The Unintended Effects of Environmental Information on Mental Health: Evidence from Air Pollution Disclosure in China

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September 9, 2021

Abstract

This paper assesses individual's psychological responses to the information on environmental risks. Exploiting the progressive implementation of a national program in China that provides real-time air pollution information to public, we find that the accessibility of pollution information leads to a substantially steeper increase in individual's risk of stress and depression in response to air pollution. We provide evidence that the information of air pollution represents a important source of stressor and create unintended psychological burden on individuals. Our findings have important policy implications on the design and delivery of environmental information disclosure programs.

Keywords: Environmental information; mental health; environmental regulations; air pollution.
JEL Codes: D80, I10, Q53, Q58.

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1 Introduction

With rising attention to environmental safety, immense amounts of environmental information are now accessible to individuals. Information disclosure policies are increasingly being proposed and issued by governments as an effective tool to promote public supervision and foster engagement in environmental protection in diverse areas, including water safety, greenhouse gas emissions, air pollution, radiation, and climate changes (see, for example, Bennear and Olmstead (2008), Neidell (2009), Deschenes et al. (2017), and Greenstone and Jack (2015)).[1] An important research agenda is to understand the role of pollution information in shaping individual's decision-making, cognition, mental well-beings, and overall welfare in response to the environment risks. Recent literature has amassed evidence on how the disclosure of environmental information improves individuals' decision making in reducing the exposure to environmental hazard, raising their willing-to-pay for means of avoidance, and mitigating health damages of environmental risks (Barwick et al., 2019; Bennear and Olmstead, 2008; Chay and Greenstone, 2005; Deschenes et al., 2017; Freeman et al., 2019; Ito and Zhang, 2020; Tu et al., 2020). Yet, we know very little about the potential psychological effects of environmental information on individual's mental health.

We provide the first study to assess individual's psychological responses to the information on environmental risks. We investigate whether an increase in the accessibility of information on air pollution may change the relationship between air pollution and individual's mental health. China's recent real-time monitoring-and-disclosure program on air pollution provides an ideal setting for this study. Before the 2010s, China was among the worst polluted in the world,[2] yet a national system of monitoring and reporting of air pollution was nonexistent. Amid rising outcry over the intransparency of air pollution information (Ghanem and Zhang, 2014; Greenstone et al., 2020), China launched a nationwide program in 2013 to undertake real-time monitoring and automated reporting of air pollution (henceforth, the information program). The information program has drastically increased the accessibility of real-time, transparent information on air pollution. The program is implemented progressively across cities and eventually covers 98% of China's population by the end of 2016. The program's comprehensive coverage and staggered roll-out provide a unique opportunity to study the population's behavioural and mental responses to such a sharp and permanent increase in the availability of pollution information. Recent studies have documented that this information program has substantially increased individual's demand for cleaner air and the adoption of various forms of avoidance behaviors in response to air pollution (Barwick et al., 2019; Ito and Zhang, 2020). This paper focuses on the unexplored psychological effects of such information on the relationship between air pollution and mental health.

1. The United States is among the earliest to disclose information on pollution through the 1986 Toxic Release Inventory (TRI) Program. Other recent practices of environmental information disclosure include the Performance Evaluation and Ratings Program (PERP) in Indonesia, the Green Rating Project (GRP) in India, and the EcoWatch Program in the Philippines.

2. In 2010s, China's annual concentration of fine particulate matter with a diameter of 2.5 μm or less (PM2.5) was over 60 $\mu g/m^3$, five times exceeding the World Health Organization (WHO) safety standard (Greenstone et al., 2021).

Our empirical strategy exploits two sources of exogenous variations. First, we adopt thermal inversions as the intrumental variable for the concentration of air pollution at the county level. Second, we take advantage of the staggered roll-out schedule of the information program across different cities to estimate the *change* in the relationship between air pollution and population mental health. Our analysis is based on a comprehensive database comprising mental health outcomes and individual covariates from nationally representative surveys, measures of air pollution and thermal inversions from satellite imagings, weather conditions from meteorological stations, search queries from online search engine, and regional socioeconomic variables from statistical yearbooks.

We find that the access to previously unavailable, real time information on air pollution has amplified the negative effect of air pollution on individual's mental health. We measure the effect of air pollution on mental health by a *gradient* term, that is, the marginal change in individual's risk of mental illnesses in response to an increase in air pollution. We find robust evidence that the implementation of the information program has more than doubled the gradient of individual's risk of mental illnesses to air pollution. This pattern is more pronounced in regions with lower prior awareness of air pollution. Our finding result echoes with Barwick et al. (2019) and Ito and Zhang (2020) that the provision of pollution information has significantly increased individual's attention and behavioral responses to air pollution, but highlights the overlooked psychological effect of pollution information on individual's mental health.

We proceed to explore the mechanism under which the increase in accessibility of pollution information may lead to a steeper gradient of the risk of stress and depression to air pollution. Two linkages are important. First, the accessibility of real-time pollution information has significantly increased individual's active search for pollution-related information in response to an increase in air pollution. The intensified information seeking leads to an accumulation of negative information shocks on individuals. Second and more importantly, having elevated attention to air pollution, individuals are more likely to experience stress and anxiety in response to these information shocks. Studies in psychology and neuroscience have found that higher concentration of particulate matters elicits the human body to produce more stress hormone (cortisol) to facilitate the "fight or flight" responses (Braithwaite et al., 2019; Li et al., 2017; Miller et al., 2016; Thomson, 2019). Better informed, more attentive individuals therefore are more likely to react to an increase in air pollution and produce more dosage of cortisol in response. Although infrequent cortisol release creates little harm on mental health and the body will naturally "cool down", prolonged elevated levels of cortisol can result in a series of physical and mental illnesses, including chronic stress and depression (Juster et al., 2010; McEwen, 2000, 2012).

We provide three pieces of supporting evidence on this mechanism. First, individuals living in regions that exhibited a larger increase in pollution-related search activities experienced a larger increase in the gradient of mental illnesses to air pollution. Second, individuals who were exposed to a longer period of air pollution—thereby sustained a longer period of cortisol—experienced a larger increase in the gradient of mental illnesses to air pollution. Third, after the information program, an increase in search intensity for pollution information leads to an increase in individual's risk of mental illnesses.

Our study provides a novel perspective to explain why individuals are willingness to pay substantially more for clean air after reliable information on air quality becomes publicly available. Following Levinson (2012)'s stated-preference approach, we find that, before the information program, individuals were willing to pay CNY 300 per year (2.51% of annual income) to compensate for the mental health damages from 1 $\mu g/m^3$ increase in PM2.5. This estimate of WTP is similar to the estimate by Freeman et al. (2019) using a residential sorting model, as well as the estimate by Zhang et al. (2017), both estimates are based on pre-information-program data. After the information program, individuals are willing to pay an *additional* CNY 530 per year (4.44% of annual income) to compensate for the mental health impacts of 1 $\mu g/m^3$ increase in PM2.5, implying a 1.78 times increase in WTP for cleaner air. In comparision, Ito and Zhang (2020) has estimated that the information program created a 1.45 to 1.77 times increase in WTP for air quality using a revealed-reference-based method.

Our study contributes to the literature on the impacts of air pollution on the risk of mental illnesses and subjective well-beings. Recent studies in psychology and neuroscience have shown that the exposure to air pollution may increase inflammation of the central nervous system (Mehta et al., 2015; Ross et al., 2018; Thomson, 2019) and increase the risk of anxiety and depression (Power et al., 2015; Pun et al., 2017). The economic literature also shows that the psychological effects of air pollution on mental health plays a critical role in the overall effect of air pollution on individual's subjective well-beings (Levinson, 2012; Zhang et al., 2017). However, few research has considered the role of pollution information in the relationship between air pollution and mental health, and large discrepencies exist in estimating the dose response of mental illness to air pollution. Such discrepencies exist between countries as well as across time periods within the same country (Greenstone et al., 2021; Greenstone and Jack, 2015). In particular, Chen et al. (2018) estimates a much larger gradient of mental health to air pollution than Xue et al. (2019), while both studies use the same nationally representative data in China but cover different sample periods. Our study reconciles the discrepencies in the estimated effects of air pollution on mental illnesses. We demonstrate that the difference in public accessibility to air pollution information can explain why Chen et al. (2018) find a much larger effect of air pollution on mental health (based on post-information-program data) than Xue et al. (2019) (based on pre-information-program data).

Our study also complements the stream of studies evaluating the impact of environmental information on individual's behavioural responses. Existing evidence has substantiated the effects of environmental information disclosure in shaping individual's decision-making, including having higher willing-to-pay for defensive devices and housing with better environmental quality (Chay and Greenstone, 2005; Deschenes et al., 2017; Freeman et al., 2019; Ito and Zhang, 2020; Tu et al., 2020), adjusting consumption and travel pattern to reduce exposure (Barwick et al., 2019; Neidell, 2009; Sun et al., 2019), reducing labor supply (Borgschulte et al., 2018; Graff Zivin and Neidell, 2012; Hanna and Oliva, 2015), and moving to locations with better environmental quality (Qin and Zhu, 2018). Yet, few studies have evaluated the effects of environmental information on individual's mental health. We provide the first study to delineate the important role of air pollution information in shaping the response of individual's mental health to environmental risks, and find that pollution information amplifies the impact of air pollution on individual's risk of stress and depression. Our estimate of the effect of air pollution information on households' WTP for clean air complements the existing studies of the value of environmental information for households in China (Barwick et al., 2019; Freeman et al., 2019; Ito and Zhang, 2020; Tu et al., 2020), and provides a stated-preference perspective to the point made by Greenstone and Jack (2015) that the environmental quality can be severely undervalued in developing countries due to the imperfect information of environmental risks available to households.

We proceed as follows. Section 2 describes the institutional background of the public information disclosure of air pollution in China. Section 3 describes the data sources and key variables. Section 4 discusses our empirical methodology, baseline results, and robustness checks. Sections 5 discusses the mechanism. Section 6 discusses the welfare implications and Section 7 concludes.

2 Background

The air of major cities in China is among the dirtiest in the world (Zhang and Wang, 2011). The average concentration of PM2.5 in the 2010s was over 60 $\mu g/m^3$, five times higher than the WHO's Air Quality Guidelines (10 $\mu g/m^3$) (Guan et al., 2014). However, much like during episodes of "killer" fog in London in 1952 (Wang et al., 2016), the air quality in China was not regularly monitored and its health effects were poorly understood prior to 2012. Severe smog episodes in major cities such as Beijing was frequent by early 2013 and outraged the Chinese public.[3] Outcry emerged over the lack of public disclosure of pollution information and the lack of effective government responses. To address the situation, the Chinese government has implemented a series of environmental regulations at both local and national levels in the past decade (see Appendix Section A.2). The national program of comprehensive monitoring and real-time reporting of air pollution is one of the key policy initiatives and marks a cornerstone moment in China's history of air pollution monitoring and disclosure. We discuss the background of this program below.

2.1 Lack of Air Pollution Information Before the Information Program

Monitoring and public disclosure of air pollution information was limited prior to 2012. Although the Ministry of Environmental Protection (MEP) had built monitor stations and collected the air pollution index (API) for some cities since early 2000s, this early system of pollution monitoring faced three key challenges. First, minitoring stations were built only in a small set of cities (26 in total), and the information on API was not readily available to the public. Second, API does not include PM2.5, which has become the primary air pollutant in

3. For example, in mid January of 2013, the air quality index (AQI) in Beijing soared as high as 993, far beyond levels WHO deems extremely dangerous. For comparison, during the same month in New York, the AQI was below 20.

most Chinese cities since the 2010s. Lastly, API was compiled by local environmental bureaus, whose incentives were often compromised by the competing economic and political interests, and API was often strategically under-reported (Ghanem and Zhang, 2014; Greenstone et al., 2020).

Public awareness of air pollution (especially for particulate matters) and its health risks was also extremely limited prior to 2012. Government agencies, the media, and the general public all referred to the low visibility due to high concentration of PM2.5 as *fog* rather than *smog*.[4] As fog, or *wu* in Chinese, was understood as a natural phenomenon that is often associated with natural beauty in poems and songs, there was little public awareness of the severity of air pollution, and few defensive behaviors against it, in China prior to 2013 (Barwick et al., 2019).

2.2 Implementation of the Information Program

The national program of monitoring and reporting of air pollution in 2013 marked a turning point in the public disclosure of air pollution information in China. It has two key provisions. First, more than 1,400 U.S. EPA-grade monitor stations, each equipped with a real-time monitoring and automated reporting system, was installed across the country to track concentrations for six key pollutants, including PM2.5.[5] Second, a data streaming system was established to stream real-time air pollution information to the cloud and to local and central governments. Private parties were also allowed to access and stream data directly from the cloud. This spurred a surge in news media, websites, and smartphone apps that tracked live air pollution data. Manipulation and misreporting of air pollution data were no longer feasible (Greenstone et al., 2020). For the general public, the information program has drastically increased the accessibility of real-time and transparent information on air pollution.

The information program was rolled out progressively across cities. Figure 1 tracks the program's coverage across time and shows that, in less than three years since 2013, the newly established monitoring network had covered more than 98% of the entire population. (Appendix Figure B1 depicts the roll-out on a map). The program had a initial pilot phase of information disclosure in 2012 in 26 cities that had at least one (older-version) monitor stations. The national roll-out started in 2013 by first constructing 1,436 new U.S. EPA-grade monitor stations in three waves: 74 provincial capitals and special administrative zones in the first wave, 116 cities from the list of Environmental Improvement Priority Cities and the list of the National Environmental Protection Exemplary Cities in the second wave (both lists were designated before 2007), and the remaining 177 cities in the third wave (Barwick et al., 2019). After the completion of the monitor stations, the debut of real-time, public disclosure of pollution information generally occurred six to ten months later, with exact timing varying due to manpower constraints of

4. For example, on November 27, 2011, Beijing newspaper headlines, as well as the China Meteorological Administration, attributed the dense fog in Beijing and northern cities as the reason for widespread flight delays and cancellations. The local environmental bureaus, however, reported the air pollution was light during the day. PM2.5 was not mentioned in media nor official announcements of the airport. NASA satellite showed an AOD reading of 4.5 or higher on that day for Beijing and many other northern cities, as compared against a standard range of 0.1 to 0.15 in the United States. See a Reuters report on the event at https://cn.reuters.com/article/instant-article/idUSLNE7B401520111205.

5. The six tracked pollutants are PM2.5, PM10, O3, CO, NO2, and SO2.

local environmental bureaus.

Importantly, the roll-out schedule of the monitor stations and the information disclosure is uncorrelated with the day-to-day variation of local pollution levels. The three-wave schedule was primarily based on the pre-determined hierarchical designations: administrative centers in the first wave, environmental priority cities in the second wave (the list was pre-determined in 2007), and remaining cities in the last wave. For each given city, the exact date of the roll-out is driven mostly by the physical constraints of installing monitor stations and integrating the data streaming system. Appendix Figure B2 shows that the variation in the concentration of air pollution was mostly random across the roll-out dates in different cities. Moreover, no national policies coincided with the schedule nor the spatial coverage of the information program. Three regional environmental policies partially overlapped in timing: CO2 cap-and-trade pilot program, the energy reduction program, and fuel switching program. We use dummy variables to control for them in all of our empirical analyses.

2.3 Rising Responsiveness to Air Pollution after the Information Program

The information program has substantially expanded the public access to pollution information, and dramatically increased individual's awareness and responsiveness to air pollution. Figure 2 plots the annual trend of daily city-level Baidu search volume of pollution-related keywords (normalized by city population). We observe a clear surge in the search volume of pollution-related keywords after the information program. Total search volume (Panel A) has increased by more than six-folds within the first two years after the program implementation in a city. The search for the primary air pollutants (Panel B), health risks (Panel C), and defensive measures (Panel D) all exhibited substantial increase.[6] In contrast, search volumes for non-pollution-related keywords, such as culture, art, entertainment, pension, and financial market, showed no sign of noticable increase in search volumes after the information program. We present formal regression analyses of individual's information seeking behaviors in Section 5.

3 Data

We have compiled a comprehensive dataset on individual's mental and physical health outcomes, air pollution, weather conditions, online search volumes of air pollution, and regional socioeconomic variables. These data are derived from a variety of sources, including national representative surveys, satellite imagings, environmental monitor stations, online search queries, and provincial statistical yearbooks. This section describes the construction of our analytical sample and the definition and summary statistics of key variables.

3.1 Data Description

Mental Health We utilize the rich measure of mental health and individual characteristics from the China Family Panel Studies (CFPS), a nationally representative survey to track pop-

6. Search for each pollution-related keyword show a consistent pattern of sharp increase after the information program (Appendix Figure B3 to B5).

ulation health and socioeconomic development in China. The CFPS covers a wide range of domains for families and individuals from 162 counties in 25 provinces of China, which represents 94.5% of the total population in China (excluding Hong Kong, Macao, and Taiwan). Appendix Figure B6 demonstrates the geographic representativeness of CFPS counties on the map of China. We use CFPS data from 2010, 2012, 2014, and 2016 waves in our analyses.

Adult mental health is measured using the Center for Epidemiologic Studies Depression scale (CES-D) developed by Radloff (1977). A six-item CESD is adopted and reported by CFPS across survey waves. The six-item CESD ranges from 0 to 24, with higher scores indicating more severe mental illness.[7] CESD has been shown to have adequate psychometric properties for sensitive and specific detection of depressive disorders (Aggarwal et al., 2008). We standardize the standardized CESD to be between zero and one and define dummy variables to indicate different severity of depressive symptoms (mild, moderate, and severe) based on different cutoff values of CESD (Burnam et al., 1988). In addition, we define three alternative measures of mental health, including an index of stress, confidence in the future, and life satisfaction.[8]

We also obtain data from the China Health and Retirement Longitudinal Study (CHARLS) as supplementary data for empirical analysis. CHARLS collects a nationally representative sample of Chinese residents aged 45 and above and measures survey respondent's mental health using CESD.

Air Pollution and Thermal Inversions The level of air pollution is measured using the concentration of fine particulate matter with a diameter of 2.5 μm or less (PM2.5). To overcome the challenge that reliable PM2.5 data are only available after the information program, we compute PM2.5 from Aerosol Optical Depth (AOD) from the MERRA-2 module retrieved by NASA's Terra satellite. Besides the extensive temporal coverage, AOD-based PM2.5 has the advantage of covering the entire China and having a geographic resolution of 10-by-10 km per grid. We compute the daily concentration of PM2.5 at grid level from AOD data following the algorithm of Buchard et al. (2016) and average from the grid to the county level. We show in Appendix Figure B7 that annual series of the AOD-based PM2.5 and monitor-station-based PM2.5 are similar.[9]

7. In CFPS, the six-item CESD conprise of questions on (1) feeling depressed and incapable to cheer up no matter what you are doing; (2) feeling nervous and stressful; (3) feeling upset and fidgety; (4) feeling hopeless about the future; (5) feeling that everything is difficult; (6) thinking life is meaningless. In each question, the respondents choose from five options: never (0 points), sometimes (1 point), half of the time (2 points), most of the time (3 points), and always (4 points).

8. Across survey waves, CFPS asked the following questions: "To what extent you feel stressed in the past month?", "To what extent do you feel confident about your future?", and "Overall, how satisfied are you with your life?" We standardize each of these three variables to be valued between zero and one.

9. We favor the AOD-based PM2.5 measure over the monitor-station-based PM2.5 for two main reasons. First, monitor-station-based PM2.5 data are not available before the information program. Second, AOD-based PM2.5 measure is available at much finer geographic resolution than the monitoring-station-based measure. The monitoring-station-based measure of PM2.5 derived from the conventional distance-weighted method may be subject to measurement error because some counties may be far away from the nearest monitor stations (Figure B6). However, a potential concern for the AOD-based PM2.5 is that it is calculated based on satellite imaging of the atmosphere, thus may be different in level from the PM2.5 at the ground level. We acknowledge this limitation but emphasize that the AOD-based PM2.5 has been shown to perform well in capturing the variation of PM2.5 at the ground level. AOD-based PM2.5 is highly correlated with the monitor-station-based PM2.5 at the region-by-day level with a correlation coefficient of over 0.8 (Kloog et al., 2014; Xie et al., 2015).

Thermal inversion is a frequently used instrumental variable for PM2.5 and other ambient pollutants (Greenstone et al., 2021). It measures the number of times the air temperature reverses in the trposphere (the region of the atmosphere nearest Earth's surface) for every six hours. We obtain the thermal inversion data also from NASA's satellite imaging and convert the data in the same format as PM2.5. Finally, we compute the 30-day average PM2.5 and thermal inversions for the CFPS county before each respondent's interview date.

Weather Conditions We include various weather covariates. Control of these weather conditions helps to isolate the impact of air pollution on mental health from weather-related factors, as weather conditions are found to affect individuals' moods, social behavior, and health (Berry et al., 2010; Cunningham, 1979). These variables include temperature, precipitation, cloud thickness, relative humidity, wind speed, and air pressure, as well as an indicator for bad weather (heavy fog, rain, snow, hail, or thunder). We obtain the weather data from the China Meteorological Data Service Center and use the inverse-distance weighting algorithm to convert the weather variables from station to county level.[10] Finally, all weather variables are matched to CFPS respondents by county and month of interview.

Baidu Search Index We use the Baidu search index to represent individual's awareness of and active search for pollution information. Baidu is the most widely used search engine in China.[11] It started publishing search intensity indices that summarize the number of queries for top keywords in a given city on a given day among internet users since 2011. The search index is generated using an algorithm similar to Google Trends (Vaughan and Chen, 2015).

We obtain the Baidu indices for three broad categories of top-searched pollution-related keywords, including the keywords for air pollution and main pollutants (such as "smog", "PM2.5", and "air pollutant"), those for health consequences of air pollution (such as "the harm of smog" and "the harm of PM2.5"), and those for the denfensive measures against air pollution (such as "face masks" and "air purifier"). A total of 27 top keywords are obtained (Appendix Table A1). We aggregate the search indices to the city-day level and normalize them by the city population. We also obtain an alternative index normalized by the number of households with internet access as a robustness check.

Regional Socioeconomic Covariates We collect city-level socioeconomic variables, such as GDP per capita (deflated to 2010) and city population, from the China Economic Database and various statistical yearbooks. We also define a list of dummies variables for contemporaneous regional environmental policies and include them as controls in our analyses. These policies include the CO2 cap-and-trade pilot program, the energy reduction program, and fuel switching program. See Appendix Section A.2 for further details.

10. We compute county-level weather variables by taking the weighted average of station-level variables within a 100-kilometer radius around the county centroid. Alternative radii are adopted and the results remain robust.

11. According to China Internet Network Information Center, China had 0.56 billion internet users by the end of 2012, among which more than 99% have heard of Baidu (seconded by Google) and more than 98% have used it in the past six months.

3.2 Sample Construction and Summary Statistics

We merge various datasets according to the county geocode and interview date. Initially merged sample contains 133,260 observations from 34,172 respondents. We exclude individuals below 16 years old because the CESD is aimed at measuring mental health for adult population. We also drop observations with missing values for CESD or key explanatory variables, reaching an analytical sample of 93,091 observations from 32,219 respondents.

Table 1 reports the summary statistics. Our primary outcome variable, the standardized CESD score, ranges between 0 and 1 and has an average of 0.14. The score distribution is right-skewed (Appendix Figure B8). About 38% of respondents have reported to have mild depressive symptoms (CESD $\geq$ 4), 12% with moderate depressive symptoms (CESD $\geq$ 8), and 4% with severe depressive symptoms (CESD $\geq$ 13). Comparatively, Kessler et al. (1996) find a slightly higher rate of severe depression in the U.S. at 6%. Gender ratio is balanced, average age is 47 years old, the majority are married (89%), average years of schooling is 7, and average annual household income per capita is about CNY 12,000.

Average monthly PM2.5 concentrations in our sample is 66.21 $\mu g/m^3$, close to the national average in early 2010s. Monthly concentrations of PM2.5 varies from 3.22 to 211.04 $\mu g/m^3$, with a standard deviation of 33.63 $\mu g/m^3$. The average monthly number of thermal inversions is 11.74. Statistics of weather conditions and metrics of regional economic development are within reasonable range.

4 Results

4.1 Methodology

In this section we elaborate the empirical methodology to assess to what extent the sharp increase in the accessibility of pollution information may change the relationship between individual's mental health and air pollution. We use a specification similar to Barwick et al. (2019) and estimate:

$$\begin{aligned} CESD_{ijt} = \alpha_0 + \beta PM2.5_{jt} + \gamma PM2.5_{jt} \times D_{jt} + \alpha_1 D_{jt} \\ + X_{ijt}\epsilon + W_{jt}\phi + C_{jt}\mu + \lambda_i + \eta_j + \delta_t + \pi_{st} + \varepsilon_{ijt}. \end{aligned} \tag{1}$$

The dependent variable, $CESD_{ijt}$, is standardized six-item CESD for respondent i in county j at date t. A higher score represents worse mental health status and a higher risk of depression (Radloff, 1977). $PM2.5_{jt}$ is the log of 30-day average concentration of PM2.5 prior to interview date t for county j. D_{jt} is the dummy variable for information program that equals to one after the air pollution information became publicly available. X_{ijt} is a set of time-varying individual covariates, including age, age squared, urban registration status (*hukou* in Chinese), marital status, household income, and the education level. W_{jt} and C_{jt} represents a vector of weather conditions and regional socioeconomic factors, respectively. We control for individual fixed effects (λ_i), residential county fixed effects (η_j), cubic functions of month (δ_t), and province-by-year fixed effects (π_{st}). In particular, δ_t accounts for seasonal fluctuations in diseases (such as flu) and macroeconomic factors, and π_{st} accounts for time-varying province-specific factors, such as provincial investment on environmental protection and economic growth, which may correlate with the regional air quality and the population's mental health. Finally, standard errors are clustered at the household level.

The causal effect of air pollution on individual's mental health is measured by a *gradient* term, that is, the marginal change in individual's risk of mental illnesses in response to an increase in air pollution. Our coefficient of interest, γ, measures the *change* of gradient after the information program, that is, how does the accessibility of air pollution information changes the effect of air pollution on individual's mental health. The coefficient of β measures the gradient before the information program. The coefficient of α_1 measures the change of mental health after the information program when $PM2.5_{jt}$ equals zero, which is extremely rare in our data. We therefore suppress α_1 in our regression table.

We exploit two sources of exogenous variations in our estimation. First, we adopt the number of thermal inversions in Earth's atmosphere as an instrumental variable (IV) for the level of PM2.5. A thermal inversion refers to a reversion of the air temperature in Earth's trposphere, which strongly correlates with the concentration of air pollution near the ground level.[12] We have presented the pseudo first-stage results in Appendix Table A2 and verified the strong correlation between PM2.5 and thermal inversions. Thermal inversion is considered as a valid instrument for two reasons. First, the formation of a thermal inversion depends on the rare co-occurrence of multiple meteorological factors across layers of Earth's atmosphere, and is independent of economic activities at the ground level.[13] Second, a thermal inversion does not present a health risk or directly affect individual's mental status (Arceo et al., 2016). Therefore, thermal inversion has been widely adopted as an instrument for air pollution in the literature (Chen et al., 2017; Deschenes et al., 2020; Fu et al., 2018; Hicks et al., 2016).

Second, we exploit the quasi-experimental variation in the roll-out schedule of the information program across cities. We have discussed in the institutional background that the roll-out schedule of the program is determined by the administrative hierarchy (e.g., provincial capitals) and pre-assigned designations (e.g., the environmental protection priority list set in 2007). Moreover, the exact date of implementation in each city is mainly driven by the physical and manpower constraints of local government. Therefore, it is unlikely to correlates with the short-term variation of local pollution levels. In particular, if one expects that cities with a higher level or a rising trend of air pollution were more likely to implement the program sooner (or later), we would observe differential pre-trends in air pollution before the start of the program. We present evidence on the lack of such pre-trends in Appendix Figure B2.

12. Normally, temperature decreases as altitude increases, air pollutants can rise to upper atmospheric layers and disperse. Only under relatively rare circumstances, temperature in an upper atmospheric layer is higher than the layers below. This constitutes a thermal inversion, under which the warm layer of air traps ambient pollutants near the ground level by reducing vertical circulation.

13. In Equation 1, we have controlled for meteorological factors, month fixed effects, and province-by-year fixed effects. The variation in thermal inversions that we exploit is therefore net of meteorological factors at the ground level, seasonal effects, permanent differences across counties, county fixed effects, and year-varying differences across provinces.

Moreover, there exist no other environmental programs that exactly coincide with the roll-out schedule or the spatial coverage of the information program. We include dummies for four regional environmental regulations which partially overlapped with the information program in the set of control variables (see Section 2.2). We also include province-by-year fixed effects to control for province-specific time-varying factors that correlate with long-term variation in air pollution. We also conduct a series of robustness tests to verify that the baseline results from Equation (1) are unlikely to be biased by unobservable confounders. We postpone the discussion of these results to Section 4.3.

4.2 Baseline Results

Table 2 reports the estimation results of Equation (1). We include the set of control variables progressively across columns. The progressive addition of household, weather, regulatory, and socioeconomic factors brings little change to the estimates of β and γ, which suggests the limited role of observed and unobserved confounding factors in our regression specification (Altonji et al., 2015). Our most preferred specification is represented in Column 5, where the full set of controls and fixed effects is included.[14]

Two findings are noteworthy. First, the estimate of β shows that, before the information program, an increase in the exposure to PM2.5 significantly worsens individual's mental health: one percent increase in the concentration of PM2.5 in the month prior to the interview date leads to a 0.047 units increase in the standardized CESD, which is estimated statistically significantly at the 5% level. The estimated negative effects of air pollution on individual's mental health is consistent with studies in psychology and neuroscience that air pollution may damage the central nervous system (Mehta et al., 2015; Ross et al., 2018; Thomson, 2019) and increase the risk of anxiety and depression (Power et al., 2015; Pun et al., 2017). In particular, among previous economics studies, our estimate of β is almost identical to that of 0.048 obtained by Chen et al. (2018), who study the effect of PM2.5 on standardized CESD in the pre-information-program period. The estimate is also similar qualitatively to that estimated by Zhang et al. (2017) based on standardized measures of subjective well-beings.

Second and more importantly, the estimate of γ shows that the introduction of the information program has led to a statistically significant increase in the *gradient* of mental health to air pollution. After the information program, one-percent increase in the concentration of PM2.5 leads to an additional 0.083 units increase in the standardized CESD, which is estimated statistically significantly at the 1% level. The estimated *change* in the gradient (γ) is almost twice as large as the *level* of pre-information gradient (β). To put the number into perspective, before the information program, one standard deviation (SD) increase in the PM2.5 concentration increases standardized CESD by 0.028 SD; after the program, one SD increase in PM2.5 leads to 0.078 SD increase in standardized CESD. This estimated effect of air pollution on individual's mental health after the information program, measured by $\beta + \gamma$, is similar in magnitude to the estimate by Xue et al. (2019) based on post-information-program data.

14. For space constraints, we only present the estimated coefficients for β and γ in the main texts. The complete estimation results are available upon request.

We further estimate the effect of the information program on the gradient of individual's risk of depression and subjective well-beings (SWB) to air pollution. We define a set of dummies indicating mild depression (CESD≥ 4), moderate depression (CESD≥ 8), and severe depression (CESD≥ 13), based on commonly used cutoff values of CESD (Radloff, 1977). Table 3 Columns 1-3 report the results and show that the information disclosure has led to a statistically significant increase in the risk of mild and moderate depression, and a positive but insignificant effect on the risk of severe depression. Column 4 reports the estimation result using an indicator of constant stress as dependent variable and shows a consistent pattern of increased gradient of stress to air pollution. Columns 5 and 6 use two measures of SWB as dependent variables—an indicator for confidence in the future and an index of life satisfaction and show that the introduction of information program has significantly reduced the gradient of SWB to air pollution.

It is worth noting that, *before* the information grogram, an increase in air pollution increased individual's risk of depression and stress, but had muted effect on SWB (i.e., small and statistically insignificant estimate of β in Table 3 Columns 5-6). This pattern is also documented by Zhang et al. (2017) based on the pre-information-program data. Zhang et al. (2017) conclude that air pollution reduces individual's short-term happiness and increases the rate of depressive symptoms, but has no immediate effect on long-term measures of SWB such as life satisfaction. Our results show that, after the information on air pollution is readily available, however, air pollution would inflict a significantly negative effect on SWB. This suggests that the information on air pollution has changed individual's "mental model" of air pollution, potentially inducing individuals to reassess the severity of local pollution level and modify their expectation on negative impacts of air pollution on their physical and mental health.

4.3 Robustness Analyses

In this section, we examine the robustness of the baseline results to alternative model specifications, sample restrictions, and variable definitions, and show that the results are unlikely to be driven by unobserved confounding factors.

Event Study We first show that there exists no change in the gradient of individual's mental health to air pollution before the introduction of the information program, analogous to the test of parallel pre-trend in conventional difference-in-differences analysis. We estimate the following event-study specification:

$$\begin{aligned} CESD_{ijt} = \alpha_0 + \alpha_1 PM2.5_{jt} + \sum_{q \neq -1} \beta_q \cdot d(t=q)_j + \sum_{q \neq -1} \gamma_q \cdot \text{ PM2.5 }_{jt} \times d(t=q)_j \\ + X_{ijt}\epsilon + W_{jt}\phi + C_{jt}\mu + \lambda_i + \pi_{st} + \varepsilon_{ijt}, \end{aligned} \tag{2}$$

where the quarter-to-program dummy $d(t=q)_j$ equals to one if the respondent is interviewed q quarters since the start of the information program at county j, and $d(t=-1)$ is the last quarter before the program and is omitted as the reference category. We set the event study window as from five quarters before the program to six quarters after the program. This window is chosen to ensure balanced panel for the estimation of each γ_q coefficient. We dummy out the remaining sample periods.

Estimates of γ_q's trace out the evolution of the change in the gradient of individual's mental health to air pollution relative to the quarter before the information program. Figure 3 plots the estimates of γ_q's with the 95% confidence interval. Results are reported in Appendix Table A3. All the pre-program coefficient estimates, γ_{-5} to γ_{-2}, are small and statistically insignificant, which demonstrates that the roll-out timing of the information program is unrelated to preexisting trends in the relationship between population mental health and air pollution. This exercise also rules out the potential explanation that cities with earlier roll-out schedule may implement other concurrent environmental regulations to improve the air quality, in which case the effects of these environmental regulations would be picked up by the pre-information-program coefficients.

Placebo Test We conduct a placebo test by replacing the information program dummy (D_{jt}) in Equation (1) with a placebo policy dummy defined as occurring one year, two years, or three years prior to the actual starting date of the information program. The rationale is that respondents in cities of different program roll-out date should not experience changes in the gradient of mental health to air pollution before the information program. The results are presented Appendix Table A4 and show no statistically significant change in the gradient of mental health to air pollution following the placebo policy time.

Alternative Measures of Air Pollution and Program Roll-out We use the concentration of sulfur dioxide (SO2) as an alternative measure of air pollution. SO2 is one of the six key pollutants under real-time monitoring and disclosure of the information program, and is an important contributor to the ambient particulate matters. Appendix Table A5 shows results are robust when using SO2 as the measure of air pollution.

We use the completion time of the monitor station instead of the online disclosure time of pollution information to define the policy dummy of the information program. The timing of online disclosure is usually six to ten months after the completion of the monitor station and the time lag depends on the manpower constraints of the local environmental bureaus. Appendix Table A6 shows results are robust based on this alternative indicator of the start of the information program.

Cognitive Functioning and Physical Health We show that the estimated change in the gradient of mental health to air pollution is unlikely to be biased by the impact of air pollution on cognitive functioning or physical health. We conduct two tests. First, in Appendix Tables A7 and A8, we estimate Equation (1) using various measures of cognitive functioning and physical health as the dependent variable.[15] Results show that the information program does not lead to

15. We adopt four measures of cognitive functioning, including the standardized test scores of math, memory, reading comprehension, and IQ tests. We use eight measures of physical health, including the indicator for (1) acute disease (2) chronic disease (3) cardiovascular disease (4) respiratory / digestive / urinary disease (5)

any statistically significant changes in the gradients of cognitive functioning or physical health outcomes to air pollution. Second, in Appendix Tables A9 and A10, we re-estimate Equation (1) after controlling for the measures of cognitive functioning and physical health. Estimation results are quantitatively similar to the baseline results in Table 2.

Labor Supply and Migration We show that the estimated change in the the gradient of mental health to air pollution is unlikely to be driven by avoidance behaviors such as reducing the labor supply or moving to cities with cleaner air. We use measures of household income and migration status as the dependent variable in Equation (1) and find no statistically significant change in the gradients of household income or migration status to air pollution after the information program (Appendix Table A11). These results suggest that the baseline results are unlikely to be driven by the information-induced avoidance behaviors through reducing the labor supply or migrating to less polluted cities.

Exclusion of Subsamples Appendix Table A12 shows our results are robust to excluding observations when the interviewer rated the respondent as lacking comprehension, interest, credibility, or expressing excessive doubt, which may generate additional measurement error on self-reported mental health. Appendix Table A13 shows results are robust to the exclusion of observations when the survey was conducted outside of the regular survey window (Column 1),[16] to the exclusion of observations when the respondent was interviewed during extreme weather (Column 2), to the exclusion of cities with U.S. embassy or consulates (Column 3), which have installed on-site PM2.5 monitors before the information program so that residents may have some prior knowledge of local air pollution, to the exclusion of cities which have implemented some forms of pollution monitoring in the early 2000s (Column 4), and to the exclusion of individuals who ever lived in a different city during the sample period (Column 5).

Clustering of Standard Error and Removal of "Bad Controls" Appendix Table A14 Columns 1 and 2 show that the estimated coefficients of interest (γ) are statistically significant at 5% level and 10% level, respectively, when we cluster the standard error at the county and city level. Column 3 shows qualitatively similar results when we remove individual fixed effects. Column 4 shows that results are almost unchanged when we remove the labor market outcomes and educational attainment from the set of covariates, which may introduce the "bad control" problem.

Alternative Dataset We conduct a sensitivity analysis based on the CHARLS data, which also measures the CESD score and provides a nationally representative sample of Chinese elderly population. We construct an analytical sample in the same way. The CHARLS sample is similar

circulatory / musculoskeletal diseaes or tumors (6) cognitive disorder (7) self-reported to be healthy (8) ever hospitalized in the past month.

16. Most of CFPS interviews are conducted in the summer and winter, when the interviewers—most of them are college students—are on school holidy. See Appendix Figure B8 for the month distribution of our sample observations.

in basic household characteristics to the CFPS sample, except that respondents' average age is 12 years older than those in CFPS (59 vs. 47 years old).

Appendix Table A15 shows the results are consistent: the introduction of information program substantially increases in the gradient of mental health to air pollution across various mental health outcomes, including standardized CESD score and dummies of depression. It is noteworthy that the estimated gradient of depression to air pollution—both before and after the information disclosure (β and $\beta + \gamma$)—are larger than those estimated in CFPS data. A potential explanation is that the older cohorts in CHARLS are more vulnerable physiologically and mentally to air pollution, and therefore would be more sensitive to the negative effects of information on air pollution. We show using a heterogeneous effect analysis that the information program has a larger effect on the the gradient of mental health to air pollution for older cohorts than younger ones.

4.4 Heterogeneous Effects

Heterogeneity to Age Group We observe that older cohorts, those aged 50 and above, experience a larger increase in their the gradient of mental health to air pollution after the information program than the younger cohorts (Appendix Table A16). This is expected as older cohorts are more vulnerable to air pollution (Neidell, 2009; Zhang et al., 2018), and therefore would be more sensitive to the news of air pollution. This age-dependent effect is also reflected in the estimated change in the gradient of CESD score and depression in the older CHARLS sample.

Heterogeneity to Gender and Socioeconomic Status Although males are in general more physically susceptible to the harm of air pollution than females (Zhang et al., 2018), Appendix Table A17 Columns 1-2 show that males are not more responsive psychologically to the news of air pollution than females. We observe a notable heterogeneity with respect to individual's socioeconomic status. Appendix Table A17 Columns 3-4 show that urban residents are more responsive to the pollution information than rural ones, and Columns 5-6 show that the more educated is more responsive to the pollution information than the less educated. This result is expected as urban residents and the better educated have more access to the pollution information—such as more likely to have Internet access and owning a smartphone—than their respective counterparts.

Heterogeneity to City Size Individuals living in larger and more developed cities, as measured by city population, GDP per capita, and provincial capital, experience a smaller increase in the the gradient of mental health to air pollution after the information program (Appendix Table A18). This is unsurprising because larger cities had some forms of pollution monitoring before the information program in 2013, therefore having a higher base level of pollution awareness (see Section A.2). As a result, individuals in larger cities were less "surprised" by the disclosure of pollution information than those in smaller cities.

Overall, we have shown that the information program has heightened the responsiveness of individual's mental health to the air pollution. Our results suggest that individuals that were more "affected" by the information program—such as those with lower prior awareness of air pollution, or those with greater access to pollution information through Internet or media—were more likely to exhibit greater increase in the the gradient of mental health to air pollution. We expect that individuals who seek and receive more information on air pollution would be more alert to the change in air pollution, and subsequently have more psychological burden from the increase of air pollution. We explore this in the next section.

5 Channel

We proceed to explore the mechanism under which the increase in accessibility of pollution information may lead to a steeper gradient of individual's risk of mental illnesses to air pollution. We first show that the information program makes individuals more attentive to air pollution and more active in seeking pollution information when air pollution worsens. The intersified information seeking suggests an accumulation of negative information shocks. We then assess the role of these information shocks on human body's stress response through the lens of allostatic load. We conjecture that, under heightened attention and awareness, individuals are more likely to respond to the news of worsening air pollution by releasing stress hormones, which increases the allostatic load and reduces mental health.

5.1 Search for Pollution Information

We show that the information program has significantly increased the active search for pollution information in response to air pollution. We measure the search intensity using the online search volume of pollution-related keyword on Baidu. Baidu is the most widely used search engine in China, with more than 98% of Internet users having used its service in the past six months. Based on the Baidu search data at the city-by-month level, we estimate an analog specification of Equation (1) as:

$$\begin{aligned} Index_{ct} = \alpha_0 + \beta PM2.5_{ct} + \gamma PM2.5_{ct} \times D_{ct} + \alpha_1 D_{ct} \\ + W_{ct}\phi + C_{ct}\mu + \eta_c + \delta_t + \pi_{st} + \varepsilon_{ct}, \end{aligned} \tag{3}$$

where the dependent variable is the total number of Baidu search queries for top pollution-related keywords per 10,000 population in city c at month t (see Appendix Table A1 for the list of included keywords).[17] Other variables are specified the same as in Equation (1): $PM2.5_{ct}$ is the log of PM2.5 concentration, D_{ct} is the information program dummy, W_{ct} and C_{ct} represent the set of weather conditions and city-level covariates, respectively. We control for city fixed effects (η_c), month fixed effects (δ_t), and province-by-year fixed effects (π_{st}). Standard errors are clustered at the city level. Our coefficient of interest, γ, denotes the *change* in the gradient

17. A potential concern is that not everyone has access to the Internet, therefore not being able to search online for pollution information. We conduct a robustness check in Appendix Table A19 and show that the results are robust when we standardize the search volume by the number of households with Internet access instead of the city population.

of online search volume for pollution information to air pollution after the information program, while the coefficient β represents the level of pre-program gradient.

Table 4 reports the estimation results. The introduction of the information program has led to a statistically significant increase in the gradient of search volume, doubling the gradient of search volume ($\beta = 0.107$ and $\gamma = 0.103$, Column 1). The pattern is consistent for main components of pollution-related searches, including the search for major air pollutants (Column 2), the health effect of air pollution (Column 3), and defensive measures against air pollution (Column 4), respectively. Appendix Table A20 reports similar results on the search for each included keyword. Overall, the results validate that the information program has led to a drastic increase in the information seeking for pollution-related information.

We conduct a series of robustness checks.[18] First, we find the drastic increase in information seeking is only observed in pollution-related information, and not in other domains of commonly searched keywords, such as culture, art, entertainment, pension, and financial market (Appendix Table A21). This rules out the case where unobserved policies or social events may coincide with the roll-out schedule of the information program and drive up the overall search activities on the Internet. Second, we conduct an event-study analysis analogous to Equation (2) and plot the coefficients of quarter-to-program dummies (Appendix Table A22 reports the results). Figure 4 shows that all the pre-program coefficients are small and statistically insignificant, confirming the absence of change in the gradient of search volume to air pollution before the information program. Third, we present evidence of a spillover effect of the information program (Appendix Table A23): The start of the program in a neighboring city prior to home city would increase the gradient of search for pollution information in the home city; subsequent start of the program in the home city would then generate a smaller increase in the gradient of search for pollution information than the estimate of γ in Equation (3). On the other hand, if no neighboring city has implemented the program, the start of program at home city generates a larger increase in the gradient than γ in Equation (3). Overall, these results substantiate that the information program makes individuals more alert and attentive to pollution-related information.

5.2 Stress Response to Air Pollution Information

The increased intensity of information seeking shows that individuals were paying more attention to the information of air pollution (Chun et al., 2011; Gottlieb, 2012). The surge in searching activities for pollution information would lead to an accumulation of information shocks. We conjecture that, under heightened attention, the information of severe air pollution may represent a source of constant stressors and generate a chronic burden on one's stress response system, which may eventually lead to a deterioration of the mental health.

The concept of allostatic load provides insight to our conjecture. Recent studies in psychology and neuroscience have found that exposure to air pollution elicits the human body to produce stress hormone (cortisol) to facilitate the "fight or flight" responses (Braithwaite et al., 2019; Miller et al., 2016; Thomson, 2019), even when individuals are not awared of their

18. For space constraint, we relegate detailed discussion of regression specifications and estimation results of these robustness checks to Appendix Section A.3.

exposure to air pollution (Li et al., 2017). Better informed, more attentive individuals therefore are more likely to react to an increase in air pollution and produce more dosage of cortisol in response. Although infrequent cortisol release creates little harm on mental health and the body will naturally "cool down", prolonged elevated levels of cortisol can increase the allostatic load of human body and result in a higher risk of physical and mental illnesses, including chronic stress and depression (Juster et al., 2010; McEwen, 2000, 2012).

Figure 5 demonstrates such a scenario where constant stressor may overwhelm one's stress response system, increase the allostatic load, and raise the risk of mental illnesses (Juster et al., 2010). In our setting, both air pollution and the news of it represent potential stressors. Because the information program has significantly increased individuals' attention to and seeking for information of air pollution, individuals became more exposed to these stressors and increased the burden of one's stress response system, and as a result, had worse mental health.

We provide three pieces of evidence on the role of pollution information in explaining the greater gradient of mental health to air pollution. First, we show that individuals living in cities with larger increase in search intensity for pollution information would experience a larger increase in the gradient of mental health to air pollution. We divide cities into two groups by the change in search intensity for air pollutants one year after the information program. Table 5 Panel A Columns 1-2 present the estimated change in the gradient of mental health to air pollution (γ in Equation (1)) across the two groups. Results show that individuals living in cities with a larger-than-average change in search intensity experience a significantly larger γ. This pattern remains consistent when the search indices are defined over different types of pollution information (Panel A Columns 3-6).

Second, after the information program, the exposure to a longer period of air pollution would lead to a larger increase in the the gradient of mental health to air pollution. Table 5 Panel B shows that the estimate of γ becomes larger if the average concentration of air pollution is measured over larger time window (from one month in Column 1 to six months in Column 6). This implies that more frequent informational stressors would further amplify the negative effect of air pollution on mental health.

Third, after the information program, an increase in search intensity for pollution information leads to worse mental health. We restrict the sample to observations after the information program and estimate the following equation:

$$CESD_{ijt} = \alpha_0 + \beta Index_{jt} + X_{ijt}\gamma + W_{jt}\phi + C_{jt}\mu + \lambda_i + \eta_j + \delta_t + \pi_{st} + \varepsilon_{ijt}, \qquad (4)$$

where the search intensity $Index$ is instrumented by thermal inversions. The set of control variables and fixed effects is specified the same as in Equation (1). Table 5 Panel C shows that an increase in the searching intensity for pollution-related information leads to a statistically significant deterioration of mental health, measured by the standardized CESD and dummies of constant stress and depression. We conduct a robustness check by replacing the aggregate search index with the search index for each keyword (Appendix Tables A24 and A25). Results are consistent. Overall, these results suggest that information of air pollution as a constant stressor to the mental system plays an important role in explaining the negative impacts of air pollution on mental health.

6 Welfare Discussion

So far we have shown that the accessibility of information on air pollution magnifies the negative effect of air pollution on individual's mental health. In this section, we aim to quantify how much individuals are willing to pay to reduce the negative psychological effect of air pollution.

Following the stated-preference approach of Levinson (2012) and Zhang et al. (2017), we calculate individual's WTP for air quality as the marginal rate of substitution between air pollution and household income to maintain the same level of subjective well-beings. In particular, we are interested to estimate the *change* in WTP after the information program. We estimate the following equation:

$$\begin{aligned} CESD_{ijt} = \alpha_0 + \beta PM2.5_{jt} + \gamma PM2.5_{jt} \times D_{jt} + \pi Income_{ijt} \\ + \alpha_1 D_{jt} + X_{ijt}\epsilon + W_{jt}\phi + C_{jt}\mu + \lambda_i + \eta_j + \delta_t + \pi_{st} + \varepsilon_{ijt}, \end{aligned} \tag{5}$$

where $Income_{ijt}$ is the log of annual household per capita income (deflated to 2010), and other model specifications are defined the same as in Equation (1).[19]

By totally differentiating Equation (5) and holding CESD constant, we calculate the average marginal rate of substitution between air pollution and household income before the information program as $\partial Income/\partial PM2.5 = -\widehat{\beta}/\widehat{\pi}$. Because both the PM2.5 and income are in log terms, we transform the pre-program WTP into the money metric value as $-\widehat{\beta}/\widehat{\pi} \times \overline{Income}/\overline{PM2.5}$, where $\overline{Income}$ and $\overline{PM2.5}$ represents the average value of household income and PM2.5, respectively. Table 6 Column 1 presents the estimates of $-\widehat{\beta} = 0.047$ and $\widehat{\pi} = -0.028$. Plugging in CNY 11,935 for the average annual household income per capita ($\overline{Income}$), and 66.8 $\mu g/m^3$ for the average concentration of PM2.5 ($\overline{PM2.5}$), we estimate that people on average are willing to pay CNY 300 (2.51% of annual income) to compensate for 1 $\mu g/m^3$ increase in air pollution per year per person. This estimate of WTP is very close to the estimate of CNY 258 by Zhang et al. (2017) (2.1% of annual income) based on pre-program data on individual's subjective well-beings, and similar to the estimate of CNY 176 per year (2.78% of annual income in 2005) by Freeman et al. (2019) leveraging the price and sales records of residential housing in 2005.

We are most interested in the *change* in WTP for air quality after the information on air pollution becomes publicly available. This change in WTP is given by $-\widehat{\gamma}/\widehat{\pi} \times \overline{Income}/\overline{PM2.5}$. Plugging in the estimate of $\widehat{\gamma} = 0.083$ and the other estimates, we find that individuals are willing to pay an additional CNY 530, or 4.44% of annual income, to compensate for 1 $\mu g/m^3$ increase in PM2.5 per year per person. This means individuals are willing to pay 1.8 times more for cleaner air when they have reliable information on the severity of air pollution. For

19. We do not include the interaction term between the program dummy and income ($Income_{ijt} \times D_{ijt}$) in Equation (5), assuming implicitly that the information program would not alter the marginal effect of income on mental health. We test this assumption by include this interaction term and report the estimation results in Appendix Table A26. The estimated coefficient of this interaction term is close to zero and statistically insignificant.

robustness, we adopt alternative measures of mental health as dependent variable, including the indicator for constant stress, and indicators for mild, moderate and severe depression. Table 6 Columns 2 to 5 show that individuals are on average willing to pay an additional CNY 543 to CNY 899, or 4.55% to 7.53% of annual income, to compensate for 1 $\mu g/m^3$ increase in the concentration of PM2.5.

Our estimated WTP for Chinese households is lower in level than the U.S. population, such as an estimate of $891 (2008 dollars) by Levinson (2012), but similar if measured in share of household income. Chinese hosueholds were willing to pay a similar share (2.51%) of their annual income as their U.S. counterparts (3.3%) to reduce air pollution even before the information program. Moreover, after the information program, the Chinese households were willing to pay much more (an additional 4.44% of annual income) for an improvement for air quality. In this perspective, the welfare gains from air pollution regulations is substantial for Chinese population when the information of air qualty is publicly available.

We provide the first stated-preference-based estimate of the effect of air quality information on hosueholds' WTP for clean air in China.[20] We compared our estimate to Ito and Zhang (2020)'s revealed-preference-based estimate of WTP. Based on transaction-level data of air purifiers from 80 Chinese cities, Ito and Zhang (2020) find that the information program in 2013 has led to a 1.45 to 1.77 times increase in WTP for clean air, a magnitude close to our estimate (1.8 times). Our finding complements the existing estimates of the value of pollution information for households in China (Barwick et al., 2019; Ito and Zhang, 2020), and provides a stated-preference perspective to the point made by Greenstone and Jack (2015) that the psychological factors may help to identify the gap between measured WTP and WTP in the absence of market failures.

7 Conclusion

This paper provides the first study to assess individual's psychological responses to the information on environmental risks. We provide empirical evidence that the information of air quality in a highly polluted environment may represent a important source of stressor and create unintended psychological burden on individuals.

We focus on a pivotal policy change in China that resulted in the comprehensive monitoring and provision of previously unavailable, real-time air quality information to the public. Based on matched data of individual's CESD from nationally representative surveys and air quality measures from satellite imaging, we find robust evidence that the increase in the accessibility of information on air pollution magnifies the negative effect of air pollution on individual's mental health. This pattern is more pronounced in regions with lower prior awareness of air pollution and in regions that exhibited a greater increase in searching for pollution information.

Our empirical work focuses on a national information program in China, but the findings have broader policy implications. With rising attention to environmental safety, information

20. See Levinson (2012) for a discussion on the advantages and disadvantages of the stated-preference approach compared to other existing methods for computing WTP.

disclosure policies are increasingly being proposed and issued by governments around the world, and recently more so in developing countries. However, the psychological effects of these policies are overlooked and understudied. The evidence of a substantial psychological response to the information of air pollution in China raises the question of the impact of the environmental information disclosure on the overeall welfare consequences in other developing countries that feature mounting environmental risks. While fully acknowledging the substantial value of disclosing environmental information in motivating avoidance and mitigating impacts of environmental risk factors, our paper highlights the important role of the population's psychological responses in the optimal design and delivery of environmental information policies in developing countries.

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8 Figures

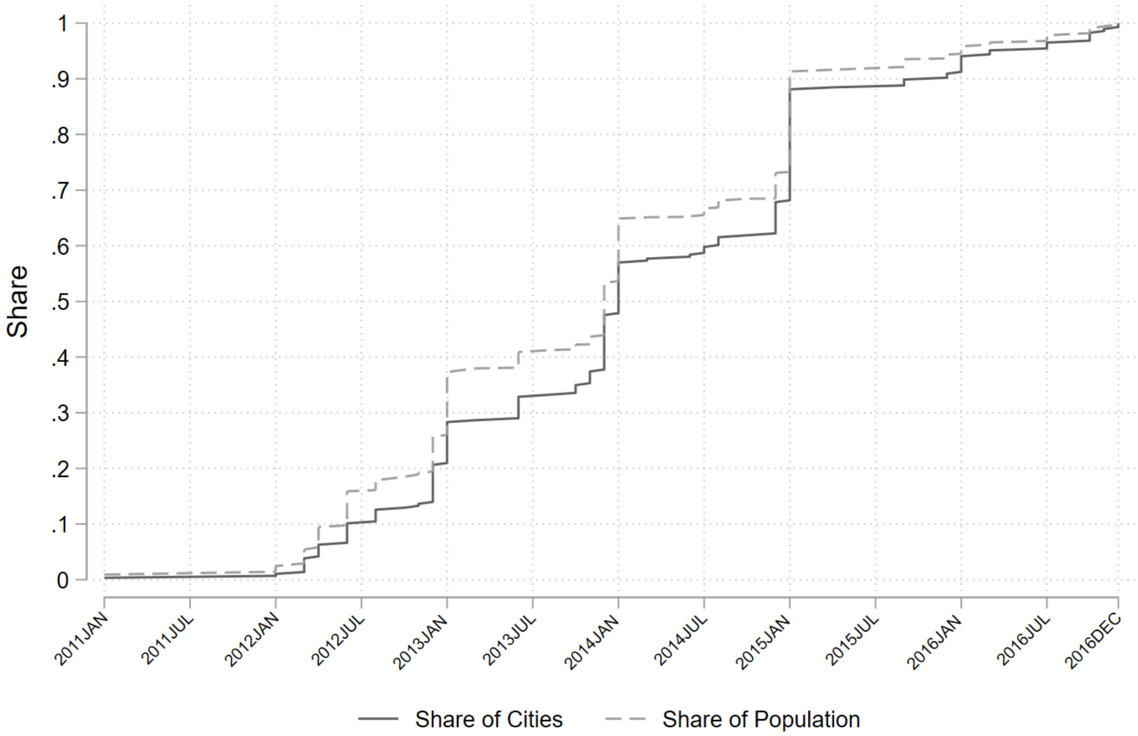


FIGURE 1
Population Coverage of the Information Program Across Time

Notes: This figure plots the share of cities and population that have started monitoring and reporting real-time air pollution across time. Solid line plots the share in cities, and dashed line plots the share in total population.

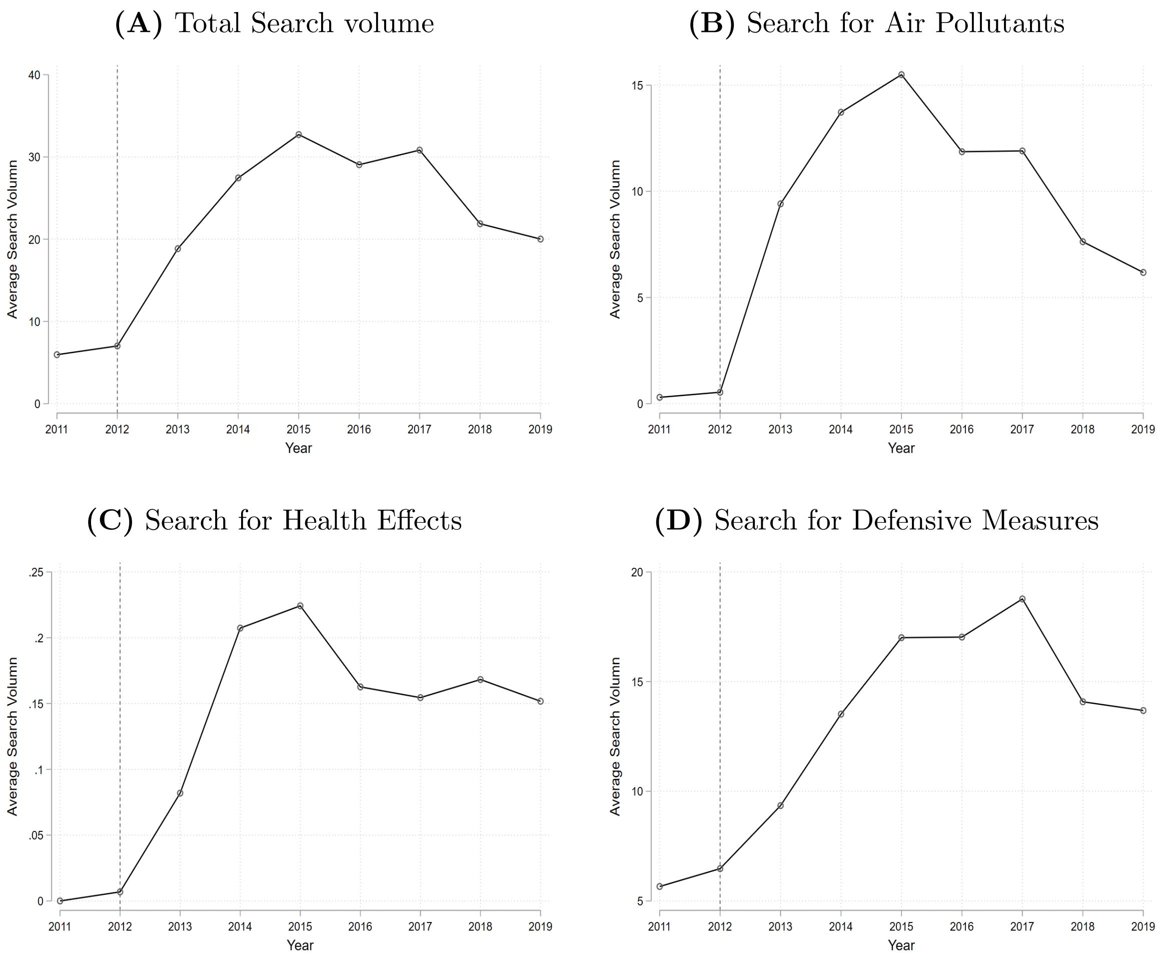


FIGURE 2
Online Search Volume for Pollution-related Keywords

Notes: This figure plots the time trend of daily online search volume for pollution-related keywords per 10,000 population, measured by the Baidu search intensity index. Panel A plots the total search index for all pollution-related keywords, which is the sum of three categories of indices, including the search index for major air pollutants (Panel B), the search index for the harms and health effects of air pollution (Panel C), and the search index for defensive measures against air pollution (Panel D). See Appendix Table A1 for the list of keywords included in each category of indices.

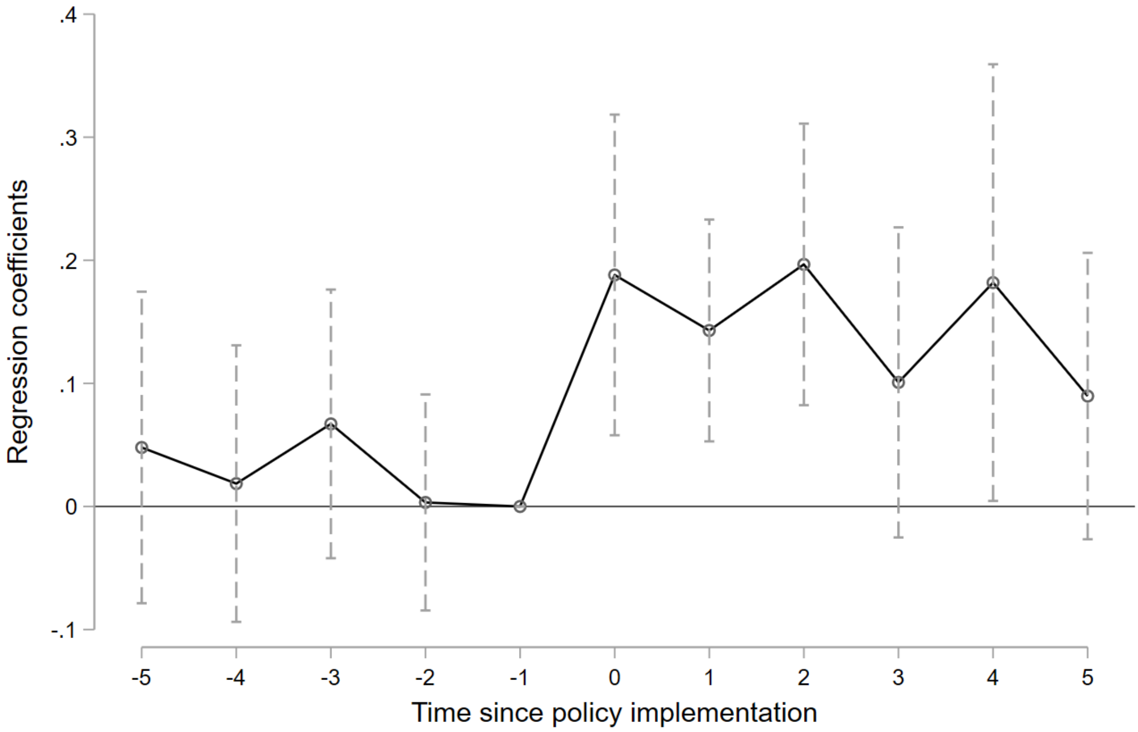
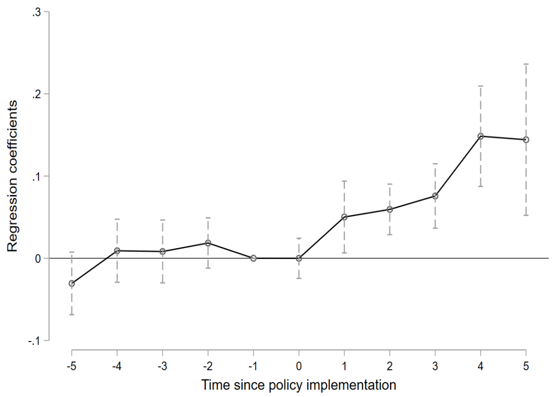


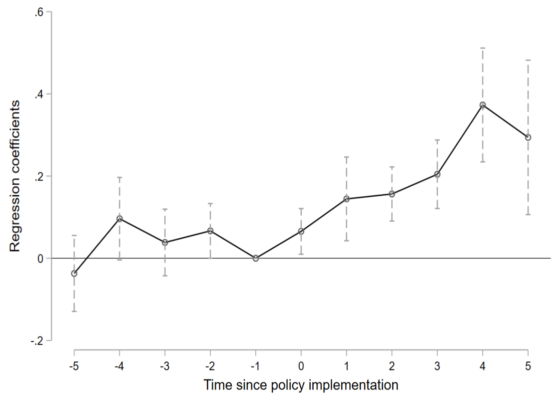
FIGURE 3
Event Study Estimates of Information Disclosure on the Gradient of Mental Health to Air Pollution

Notes: This figure plots the event study estimates of the the gradient of mental health to air pollution before and after the information program. The regression equation is specified in Equation (2). The dependent variable, the standardized CESD, is the standardized six-item CESD scores. Coefficients of interaction terms between log PM2.5 and month-to-introduction dummies, as well as the 95% confidence intervals, are plotted in the figure. Regression results are reported in Appendix Table A3.

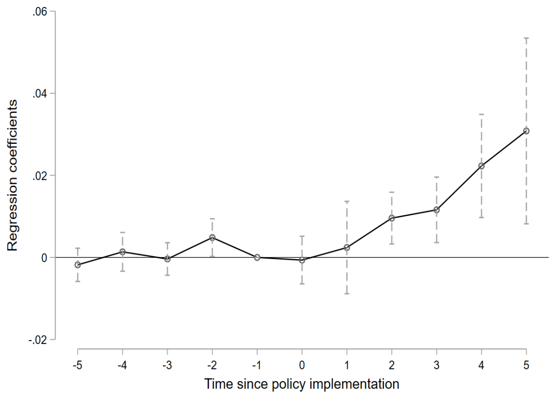
(A) Total Search volume



(B) Search for Air Pollutants



(C) Search for Health Effects



(D) Search for Defensive Measures

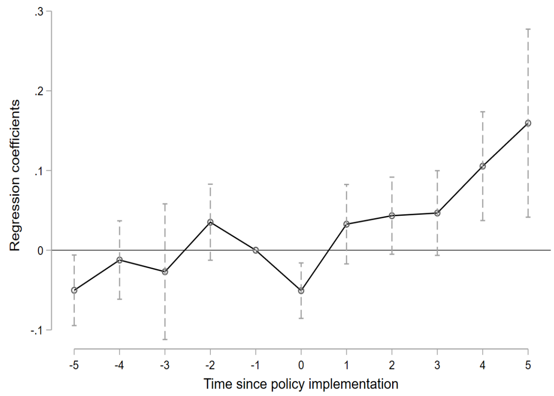


FIGURE 4
Event Study Estimates of Information Disclosure on the Gradient of Search Volume to Air Pollution

Notes: This figure plots the event study estimates of the change in online pollution gradient of search volume before and after the information program. The dependent variable, the online search index, is the daily online search volume for pollution-related keywords per 10,000 population. Panel A plots the total search index for all pollution-related keywords, which is the sum of three categories of indices, including the search index for major air pollutants (Panel B), the search index for the harms and health effects of air pollution (Panel C), and the search index for defensive measures against air pollution (Panel D). Regression results are reported in Appendix Table A22. See Appendix Table A1 for the list of keywords included in each category of indices.

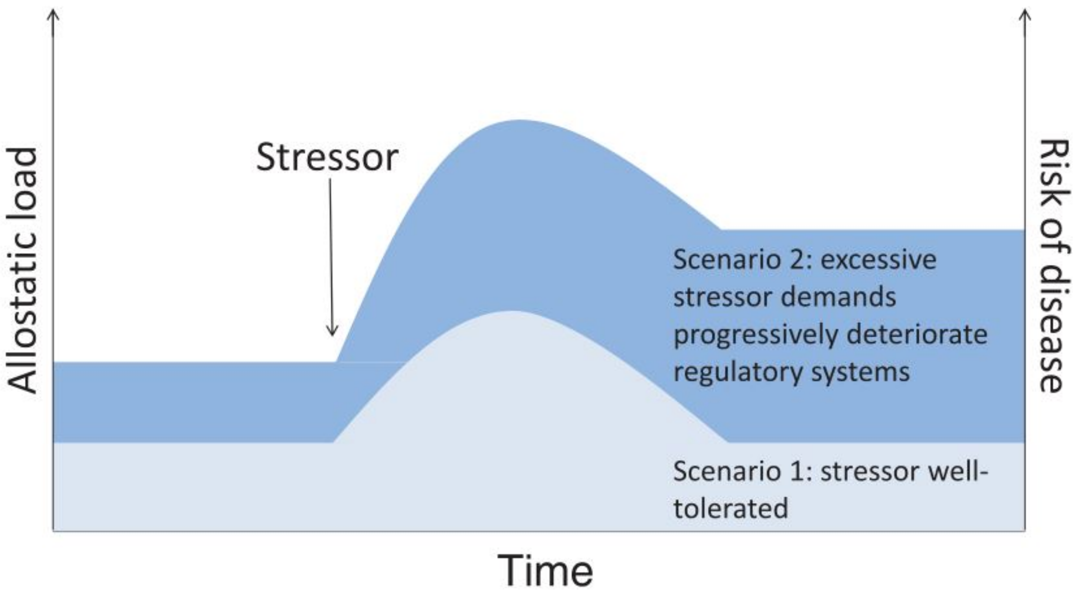


FIGURE 5
Scenarios of Stressors, Allostatic Load, and Risk of Diseases

Source: Thomson (2019).
Notes:This figure demostrates two scenarios under which different level of stressors (i.e., from prior and concurrent exposure to psychosocial, physical, or environmental risk factors) will affect the stress responses of our regulatory system, and lead to different level of physiological dysfunction, or allostatic load, and the risk of physical or mental diseases.

9 Tables

TABLE 1
Summary Statistics

Variable	Obs	Mean	S.D.	Min	Max
Panel A: Individual Mental Health					
CESD score (standardized)[a]	93,091	0.14	0.17	0	1
Mild depression (CESD$\geq$ 4)	93,091	0.38	0.48	0	1
Moderate depression (CESD$\geq$ 8)	93,091	0.12	0.33	0	1
Severe depression (CESD$\geq$ 13)	93,091	0.04	0.20	0	1
Constantly stressful	93,091	0.17	0.19	0	1
Panel B: Individual Covariates					
Female	93,091	0.51	0.50	0	1
Age	93,091	46.82	16.10	16	98
Years of schooling	93,091	7.03	4.82	0	22
Annual income per member [b]	93,091	11,935	18,531	0	1,483,971
Agricultural Hukou	93,091	0.72	0.45	0	1
Married	93,091	0.89	0.32	0	1
Household Expenditure	93,091	53,592	93,002	0	5,169,220
Panel B: Pollution and Weather Variables					
Information program dummy	93,091	0.48	0.50	0	1
PM2.5 ($\mu g/m^3$)	93,091	66.78	33.25	3.26	195.92
Thermal inversions[c]	93,091	9.29	8.20	0	31
Cloud thickness (km)[d]	93,091	4.94	1.70	0	7.59
Temperature	93,091	14.10	5.12	0.45	24.52
Wind speed (m/s)	93,091	25.56	9.35	6.71	65.96
Precipitation (mm)	93,091	684.45	487.83	0	2517.58
Relative humidity (%)	93,091	65.00	11.20	32.48	89.03
Bad weather dummy[e]	93,091	0.18	0.38	0	1
Panel C: Regional Development and Environmental Policy Variables					
GDP per capita	93,091	55,431	34,400	5,441	262,922
GDP growth rate (%)	93,091	9.95	6.52	-15.3	109
Sec indus ratio (%)[f]	93,091	46.81	11.38	13.57	85.45
Total population (10,000)	93,091	593.11	441.14	89.08	3391
Environmental policy dummy[g]	93,091	0.30	0.46	0	1

Notes: This table presents summary statistics for main variables in the empirical analyses.

[a]: CESD score is the sum of six-item CESD, normalized to be between zero and one.

[b]: Household annual income per household member.

[c]: Thermal inversions is the average daily number of thermal inversions in the month prior to the interview date.

[d]: Cloud thickness is related to various weather conditions, such as precipitation.

[e]: Bad weather dummy indicates the weather to be heavy fog, rain, snow, hail, or thunder.

[f]: Secondary industry ratio is the share of total value-added of secondary industries in city GDP.

[g]: Environmental policy dummy indicates whether the city implemented the CO2 cap-and-trade pilot program, the energy reduction program, or fuel switching program.

TABLE 2
Effects of Information Disclosure on the Gradient of Mental Health to Air Pollution

VARIABLES	(1) CESD	(2) CESD	(3) CESD	(4) CESD	(5) CESD
PM2.5 (β)	0.049**	0.050**	0.046**	0.047**	0.047**
	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)
$PM2.5 \times Disclosure$ (γ)	0.076**	0.076**	0.081***	0.084***	0.084***
	(0.030)	(0.030)	(0.030)	(0.030)	(0.030)
Observations	93,091	93,091	93,091	93,091	93,091
Individual FE	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes
Interviewer FE	Yes	Yes	Yes	Yes	Yes
Prov×Year FE	Yes	Yes	Yes	Yes	Yes
Cubic Month Controls	Yes	Yes	Yes	Yes	Yes
Individual Controls	No	Yes	Yes	Yes	Yes
Weather Controls	No	No	Yes	Yes	Yes
City Economic Controls	No	No	No	Yes	Yes
Env. Policy Controls	No	No	No	No	Yes
Kleibergen-Paap F-stat	592	593	616	601	601
Mean Dep. Var.	0.141	0.141	0.141	0.141	0.141

Notes: This table presents the estimated effects of the information disclosure on the the gradient of mental health to air pollution. Dependent variable is the standardized CESD. $PM2.5$ is log of average concentration of PM2.5 in the month prior to the respondent's interview date at the respondent's county of residence. $Disclosure$ is the dummy variable that equals to one if the real-time air pollution information is publically available at the county. $PM2.5$ and its interaction with $Disclosure$ are instrumented by log of thermal inversions and its interaction with $Disclosure$. Regression models are specified in Equation (1). All regressions across columns control for individual fixed effects, county fixed effects, interviewer fixed effects, a cubic function in month, and province-by-year fixed effects. Individual controls include age, age squared, years of schooling, hukou status, marriage status, and family size. Weather controls include temperature, wind speed, cloud thickness, precipitation, relative humidity, and an indicator for extreme weather conditions (heavy fog, rain, snow, hail, or thunder). City economic controls include GDP per capita (price deflated to 2010), GDP growth rate, and share of value-added from secondary industry to total city GDP. Environmental policy dummy indicates whether the city implemented the CO2 cap-and-trade pilot program, the energy reduction program, or fuel switching program. Standard errors in parentheses are clustered at the household level. *** p <0.01, ** p <0.05, * p <0.1.

TABLE 3
Effects of Information Disclosure on the Gradient of Mental Health to Air Pollution

VARIABLES	(1) Mild Depression	(2) Moderate Depression	(3) Severe Depression	(4) Constant Stress	(5) Confidence in Future	(6) Life Satisfaction
PM2.5 (β)	0.210***	0.008	-0.013	0.078***	0.085	0.024
	(0.066)	(0.049)	(0.031)	(0.026)	(0.145)	(0.141)
$PM2.5 \times Disclosure$ (γ)	0.301***	0.166**	0.053	0.077**	-0.558***	-0.603***
	(0.096)	(0.068)	(0.042)	(0.037)	(0.205)	(0.204)
Observations	93,091	93,091	93,091	93,301	92,695	92,695
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Interviewer FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Kleibergen-Paap F-stat	597	597	597	598	595	595
Mean Dep. Var.	0.373	0.125	0.040	0.166	0.64	0.70

Notes: This table presents the estimated effects of the information disclosure on the the gradient of mental health to air pollution. Dependent variables are the indicator for mild depression (CESD $\geq$ 4), moderate depression (CESD $\geq$ 8), severe depression (CESD $\geq$ 13), the indicator for feeling stressful constantly, the indicator of confidence in the future, and self-reported life satisfaction. $PM2.5$ is log of average concentration of PM2.5 in the month prior to the respondent's interview date at the respondent's county of residence. $Disclosure$ is the dummy variable that equals to one if the real-time air pollution information is publically available at the county. $PM2.5$ and its interaction with $Disclosure$ are instrumented by log of thermal inversions and its interaction with $Disclosure$. Regression models are specified in Equation (1). All regressions control for individual fixed effects, county fixed effects, interviewer fixed effects, a cubic function in month, and province-by-year fixed effects. Control variables are specified the same as in Table 2. Standard errors in parentheses are clustered at the household level. *** p <0.01, ** p <0.05, * p <0.1.

TABLE 4
Effects of Information Disclosure on the Gradient of Search for Pollution Information to Air Pollution

Search Category	(1) All Keywords	(2) Air Pollutants	(3) Pollution's Harm	(4) Defensive Devices
PM2.5 (β)	0.107***	0.341***	0.009***	0.005
	(0.018)	(0.051)	(0.003)	(0.012)
$PM2.5 \times Disclosure$ (γ)	0.103***	0.272***	0.018***	0.049**
	(0.027)	(0.068)	(0.006)	(0.024)
Observations	15,309	15,309	15,309	15,309
Month FE	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes
Prov×Year FE	Yes	Yes	Yes	Yes
Control Variables	Yes	Yes	Yes	Yes
Kleibergen-Paap F-stat	24	24	24	24
Mean Dep. Var.	0.200	0.314	0.008	0.341

Notes: This table presents estimated effects of information disclosure on the pollution gradient of search volume for pollution-related information. Dependent variable is log monthly search volume per 10,000 city population for specified keywords. $PM2.5$ is log of average concentration of PM2.5. $Disclosure$ equals to one if the real-time air pollution information is publically available. $PM2.5$ and its interaction with $Disclosure$ are instrumented by log of thermal inversions and its interaction with $Disclosure$. Regression models are specified in Equation (3). All regressions control for city fixed effects, month fixed effects, and province-by-year fixed effects. Weather controls include temperature, wind speed, cloud thickness, precipitation, relative humidity, and an indicator for extreme weather conditions (heavy fog, rain, snow, hail, or thunder). Socioeconomic controls include GDP per capita (price deflated to 2010), GDP growth rate, and share of value-added from secondary industry to total city GDP. Environmental policy dummies include whether the city implemented the CO2 cap-and-trade pilot program, the energy reduction program, or fuel switching program. Standard errors in parentheses are clustered at the city level. *** p <0.01, ** p <0.05, * p <0.1.

TABLE 5
Exploring the Role of Pollution Information in the Relationship between Air Pollution and Mental Health

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Effect of Information Disclosure by Different Change in Search Intensity						
VARIABLES	CESD	CESD	CESD	CESD	CESD	CESD
Search Category	**Air Pollutants**		**Harmful effects**		**Defensive devices**	
	Below Mean	Above Mean	Below Mean	Above Mean	Below Mean	Above Mean
PM2.5	0.172***	-0.007	0.060*	0.024	-0.022	0.161***
	(0.053)	(0.031)	(0.031)	(0.035)	(0.034)	(0.036)
$PM2.5 \times Disclosure$	0.094	0.143***	0.056	0.118**	0.096**	0.164***
	(0.059)	(0.049)	(0.050)	(0.046)	(0.047)	(0.046)
Observations	38,169	54,362	38,311	54,256	36,685	55,861
Panel B: Effect of Information Disclosure by Different Window of Air Pollution Exposure						
VARIABLE	CESD	CESD	CESD	CESD	CESD	CESD
Window of Pollution	1-month	2-month	3-month	4-month	5-month	6-month
PM2.5	0.047**	0.024*	0.029**	0.058***	0.104***	0.226***
	(0.022)	(0.014)	(0.014)	(0.017)	(0.021)	(0.043)
$PM2.5 \times Disclosure$	0.083***	0.150***	0.222***	0.275***	0.227***	0.320***
	(0.030)	(0.042)	(0.050)	(0.059)	(0.057)	(0.077)
Observations	93,091	93,091	93,091	93,091	91,769	87,951
Panel C: Effect of Search for Pollution Information on Measures of Mental Health						
VARIABLES	CESD	Mild Depression	Moderate Depression	Severe Depression	Constant Stress	Confidence in Future
Search Index	0.666***	2.158***	0.935**	0.374*	0.816***	-0.632**
	(0.168)	(0.559)	(0.371)	(0.220)	(0.212)	(0.282)
Observations	31,831	31,831	31,831	31,831	31,831	31,831

Notes: Panel A presents the heterogeneous effects of information disclosure by the extent of change in search intensity. The sample is divided into two groups by whether the one-year change in search volume is above or below the mean. Columns 1-2 divide the sample by the change in search volume of major air pollutants; Columns 3-4 divide the sample by the change in search volume of health effects of air pollution; and Columns 5-6 divide the sample by the change in search volume of defensive measures against air pollution. Panel B presents estimated effects of information disclosure on the the gradient of mental health to air pollution across different windows of air pollution exposure. Columns 1-6 present the results when the concentration of PM2.5 is measured by 1-month, 2-month,..., 6-month average prior to the interview date, respectively. Panel C presents the estimated effects of search for air pollution information on various measures of mental health. Search index is the log monthly search volume per 10,000 city population for top pollution-related keywords. Search index is instrumented by the log of thermal inversions. Sample in Panel C is restricted to observations after the information program. All regressions across columns control for individual fixed effects, county fixed effects, interviewer fixed effects, a cubic function in month, and province-by-year fixed effects. Control variables are specified the same as in Table 2. Standard errors in parentheses are clustered at the household level. *** p <0.01, ** p <0.05, * p <0.1.

TABLE 6
Effects of Information Disclosure on the Willing-to-Pay for Air Quality

VARIABLES	(1) CESD	(2) Constant Stress	(3) Mild Depression	(4) Moderate Depression	(5) Severe Depression
PM2.5 (β)	0.047**	0.076***	0.210***	0.008	-0.013
	(0.022)	(0.026)	(0.066)	(0.049)	(0.031)
$PM2.5 \times Disclosure$ (γ)	0.083***	0.079**	0.301***	0.166**	0.053
	(0.030)	(0.037)	(0.096)	(0.068)	(0.042)
Income (π)	-0.028***	-0.026***	-0.069***	-0.033**	-0.015
	(0.007)	(0.009)	(0.023)	(0.017)	(0.011)
Observations	93,091	93,091	93,091	93,091	93,091
Individual FE	Yes	Yes	Yes	Yes	Yes
Interviewer FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
Prov× FE	Yes	Yes	Yes	Yes	Yes
Control Variable	Yes	Yes	Yes	Yes	Yes
Kleibergen-Paap F-stat	597	597	597	597	597
Mean Dep. Var.	0.141	0.166	0.373	0.125	0.040
Implied Change in WTP	530	543	779	899	631

Notes: This table presents the estimated effects of the information disclosure on individual's willingness-to-pay for air quality. Dependent variables are the standardized CESD, an indicator for constant stress, the indicator for mild depression (CESD ≥ 4), moderate depression (CESD ≥ 8), and severe depression (CESD ≥ 13). $PM2.5$ is log of average concentration of PM2.5 in the month prior to the respondent's interview date at the respondent's county of residence. $Disclosure$ is the dummy variable that equals to one if the real-time air pollution information is publically available at the county. $PM2.5$ and its interaction with $Disclosure$ are instrumented by log of thermal inversions and its interaction with $Disclosure$. Regression models are specified in Equation (1). All regressions control for individual fixed effects, county fixed effects, interviewer fixed effects, a cubic function in month, and province-by-year fixed effects. Control variables are specified the same as in Table 2. Implied change in willingness-to-pay (WTP) per person per year after the information program is computed as $-\gamma/\pi \times \overline{Income}/\overline{PM2.5}$ and reported at the bottom of table. Standard errors in parentheses are clustered at the household level. *** p <0.01, ** p <0.05, * p <0.1.