short-term changes; thus, we cannot rule out the possibility that there have been some that affected air quality. Even if there were, changes in air quality often take relatively long periods of time to be observed. In this vein, the biased estimation is less of a concern in this analysis. Second, different from most of the extant studies that involve rigorous analyses at the individual level, our estimation of depression index is conducted based on less explored macro-city level, and we identified the PM2.5 as one potential risk factor that is negatively associated with implied depression; however, what drives such relationship remains unsolved, making the city-level pattern less intuitive. Note that due to difficulties of accessing data at macro-level and the wide concern of ecological fallacy, macro-level analyses remain rare in public health field, making the development of macro-theory stagnated. This analysis, although unsound, is a critical interrogation of available big data to harness their strength at the macro-level and from a macro perspective. It, to the least degree, can be taken as the first step to tap into the exploration of macro-theory.

Conclusion

To examine the possible correlation between $PM_{2.5}$ and depression, we matched IPD with city-level weekly $PM_{2.5}$ and weather condition variables. The results show that 1-week lag of $PM_{2.5}$ can positively predict the IPD of the following week, holding constant weekly internet usage and various meteorological factors, and such effects are more prominent in spring and summer and in the East and South.

Author Contributions

G.H., Y.C., S.W., and Y.D. developed the ideas, analyzed the data, and drafted the paper. G.J and B.C collected the data and revised the paper.

Declaration of Conflicting Interests

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