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AIR POLLUTION AND MENTAL HEALTH: EVIDENCE FROM CHINA

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ABSTRACT

A large body of literature estimates the effect of air pollution on health. However, most of these studies have focused on physical health, while the effect on mental health is limited. Using the China Family Panel Studies (CFPS) covering 12,615 urban residents during 2014 – 2015, we find significantly positive effect of air pollution – instrumented by thermal inversions – on mental illness. Specifically, a one-standard-deviation (18.04 μg/m3) increase in average $PM_{2.5}$ concentrations in the past month increases the probability of having a score that is associated with severe mental illness by 6.67 percentage points, or 0.33 standard deviations. Based on average health expenditures associated with mental illness and rates of treatment among those with symptoms, we calculate that these effects induce a total annual cost of USD 22.88 billion in health expenditures only. This cost is on a similar scale to pollution costs stemming from mortality, labor productivity, and dementia.

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1 Introduction

Understanding the health costs associated with air pollution is important from a public and private perspective. From a public perspective, correctly quantifying the totality of health costs is important as regulators set air pollution standards partly based on cost-benefit calculations.[1] As of today, the benefit side of the cost-benefit analysis used for policy purposes is mostly comprised of avoided mortality and morbidity costs, for which there is ample empirical evidence (Chay and Greenstone, 2003; Neidell, 2004; Currie and Neidell, 2005; Neidell, 2009; Currie and Walker, 2011; Chen et al., 2013; Anderson, 2015; Arceo et al., 2016; Deryugina et al., 2016; Knittel et al., 2016; Schlenker and Walker, 2016; Deschênes et al., 2017; Ebenstein et al., 2017). A more comprehensive calculation of the costs associated with air pollution acknowledges that individuals optimize their level of protection through actions such as staying indoors (Neidell, 2009), medication purchases (Deschênes et al., 2017), purchases of air purifiers and facemasks (Ito and Zhang, 2016; Zhang and Mu, 2017), and location choices (Chen et al., 2017); all of which are costly (Harrington and Portney, 1987). Up to now, most of the epidemiological and economics studies have focused on physical health outcomes, while studies of the effect on mental health are limited.[2] This paper contributes to filling this research gap by estimating the short-run effect of air pollution on mental health.

Mental health refers to a state of well-being in which an individual can cope with stress, work productively, and is able to make contribution to the community (World Health

[1] U.S. Environmental Protection Agency (EPA), “Benefits Mapping and Analysis Program”, https://www.epa.gov/benmap/how-benmap-ce-estimates-health-and-economic-effects-air-pollution.

[2] An important exception is the recent work by Bishop et al. (2017) on the effect of chronic air pollution exposure on dementia. Dementia and mental illness are closely related, but differ in terms of symptoms (Regan, 2016). The most common form of dementia is the Alzheimer’s disease, which significantly damages the memory function in the brian and causes a variety of symptoms including difficulty in communicating, increased memory issues, general confusion, and personality and emotional changes. The Alzheimer’s disease is more likely to occur for the elderly aged 65 or above. The most common symptoms of mental illness, on the other hand, are depression and anxiety.

Organization (WHO), 2014). According to the WHO, "*Health is a state of complete physical, mental and social well-being and not merely the absence of disease or infirmity*".[3] Mental illness has received increased public attention as we learn more about the size of the population worldwide that is likely affected and the costs associated with it. The WHO estimated that 450 million people suffered from mental illness worldwide (WHO, 2007). It is estimated that mental illness is responsible for 13% of the global disease burden (Collins et al., 2011), accounts for more than 140 million disability-adjusted life years (Whiteford et al., 2013), and cost USD 2.5 trillion in 2010; which is roughly 50% of the entire global health spending for that year (WHO, 2010).

In this paper, we aim to estimate the causal effect of air pollution on mental health in China. We measure air pollution as the concentration of very fine particulate matter, or particulates with a diameter less than 2.5 micrometers ($PM_{2.5}$). However, because of our research design, we will not be able to isolate the effects of different air pollutants on mental health. Our focus on $PM_{2.5}$ follows the findings in health sciences, which show that $PM_{2.5}$ could be inhaled into the human body and increase oxidative stress and systemic inflammation. These reactions, in turn, can exacerbate depression and anxiety (Calderon-Garciduenas et al., 2003; Sørensen et al., 2003; MohanKumar et al., 2008, Salim et al., 2012, Power et al., 2015). In addition, $PM_{2.5}$ could induce respiratory or cardiac medical conditions (Delfino, 2002; United States Environmental Protection Agency (EPA), 2008, 2009; Ling and van Eeden, 2009), which may further increase depression and anxiety through several channels (Brenes, 2003; Scott et al., 2007; Yohannes et al., 2010; Spitzer et al., 2011). Because the main measure of air pollution we use is $PM_{2.5}$, we use air pollution and $PM_{2.5}$ interchangeably throughout the paper.

Identifying the causal effect of air pollution on mental health illness is challenging for three reasons. First, air pollution is typically correlated with confounders such as income and

[3] http://www.who.int/features/factfiles/mental_health/en/.

local economic conditions, which are also important determinants of mental illness (Gardner and Oswald, 2007; Charles and DeCicca, 2008). Omitting such confounders may bias the estimates downward if they are positively correlated with pollution and negatively affect the incidence of mental illness. The second empirical challenge is the reverse causality. Since mental health may have a direct effect on human productivity (WHO, 2002), this could, in turn, affect the level of emissions related to economic activity. This type of reverse causality would further bias the estimates downward. The third challenge is classic measurement error, as air pollution at a specific location is likely to be measured with error or subject to human manipulation (Ghanem and Zhang, 2014; Sullivan, 2017). This will attenuate the estimates towards zero.

To overcome the endogeneity of air pollution, we apply an instrumental variables (IV) approach, where we instrument air pollution using thermal inversions. Thermal inversions occur when a mass of hot air is above the cold air and thus air pollutants near the ground are trapped. As a meteorological phenomenon, the occurrence of a thermal inversion is independent of economic activity. Thermal inversions significantly affect air pollution concentrations and have been used as an IV for air pollution in several previous studies (Jans et al., 2014; Hicks et al., 2015; Arceo et al., 2016; Fu et al., 2017; Chen et al., 2017).

Our measure of mental health comes from the nationally representative China Family Panel Studies (CFPS) in 2014, which interviewed 15,618 rural and 12,650 urban adult residents across 162 counties from July 3rd 2014 to March 31th 2015 in China. The CFPS includes six questions which comprise the internationally validated Kessler Psychological Distress Scale (K6) ranging from 0 – 24 on the frequency of the following mental illness symptoms over the past month prior to interview: depression, nervousness, restlessness, hopelessness, effort, and worthlessness (Kessler et al., 2002, 2003; Prochaska et al., 2012). We exploit variation in short-run $PM_{2.5}$ exposure induced by thermal inversions in the month prior to the interview date. In order to avoid confounding mechanisms stemming from sorting or demographic differences across areas with high and low mean frequencies of thermal inversions, we only exploit thermal inversions variation over time (i.e., conditional on location fixed effects). In addition, the variation we use is net of flexible functions of weather and seasons that could have an independent effect on mental health.

We find both economically and statistically significant positive effect of $PM_{2.5}$ on mental illness. In particular, a one-standard-deviation (18.04 microgram per cubic meter ($\mu g/m^3$)) increase in average $PM_{2.5}$ concentrations in the past month increases the K6 score by 0.38 standard deviations. As a comparison, the OLS estimate is close to zero and even negative in some specifications, with no statistical significance. Following the prior literature in psychology and medicine, we then define a dummy variable for severe mental illness when the K6 score is equal or above 13 (Kessler et al., 2002; Prochaska et al., 2012). We find that a one-standard-deviation increase in average $PM_{2.5}$ concentrations in the past month increases the probability of having severe mental illness by 6.67 percentage points, or 0.33 standard deviations.

Taking advantage of the rich survey questionnaire, we explore several indirect channels through which $PM_{2.5}$ affects mental health, including exercise and physical health (Taylor, Sallis, and Needle, 1985; Brenes, 2003). We find weak and small effect of $PM_{2.5}$ on exercise and physical health, suggesting that $PM_{2.5}$ mainly affects mental health through direct channels (brain function) or other indirect channels beyond the observable measures of exercise and physical health that the survey includes. We also conduct a heterogeneity analysis and find that the effect is the largest for male, ages above 60, and highly educated (with a college degree or above).

This paper makes three primary contributions. First, to our best knowledge, this is the first estimate on the *causal* effect of short-run air pollution on mental health.[4] Second, an emerging literature has been focused on the determinants of psychological well-being and mental health, such as money (Gardner and Oswald, 2007), local labor market conditions (Charles and DeCicca, 2008), neighborhood (Katz et al., 2001; Kling et al., 2007), migration (Stillman et al., 2009), temperature shocks *in utero* (Adhvaryu et al., 2015), and early life circumstances (Adhvaryu et al., 2016). This paper adds to this growing literature by providing a new determinant: air pollution. Third, a rapidly growing literature has focused on the effect of air pollution on outcomes that are beyond physical health, such as school attendance (Currie et al., 2009), test scores (Ebenstein et al., 2016), labor productivity (Graff Zivin and Neidell, 2012; Chang et al., 2016; Fu et al., 2017; Chang et al., forthcoming; He et al., forthcoming), labor supply (Hanna and Oliva, 2015), and decision making (Heyes et al., 2016; Chew et al., 2018; Chang et al., forthcoming). This paper provides a new outcome of interest, which is mental health, and sheds light on whether our effects are partially a biproduct of other adjustments to air pollution such as exercise and physical health.

The effects we find are economically meaningful. Our low-bound estimate indicates that a one-standard-deviation increase in $PM_{2.5}$ concentrations induces a total annual cost of USD 22.88 billion, or 0.22% of China's GDP in terms of additional medical expenditure on mental illness.[5] These estimates are comparable to studies focus on the effect of $PM_{2.5}$ on mortality (Deryugina et al., 2016), labor productivity (Chang et al., 2016; Fu et al., 2017), and dementia (Bishop et al., 2017).[6] Our results suggest that omitting mental health effects is likely to underestimate the overall health cost of air pollution.

[4] Various studies in the health science literature (Mehta et al., 2015; Power et al., 2015; Pun et al., 2016) and one study in the economics literature (Zhang et al., 2017) find correlations between air pollution and mental health.

[5] China's norminal GDP in 2014 is USD 10.48 trillion.

[6] For example, a one-standard-deviation decrease in $PM_{2.5}$ concentrations brings an annual benefit of USD 30.16 billion in terms of avoided mortality in the U.S. (Deryugina et al., 2016), an annual benefit of USD 7.09

The remainder of the paper is organized as follows. Section 2 describes the possible channels through which air pollution affects mental health. We discuss our empirical model and identification strategy in Section 3 and describe the data sources and summary statistics in Section 4. Section 5 presents the regression results, robustness checks, mechanism tests, and heterogeneity analysis. We discuss the welfare implications and conclude in Section 6.

2 Mechanisms

There are several mechanisms through which $PM_{2.5}$ could affect mental health. Fine particulate matter could affect mental health directly through induction of systemic or brain-based oxidative stress and inflammation (Power et al., 2015).[7] Many studies find that air pollutants, especially particulate matter, induce systemic or brain-base oxidative stress and inflammation (Calderon-Garciduenas et al., 2003; Sørensen et al., 2003; MohanKumar et al., 2008), which significantly damage cytokine signaling (Salim et al., 2012). Cytokines, a broad and loose category of small proteins, play an important role in regulating brain functions including neural circuitry of mood. Dysregulation in cytokine signaling could lead to occurrence of depression, anxiety, and cognitive dysfunction (Salim et al., 2012).

$PM_{2.5}$ could also affect mental health through induction of respiratory or cardiac medical conditions (Power et al., 2015). A large body of literature has found that air pollution can reduce lung function, induce reactive airway diseases – such as asthma and chronic obstructive pulmonary disease, and congestive heart failure (Delfino, 2002; EPA, 2008, 2009; Ling and van Eeden, 2009) – which can further increase anxiety and other mental illness (Brenes, 2003; Scott et al., 2007; Yohannes et al., 2010; Spitzer et al., 2011). For example,

billion in terms of increased labor productivity in the U.S. (Chang et al., 2016) and USD 76.11 billion in China (Fu et al., 2017). See detailed discussion in Section 6.

[7] Oxidative stress refers to a state where the level of oxidants produced by biological reactions exceeds the oxidants scavenging capacity of the cell.

anxiety may occur because of fear, stress, and misinterpretation of respiratory or cardiac symptoms. Dysfunctional breathing and heart performance may also lead to mental illness through a purely physiological reaction to oxygenation changes.

It is possible that air pollution affects mental health through other indirect channels. For example, evidence shows that air pollution could significantly reduce labor productivity (Graff Zivin and Neidell, 2012; Chang et al., 2016; Fu et al., 2017; Chang et al., forthcoming; He et al., forthcoming) and may further reduce workers' income, which is an important determinant of mental health (Gardner and Oswald, 2007; Golberstein, 2015). The reduced labor productivity due to air pollution may create work stress and fear of unemployment; both of which are found to significantly affect mental health (Kopp et al., 2007; Charles and DeCicca, 2008; Wang et al., 2008; Paul and Moser, 2009).

Air pollution may also affect mental health through adaptive responses such as the reduction of physical activity. Neidell (2009) finds that people tend to stay indoors to avoid air pollution; and thus, may spend less time on outdoor exercise and other physical activities, which alleviate mental illness (Taylor, Sallis, and Needle, 1985; Glenister, 1996; Beebe et al., 2005).

3 Empirical Strategy

Our goal is to estimate the causal effect of air pollution, measured as $PM_{2.5}$ concentration, on mental health. There are three potential empirical challenges. The first one is omitted-variable bias. Air pollution is typically correlated with local economic conditions. For example, economically developed regions may also be more polluted. If one compares two counties with different pollution levels, people in the polluted county may have a lower prevalence of mental illness because of better access to treatment, or because of higher income. In other words, the confounding factor (local economic conditions) induces a negative correlation between air pollution and mental illness. Note that county fixed effects will absorb permanent differences in economic activity across counties; but cannot absorb time-varying differences within county, which can still bias the estimates downward. One can also directly control for these time-varying differences, such as GDP or income, but the inclusion of these endogenous control variables may induce the "over controlling problem", as they themselves may be the outcome of the variable of interest: air pollution. In addition, GDP or income measures available are often imperfect measures of the economic conditions each individual in the sample is exposed to.

The second empirical challenge is reverse causality. Mental health can have an effect on human productivity (WHO, 2002), which can in turn affect anthropogenic emissions and air pollution. This reverse causality can potentially further bias the estimates downwards. The third challenge is the measurement error. Since pollution is likely to be measured with error (Sullivan, 2017) and, in developing countries, may also be subject to human manipulation (Ghanem and Zhang, 2014), estimates will be biased towards zero.

Our approach to overcoming these identification challenges is to use short-run random variation in air pollution across interview dates induced by exogenous variation in thermal inversions within each county. A thermal inversion is a common meteorological phenomenon that frequently increases the concentration of air pollution near the ground. Normally, temperature decreases as altitude increases. Under these normal conditions, air pollutants can rise to upper atmospheric layers and disperse. Only under relatively rare meteorological circumstances, temperature in an upper atmospheric layer is higher than the layers below. This constitutes a thermal inversion. The warm layer of air traps pollution near the ground by reducing vertical circulation. The formation of a thermal inversion depends on the confabulation of multiple meteorological factors (Arceo et al., 2016), and it is thus independent of economic activity. A thermal inversion in itself does not present a health risk (Arceo et al., 2016). Thermal inversions, however, do coincide with meteorological patterns at ground-level such as low temperatures in some regions and high temperatures in others (Chen et al., 2017). Therefore, it is important to control for weather at ground level, which could have an independent effect on economic activity and/or mental health. Thermal inversions have been used as IV for pollution in multiple studies (Jans et al., 2014; Hicks et al., 2015; Arceo et al., 2016; Fu et al., 2017; Chen et al., 2017).

Figure 1 plots the daily time trend of thermal inversion frequency and $PM_{2.5}$ from July 3rd 2014 to March 31th 2015, the course of our study period. The blue line represents average $PM_{2.5}$ in μg/m^3 for all 162 counties across every day, while the red line represents average number of thermal inversions in the same counties and days. Because the occurrence of a thermal inversion is determined for each six-hour period (see Section 4.3 for details), it ranges from zero to four for each day-county observation. The figure shows a strong positive correlation between daily thermal inversions and $PM_{2.5}$.

[Insert Figure 1 here]

We propose to estimate the following 2SLS model to measure the causal effect of air pollution on mental health

$$H_i = \beta_0 + \beta_1 P_{c(i),t(i)} + f\big(W_{c(i),t(i)}\big) + \gamma_{c(i)} + g\big(t(i)\big) + \varepsilon_i \qquad (1)$$

$$P_{c(i),t(i)} = \alpha_0 + \alpha_1 I_{c(i),t(i)} + f\big(W_{c(i),t(i)}\big) + \gamma_{c(i)} + g\big(t(i)\big) + \mu_i, \qquad (2)$$

where the variable H_i denotes the mental illness for each respondent i. We have two measures for H_i. The first is the raw K6 score, which is the sum of points across the six questions regarding the state of an individual's mental illness in the past month prior to the interview. We do not use the logarithm of the K6 score since around 34% observations are zero. The second measure is a dummy variable which equals to one if the K6 score is equal or larger than 13, to indicate severe mental illness (Kessler et al., 2002; Prochaska et al., 2012). The details of the mental health data are described in Section 4.1.

We use c_i to represent the county in which individual i resides, and t_i to denote the date individual i is interviewed. Our variable of interest in the right-hand side in equation (1) is $P_{c(i),t(i)}$, which measures the average concentration of $PM_{2.5}$ in the past month prior to interview date t for county c in which individual i resides. We explore the robustness of different exposure windows in Section 5.1. We instrument $PM_{2.5}$ using the total number of thermal inversions in the same period and county, denoted by $I_{c(i),t(i)}$ (see Section 4.2 for details). We include flexible weather controls, denoted by $f(W_{c(i),t(i)})$. These controls include the number of days within each 5 °C interval constructed using daily average temperature,[8] second order polynomials in average relative humidity, wind speed, and sunshine duration, and cumulative precipitation in the past month. We include these weather controls because they may be correlated with thermal inversions (Arceo et al., 2016) and may also have an independent effect on mental health (Adhvaryu et al., 2015). Importantly, our results are robust to excluding those weather controls. We use county fixed effects, $\gamma_{c(i)}$, to control for permanent differences in air pollution concentrations across counties. In addition, because thermal inversions are highly seasonal (see Figure 1), we use year-by-month fixed effects, $g(t(i))$, to pick up any country-wide seasonal trends seasonal illness (such as the flu), macroeconomic trends, etc., that could also be correlated with mental health. These controls are important, as thermal inversions may also have a seasonal nature independently of weather. In sum, the variation in thermal inversions that we use as an instrument is net of permanent differences across counties, weather at the ground level, and seasonal effects.

[8] We do not construct finer bins such as 1°C because our exposure window is only one month. Therefore, there will be too many empty values if we use finer bins. Our results are also robust when we use polynomials in month averaged temperature.

Two econometric specification details are worth noting. First, we employ the two-way clustering (Cameron et al., 2011) and cluster the standard errors at both county and date level, which is the variation we are using for our IV. Second, our baseline regression models are weighted by sample weights of each individual, which is the ratio of local population to the interviewed population, to make our estimates nationally representative. Our results are robust to omitting these weights.

4 Data

4.1 Mental Health

Our data on mental health is from the CFPS on adult population with age equal or above 16 in 2014.[9] The CFPS 2014 is a nationally representative survey on detailed demographic information covering 15,618 rural and 12,650 urban adult residents across 162 counties in 25 provinces in China from July 3rd 2014 to March 31th 2015. Figure 2 depicts the location of the counties represented in the survey. Dark color indicates higher number of urban residents who are interviewed. Most surveyed counties are located in the east and central China, which also has the highest population density. Figure 2 also depicts the location of the pollution stations. There are 1,498 stations in total. We focus on urban residents as most pollution monitoring stations are located in urban areas.[10] In our estimation we have 12,615 observations because 35 people refuse to answer the question on mental health.

[Insert Figure 2 here]

9 The CFPS can be downloaded at http://www.isss.edu.cn/cfps/. Althought the survey was conducted in 2010, 2012, and 2014, we only use data from 2014 onwards because the daily pollution data on detailed air pollutants are only available since 2013.

10 We do not find significant effects for rural residents and for the whole sample including both rural and urban residents. Rural residents account for 55% of total observation. Table A1 in the online appendix reports estimates for rural residents and the whole sample.

The CFPS includes six questions on the state of an individual's mental health in the month prior to being interviewed. These questions comprise the K6 scale, which was developed by Kessler et al. (2002) and supported by the U.S. National Center for Health Statistics and is used by the U.S. National Health Interview Survey as well as in the annual National Household Survey on Drug Abuse.[11] The K6 screening instrument is internationally validated and has proven to be as effective as the longer K10 instrument which has been widely used in the literature (Kessler et al., 2003; Prochaska et al., 2012). The screening performance of the K6 instrument has also shown to have comparable screening performance to CES-D, another widely used screening instrument for depressive symptoms (Sakurai et al., 2011).

The 6 questions in the K6 instrument ask: During the past month, about how often did you feel

- so depressed that nothing could cheer you up?
- nervous?
- restless or fidgety?
- hopeless?
- that everything was an effort?
- worthless?

Respondents have five options to choose: Never (zero points), a little of the time (one point), half of the time (two points), most of the time (three points), and almost every day (four points). The K6 score is then computed by summing up points across all six questions. Therefore, the K6 score ranges from zero to 24, with higher scores indicating worse mental illness. Other than using the K6 score to measure the mental illness, we also use a dummy

[11] See https://www.cdc.gov/nchs/products/databriefs/db203.htm.

variable to indicate severe mental illness, which is defined when the K6 score is equal or larger than 13 (Kessler et al., 2002; Prochaska et al., 2012). The CFPS reports the county code and interview date for each respondent, which we use to match with pollution exposure in the prior month, as well as thermal inversions and weather data.

4.2 Pollution

Data on $PM_{2.5}$ are obtained from web-scratching the website of the China National Environmental Monitoring Center (CNEMC), which is affiliated to the Ministry of Environmental Protection of China. Starting from January 2013, the CNEMC publishes real-time hourly Air Quality Index (AQI) and specific air pollutants including $PM_{2.5}$, PM_{10}, ozone (O_3), sulfur dioxide (SO_2), nitrogen dioxide (NO_2), and carbon monoxide (CO) for around 1,400 monitoring stations.[12] See Figure 2 for spatial distribution of these stations.

We match the pollution data to the CFPS data using the following methods. First, we use the inverse-distance weighting (IDW) method to convert pollution data for each hour from station to county. The IDW method is widely used in the literature to impute either pollution or weather data (Currie and Neidell, 2005; Deschênes and Greenstone, 2007; Schlenker and Walker, 2016).[13] The basic algorithm takes the weighted average of all monitoring stations within a certain radius of the centroid of each county. We choose 100 kilometers (km) as our threshold radius and our results are robust to different radii. Second, we match pollution data to each respondent by the county code and then average pollution hourly pollution concentrations in the month prior to the date of the interview.

[12] The data can be viewed at http://106.37.208.233:20035/. One may need to install the Microsft Siverlight.
[13] This method has been recently criticized by Sullivan (2017) in the context of point pollution sources. In the context of a difference-in-difference design that uses opening and closing of point sources as the source of random variation in air pollution, the interpolation created by the IDW may smooth out sharp spatial differences in exposure creating bias in the estimates in either direction. However, when using thermal inversions as the source of variation for air pollution, there are no sharp spatial differences and IDW will not create bias in the estimates.

4.3 Thermal Inversions

We obtain thermal inversion data from the product M2I6NPANA version 5.12.4 from the Modern-Era Retrospective analysis for Research and Applications version 2 (MERRA-2) released by the National Aeronautics and Space Administration (NASA) of the U.S.[14] MERRA-2 divides the earth by 0.5 × 0.625-degree grid (around 50 × 60-km grid), and reports the air temperature for each 42 sea-level pressure layers for every six hours starting from 1980. We average temperatures across grid points within a county for each six hour and for each layer, and define a thermal inversion for each six-hour period in each county if the temperature in the first layer (110 meters) is lower than that in the second layer (320 meters). We also conduct a robustness check by coding inversions using differences in temperature between the first and third layers (540 meters). We then aggregate the number of thermal inversions in the month prior to each interview date and match to each respondent in the CFPS data by county and date of interview.

4.4 Weather

We obtain the weather data from the China Meteorological Data Service Center (CMDC), which is affiliated to the National Meteorological Information Center of China.[15] The CMDC records daily maximum, minimum, and average temperatures, precipitation, relative humidity, wind speed, and sunshine duration for 820 weather stations in China. We convert weather data from station to county again using the IDW method. We then match with each respondent by county. We use averages of relative humidity, wind speed, and sunshine duration and aggregate precipitation for the month prior to the interview. We calculate the

[14] The data can be downloaded at https://disc.sci.gsfc.nasa.gov/uui/datasets/M2I6NPANA_V5.12.4/summary?keywords=\%22MERRA-2\%22\%20M2I6NPANA\&start=1920-01-01\&end=2017-01-16.
[15] The data can be obtained at http://data.cma.cn/.

number of days within each 5 °C interval using daily average temperature (the average between daily maximum and minimum temperatures) to allow for non-linear impacts of temperature on mental health (Deschênes and Greenstone, 2011).

4.5 Summary Statistics

Table 1 reports the summary statistics for mental health, air pollutants, and thermal inversions. The unit of each observation is the respondent. We have 12,615 respondents from 162 counties during the period of July 3rd 2014 to March 31th 2015. Figure A1 in the online appendix plots the number of people interviewed each day.

[Insert Table 1 here]

First, we discuss our mental health statistics. We use the raw K6 score as one of our measurements of mental illness. The K6 score ranges from zero to 24, with an average of 2.96. This is equivalent to a respondent who chooses the option “a little of the time" to three of the six questions. Figure 3 plots the histogram of the K6 score. Overall, the density is decreasing with the size of the score, but one can observe a great variation across respondents. We also define a dummy variable which is equal to one if the K6 score is equal or greater than 13 and zero otherwise to denote severe mental illness. In our sample, around 4.38% of respondents have symptoms consistent with severe mental illness. This rate is slightly lower than the rate found in the U.S., which is 6% (Kessler et al., 1996).

Given that the survey is nationally representative, we estimate that around 49.93 million (1.14 billion × 0.0438) of the adult population in China suffer from severe mental illness. We also present the summary statistics for each individual question on mental illness. The mean varies from 0.28 to 0.75, with the symptom described as “feeling depressed” having the highest mean value. Figure A2 in the online appendix plots the histogram of each specific mental illness symptom.

[Insert Figure 3 here]

Next, we discuss summary statistics for air pollution and thermal inversions. The mean of the monthly average of $PM_{2.5}$ concentrations is 47.71 μg/m^3, which is nearly five times higher than the standard of 10 μg/m^3 of annual mean recommended by WHO (WHO, 2005). It varies from 13.46 to 160.19 μg/m^3, with a standard deviation of 18.04 μg/m^3. In terms of our IV, the average number of thermal inversions in the past month prior to the interview is 11.74. Note that the occurrence of a thermal inversion is determined within each six-hour period, and thus the probability of occurrence of a thermal inversion in at least one of a day's four 6-hour intervals is 9.78%.

5 Results

5.1 First-stage Results

Figure 1 shows a strong raw correlation between thermal inversions and air pollution. In this section, we formally test the first stage by estimating Equation (2), which includes our full set of controls. Table 2 reports our estimates for various specifications. In column (1) we include county fixed effects which control for county-specific time-invariant characteristics. We also include year-by-month fixed effects to control for year-specific seasonality, as one can observe a seasonal pattern of thermal inversions in Figure 1. In column (2) we add weather controls, including 5 °C temperature bins, second order polynomials in average relative humidity, wind speed, sunshine duration, and cumulative precipitation. In the last column we weight our regression by sample weights to make our estimates nationally representative.

[Insert Table 2 here]

We find significantly positive effects of thermal inversions on $PM_{2.5}$ concentrations. Take column (3), the baseline specification, as an example. We find that one more occurrence of a thermal inversion during the past month increases the monthly average $PM_{2.5}$ concentrations by 0.30 μg/m^3, or 0.63% evaluated at the mean. Put in another way, we find that a one-standard-deviation increase in thermal inversions (13.32 units) increases the concentration of $PM_{2.5}$ by 0.22 standard deviations. We also report the Kleibergen-Paap rk Wald (KP) *F*-statistic (Kleibergen and Paap, 2006), which are all larger than the Stock-Yogo weak identification test critical values at 10% maximal IV size of 16.38 (Stock and Yogo, 2005), indicating a strong first stage.

5.2 Second-stage Results

Panel A of Table 3 presents the IV estimate on the effect of $PM_{2.5}$ on mental illness across various specifications. The regression models are estimated using Equation (1). As a comparison, we also include the OLS estimate in Panel B. We have two measures of mental illness: The K6 score (columns (1) – (3)) and an indicator function for the K6 score being equal or greater than 13 (columns (4) – (6)), which indicates severe mental illness.

[Insert Table 3 here]

We find an economically and statistically significant positive effect of $PM_{2.5}$ on the K6 score using the IV estimate. In column (1), we start by only including county fixed effects and year-by-month fixed effects. Our estimate suggests that a 1 μg/m^3 increase in $PM_{2.5}$ concentrations increases the K6 score by 0.0480 units, which is statistically significant at the 5% level. In column (2), we add weather controls, to ensure that air pollution is the only channel through which thermal inversion affects mental illness. The estimate slightly increases to 0.0527 and remains statistically significant at the 5% level. In the last column, we weight our regression by sample weights, to make our estimate nationally representative of the urban population. The estimate further increases to 0.0788 and becomes statistically significant at the 1% level. This is our preferred estimate (here forth baseline estimate) as it includes the full set of controls and is representative of the average urban adult. Since the standard deviations of $PM_{2.5}$ and the K6 score are 18.04 and 3.76, our baseline estimate implies that a one-standard-deviation increase in $PM_{2.5}$ increases the K6 score by 0.38 standard deviations.

We find an effect that is similar in magnitude when the dependent variable is severe mental illness. Our baseline estimate in column (6) suggests that a 1 μg/m^3 increase in $PM_{2.5}$ concentrations increases the probability of having severe mental illness by 0.37%. Since the percentage having a K6 score consistent with severe mental illness in our sample is 4.38%, the marginal effect is equivalent to 8.45% of the mean. Converting to standard deviations, we find that a one-standard-deviation increase in $PM_{2.5}$ concentration increases the probability of having severe mental illness by 6.67%, or 0.33 standard deviations. The adult population in China in 2014 is 1.14 billion (China Statistical Yearbook, 2015). Therefore, our estimates suggest that a one-standard-deviation increase in $PM_{2.5}$ (18.04 μg/m^3) induces a K6 score consistent with mental illness in 76.04 million adults. Note that the above estimates are estimated using 2SLS for both the continuous and the discrete measures of mental health. The estimates on the effect of air pollution on severe mental illness using the IV probit model are presented in Table 5 (Column 6) and remain robust.

Our IV estimates suggest a significantly positive effect of $PM_{2.5}$ on mental illness. On the contrary, the OLS estimates (reported in Panel B of Table 3) are not statistically significant and much smaller in magnitude. These findings are consistent with OLS estimates being severely biased downwards because of the omitted variables, reverse causality, and classical measurement error.

In our baseline models, we use either continuous or discrete versions of the K6 score, which is the sum of points across all six questions regarding each symptom. To explore whether our estimates are driven by any symptom in particular, we report the IV estimates on the effect of $PM_{2.5}$ on the score of each individual symptom ranging from zero to four in Table 4. Note that a higher score means a stronger prevalence of that symptom.

We find statistically positive effects of $PM_{2.5}$ and similar magnitudes on five of the symptoms, including depression, restlessness, hopelessness, difficulty, and worthlessness. Though the effect on nervousness is not statistically significant, the sign remains positive. Therefore, we conclude that our estimates are not driven predominantly by any single symptom.

[Insert Table 4 here]

In our baseline estimation we explore the effect of air pollution during the past month prior to the interview. However, having variation in the date of the interview in our sample allows us to investigate whether the effects of pollution are cumulative or influence the respondent's answer only on the day they were interviewed. In Figure 4 we explore different exposure windows, ranging from past one year to the contemporaneous $PM_{2.5}$ on the same day of the interview. We also explore the effect of $PM_{2.5}$ in subsequent days, from one week to one year. Estimating the effect of leads in the exposure window serves as a placebo test, as truly exogenous variation in pollution captured by thermal inversions should not be correlated with past mental health. Circles denote the point estimates and whispers indicate the 95% confidence interval. Due to space limitations, we only report one side of the 95% confidence interval for one-year lag, half-year lag, two-week lead, three-week lead, and one-month lead. Our baseline estimation, which is one-month lag, is labelled in red. We also highlight the estimate on the interview day using red dash lines. The dependent variables are the K6 score in Panel A and an indicator for severe mental illness in Panel B.

[Insert Figure 4 here]

We find insignificant effects of $PM_{2.5}$ in one year, half year, three months, and two months prior to the interview. The effect is very imprecisely estimated for long lags. Our baseline specification, which perfectly matches the recall window in the mental health survey, finds a significantly positive effect of $PM_{2.5}$ on mental illness that is larger than any shorter window. However, shorter windows – including three weeks, two weeks, and one week – also have significantly positive effects. This is intuitive since these exposure windows still lie within one month. Interestingly, when we use the $PM_{2.5}$ on the interview day, we find a very precisely estimated zero effect. This gives us confidence that we are not capturing same-day effects in mood or decision making, which have been explored by previous literature (Heyes et al., 2016). Our interpretation of these results are that (a) we do not find evidence that the effects of air pollution on the mental health symptoms we study persist for longer than three months; and (b) our results are not capturing the effects of same-day-exposure on mood or decision making. Also, people seem to match well their recollection of mental health symptoms to the window specified in the survey.

When we construct the exposure window using $PM_{2.5}$ after the interview date, we find insignificant and very imprecise effects for all exposure windows, ranging from one week to one year. This lends confidence to the validity of our exclusion restriction and suggests that our estimates are indeed causal and are not driven by any spurious correlations.

We conduct various robustness checks in Table 5. Dependent variables are the K6 score in Panel A and severe mental illness in Panel B. We start by testing the robustness of interpolation on air pollution data. In our baseline model, we use the IDW method to convert pollution data from station to county with a radius of 100 km. In column (2), we narrow the radius to 50 km and, consequently, lose around 14% observations from counties that do not have pollution stations within a 50-km radius. The estimate remains of similar magnitude and also statistically significant at the 5% significance level. Importantly, the standard errors in this specification are not smaller than in our baseline specification, suggesting that the 2SLS estimation is eliminating the classical measurement error bias. In column (3), we use a radius of 150 km and the estimate remains of similar magnitude and significance than in our baseline.

In column (4), we assign the air pollution data to the county using the nearest pollution station. In this specification, the estimate increases from 0.0788 to 0.1207. However, the KP *F*-statistic decreased from 36.04 to 19.86. Although this value is still above the Stock-Yogo critical value for at 10% maximal size, we believe the estimates using the IDW method, which have a much stronger first stage, are more reliable.

We then test the robustness to alternative ways of constructing our instrumental variable. In our baseline model, we code the existence of a thermal inversion whenever the temperature in the second layer (320 meters) is higher than the temperature in the ground layer (110 meters). In column (5), we replace the layer at 320 meters with the layer at 540 meters. This changes the estimate little but the KP *F*-statistics become smaller.

Finally, we test the robustness of our functional form in the last column. Our baseline model uses the 2SLS model to estimate the effect of $PM_{2.5}$ on severe mental illness. In column (6), we use the IV-probit model and report the marginal effect evaluated at the mean $PM_{2.5}$. The estimate remains significant at the 5% significance level and is quite close to the baseline in terms of magnitude.

[Insert Table 5 here]

5.3 Mechanisms and Heterogeneity

As discussed in Section 2, there are both direct (brain function) and indirect (physical health, productivity, and behavior) channels through which air pollution could affect mental health. Although we cannot test for the importance of the direct channels, we can test for the role of some indirect channels such as exercise and physical health in Table 6.[16]

[16] We do not test the channel through labor productivity since there is no accurate measurement of labor productivity in the data. There are numerous studies focus on air pollution and labor productivity. For example, see Graff Zivin and Neidell (2012), Adhvaryu et al. (2014), Chang et al. (2016), Fu et al., (2017), Chang et al., (forthcoming), and He et al., (forthcoming). We also do not test the channel through income because income is reported within the past year, which does not match the time window of mental health (one month).

[Insert Table 6 here]

Columns (1) to (3) report the effect of $PM_{2.5}$ on exercise. In column (1), the dependent variable is a dummy variable which equals one if the respondent exercised in the week prior to the interview, and zero otherwise. We find that a 1 μg/m^3 increase in $PM_{2.5}$ concentration in the past week decreases the probability of exercising by 0.49%, which is 1.05% of the mean. In column (2), the dependent variable is the number of times in the last week that the person exercised. We find that a 1 μg/m^3 increase in $PM_{2.5}$ concentrations in the past week decreases exercise by 0.0068 times, or 0.28% of the mean. In column (3), the dependent variable is hours of exercise. We find that 1 μg/m^3 increase in $PM_{2.5}$ concentrations decreases exercise time by 0.0448 hours, or 1.33% of the mean, which is only significant at the 10 percent level.

To compare the magnitude of the pollution effect on exercise and mental health, we convert the estimated impacts to standard deviation units. We find that a one-standard-deviation increase in $PM_{2.5}$ concentrations reduces exercise times by 0.04 standard deviations and exercise hours by 0.13 standard deviations. This is much smaller than the pollution effect on mental health, in which we find that a one-standard-deviation increase in $PM_{2.5}$ concentrations increases the K6 score by 0.38 standard deviations and the probability of having severe mental illness by 0.33 standard deviations.

Columns (4) and (5) report the effect of $PM_{2.5}$ on physical illness. The dependent variable in column (4) is a dummy variable which equals to one if the respondent was sick in the past two weeks before the interview and zero otherwise. Though the sign of the estimate is positive, it is statistically insignificant and very small in magnitude. In column (5), the dependent variable is the degree of sickness from one to five with one for not serious and five for very serious. This measure is conditional on the respondent having reported being sick. Thus, we only have 30% of observations compared to column (4). We find a weakly significant positive effect of $PM_{2.5}$ on the degree of sickness, and again, the estimate is quite small in magnitude. Specifically, a 1 μg/m^3 increase in $PM_{2.5}$ concentrations increases the degree of sickness by 0.0089 units, or 0.29% of the mean. In the last column, the dependent variable is the self-rated health status in the past month. The health status varies from one to five, with one for very healthy and five for very unhealthy. Thus, a higher value indicates a higher degree of unhealthiness. We find a weakly significant positive effect of $PM_{2.5}$ on self-reported unhealthiness. Specifically, a 1 μg/m^3 increase in $PM_{2.5}$ concentrations increases the degree of unhealthiness by 0.0092 units, or 0.31% of the mean.

We again convert all estimated coefficients on illness and self-rated health to standard deviation units to compare with the pollution effect on mental health. We find that a one-standard-deviation increase in $PM_{2.5}$ concentrations increases the degree of sickness by 0.11 standard deviations and the degree of self-rated unhealthiness by 0.14 standard deviations. These effects are smaller than the pollution effect on mental health.

Overall, we find weaker and smaller pollution effects on exercise and physical health. To us, this suggests that important mechanisms linking air pollution to mental health could be either direct (brain function) or outside of the ones studied and measured in Table 6.

In addition to studying self-reported health and exercise measures, we can explore whether the effects are heterogeneous across different populations. We start by focusing on gender and education in Table 7. Dependent variables are the K6 score in columns (1) – (4), and severe mental illness in columns (5) – (8). Regression models are estimated separately for each subsample. We also report the mean and the standard deviation of the dependent variable for each subsample.

[Insert Table 7 here]

Male respondents account for about 48% of our sample and have a lower average K6 score and severe mental illness prevalence than female respondents. This pattern has been well documented in the past and attributed to lower self-esteem and higher rates of interpersonal stressors among women, as well as higher rates of violence and childhood sexual abuse (Riecher-Rössler, 2017). Interestingly, we find that the marginal effect of $PM_{2.5}$ on mental illness is larger for male than for female. In particular, we find that for men a 1 μg/m^3 increase in $PM_{2.5}$ concentration increases the K6 score by 0.0986 units (3.74%) and the probability of having severe mental illness by 0.55%. In contrast, the respective increases for women are 0.0575 units (1.75%) and 0.18%, and the latter is also not statistically significant. Although these results seem slightly puzzling, there are several plausible reasons why this could be the case: differences in exposure to outdoor pollution (which is the type of pollution captured by our main variable of interest), non-linear effects of pollution on mental health, or larger vulnerability of male individuals to air pollution.

In terms of age, elderly (age >=60) account for nearly 25% of the total sample, with slightly higher K6 score, but they have a much higher prevalence of severe mental illness than the population aged below 60. The age differences we find are consistent with prior literature, which also finds that controlling for physical health substantially reduces the correlation between age and mental health (Lei et al. 2014a). We find much larger effects of $PM_{2.5}$ among the elderly, suggesting that their mental well-being is more vulnerable to air pollution.

We further explore the heterogeneity by educational level in Table 8. We divide the sample by three educational groups: primary school or below (columns (1) and (4)), junior high or high school (columns (2) and (5)), and college or above (columns (3) and (6)). The summary statistics (the fourth row) shows that mental illness is most severe among the lower educated. This is also consistent with other studies in China that focus on mental health correlates among adults (Lei et al. 2014a). However, we find that the marginal effect of air pollution is the highest among the highly educated population. This finding is somewhat surprising, as self-reported and objective health measures are the highest among the highly educated (Lei et al. 2014b) and it is reasonable to believe that poor baseline health could increase the vulnerability to the effects of air pollution. Potential reasons for this difference include higher rates of exercise among the highly educated and jobs that are more demanding on cognitive ability. If pollution affects cognitive ability, the economic cost induced by air pollution may be particularly high for the highly educated.

[Insert Table 8 here]

We also divide the sample by indoor or outdoor based on their workplace and report the estimates in Table 9. Noted that this is conditional on the respondent is employed. Therefore, we only have 36% of the observations in our main sample. We find both significant and similar effects of air pollution on indoor and outdoor workers, suggesting that exposure does not change substantially with time spent outdoors for work.

[Insert Table 9 here]

6 Discussion and Conclusion

We find significantly positive effects of air pollution on mental illness. In particular, a one-standard-deviation increase in $PM_{2.5}$ concentrations (18.04 μg/m^3) increases the probability of having severe mental illness by 6.67%, or induces severe mental health symptoms among 76.04 million adults. How large are these estimates? According to Xu et al. (2016), the annual cost of mental illness in China is USD 3,665 in 2013 for individual patients. If all patients get treated, the corresponding annual cost is USD 279 billion. Phillips et al. (2009) find that 8.2% of patients with mental illness would seek medical treatment in China. Therefore, our lower-bound estimate suggests a one-standard-deviation increase in $PM_{2.5}$ is associated with an annual economic cost of USD 22.88 billion in terms of additional medical expenditure on mental illness.

We compare our estimates with several strands of literature that focus on the economic cost of air pollution. To make the estimates comparable, we only include papers that report economic benefits of reducing $PM_{2.5}$ and normalize the estimates by per one-standard-deviation change in $PM_{2.5}$ concentrations.

First, we compare our estimate with Deryugina et al. (2016), which estimate the effect of $PM_{2.5}$ on mortality in the U.S. They find that the national average $PM_{2.5}$ concentrations in the U.S. decreased by 3.65 $\mu g/m^3$ during the period of 1999-2011, which led to a corresponding benefit of USD 15 billion per year in term of avoided mortality. This implies that a one-standard-deviation decrease in $PM_{2.5}$ (7.34 $\mu g/m^3$) brings an annual benefit of USD 30.16 billion, which is comparable to our estimate. Note that the magnitude of the standard deviations in $PM_{2.5}$ in the US are much smaller than in China. However, even for a comparable amount of variation, the calculations would remain of a similar order of magnitude.

Second, we compare our estimate with two studies that focus on labor productivity. Chang et al. (2016) find that during the period 1999-2008, the national average of $PM_{2.5}$ concentrations in the U.S. decreased by 2.79 $\mu g/m^3$, which led to an aggregate labor savings of USD 19.5 billion. Therefore, we can conclude that a one-standard-deviation decrease in $PM_{2.5}$ concentrations (10.14 $\mu g/m^3$) increases labor productivity in the U.S. by USD 7.09 billion annually. A similar exercise is conducted by Fu et al. (2017) in China, but with more comprehensive manufacturing data. They find that a one-standard-deviation decrease in $PM_{2.5}$ concentrations (25.46 $\mu g/m^3$) increases manufacturing productivity in China by USD 76.11 billion annually. Our estimate lies between these two estimates.

Third, we compare our estimate with Bishop et al. (2017), which study the long-term exposure to $PM_{2.5}$ on dementia in the U.S. They find that reducing annual average concentrations of $PM_{2.5}$ by 1 $\mu g/m^3$ reduces the rate of dementia by 1-3%, which corresponds to a reduction in direct medical expenditures on dementia by USD 3.5-10.5 billion per year. Because the standard deviation of $PM_{2.5}$ is not reported in Bishop et al. (2017), we convert our estimate from USD 22.88 billion per standard deviation increase (18.04 $\mu g/m^3$) to USD 1.27

billion per μg/m^3. Our estimate is smaller than the estimate in Bishop et al. (2017) but is of the same order of magnitude.

Our estimates have important policy implications in designing optimal environmental policy in China. For example, on September 10th 2013, the State Council issued the "Air Pollution Prevention and Control Action Plan".[17] The plan aims at reducing the urban concentration of $PM_{2.5}$ by 25%, 20%, and 15% in Beijing-Tianjin-Hebei, the Yangtze River Delta, and the Pearl River Delta regions respectively by 2017 relative to 2012. Using the lower-bound of our estimates and the midpoint of these three goals (20%), we find a gain of USD 12.10 billion (0.12% of GDP) in terms of avoided medical expenditure on mental illness.

The Chinese government has made several policies to address the mental illness issues. For example, in 2009, the government has issued the New Healthcare Reform Plan, which includes major mental disorders in the public health care scheme.[18] In 2012, the first National Mental Health Law was approved by the National People's Congress.[19] In 2015, the State Council launched the National Mental Health Working Plan (2015-2020) to improve mental health care services.[20] Our paper shows that reducing air pollution could be an important additional way to address the prevalence of mental health illness.

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[17] See http://www.gov.cn/zwgk/2013-09/12/content_2486773.htm (in Chinese).
[18] See http://www.gov.cn/zwgk/2009-04/07/content_1279256.htm (in Chinese).
[19] See http://www.moh.gov.cn/zwgkzt/pfl/201301/20969fdf44934b86a0729fb4de33e1ff.shtml (in Chinese).
[20] See http://www.nhfpc.gov.cn/jkj/s5888/201506/1e7c77dcfeb4440892b7dfd19fa82bdd.shtml (in Chinese).

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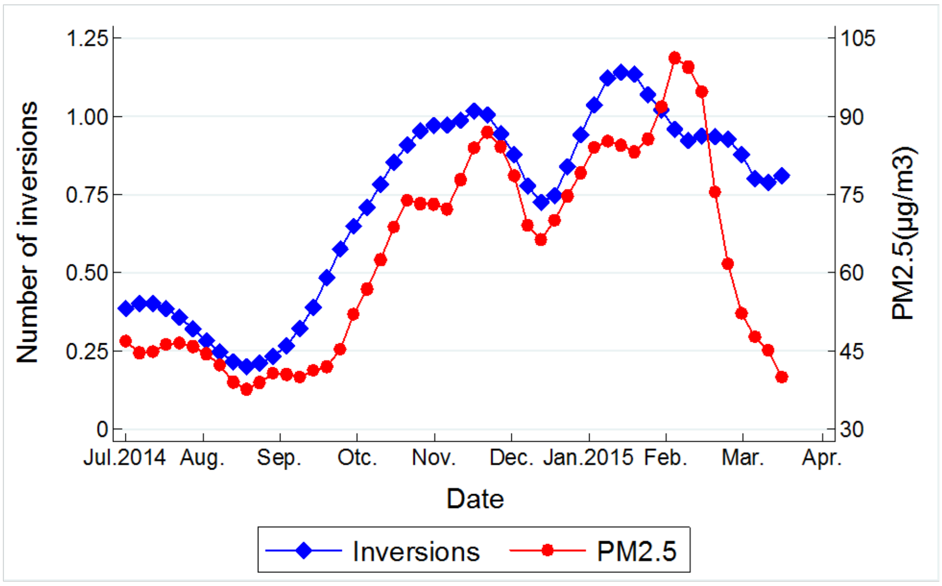


Figure 1. Time Trend of $PM_{2.5}$ and Thermal Inversion

Notes: This figure plots the average concentrations of $PM_{2.5}$ and average number of thermal inversions for all 162 counties in each day from July 3rd 2014 to March 31th 2015, the course of our study period.

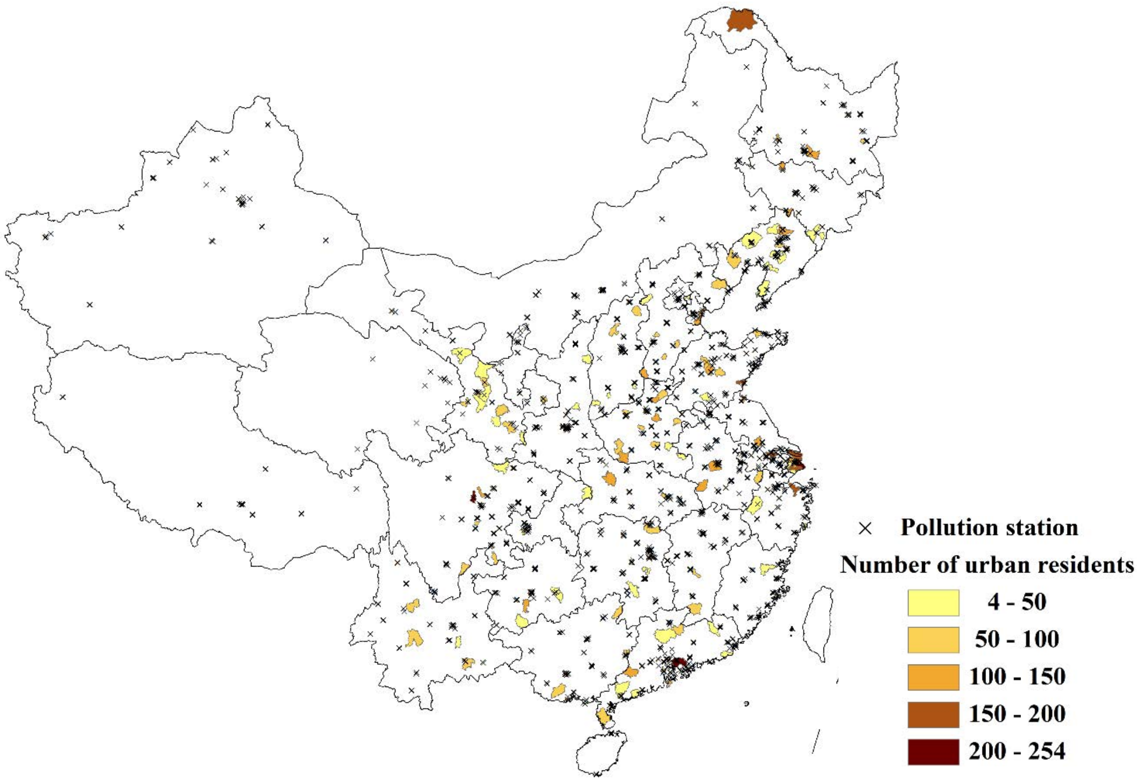


Figure 2. Survey Counties and Pollution Stations

Notes: This figure depicts the survey counties and pollution monitoring stations. Dark color indicates higher number of urban residents who are interviewed. Number of urban residents=12,615. Number of counties=162. Number of pollution stations=1,498.

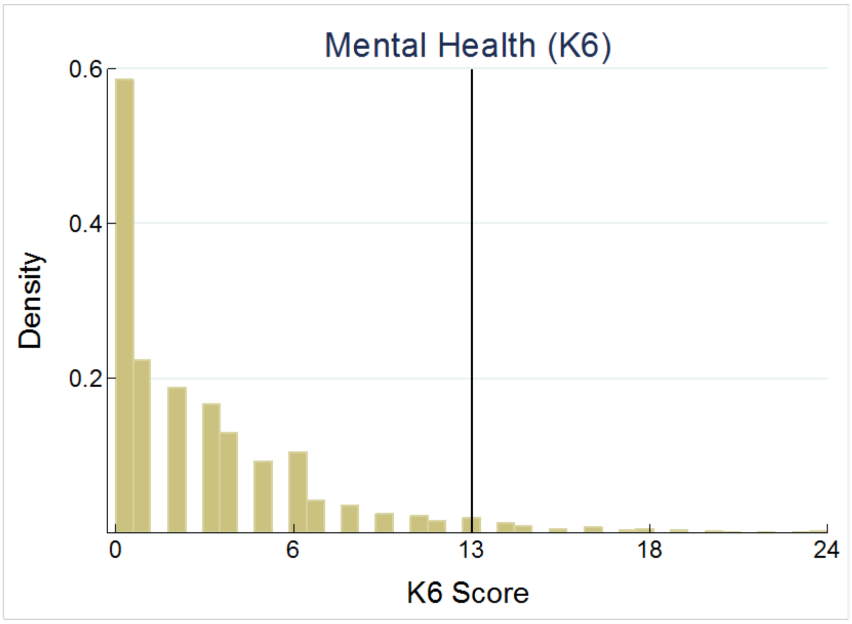
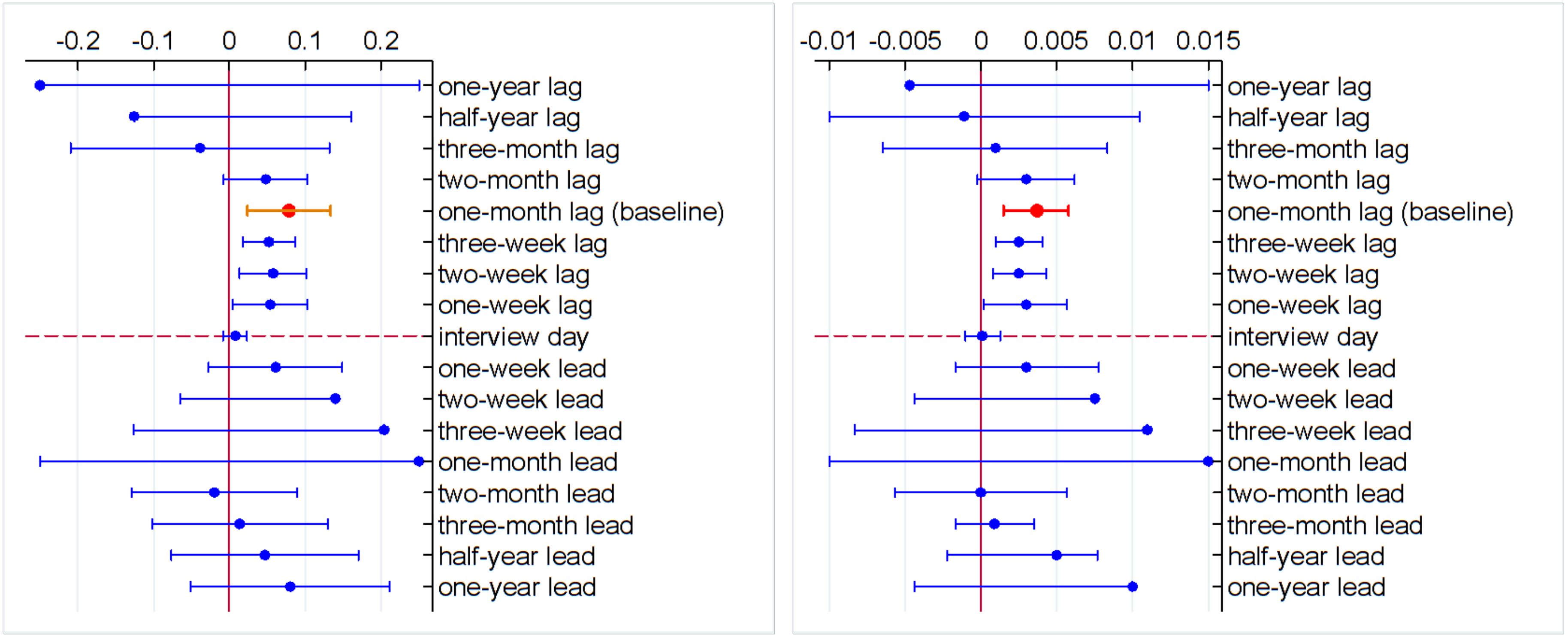


Figure 3. Histogram of the K6 Score

Notes: This figure plots the histogram of the K6 score, ranging from 0 to 24. The vertical black line indicates the cutoff of 13, which is used to define severe mental illness if the K6 score is equal or above the cutoff.



Panel A: Impact of $PM_{2.5}$ on the K6 score

Panel B: Impact of $PM_{2.5}$ on severe mental illness

Figure 4. Lagged and Lead Impacts

Notes: This figure depicts the impacts of $PM_{2.5}$ on the K6 score (Panel A) and severe mental illness (Panel B). $PM_{2.5}$ is calculated using the average from one-year lag to one-year lead. The circle denotes the point estimate and the whisker denotes the 95% confidence interval. The red circle denotes the baseline estimate, in which pollution is constructed using the average one month prior to the interview. Due to space limitations, we only present one side of the 95% confidence intervals for certain periods.

Table 1. Summary Statistics

Variable	Unit	Mean	SD	Min	Max
Mental health					
The K6 score	Index (0-24)	2.96	3.76	0	24
Severe mental illness	%	4.38	20.47	0	100
Depression	0-never; 4-almost everyday	0.75	0.92	0	4
Nervousness	0-never; 4-almost everyday	0.59	0.87	0	4
Restlessness	0-never; 4-almost everyday	0.50	0.82	0	4
Hopelessness	0-never; 4-almost everyday	0.31	0.72	0	4
Difficulty	0-never; 4-almost everyday	0.51	0.85	0	4
Worthlessness	0-never; 4-almost everyday	0.28	0.69	0	4
Air pollution					
$PM_{2.5}$	μg/m^3	47.71	18.04	13.46	160.19
Thermal inversions					
Inversions	Number	11.74	13.32	0	93

Notes: *N*=12,615. Unit of observation is respondent. The survey covers 162 counties during the period of July 3rd 2014 to March 31th 2015. The interview surveyed the mental health one month prior to the interview day for adult population (age >=16). The K6 score is the sum of the points across the six individual symptoms. The severe mental illness is a dummy variable which equals to one if the K6 score is above or equal to 13, and zero otherwise. Each specific symptom is coded from zero to four, with zero indicating never, one a little of the time, two half of the time, three most of the time, and four all most every day. The concentrations of air pollutants are reported in each day, and then is averaged to the month. The existence of thermal inversion is determined within each six-hour period, and then aggregated to the month.

Table 2. First-stage Estimation: Effect of Thermal Inversions on $PM_{2.5}$

	$PM_{2.5}$		
	(1)	(2)	(3)
Thermal inversions	0.3506***	0.3013***	0.3024***
	(0.0370)	(0.0239)	(0.0317)
R-squared	0.8587	0.8926	0.9022
County FE	Yes	Yes	Yes
Year-by-month *FE*	Yes	Yes	Yes
Weather controls	No	Yes	Yes
Sample weights	No	No	Yes
KP *F*-statistic	35.26	50.59	36.04

Notes: N=12,615. Dependent variable is $PM_{2.5}$. Regression models are estimated using Equation (2). Weather controls include 5 °C temperature bins, second order polynomials in average relative humidity, wind speed, sunshine duration, and cumulative precipitation. Standard errors are listed in parentheses and clustered by both county and date (two-way clustering). *** p<0.01, ** p<0.05, * p<0.1.

Table 3. Second-stage Estimation: Effect of Air Pollution on Mental Health

	The K6 Score			Severe Mental Illness		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: IV						
$PM_{2.5}$	0.0480**	0.0527**	0.0788***	0.0022***	0.0024***	0.0037***
	(0.0212)	(0.0252)	(0.0280)	(0.0008)	(0.0009)	(0.0011)
KP *F*-statistics	35.26	50.59	36.04	35.26	50.59	36.04
Panel B: OLS						
$PM_{2.5}$	0.0005	-0.0045	-0.0110	0.0002	-0.0002	-0.0004
	(0.0066)	(0.0074)	(0.0075)	(0.0002)	(0.0003)	(0.0005)
County *FE*	Yes	Yes	Yes	Yes	Yes	Yes
Year-by-month *FE*	Yes	Yes	Yes	Yes	Yes	Yes
Weather controls	No	Yes	Yes	No	Yes	Yes
Sample weights	No	No	Yes	No	No	Yes

Notes: *N*=12,615. Dependent variables are the K6 score in columns (1) – (3) and severe mental illness in columns (4) – (6). Severe mental illness is a dummy variable which equals to one if the K6 score is equal or larger than 13. Panel A is the IV estimate, in which we use number of thermal inversions to instrument $PM_{2.5}$. Panel B is the OLS estimate. Weather controls include 5 °C temperature bins, second order polynomials in average relative humidity, wind speed, and sunshine duration, and cumulative precipitation. Standard errors are listed in parentheses and clustered by both county and date (two-way clustering). *** p<0.01, ** p<0.05, * p<0.1.

Table 4. Effect of Air Pollution on Mental Health: By Symptom

	About how often do you feel					
	Depression	Nervousness	Restlessness	Hopelessness	Difficulty	Worthlessness
	(1)	(2)	(3)	(4)	(5)	(6)
$PM_{2.5}$	0.0155**	0.0045	0.0134***	0.0150***	0.0183***	0.0123**
	(0.0073)	(0.0062)	(0.0044)	(0.0048)	(0.0055)	(0.0049)
Observations	12,657	12,659	12,660	12,638	12,657	12,649
County *FE*	Yes	Yes	Yes	Yes	Yes	Yes
Year-by-month *FE*	Yes	Yes	Yes	Yes	Yes	Yes
Weather controls	Yes	Yes	Yes	Yes	Yes	Yes
Sample weights	Yes	Yes	Yes	Yes	Yes	Yes
KP *F*-statistic	36.17	36.19	36.20	36.11	36.15	36.09

Notes: Dependent variables are scores of each specific symptom ranging from zero to four. Higher score means stronger prevalence of that symptom. Weather controls include 5 °C temperature bins, second order polynomials in average relative humidity, wind speed, and sunshine duration, and cumulative precipitation. Standard errors are listed in parentheses and clustered by both county and date (two-way clustering). *** p<0.01, ** p<0.05, * p<0.1.

Table 5. Robustness Checks

	Baseline	IDW Interpolation			Alternative layer of inversion	Functional form
		Radius=50km	Radius=150km	Nearest station		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: The K6 score						
$PM_{2.5}$	0.0788***	0.0664**	0.0819***	0.1207***	0.0807**	
	(0.0280)	(0.0320)	(0.0287)	(0.0428)	(0.0357)	
KP *F*-statistic	36.04	27.69	35.59	19.86	16.64	
Panel B: Severe mental illness						IV-Probit
$PM_{2.5}$	0.0037***	0.0038***	0.0038***	0.0054***	0.0041**	0.0040**
	(0.0011)	(0.0011)	(0.0010)	(0.0017)	(0.0018)	(0.0019)
KP *F*-statistic	36.04	27.69	35.59	19.86	16.64	----
Observations	12,615	10,910	12,844	12,430	12,615	12,615

Notes: Dependent variables are K6 score in Panel A and a dummy variable for severe mental illness in Panel B. Column (1) is the baseline model. Columns (2) – (4) tests the robustness of interpolation of air pollution data. Columns (2) and (3) use the IDW method with 50 km and 150 km radius respectively. In column (4), we assign the pollution data from station to county using the nearest station. Column (5) tests the robustness of construction of the IV. In the baseline model, we determine an existence of a thermal inversion if the temperature in the higher layer (320 meters) is higher than that in the ground layer (110 meters). We change the higher layer to 540 meters in column (5). Column (6) tests the robustness of the functional form. In Panel B, since the dependent variable is a dummy variable, we use the IV probit model, instead of the 2SLS model in the baseline. The estimates reported here is the marginal effects evaluated at the mean level. All models include county fixed effects, year-by-month fixed effects, and weather controls. Weather controls include 5 °C temperature bins, second order polynomials in average relative humidity, wind speed, and sunshine duration, and cumulative precipitation. Standard errors are listed in parentheses and clustered by both county and date (two-way clustering) . *** p<0.01, ** p<0.05, * p<0.1.

Table 6. Mechanism Tests

	Exercise (past 1 week)			Sickness (past 2 weeks)		Self-rated health (past 1 month)
	(1)	(2)	(3)	(4)	(5)	(6)
	1-yes, 0-no	times	hours	1-yes, 0-no	1-not serious, 5-very serious	1-very healthy, 5-very unhealthy
$PM_{2.5}$	-0.0049**	-0.0068*	-0.0448**	0.0020	0.0089*	0.0092*
	(0.0022)	(0.0035)	(0.0209)	(0.0019)	(0.0052)	(0.0056)
Observations	12,664	12,663	12,670	12,670	3,806	12,668
Mean of Dep. Var.	0.4670	2.4008	3.3681	0.2917	3.1140	2.9698
S.D. of Dep. Var.	0.4989	3.1324	6.4268	0.4545	1.4053	1.1816
County *FE*	Yes	Yes	Yes	Yes	Yes	Yes
Year-by-month *FE*	Yes	Yes	Yes	Yes	Yes	Yes
Weather controls	Yes	Yes	Yes	Yes	Yes	Yes
Sample weights	Yes	Yes	Yes	Yes	Yes	Yes
KP *F*-statistic	48.73	48.57	48.72	44.92	59.36	36.30

Notes: Dependent variables are a dummy variable which equals to one if respondent exercises in the past week in column (1), times of exercise in column (2), hours of exercise in column (3), a dummy variable which equals to one if respondent was sick in the past two weeks in column (4), degree of illness from one to five with one for not serious and five for very serious in column (5), degree of self-rated health status from one to five with one for very healthy and five for very unhealthy in column (6). $PM_{2.5}$ is calculated using the average for the corresponding exposure window and is instrumented using thermal inversion. Weather controls include 5 °C temperature bins, second order polynomials in average relative humidity, wind speed, and sunshine duration, and cumulative precipitation. Standard errors are listed in parentheses and clustered by both county and date (two-way clustering). *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 7. Effect of Air Pollution on Mental Health: By Gender and Cohort

	The K6 Score				Severe Mental Illness			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Male	Female	Age 16-60	Age >=60	Male	Female	Age 16-60	Age >=60
$PM_{2.5}$	0.0986***	0.0575*	0.0611**	0.1499**	0.0055***	0.0018	0.0031***	0.0059
	(0.0268)	(0.0342)	(0.0298)	(0.0599)	(0.0018)	(0.0014)	(0.0011)	(0.0037)
Observations	6,093	6,522	9,446	3,169	6,093	6,522	9,446	3,169
Mean of Dep. Var.	2.6378	3.2799	2.9504	3.0281	0.0361	0.0512	0.0377	0.0626
S.D. of Dep. Var.	3.5378	3.9405	3.5819	4.2683	0.1867	0.2204	0.1905	0.2422
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-by-month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Weather controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample weights	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
KP *F*-statistic	25.14	43.22	32.11	27.20	25.14	43.22	32.11	27.20

Notes: Dependent variables are the K6 score in columns (1) – (4) and severe mental illness in column (5) – (8). Regression models are estimated separately for each subsample. Weather controls include 5 °C temperature bins, second order polynomials in average relative humidity, wind speed, and sunshine duration, and cumulative precipitation. Standard errors are listed in parentheses and clustered by both county and date (two-way clustering). *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 8. Effect of Air Pollution on Mental Health: By Education

	The K6 Score			Severe Mental Illness		
	(1)	(2)	(3)	(4)	(5)	(6)
	Primary school or below	Junior high or high school	College or above	Primary school or below	Junior high or high school	College or above
$PM_{2.5}$	0.0046	0.1200**	0.1700***	0.0004	0.0058**	0.0115**
	(0.0407)	(0.0516)	(0.0611)	(0.0020)	(0.0029)	(0.0057)
Observations	4,448	3,478	3,416	4,448	3,478	3,416
Mean of Dep. Var.	3.3757	2.7713	2.6825	0.0625	0.0356	0.0282
S.D. of Dep. Var.	4.2096	3.5471	3.3062	0.2421	0.1854	0.1655
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-by-month FE	Yes	Yes	Yes	Yes	Yes	Yes
Weather Controls	Yes	Yes	Yes	Yes	Yes	Yes
Sample weights	Yes	Yes	Yes	Yes	Yes	Yes
KP *F*-statistic	23.15	34.94	21.67	23.15	34.94	21.67

Notes: Dependent variables are K6 score in columns (1) – (3) and severe mental illness in column (4) – (6). Regression models are estimated separately for each subsample. Weather controls include 5 °C temperature bins, second order polynomials in average relative humidity, wind speed, and sunshine duration, and cumulative precipitation. Standard errors are listed in parentheses and clustered by both county and date (two-way clustering). *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 9. Effect of Air Pollution on Mental Health: By Workplace

	K6 Score		Severe Mental Illness	
Workplace	Indoor	Outdoor	Indoor	Outdoor
	(1)	(2)	(3)	(4)
$PM_{2.5}$	0.0714**	0.0847***	0.0029*	0.0038***
	(0.0355)	(0.0304)	(0.0015)	(0.0011)
Observations	3,232	1,248	3,232	1,248
Mean of Dep. Var.	2.8122	2.9113	0.0317	0.0397
S.D. of Dep. Var.	3.4184	3.4823	0.1754	0.1954
County FE	Yes	Yes	Yes	Yes
Year-by-month FE	Yes	Yes	Yes	Yes
Weather controls	Yes	Yes	Yes	Yes
Sample weights	Yes	Yes	Yes	Yes
KP *F*-statistic	26.19	21.61	26.19	21.61

Notes: Dependent variables are K6 score in columns (1) – (2), and a dummy variable for severe mental illness in columns (3) – (4). In columns (1) and (3), we focus on respondents whose workplace is indoor only. In columns (2) and (4), we focus on respondents whose workplace is outdoor only. Weather controls include 5 °C temperature bins, second order polynomials in average relative humidity, wind speed, and sunshine duration, and cumulative precipitation. Standard errors are listed in parentheses and clustered by both county and date (two-way clustering). *** p<0.01, ** p<0.05, * p<0.1.

Online Appendix

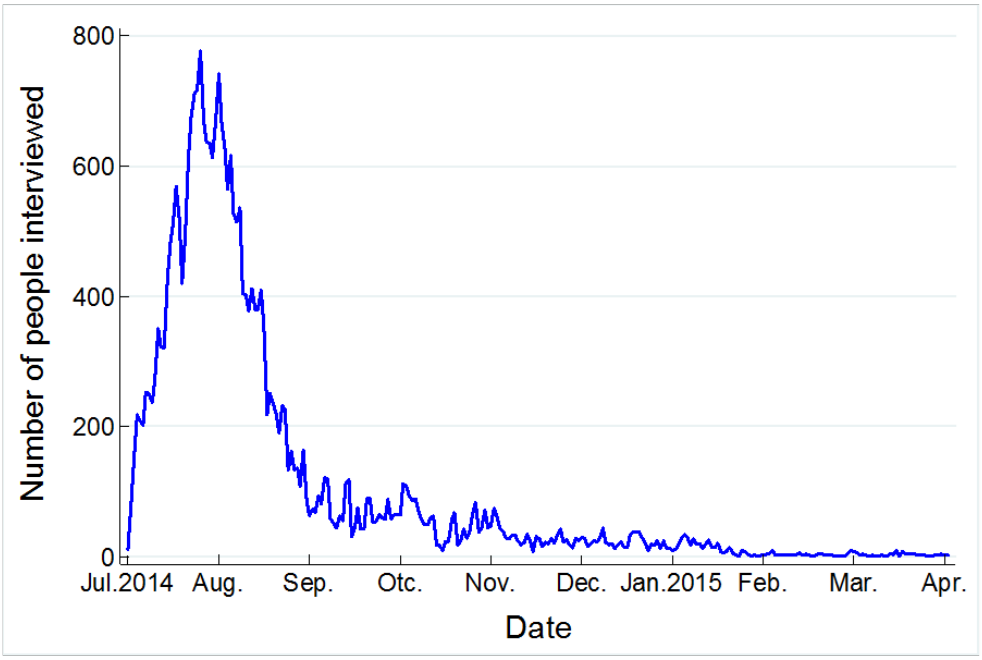
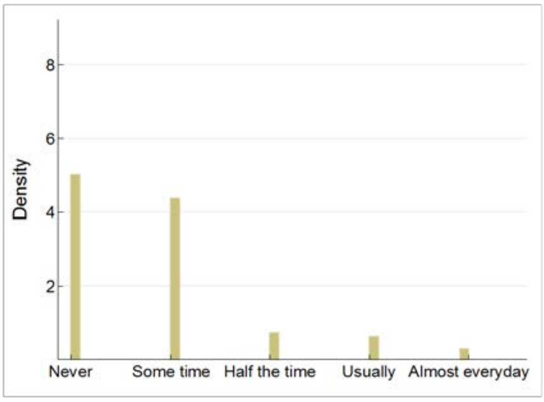
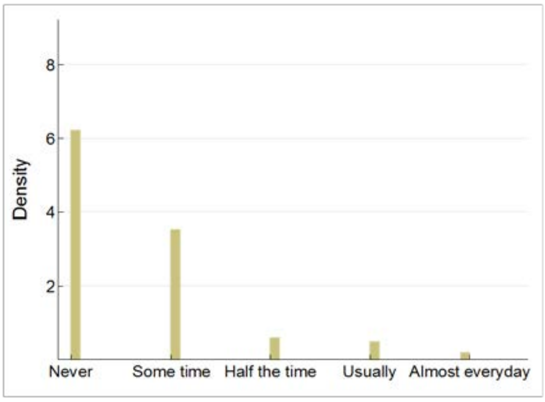


Figure A1. Number of People Interviewed in Each Day

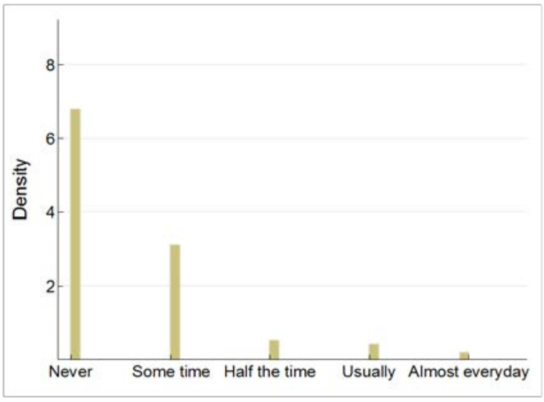
Notes: This figure plots the number of people interviewed in each day from July 3rd 2014 to March 31th 2015, the course of our study period.



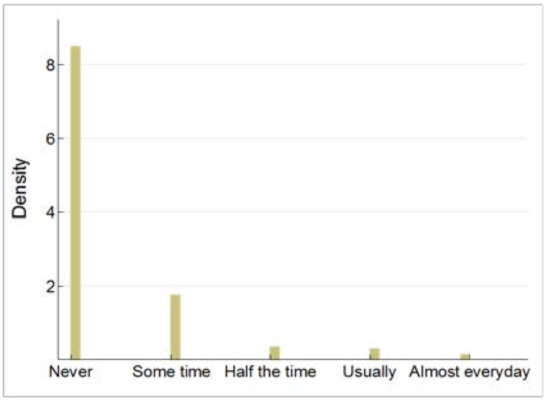
Panel A: Depression



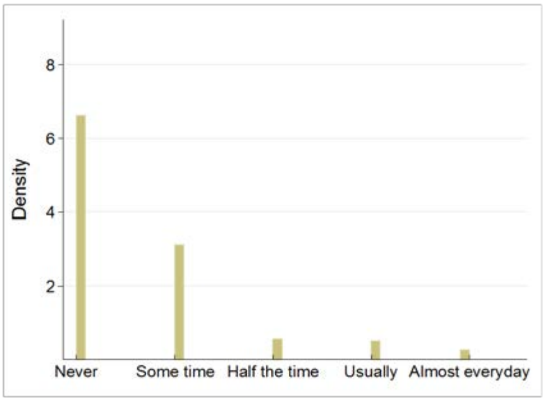
Panel B: Nervousness



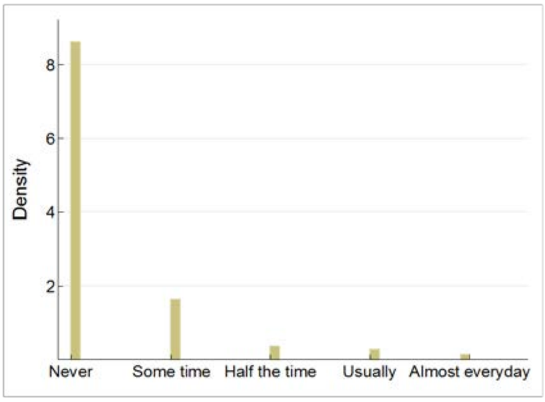
Panel C: Restlessness



Panel D: Hopelessness



Panel E: Difficulty



Panel F: Worthlessness

Figure A2. Histogram of Specific Mental Illness Symptom

Notes: This figure plots the histogram of each specific mental disorder symptom.

Table A1. Effect of Air Pollution on Mental Health: By Residence

	The K6 Score			Severe Mental Illness		
	Urban	Rural	Total	Urban	Rural	Total
	(1)	(2)	(3)	(4)	(5)	(6)
$PM_{2.5}$	0.0788***	-0.0513	0.0187	0.0037***	-0.0009	0.0008
	(0.0280)	(0.0446)	(0.0261)	(0.0011)	(0.0010)	(0.0013)
Observations	12,615	15,618	28,233	12,615	15,618	28,233
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-by-month FE	Yes	Yes	Yes	Yes	Yes	Yes
Weather controls	Yes	Yes	Yes	Yes	Yes	Yes
Sample weights	Yes	Yes	Yes	Yes	Yes	Yes
KP *F*-statistic	36.04	17.62	52.24	36.04	17.62	52.24

Notes: Dependent variables are K6 scores in columns (1) – (3), and a dummy variable for severe mental disorders in columns (4) – (6). In columns (1) and (4), we focus on urban residents only. In columns (2) and (5), we focus on rural residents only. In columns (3) and (6), we focus on both urban and rural residents. Weather controls include 5 °C temperature bins, second order polynomials in average relative humidity, wind speed, and sunshine duration, and cumulative precipitation. Standard errors are listed in parentheses and clustered by both county and date (two-way clustering). *** p<0.01, ** p<0.05, * p<0.1.