Air Pollution and Health of Working-Age Population: Evidence from Thermal Inversion

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Abstract

Despite the significant impact of air pollution on public health, its causal effects on a national scale have not been extensively studied. In this paper, we examine the impact of PM2.5 on adult health in the United States using data from the Behavioral Risk Factor Surveillance System for 2001-2012, focusing on a period of relatively low pollution levels. To address the endogeneity issue, we use the two-stage least-squares regression with thermal inversion as an instrumental variable. Our findings provide evidence of the ongoing negative impact of air pollution on overall health. Specifically, we observe that a 1 $\mu g/m^3$ rise in PM2.5 is associated with a significant increase in the number of mentally unwell days by 0.11 and an increase in asthma incidence by 0.16 percentage points. Additionally, our cost-benefit analysis demonstrates that the marginal benefit of improving PM2.5 standards far exceeds the associated marginal cost.

Keywords: PM2.5; Thermal inversion; General public health; Cost–benefit analysis
JEL codes: I10; Q53; D61

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1 Introduction

A considerable amount of research has explored the link between air pollution and health. One strand of studies has focused on the impact of air pollution on mortality, with consistent findings showing adverse effects on both children and adults.[1] Another body of literature has examined specific health outcomes, such as low birth weight or premature birth in newborns and asthma in children.[2] However, the majority of studies have predominately examined the impact of air pollution in specific age groups such as children and the elderly, leaving limited research on the causal effects of air pollution on populations in the middle of the age spectrum in the United States. This paper aims to address the gap in the literature by examining the impact of PM2.5, a prominent air pollutant, on working-age adults.

PM2.5, also known as fine particulate matter, refers to a mixture of solid particles and liquid droplets found in the air with a diameter smaller than 2.5 micrometers.[3] To investigate the impact of PM2.5 on health, we use data from the Behavioral Risk Factor Surveillance System (BRFSS) for 2001 to 2012, which provides comprehensive information on respondents' health status across all US states. The BRFSS dataset offers several advantages over other datasets. Firstly, it records both health outcomes and health behaviors for each respondent, allowing us to analyze individual responses to air pollutants. Secondly, the publicly available geographic information in the BRFSS dataset enables us to fully exploit the within-county variation in PM2.5. Finally, the inclusion of interview dates in the BRFSS data makes it possible to study the short-run impact (days or weeks) of air pollution.

One challenge in our study is the endogeneity of air pollutants, which could bias our estimates. To address this, we use the instrumental variable approach, which requires an exogenous variable that is relevant to PM2.5 but impacts people's health status only through PM2.5. Previous literature has verified two categories of instrumental variables. The first category pertains to exogenous shocks stemming from human activities, such as the environmental regulation stringency (Li and Li, 2022), refinery

[1]Related literature includes Dockery et al. (1993), Samet et al. (2000), Chay and Greenstone (2003), Peng et al. (2005), Currie and Neidell (2005), Jerrett et al. (2005), Wong et al. (2008), Janke et al. (2009), Jerrett et al. (2013), Di et al. (2017b), Di et al. (2017a), Anderson (2020), Wei et al. (2020), He et al. (2020), and Barreca et al. (2021).

[2]Related literature includes Wang et al. (1997), Bobak (2000), Neidell (2004), Bell et al. (2007), Jerrett et al. (2008), Currie et al. (2009), Pénard-Morand et al. (2010), Currie and Walker (2011), Nishimura et al. (2013), Guarnieri and Balmes (2014), Laurent et al. (2016), Jans et al. (2018), Arroyo et al. (2019), Tiotiu et al. (2020), Simeonova et al. (2021), Colmer et al. (2021), and Shin et al. (2021).

[3]Apart from natural factors such as wildfire smoke, forest, and dust storms, human activities are a major source of PM2.5, including burning fossil fuels, construction sites, road dust, and exhaust gases from power plants. Such inhalable matter can directly undermine one's health by infiltrating the lungs and bloodstream, and long-term exposure to PM2.5 causes respiratory diseases, heart attacks, and even cancer.

closures (Hanna and Oliva, 2015), the presence of a Democratic governor in US states (Beland and Boucher, 2015), nonattainment status of air quality standards (Chay and Greenstone, 2005), traffic congestion (Currie and Walker, 2011; Simeonova et al., 2021), and the Clean Air Act of 1970 (Isen et al., 2017). The second category involves meteorological phenomena that occur naturally and have been shown to be independent of economic activities. This category includes thermal inversions (Arceo et al., 2016; Jans et al., 2018; Deschenes et al., 2020; Chen and Zhang, 2021; Chen et al., 2022; Colmer et al., 2021), wind direction (Deryugina et al., 2019), air stagnation (Kerr and Waugh, 2018), and ventilation coefficients (Hering and Poncet, 2014; Zhang et al., 2020). In our study, we utilize thermal inversion as an instrumental variable to estimate PM2.5 levels. To the best of our knowledge, this is the first study to employ thermal inversion as an instrumental variable in the US context on a national scale.[4] We present robust first-stage results and provide additional evidence to support the validity of our instrumental variable approach.

Our study reveals that PM2.5 has immediate adverse effects on both physical and mental health. Specifically, we find that a 1 $\mu g/m^3$ increase in PM2.5 is associated with a 0.16 percentage point increase in the odds of developing asthma and a 0.11-day increase in mentally unwell days, but we do not observe any other health issues such as poor self-reported health status, days of feeling physically unwell, and obesity at low levels of PM2.5 exposure. Moreover, we construct a health index to assess the overall health status of individuals, and the results suggest that exposure to PM2.5 leads to a deterioration in general health. Our study identifies that the adverse health effects of PM2.5 are more pronounced in certain socioeconomic groups, such as the unemployed, non-Whites, individuals with low socioeconomic status, and individuals aged 45-64.

This paper makes several contributions to the study of adverse health effects of air pollution. Firstly, it contributes to the causal impact of air pollution on the health of the adult population in the United States. Unlike prior literature, which has mostly focused on either children or the elderly, our study examines the adverse health effects for adults aged 25–64, enabling us to fill the gap in the literature on the overall health of the working-age population. Several exceptions also study this middle-aged group, but our paper differs in terms of the outcome variables. For example, Graff Zivin et al. (2023) found the joint impacts of air pollution and vaccine protection on influenza hospitalizations. Persico and Johnson (2021) and Austin et al. (2023) used different exogenous variations in air pollution to explore its adverse effects on COVID-19 cases and deaths. Our work provides complementary results by focusing on another set of

[4]Thermal inversion has been employed as an IV in various contexts, including mainland China (Deschenes et al., 2020; Chen and Zhang, 2021; Chen et al., 2022), Hong Kong (Colmer et al., 2021), Mexico city (Arceo et al., 2016), and Sweden (Jans et al., 2018).

adult health outcomes such as mental health and asthma.

Secondly, our study utilizes sampling weights and comprises a nationally representative sample of individuals from 730 counties in the United States, making our results more generalizable than previous literature. Many prior studies have limited their analysis to specific regions or states, which may hinder the generalizability of their results. The most relevant paper to our study is that of Deryugina et al. (2019), who conducted an instrumental variable estimation based on data from 902 counties in the United States and found a positive association between PM2.5 and mortality and healthcare use for the elderly at the county–day level. By comparison, our paper investigates the causal impact of PM2.5 on physical and mental health outcomes at the individual–day level, which enables us to exploit more variation at a more granular level and examine the potential heterogeneous effects. Additionally, we use thermal inversion as an exogenous variation to identify the causal effects of air pollution on health. Our first-stage results suggest that thermal inversion can significantly predict the level of PM2.5 in the United States.

Thirdly, our findings indicate a direct impact of PM2.5 on health without significant short-term changes in individuals' health-related behaviors in response to poorer air quality (Deschenes et al., 2020; Liao et al., 2021; Jones, 2023). Prior research suggests that direct damage to the body may explain the observed relationship between PM2.5 and health outcomes. For example, PM2.5 is associated with disorders of neurotransmitters and deposition of toxic elements, which can cause depressive-like responses (Chu et al., 2019). Additionally, air pollutants can cause oxidative damage to the airways, leading to inflammation, remodeling, and increased risk of sensitization (Guarnieri and Balmes, 2014). Our findings are supported by data from the BRFSS and the American Time Use Survey, through which we find no significant impact of PM2.5 on exercise, smoking, drinking, sleep, or leisure time. These results indicate that the effect of PM2.5 on health outcomes is not primarily mediated by changes in health behaviors in response to PM2.5 exposure.

Finally, we conduct a cost–benefit analysis that simultaneously estimates the marginal costs and marginal benefits of air pollution control. Our results demonstrate that the benefit of further reducing PM2.5 by 1 $\mu g/m^3$ exceeds its cost, even at relatively low pollution levels. Specifically, we estimate the household's average willingness to pay for a marginal reduction in PM2.5 given constant health outcomes and extrapolate the cost of such reduction based on estimates in an EPA report. Our analysis suggests that the marginal benefit ranges from \$360.15 billion to \$492.3 billion, while the marginal cost is between \$75 million and \$229 million. This contends with the extant safe PM2.5 values set by the EPA and provides strong support for a more stringent PM2.5 standard in the future.

The remainder of this paper is organized as follows: Section 2 introduces the major variables and the primary sample. Section 3 shows the empirical model and the validity of the instrument. Section 4 reports our main results, robustness checks, and heterogeneous effects. Section 5 evaluates alternative explanations for the adverse effect of PM2.5 on health outcomes. Section 6 discusses the cost–benefit of future pollution abatement. Section 7 draws the final conclusions.

2 Data and Sample

2.1 Health Outcomes and Behaviors

To examine the effects of PM2.5 on health outcomes, we utilize data from the Behavioral Risk Factor Surveillance System (BRFSS) for the period of 2001 to 2012.[5] BRFSS, administered and supported by the CDC's Population Health Surveillance Branch, is a national system of telephone surveys designed to gather information on health-related risk behaviors, chronic health conditions, access to health care, and use of preventive services from the non-institutionalized adult population residing in the United States.

The BRFSS dataset offers two significant advantages over other datasets. First, it provides county and interview date information for respondents. Nearly 97% of completed surveys have a Federal Information Processing System (FIPS) county code, and almost all of them indicate the interview date. This allows us to measure the pollution level that occurred close to the date of their health-related responses. Second, BRFSS has recorded comprehensive health information for over 200,000 adults, encompassing data from 50 states and the District of Columbia. The complete geographic coverage of the BRFSS enhances the representativeness of our final results compared to previous studies.

We extract a set of variables from BRFSS, including individual physical and mental health. Firstly, respondents are asked to evaluate their health status on a five-point scale from "poor" to "excellent". We construct a dummy variable that equals 1 if the answer is "poor" or "fair" and 0 otherwise. Respondents are also asked about the number of days in the past 30 days when their physical and mental health were not good. Based on this information, we create extensive margin variables, which are dummy variables equal to 1 if the answer is a positive number between 1 and 30, and intensive margin variables, which are continuous variables representing the exact number of days the respondents reported having poor physical or mental health. We

[5] We restrict the sample to the period of 2001-2012 because county codes in BRFSS are publicly available until 2012, and PM2.5 observations have been more complete since 2001.

construct additional extensive and intensive margin variables based on the number of days that poor physical or mental health kept respondents from their usual activities, such as self-care, work, or recreation. In addition, we generate an indicator for current asthma status, which equals one if the respondent has ever been diagnosed with asthma and still suffers from the condition. Our health outcomes also include body mass index (BMI), overweightness (BMI$\geq$25 kg/m^2), and obesity (BMI$\geq$30 kg/m^2). To measure the overall health status of each person, we calculate a health index by taking the arithmetic mean of z-scores for various health-related variables,[6] including the number of days the respondents felt physically or mentally unwell, self-rated health status, activity limitation days, asthma, BMI, and history of diabetes.[7]

2.2 Air Pollution and Weather

We utilize the EPA's daily PM2.5 concentration data, which provides the detected contaminant levels and the location of each monitoring station. In counties with multiple monitoring stations, we calculate the pollution level by averaging the readings on a daily basis. The data covers 901 counties in the United States. Unlike previous literature that fills in missing values by using weighted averages of readings from monitoring stations within 20 miles of the county centroid (Currie and Neidell, 2005; Janke et al., 2009), our sample only comprises counties with monitoring stations to avoid measurement errors. We define our primary exposure variable as the maximum PM2.5 level over the past week because we aim to identify short-term effects (days or weeks) and because extreme levels of pollutants have deterministic effects on individual health compared to average levels of pollutants.[8]

Since weather conditions may confound our estimates, we obtain daily weather data for each county from PRISM Spatial Climate Datasets, including precipitation, daily maximum temperature, and daily minimum temperature.[9] These variables are

[6]The construction of our health index is very similar to the summary index from Anderson (2008). The only difference is that the summary index assigns lower weights to highly correlated outcome variables, while ours assigns equal weights to each outcome. Thus, the effect on the health index is, in a sense, a statistical test of whether a program has a "general effect" on a set of outcomes. We will show the p-value from the summary index in Section 4.

[7]A higher health index value indicates poorer overall health. Zero is included when computing the health index using these days. To provide a more comprehensive reflection of an individual's general health status, we include the history of diabetes as one component of the health index. This variable is associated with comorbidities such as hypertension, heart disease, sleep disorders, and other diseases not specifically mentioned in the BRFSS (Jehan et al., 2018). Excluding diabetes from the health index does not qualitatively affect our main results. However, it is not one of the main outcome variables as we do not know the timing of having diabetes.

[8]For example, Pignon et al. (2022) found that there is an increase in the daily number of emergency visits for psychotic disorders during peak periods of PM2.5 concentration.

[9]The weather data were collected from PRISM (Parameter elevation Regression on Independent Slopes Model) datasets: https://prism.oregonstate.edu/.

also averaged over the past 7 days and serve as covariates in our main results.

Our PM2.5 and weather variables are all defined based on the values over the past 7 days, which may seem inconsistent with the temporal duration of some outcome variables. Survey questions in BRFSS regarding physical health, mental health, and activity limitation ask about an individual's experiences over the past 30 days. However, potential recall errors among survey respondents may make their responses more reflective of recent experiences (De Nicola and Giné, 2014; Kjellsson et al., 2014), thus making more recent air pollution levels a more sensible predictor.

To investigate potential recall errors, we estimate Eq. (1) using the IV approach, which will be discussed in detail in Section 3. We examine physical health, mental health, and activity limitation outcomes by incorporating PM2.5 measures and the number of thermal inversions over different durations: 7, 14, 21, 28, and 30 days. As shown in Figure A.2, confidence intervals widen as the duration of measurement increases, indicating the presence of recall errors. Furthermore, the F-statistics of the first-stage equation, represented by the cross marks, drop below 10 for several outcomes when the measurement duration exceeds 14 days. Therefore, our choice of 7-day pollution measures is reasonable and practical.

2.3 Thermal Inversion

Thermal inversion is a meteorological phenomenon that occurs when there is a reversal of temperature in the troposphere, which can cause air pollutants to become trapped within a region, leading to worsening air quality. This phenomenon is caused by various factors, such as radiation during a clear night, warm air subsidence, or horizontal collision of hot and cold air (Arceo et al., 2016). It is independent of economic factors and depends solely on weather and geography. Therefore the thermal inversion is relatively exogenous after controlling for weather conditions and the fixed effects of time and county. Using atmospheric temperature data from MERRA-2,[10] the thermal inversion variable is created by first using four-dimensional temperature data at the grid level on a 6-hour basis with 42 layers of air above the ground. We define thermal inversion as occurring if the temperature of the first layer (approximately 110 meters above the ground) is lower than that of the second layer (approximately 320 meters above the ground), and then aggregate the data to the daily level. Next, we convert the thermal inversion count from the grid level to the county level by averaging the daily number of thermal inversions for all grid points within 100 kilometers from the centroid of each county using inverse distance weighting. Finally, we compute the total

[10]The atmospheric temperature data were sourced from MERRA-2: https://disc.gsfc.nasa.gov/datasets/M2I6NPANA_5.12.4/summary.

number of thermal inversions that occurred during the past week to obtain the IV. This IV is expected to be positively related to PM2.5.

Figure 1 displays the average PM2.5 concentration, using the daily maximum value of PM2.5 and the number of thermal inversions from 2001 to 2012. We observe a roughly parallel time trend for these two variables with a correlation coefficient of 0.70, indicating that thermal inversion can be a predictor for PM2.5 concentration. Figure A.1 shows the maps for PM2.5 and thermal inversion in 2001 and 2012, and we observe a large cross-sectional variation in PM2.5 and thermal inversion, which supports our empirical identification.

2.4 Sample Selection and Summary Statistics

We focus our analysis on the working-age population, including individuals who are aged 25 to 64, from the BRFSS survey conducted between 2001 and 2012, which accounts for 67.6% of the entire sample. To ensure accuracy in our estimates, we further exclude students and retirees (N = 124,281), whose exposure to air pollutants may not be accurately measured as they may spend limited time in their county of residency, and exclude unable-to-work individuals (N = 105,343), who are more likely to have very poor health and confound the effect of air pollution on health outcomes. This leaves 1,161,110 observations in our primary sample.

A limitation of BRFSS is the lack of information about the geographic location of the respondent's workplace, which can result in measurement errors for exposure to air pollutants. However, data from the American Community Survey (ACS) can minimize this concern as it indicates that approximately 27% of workers aged 16 and above worked outside of their county of residence in 2012. By merging the PM2.5 data with individual-level ACS data for 2005-2012, we found that the difference in PM2.5 exposure between the county of residence and the working county accounts for 0.4% relative to the sample mean of the working county.[11] This suggests that bias due to measurement errors for exposure to air pollutants should be limited.

Table 1 presents summary statistics for major variables used in the analysis. About 10.7% of adults report fair or poor health, while 32.5%, 35.7%, and 37.3% of adults experience at least one day with physical issues, mental issues, and activity limitations, respectively. Additionally, 7.2% of the adults suffer from asthma at present, and there is a high prevalence of overweightness (63.1%) and obesity (24.9%).

The average PM2.5 level during the sample period is approximately 17.4 $\mu g/m^3$, which is slightly higher than the annual standard of 15 $\mu g/m^3$ during 1997–2011 and

[11] The county information has been available since 2005, and the publicly-available ACS data contains 475 unique counties during the sample period.

12 $\mu g/m^3$ since 2012, but significantly lower than the 24-hour standard of 65 $\mu g/m^3$ during 1997–2005 and 35 $\mu g/m^3$ since 2006. The sample mean of thermal inversion is 0.319, indicating that this meteorological phenomenon happens approximately 0.319 times per week on average. Our model also includes control variables for demographic characteristics, such as gender, race, and education, as well as weather variables. The relevant summary statistics for these variables are presented in Table A1.

3 Empirical Strategy

Our objective is to investigate whether an individual's health is still at risk from air pollution, despite the decline in PM2.5 concentration levels over time. The econometric model is presented as Eq. (1) below:

$$H_{ict} = \beta_0 + \beta_1 P_{ct} + X_{ict}\gamma + W_{ct}\zeta + \phi_c + \lambda_t + \varepsilon_{ict} \tag{1}$$

where H_{ict} represents the adverse health outcome for individual i residing in county c at time t. P_{ct} is the maximum value of PM2.5 in the past week. X_{ict} is a vector consisting of demographics, including gender, dummy variables for age cohorts, race, educational attainment, employment status, income categories, and a dummy variable for any health insurance coverage. W_{ct} contains weather variables including the average precipitation and the average daily maximum and minimum temperatures for the past week. The model includes county fixed effects, ϕ_c, to control for time-invariant and county-specific unobservables such as population density and the industrial structure. The model also includes year, month, and weekend fixed effects, represented by λ_t, to capture the effects of county-invariant and time-specific factors, such as the seasonality of air pollution concentration. All standard errors are clustered at the county level to account for the correlation of unobservables within each county, and sampling weights from BRFSS are applied to all regressions.

We will begin by estimating Eq. (1) using ordinary least squares (OLS). The coefficient of interest is β_1, which is expected to be positive and interpreted as the detrimental effect of PM2.5 on health. However, the potential endogeneity of air pollutants may lead to bias in the OLS estimator $\hat{\beta}_1$. The first source of bias arises from measurement error. While PM2.5 data collected from monitoring stations are sufficiently accurate, some studies suggest that monitoring stations may be located in rural areas with better air quality, leading to an underestimation of exposure to PM2.5 and attenuation bias in the OLS estimators (Grainger and Schreiber, 2019; Mu et al., 2021). Another potential source of bias is omitted variable bias. For example, traffic flow, which is a significant source of particulate matter, may proxy for life burden or mental stress in a county and negatively affect residents' health status.

To address the potential endogeneity problem, we adopt the instrumental variable (IV) approach. This approach involves two stages: in the first stage, we use thermal inversion to predict the PM2.5 concentration at the county–time level; in the second stage, we replace the actual PM2.5 with the predicted PM2.5 in Eq. (1) to obtain unbiased estimates. The IV approach identifies the portion of PM2.5 that is exogenous and uncorrelated with omitted variables, so that the estimated coefficient β_1 is not biased. As we discussed in Section 2.3, thermal inversion is a good predictor of particulate matter concentration since it inhibits the diffusion of particulate matter. The first-stage equation is as follows:

$$P_{ct} = \alpha_0 + \alpha_1 T_{ct} + X_{ict}\delta + W_{ct}\eta + \phi_c + \lambda_t + \xi_{ict} \tag{2}$$

here, T_{ct} represents the total number of thermal inversions in the past week in county c at time t. P_{ct} is the PM2.5 concentration. The remaining variables are the same as those in Eq. (1).

To ensure the validity of our instrument, we need to satisfy both inclusion and exclusion restrictions. For thermal inversion, the inclusion restriction can be tested using Eq. (2). Table A2 presents the first-stage results for various specifications, which show that the coefficients of thermal inversion are significantly different from 0 and feature F-statistics that are greater than 10. This indicates a strong correlation between PM2.5 and thermal inversion. However, we cannot directly verify the exclusion restriction. Previous studies have shown that thermal inversion is a valid instrument because it is unrelated to the local economy (Deschenes et al., 2020; Chen et al., 2022) or other confounders linked to health. Furthermore, we have some circumstantial evidence to support the exogeneity of our IV. As shown in Table A3, no effects of thermal inversion are observed on health-related behaviors that are closely linked to individual health status. If the exclusion restriction were invalid, thermal inversion could indirectly affect health at least through these behaviors, once people are aware that thermal inversions prevent particle diffusion. Our results partially validate this restriction by showing no effects on some behaviors, but it is impossible to exclude all potential channels between thermal inversion and health.

Despite the exogenous nature of thermal inversion, it may lead to a compositional change in our sample and pose a threat to the research design. To address this concern, we conduct a balance test by regressing major demographics separately on thermal inversion. Table A4 reports the balance test results with one of the demographics being the outcome each time. We do not find any statistically significant impact of thermal inversions on these demographics (p-value<0.05). Therefore, the estimated impact of

PM2.5 on health is not driven by the composition imbalance of our sample. Overall, the balance test results suggest that the thermal inversion is sufficiently random, supporting the validity of the exclusion restriction.

Another concern relates to sample attrition due to mortality. Deryugina et al. (2019) found that a 1 $\mu g/m^3$ increase in daily PM2.5 causes 0.69 additional deaths per million of the elderly. As individuals with severe symptoms may die indirectly from PM2.5 and are not counted in our sample, our estimates may substantially deviate from the actual effects. However, given the coefficient in Deryugina et al. (2019), the estimated sample attrition due to mortality is not large enough to materially drive our estimates.[12]

4 Results

4.1 Main Results

Table 2 presents the impact of PM2.5 on physical, mental, and overall health status using both OLS and IV approaches. In Section 3, we have highlighted the potential bias of OLS estimates arising from measurement error or omitted variable bias. Comparing the OLS results with the corresponding IV estimates gives us the insight that the OLS coefficients are biased downward towards zero for most health outcomes. Henceforth, we primarily focus on the IV estimates.

The IV estimates show that PM2.5 has significant impacts on mental health, asthma, and overall health status measured by the health index. Specifically, we find that PM2.5 has no effect on the extensive margin of mentally unwell days (row 4) but has a significant and positive impact on its intensive margin (row 5). Not finding effects on the extensive margin simplifies our analysis since we do not need to consider the participation of new risky groups in marginal effects. The IV estimate in row (5) indicates that every 1 $\mu g/m^3$ increase in PM2.5 leads to an average increase of 0.11 days that respondents feel mentally unwell (or approximately 1.2% increase relative to the sample mean) for individuals who already have depression or stress symptoms. We further investigate whether the adverse mental effect of PM2.5 remains constant across the spectrum of mental illness. To do this, we replace the number of mentally unwell days with indicators for whether the respondent felt mentally unwell for more

[12] Based on estimates from Deryugina et al. (2019), we assume that the association between PM2.5 and mortality also holds for younger cohorts and calculate the loss in the number of observations due to mortality in our sample, which equals 0.80 ($= (0.69 \times 1,161,110)/(1,000,000 - 0.69))$), where 1,161,110 is the sample size of our work. This gives us a loss in observations of approximately 0.80. Losing around 0.80 observations does not substantially affect our estimates, considering the large sample size of 1,161,110.

than 5 days, 10 days, 15 days, 20 days, or 25 days. Our IV results in Table A5 show that PM2.5 significantly increases the probabilities of feeling mentally unwell for more than 15 days and 20 days. These results imply that the adverse marginal effects of PM2.5 are concentrated in individuals with moderately severe symptoms ($\geq$ 15 days or $\geq$ 20 days) rather than in individuals with mild ($\geq$ 5 days or $\geq$ 10 days) or severe symptoms ($\geq$ 25 days).

In row (8) of Table 2, we find a significant association between PM2.5 and asthma. The estimate suggests that a 1 $\mu g/m^3$ increase in PM2.5 raises the probability of developing asthma by 0.16 percentage points, which corresponds to a 2.2% increase relative to the sample mean. We also examine the effects of PM2.5 on BMI, overweightness, and obesity in rows (9)-(11). Our results indicate that PM2.5 does not lead to a higher likelihood of becoming overweight or obese due to a decline in outdoor activities, which contrasts with findings from countries with high PM2.5 concentrations. For example, Deschenes et al. (2020) reported a significant positive effect of PM2.5 on body weight in China, where the average PM2.5 concentration reaches 64.75 $\mu g/m^3$.

One concern regarding the statistical power is that too many outcome variables in Table 2 may lead to the multiple inference problem. Following the correction approach in Anderson (2008), we obtain the corresponding summary index p-value, 0.045, which indicates statistically significant general effects of PM2.5 on these outcomes.

Moreover, in row (12), we find that the impact of PM2.5 on the health index is statistically significant at the 1% level, with a positive sign. This result suggests that PM2.5 adversely affects individuals' general health status even at low concentrations (approximately 17.4 $\mu g/m^3$ on average). As a robustness check, we investigate whether the effects on the health index are primarily driven by mentally unwell days and asthma. To do so, we construct an alternative health index measure that excludes these components and re-estimate the model using this alternative measure. We find that the coefficient for PM2.5 is 0.0047 and statistically significant at the 5% level, which is very close to our baseline results.[13] This suggests that the detrimental effect of PM2.5 on overall health is reflected not solely in mentally unwell days and asthma, but also in other health outcomes.

Our findings support the need for continued efforts to ambient air quality, even at low levels of PM2.5. Policymakers may be hesitant to set new air quality standards due to the associated costs, but our research calls for more stringent PM2.5 standards. For example, a future rise in the national standard from 12 to 11 $\mu g/m^3$ would be beneficial to public health.

[13] When diabetes is further excluded from the health index, the corresponding coefficient (standard error) is 0.0046 (0.0022). The corresponding coefficient (standard error) is 0.0060 (0.0022) when excluding only diabetes and adding back mental health days and asthma.

4.2 Robustness Checks

To enhance the robustness of our model specification, we perform various sensitivity analyses, as presented in Table 3. We report our benchmark results from Table 2 in column (1) for reference purposes.

First, we add state-by-month fixed effects in column (2) to capture state-specific unobservable factors that vary over time but are constant across years. For instance, some states may have distinct seasonal patterns that correlate with meteorological phenomena and health outcomes, like the influenza season, which may bias our estimates. We find that the results from column (2) are in accordance with our benchmark findings.

In column (3), we introduce state-by-year fixed effects to the baseline model to control for state-specific unobservable factors that may vary across years. For instance, the impact of the Great Recession in 2008 on PM2.5 levels and health outcomes may vary across states. However, upon including these fixed effects, we do not observe any significant changes in the estimates or statistical significance of PM2.5.

In column (4), we employ a more flexible two-way cluster approach by adding the state–year cluster, which accounts for the correlation of error terms within each state–year block. We find that the more conservative standard errors are slightly larger than those in column (1) for asthma and health index outcomes. Nonetheless, the significance levels remain practically unaffected.

To account for the potential confounding effect of weather conditions that may be simultaneously related to thermal inversion and health outcomes, we have controlled for precipitation and daily minimum and maximum temperatures in Eq. (1). However, due to data limitations, we cannot include all weather variables that may affect health outcomes, and our estimates may still be biased with limited controls. To address this concern, we exclude the weather controls in column (5). We find that our estimates are very similar to the baseline results, suggesting that thermal inversion is less likely to be correlated with other omitted weather conditions that we fail to control for.

The PM2.5 data are collected by monitoring stations. However, the number of these stations varies throughout our sample period, as new stations were established and old ones were decommissioned. A study by Grainger and Schreiber (2019) found evidence of strategic selection of new monitoring stations, as they tend to be located in areas with relatively clean air. To test whether our results are robust to variations in monitoring locations, we apply a filter to exclude some monitors based on the requirement of continuous operation. Specifically, we only include monitors that have operated for at least five years during our sample period. We re-estimate Eq. (1) with the filtered dataset and report the results in column (6). We only note minor discrepancies between the estimates in column (6) and those in column (1).

In our study, PM2.5 is defined as the maximum daily level in the past week, as extreme values can have significant effects on short-term health outcomes. However, this measure is not commonly used in extant literature. To test the robustness of our results to the choice of PM2.5 measure, we replace the maximum daily level with the average daily maximum PM2.5 for the past week in column (7) of Table 3. We find that our main conclusions remain unchanged: the estimates are still statistically significant for the three outcomes, although the magnitudes are slightly larger than the benchmark results.

4.3 Heterogeneous Effects

Figure 2 illustrates the heterogeneous effects of PM2.5 on major health outcomes, stratified by gender, race, socioeconomic status (SES), age cohorts, and employment status. We find that PM2.5 has a greater adverse effect on the health index for those who are unemployed, aged 45-64, have low SES,[14] belong to non-White racial groups, and are female. Furthermore, PM2.5 causes a larger increase in mentally unwell days for those who are unemployed, have low SES, belong to non-White racial groups, and are male. Additionally, we observe a significant effect of PM2.5 on asthma for those who are unemployed and white.

These findings suggest that the adverse health effects of PM2.5 are more pronounced for vulnerable groups, such as those who are unemployed, belong to non-White racial groups, have low SES, and are middle-aged adults. Our results align with prior studies[15] and highlight the importance of addressing health disparities between different socioeconomic groups. Improving air quality may be an effective way to reduce the burden of PM2.5-related health issues, especially for vulnerable groups, and narrow health inequality.

5 Extension

Our baseline model is designed to provide an unbiased estimate of the effect of PM2.5. In this section, we describe a series of extensions and evaluate alternative hypotheses for the adverse effect of PM2.5 on health outcomes.

[14]Low SES refers to individuals who have, at most, a high school degree and a household income of no more than $25,000.

[15]For example, a recent study by Nguyen et al. (2021) revealed that the elderly and females experience the highest percentage change in mental health risk due to exposure to ozone and PM2.5. The study also identified Asians and Hispanics as significant risk groups in California.

5.1 Other Pollutants

We heavily rely on our identification strategies that utilize the number of thermal inversions as an instrument for PM2.5 to draw our benchmark conclusion. However, our understanding of the causal relationship between PM2.5 and health may be biased by other coexisting pollutants such as PM10, sulfur dioxide (SO2), and carbon monoxide (CO) that can also be transported through thermal inversions and affect health outcomes. To examine the possibility that other pollutants are biasing the coefficient estimates, we assemble the county-day level data on other pollutants from the EPA, which spans from 2001 to 2012. We replace PM2.5 with other pollutants in Eq. (2) and examine whether our model can accurately identify their effects.

According to the results presented in Table 4, we observe that all coefficients are statistically insignificant, and the F statistics are small, thus thermal inversion is not a valid predictor for the other pollutants we tested. This finding suggests that our identification strategy is exclusively capturing the effect of PM2.5 and not confounded by other pollutants.[16]

5.2 Harvesting Effect and Autocorrelation of PM2.5

In order to investigate the possibility of the harvesting effect (Currie and Neidell, 2005) that may explain the positive effect of PM2.5 on health outcomes, we estimate Eq. (1) with one- and two-week lagged PM2.5 as additional predictors in column (1) of Table 5, and these lagged variables are also instrumented by the corresponding lagged thermal inversion counts. The harvesting effect refers to the phenomenon where an increase in pollution levels leads to a temporary acceleration of mortality among individuals who are already in poor health. In our study, we redefine the harvesting effect to mean that PM2.5 accelerates the onset of diseases for those who would otherwise have suffered from them a little later. If the harvesting effect exists, the coefficients on the lagged PM2.5 would be significantly negative. However, our results in column (1) show that the estimates of the current level of PM2.5 are statistically significant, and the lagged PM2.5 coefficients are not significantly different from zero. Therefore, we do not find any evidence supporting the existence of the harvesting effects in our analysis.

Since PM2.5 concentration decreases over the sample period, the coefficients in our model may capture future effects due to autocorrelation and thus be overestimated. To investigate this, we include one- and two-week leads of PM2.5 and its contemporaneous

[16]Limited predictive power is less likely to be caused by smaller sample sizes due to missing values. This is partly because the F-statistics are too small to indicate a strong predictor, and partly because the number of observations is still greater than that of the health index in Table 2.

level in column (2) of our analysis. However, we do not find any significant impact of the leads, and the magnitudes of the current PM2.5 coefficients remain close to the baseline results. Therefore, our model exclusively captures the impact of PM2.5 in the current week.

5.3 Migration

Previous studies have highlighted avoidance behaviors in response to air pollution, such as spending less time outdoors or relocating to areas with better air quality. However, this behavior may mechanically drive our results if people who engage in avoidance behaviors are more likely to live in areas with cleaner air and have better health outcomes.

To address this issue, we build upon the work of Lai et al. (2021) and Chen et al. (2022) and examine the effect of PM2.5 on migration patterns. Using data from the Annual Social and Economic Supplement (ASEC) of the Current Population Survey for the years 2001-2012, we focus on the labor force aged 25–64 and use the monthly PM2.5 concentration in March as the primary explanatory variable, along with the monthly thermal inversion count as the IV. Based on information in the ASEC about whether the respondent has changed their place of residence within the past year, we created two indicators for moving within the same state and between states. A negative coefficient of PM2.5 indicates that areas with lower levels of pollutants attract new residents to move in.[17]

The results of our regression analysis are presented in Table 6. The F-statistics, which are greater than 10, show that the thermal inversion is still a strong IV. None of the estimates in columns (1) and (2) are statistically significant, therefore individuals do not intentionally migrate to other counties within the same state or to other states with low PM2.5 levels. These results imply that migration patterns cannot explain the positive relationship between PM2.5 and adverse health outcomes found in our analysis.

5.4 Health Behaviors

Poor air quality has the potential to, directly and indirectly, impact individual health, but it remains unclear whether health behaviors play a mediating role in this relationship. We investigate several health behaviors, including smoking, drinking, exercising, and time spent on exercise, sleeping, and leisure activities. Our analysis

[17]The ASEC only provides more complete geographic information for the move-in county than the previous residence county. Therefore, we merge the monthly PM2.5 data with the ASEC data using the move-in county as the matching variable.

draws on data from the 2001– 2012 BRFSS for the first three behaviors and from the 2004–2012 American Time Use Survey (ATUS) for the remaining three.[18]

In Table 7, we report the IV regression results for each health behavior. We find no evidence of a significant association between PM2.5 and smoking, drinking, exercise, sleep, or leisure time. These behaviors do not appear to mediate the observed relationship between PM2.5 and health. Consequently, it is highly likely that PM2.5 directly impacts individual health without being mediated through changes in other unobserved behaviors.

6 Cost–Benefit Analysis of PM2.5 Containment

In this section, we attempt to compare the cost and benefit of further reducing PM2.5 concentration through a back-of-the-envelope calculation.

Table 8 replicates our baseline results using the IV approach, with the only difference being the use of a continuous measure of annual household income in order to calculate the willingness to pay (WTP) for a marginal reduction in PM2.5 (Zhang et al., 2017b; Sanduijav et al., 2021).[19] Specifically, we use the midpoint of each income category to generate a continuous measure of annual household income with the income conservatively top-coded at \$100,000.[20]

The results in column (1) of Table 8 suggest that a 1 $\mu g/m^3$ decrease in PM2.5 concentration can reduce the number of days that a person feels mentally unwell by about 0.112 on average each month, while a \$1,000 increase in annual household income can decrease the number of such days by 0.022. The estimated marginal benefit due to better air quality, viewed as the WTP for PM2.5 containment, would be approximately \$220.67 billion in 2012 USD ($= 0.1118/0.0219 \times 121.08 \times 0.357$).[21] Moreover, a decrease of 1 $\mu g/m^3$ in PM2.5 concentration is associated with a 0.2 percentage point decline in the probability of developing asthma (column (2)), resulting in an estimated marginal benefit of \$139.48 billion in 2012 USD for reducing asthma ($= 0.0016/0.0001 \times 121.08 \times 0.072$).[22] Combining the marginal benefits related to mental health and asthma, the

[18] In the ATUS, county information is available starting from 2004. The ATUS collects data on the amount of time individuals spend on various activities, including paid work, childcare, volunteering, and socializing. For our analysis, we focus on individuals in the labor force aged 25-64.

[19] Suppose the health outcome H is precisely equal to the total utility for each household. Let P represent the demand for PM2.5 reduction, and I represent the household income. We can calculate the marginal rate of substitution (MRS) as $(\partial H/\partial P)/(\partial H/\partial I) = \beta_P/\beta_I$, where β_P and β_I are the coefficients on PM2.5 and household income in the regression, respectively. This MRS can be interpreted as the WTP for a 1-unit decrease in PM2.5 while holding the health status constant.

[20] This continuous income variable is finally adjusted to 2012 USD.

[21] The coefficients on PM2.5 and household income are 0.1118 and 0.0219, respectively. Their ratio represents the WTP for a 1-unit decrease in PM2.5. The number of households in 2012, 121.08 million, is sourced from the US Census Bureau. The prevalence of mental health, 35.7%, is from Table 1.

[22] The coefficients on PM2.5 and household income are 0.0016 and 0.0001, respectively. The asthma

WTP is estimated to be \$360.15 billion. Moreover, to show the robustness of our estimates, we further calculate the WTP using the health index results in column (3), and the corresponding value is approximately \$492.39 billion ($= 0.0061/0.0015 \times 121.08$), which is greater than the total WTP related to mental health and asthma as the health index contains more than just these two health outcomes.

To estimate the cost of PM2.5 containment, we refer to the Regulatory Impact Analysis conducted by the EPA, which reports the total annualized engineering costs for reducing PM2.5 concentration to 13, 12, and 11 $\mu g/m^3$ as \$2.9 million, \$69 million, and \$270 million, respectively.[23] Based on these figures, we calculate the annual marginal cost of reducing PM2.5 by 1 unit to range from \$66.1 million to \$201 million in 2006 USD[24] or \$75 million to \$229 million in 2012 USD (CPI=1.14).

Overall, the estimated marginal benefits of PM2.5 containment (\$360.15 billion - \$492.39 billion) far exceed the estimated marginal costs of \$75 million - \$229 million, which suggests that developing policies to reduce the nationwide PM2.5 level, such as improving the current PM2.5 national standard by 1 $\mu g/m^3$, could produce significantly greater social benefits.

7 Conclusion

This paper examines the relationship between PM2.5 and health outcomes among the working-age population, using the BRFSS data from 2001 to 2012. Leveraging the instrumental variable approach, we find significant effects of PM2.5 on the health index, mentally unwell days, and the probability of developing asthma. These findings suggest that even low concentrations of PM2.5 have detrimental impacts on individuals' health.

Specifically, our study reveals that a one-unit increase in the PM2.5 level is associated with a 0.11-day decrease in mental health severity. This contributes to the growing literature exploring the connection between air pollution and mental health, as evidenced by previous works (Pun et al., 2017; Vert et al., 2017; Zhang et al., 2017b,a; Xue et al., 2019; Roberts et al., 2019; Shi and Yu, 2020; Bakolis et al., 2021; Sanduijav et al., 2021). For instance, Pun et al. (2017) found that PM2.5 was linked to depressive and anxiety symptoms, with stronger associations observed among individuals with lower socioeconomic status or specific health-related characteristics. Our study

prevalence is 0.072 from Table 1.

[23]See Tables 4-2 and 7-4 in EPA Regulatory Impact Analysis (June 2012): https://www.epa.gov/sites/default/files/2020-07/documents/naaqs-pm_ria_proposed_2012-06.pdf.

[24]We compute the annualized marginal cost of decreasing PM2.5 by one unit from 13 to 12 $\mu g/m^3$ as \$66.1 million (=\$69 million-\$2.9 million) and from 12 to 11 $\mu g/m^3$ as \$201 million (=\$270 million-\$69 million).

differs from these previous works in terms of the target group and measures of mental health. By examining detailed information on mentally unwell days, we also discern that individuals with moderately severe mental issues are most affected.

Our results also confirm the well-documented sensitivity of asthma to air pollutants, as supported by previous literature (Neidell, 2004; Zhang et al., 2020; Aguilera et al., 2021). Specifically, we observe a 0.16 percentage point increase in asthma incidence for each one-unit rise in PM2.5 concentration. However, our paper distinguishes itself from others by employing a more nationally representative sample and focusing on the working-age population, including individuals with mild symptoms that do not require hospitalization. Furthermore, there is limited research on the causal effects of PM2.5 on asthma incidence using US data. Some studies have utilized alternative air pollutants as the primary regressor, while others have not established causal identification.

Our analysis of heterogeneous effects reveals that high-risk groups, such as the unemployed, non-Whites, the elderly, and individuals with low SES, experience a decline in health due to PM2.5 exposure. This highlights the importance of addressing health inequalities between different socioeconomic groups. Improving air quality can be an effective measure in narrowing these potential disparities, as vulnerable groups stand to benefit more from such improvements.

Moreover, we address several alternative explanations for the positive relationship between PM2.5 and adverse health outcomes. Firstly, our findings do not support the hypothesis that increased PM2.5 concentrations incentive individuals to relocate to counties with better air quality, thus ruling out the migration patterns as an explanation for the positive association. Additionally, we find that individuals do not significantly alter their health behaviors in response to high PM2.5 concentrations. It is highly likely that PM2.5 directly affects individual health without being mediated through changes in avoidance behaviors.

Understanding the impact of low PM2.5 levels on health is crucial for shaping future air quality policies. Our cost-benefit analysis demonstrates that strengthening the nationwide PM2.5 standard would yield overall positive social benefits. Furthermore, if we take into account the labor market benefits associated with the effects of air pollution on the workforce, as observed in other studies (Graff Zivin and Neidell, 2012; Li and Li, 2022), reducing the average PM2.5 concentration by 1 $\mu g/m^3$ would result in benefits that significantly outweigh the costs. These findings offer valuable insights for informing future environmental policy formulation.

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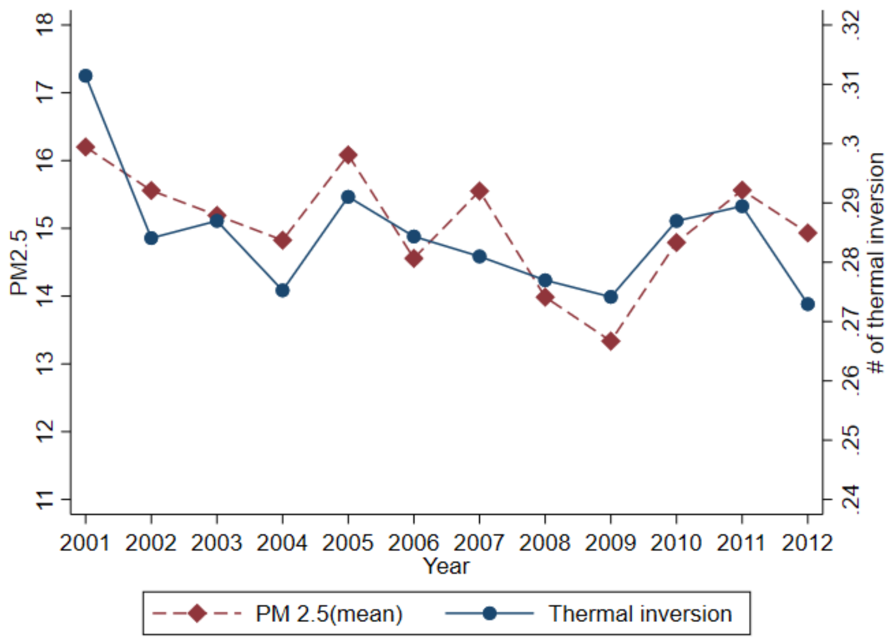
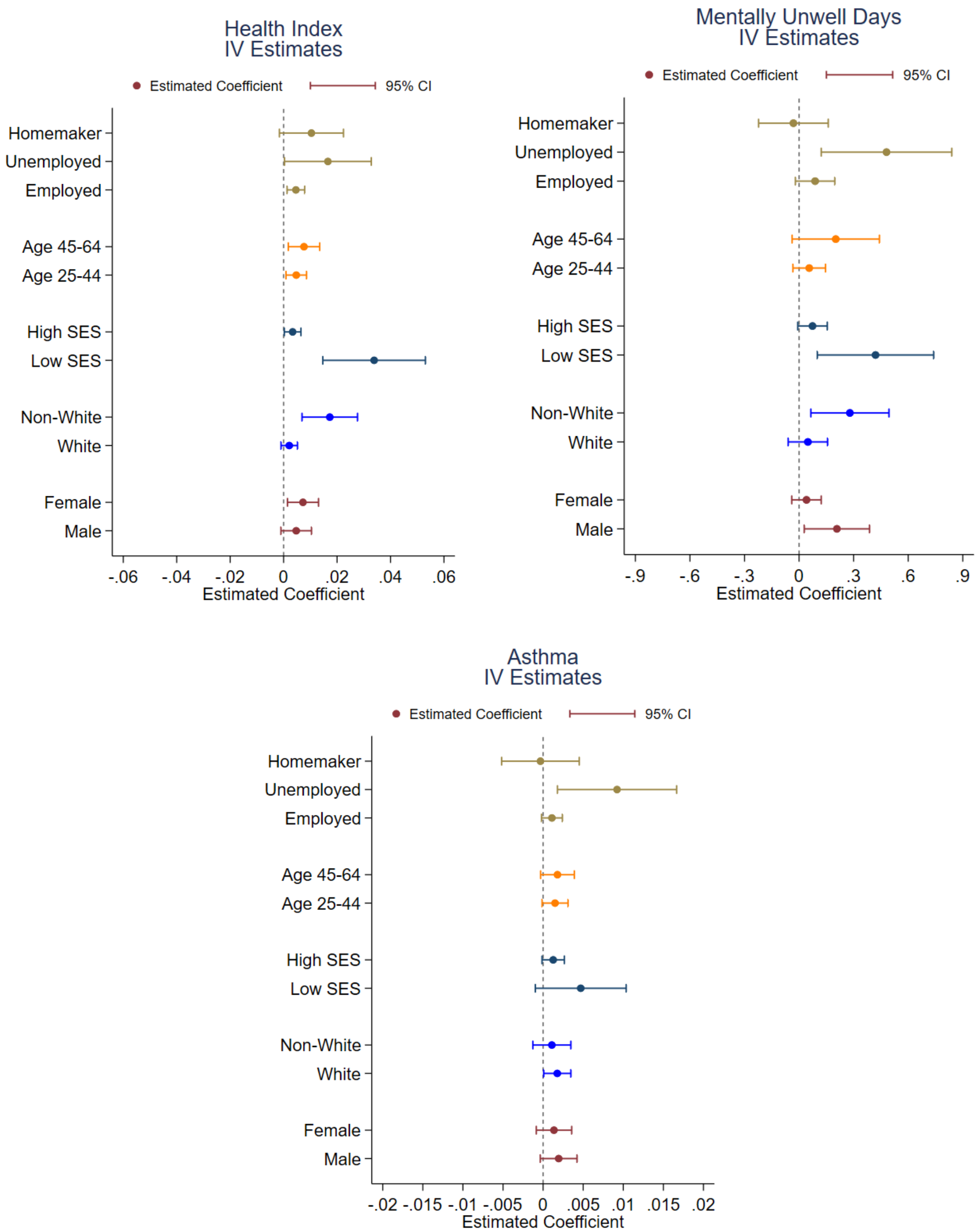
Figures

Figure 1: Trends of PM2.5 Concentration and Thermal Inversion



Notes: This figure plots the national time trends of the key regressor, PM2.5, and the instrumental variable (IV), thermal inversion, based on the county-level data. PM2.5 represents the annual average of the daily maximum measured in $\mu g/m^3$, while thermal inversion is measured by the yearly average of occurrences over the past week.

Figure 2: Heterogeneous Effects on Health



Notes: These figures exhibit the IV estimates, along with the corresponding 95% confidence intervals, stratified by gender, race, socioeconomic status, age cohorts, and employment status. "Low SES" refers to individuals with education attainment of high school or below and a household annual income of no more than $25,000. All regressions include controls for demographics, weather variables, year, month, weekend, and county fixed effects. Standard errors are reported in parentheses and are clustered at the county level.

Tables

Table 1: Summary Statistics for Major Variables

Variable	Mean	SD	Obs
Health outcomes:			
Fair or Poor Health	0.107	0.309	1,161,110
1{Physically Unwell Days>0}	0.325	0.468	1,106,275
# of Physically Unwell Days	7.562	8.890	362,871
1{Mentally Unwell Days>0}	0.357	0.479	1,104,706
# of Mentally Unwell Days	8.976	9.392	397,306
1{Activity Limitation Days>0}	0.373	0.484	580,657
# of Activity Limitation Days	7.263	8.434	216,616
Asthma	0.072	0.259	1,155,889
Body Mass Index(BMI)	27.228	5.292	1,115,118
1{BMI≥25} (Overweight)	0.631	0.483	1,115,118
1{BMI≥30} (Obesity)	0.249	0.433	1,115,118
Health Index	-0.145	0.428	540,403
Air Pollutant:			
PM2.5	17.417	10.773	1,161,110
Instrument:			
# of Thermal Inversions	0.319	1.092	1,161,110

Notes: This table shows summary statistics, including sample means, standard deviations, and the number of observations for all outcomes, the key regressor, and the instrumental variable used in the analysis. The indicator $1\{\cdot\}$ represents a binary variable, which equals one if the condition is satisfied and zero otherwise. For physically unwell days, mentally unwell days, and activity limitation days, the value of zero is excluded since we focus on the intensive margin. PM2.5 is measured in $\mu g/m^3$. The sample includes employed individuals, unemployed individuals, and homemakers aged 25-64. The sampling weight from BRFSS is applied for computation.

Table 2: Effects of PM2.5 on Health Outcomes

	Outcomes	**OLS**	**IV**	Obs	First-stage F-statistic
(1)	Fair or Poor Health	0.0001 (0.0001)	0.0011 (0.0008)	1,161,110	16.2388
(2)	1{Physically Unwell Days>0}	0.0001 (0.0001)	0.0013 (0.0014)	1,108,666	17.3293
(3)	Physically Unwell Days	-0.0046* (0.0026)	0.0539 (0.0407)	363,754	19.2929
(4)	1{Mentally Unwell Days>0}	0.0000 (0.0001)	-0.0017 (0.0014)	1,107,150	17.3187
(5)	Mentally Unwell Days	0.0026 (0.0026)	0.1106** (0.0475)	398,213	19.5126
(6)	1{Activity Limitation Days>0}	0.0001 (0.0001)	-0.0007 (0.0021)	582,105	18.6585
(7)	Activity Limitation Days	-0.0014 (0.0037)	0.0595 (0.0434)	217,215	21.7266
(8)	Asthma	0.0001 (0.0001)	0.0016** (0.0007)	1,158,573	16.2230
(9)	Body Mass Index (BMI)	-0.0008 (0.0013)	-0.0015 (0.0124)	1,117,669	15.3863
(10)	Overweight	-0.0001 (0.0001)	0.0005 (0.0011)	1,117,669	15.3863
(11)	Obesity	0.0001 (0.0001)	-0.0001 (0.0010)	1,117,669	15.3863
(12)	Health Index	0.0001 (0.0002)	0.0059*** (0.0019)	540,403	17.1629

Notes: This table presents the baseline estimates of Eq. (1) using both OLS and IV approaches. The covariates include the demographics and weather variables in Table A1. Each row shows the OLS and IV estimates, along with the number of observations and the first-stage F-statistic for each health outcome. All regressions control for year, month, weekend, and county fixed effects. Standard errors are reported in parentheses and are clustered at the county level. The Anderson (2008) summary index p-value is 0.045 to account for the multiple inference problem. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 3: Robustness Checks

	Baseline	State-by-month FES	State-by-year FEs	Two-way Cluster	No Weather Controls	Monitors Exist for >=5 Years	Alternative PM2.5
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Mentally Unwell Days							
PM2.5	0.1106**	0.0981**	0.1135**	0.1106**	0.0940**	0.1046**	0.1537***
	(0.0475)	(0.0416)	(0.0460)	(0.0436)	(0.0427)	(0.0460)	(0.0590)
Observations	398,213	398,213	398,213	398,213	398,213	383,183	398,213
Panel B: Asthma							
PM2.5	0.0016**	0.0016***	0.0016**	0.0016**	0.0013**	0.0016**	0.0022**
	(0.0007)	(0.0006)	(0.0007)	(0.0008)	(0.0007)	(0.0008)	(0.0010)
Observations	1,158,573	1,158,573	1,158,573	1,158,573	1,158,573	1,112,265	1,158,573
Panel C: Health Index							
PM2.5	0.0059***	0.0053***	0.0059***	0.0059***	0.0052***	0.0058***	0.0082***
	(0.0019)	(0.0015)	(0.0019)	(0.0021)	(0.0018)	(0.0019)	(0.0023)
Observations	540,403	540,403	540,403	540,403	540,403	520,056	540,403

Notes: All regressions include controls for demographics, year, month, weekend, and county fixed effects. Column (1) shows the benchmark results from Table 2. Column (2) adds state-by-month fixed effects. Column (3) includes state-by-year fixed effects. Column (4) employs a two-way cluster at the county and state-year levels. Column (5) excludes the weather controls. Column (6) considers only the PM2.5 readings from monitoring sites that have operated for at least five years during our sample period. Column (7) uses the average daily maximum PM2.5 in the past week as the regressor. Standard errors, shown in parentheses, are clustered at the county level. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 4: First Stage: Effects of Thermal Inversion on Other Pollutants

	PM10	SO2	CO	Ozone
	(1)	(2)	(3)	(4)
Thermal Inversion	0.3894	0.0324	0.0126	-0.0004
	(0.3867)	(0.2357)	(0.0262)	(0.0004)
First-stage F-statistic	1.0139	0.0189	0.2322	0.7739
Observations	772,913	611,424	664,806	798,835

Notes: The daily data for these pollutants were collected from the EPA. Each pollutant is defined as the maximum value within the past week. All regressions control for demographics, weather variables, year, month, weekend, and county fixed effects. Standard errors, shown in parentheses, are clustered at the county level. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 5: Harvesting Effect and Autocorrelation

	Lags (1)	Leads (2)
Panel A: Mentally Unwell Days		
PM2.5	0.0984**	0.0921**
	(0.0460)	(0.0413)
$PM2.5_{t-1}$ or $PM2.5_{t+1}$	0.0507*	0.0485
	(0.0301)	(0.0601)
$PM2.5_{t-2}$ or $PM2.5_{t+2}$	0.0066	0.0624
	(0.0401)	(0.0481)
Observations	392,077	391,614
Panel B: Asthma		
PM2.5	0.0015**	0.0014**
	(0.0008)	(0.0007)
$PM2.5_{t-1}$ or $PM2.5_{t+1}$	0.0010	0.0008
	(0.0006)	(0.0010)
$PM2.5_{t-2}$ or $PM2.5_{t+2}$	0.0002	0.0007
	(0.0006)	(0.0007)
Observations	1,140,428	1,139,237
Panel C: Health Index		
PM2.5	0.0050***	0.0047***
	(0.0019)	(0.0016)
$PM2.5_{t-1}$ or $PM2.5_{t+1}$	0.0028	0.0048
	(0.0020)	(0.0032)
$PM2.5_{t-2}$ or $PM2.5_{t+2}$	0.0024	0.0035
	(0.0024)	(0.0023)
Observations	531,997	531,446

Notes: All regressions control for demographics, year, month, weekend, and county fixed effects. In Column (1), we add one- and two-week lagged PM2.5 into the model, where $PM2.5_{t-1}$ and $PM2.5_{t-2}$ represent the maximum PM2.5 during the past 8-14 days and 15-21 days, respectively. In Column (2), we add one- and two-week leads of PM2.5, where $PM2.5_{t+1}$ and $PM2.5_{t+2}$ represent the maximum PM2.5 for the leading 1-7 days and 7-15 days, respectively. Note that the results in columns (1)-(2) are still IV estimates. For example, column (1) uses the thermal inversion counts for the past 1-7 days, 8-14 days, and 15-21 days as instruments for current and lagged PM2.5. In this way, we use either lagged or leading IVs in columns (1)-(2) to predict PM2.5. Standard errors, shown in parentheses, are clustered at the county level. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 6: Effects of PM2.5 on Migration

	Migration within 1 Year	
	Within State (1)	Across State (2)
PM2.5	-0.0024	-0.0021
	(0.0015)	(0.0015)
First-stage F-statistic	20.9460	20.9237
Observations	360,766	367,579

Notes: PM2.5 is measured at the county-month level since ASEC does not provide the interview date. All regressions control for demographics, weather variables, year, month, and county fixed effects. In Columns (1)-(2), we examine the effects of PM2.5 on migration within the state or county (Column(1)) and within or between states (Column(2)) in the past year. The first-stage F-statistic is reported. Standard errors, shown in parentheses, are clustered at the county level. The CPS sampling weight is used for estimation. Significance levels: * p < 0.1, ** p < 0.05, *** p < 0.01.

Table 7: Effects of PM2.5 on Health Behaviors

	Current Smoker (1)	Binge Drinking (2)	Not Doing Exercise (3)	Exercise Time (4)	Sleeping Time (5)	Leisure Time (6)
PM2.5	-0.0001	0.0006	-0.0007	-0.3536	-0.3282	0.8154
	(0.0012)	(0.0011)	(0.0009)	(0.9236)	(1.8339)	(2.7553)
First-stage F-statistic	16.2215	15.9623	16.0243	10.2945	10.2945	10.2945
Dep Mean	0.1984	0.1798	0.2088	14.9084	498.7101	180.2121
Observations	1,159,109	1,140,124	1,158,833	21,798	21,798	21,798

Notes: PM2.5 is measured at the county-day level. All regressions control for demographics, weather variables, year, month, weekend, and county fixed effects. The dependent variables in columns (1)-(3) are dummies for smoking, binge drinking, and lack of exercise, respectively. In columns (4)-(6), the dependent variables represent the duration in minutes per day spent on exercise, sleeping, and leisure activities, respectively. For smoking, we categorize individuals as current smokers if they smoke every day or on some days. Binge drinking is defined as adults consuming five or more drinks on a single occasion. The first-stage F-statistic and the sample mean of the outcome variables are reported. Standard errors are reported in parentheses and are clustered at the county level. Significance levels: * p < 0.1, ** p < 0.05, *** p < 0.01.

Table 8: Effects of PM2.5 and Household Income on Health Outcomes

	Mentally Unwell Days	Asthma	Health Index
	(1)	(2)	(3)
PM2.5	0.1118**	0.0016**	0.0061***
	(0.0471)	(0.0007)	(0.0020)
Household Income	-0.0219***	-0.0001***	-0.0015***
	(0.0012)	(0.0000)	(0.0000)
Observations	398,213	1,158,573	540,403

Notes: All regressions control for demographics, weather variables, year, month, weekend, and county fixed effects. They differ from the baseline results in that they include continuous annual household income (in $1,000), which has been adjusted by the CPI in 2012 USD. Standard errors are reported in parentheses and are clustered at the county level. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Appendix

Table A1: Summary Statistics for Demographics and Weather Controls

Variable	Mean	SD
Demographic Variables:		
Male	0.503	0.500
Age 30-39	0.273	0.446
Age 40-49	0.271	0.444
Age 50-59	0.209	0.407
Age 60-64	0.055	0.228
Black only	0.113	0.317
Hispanic	0.175	0.380
Other races	0.076	0.265
Less than high school	0.095	0.293
College but no degree	0.260	0.439
College degree or above	0.414	0.493
Never married	0.146	0.354
Other marital status	0.190	0.392
Self employed	0.114	0.318
Unemployed for more than 1 year	0.034	0.181
Unemployed for less than 1 year	0.044	0.205
Homemaker	0.086	0.281
Income \$15k	0.068	0.253
Income 15$k-$25k	0.121	0.326
Income 25$k-$35k	0.101	0.301
Income 35$k-$50k	0.147	0.355
Any health insurance	0.838	0.369
Weather Variables:		
Precipitation	0.102	0.150
Maximum temperature	46.487	17.663
Minimum temperature	66.370	20.483

Notes: This table shows the statistical summary for the demographic variables and weather controls used in the analysis. The number of observations is 1,161,110. Demographic information is obtained from the BRFSS, while weather variables are sourced from PRISM Spatial Climate datasets. The sampling weight from BRFSS is applied in the computation.

Table A2: First Stage Results: Effects of Thermal Inversion on PM2.5

	PM2.5				
	(1)	(2)	(3)	(4)	(5)
Thermal Inversion	0.8231***	0.7495***	0.8389***	0.7807***	0.7495***
	(0.2143)	(0.1860)	(0.1183)	(0.1817)	(0.1832)
Weather Controls		Y	Y	Y	Y
Time FE	Y	Y	Y	Y	Y
County FE	Y	Y	Y	Y	Y
State-by-month FE			Y		
State Linear Trend				Y	
Two-way Cluster					Y
First-stage F-statistic	14.7535	16.2388	50.2916	18.4658	16.7429
Observations	1,161,110	1,161,110	1,161,110	1,161,110	1,161,110

Notes: This table reports the first-stage results under different specifications. Column (1) does not control for weather conditions. Column (2) represents the first-stage results of the baseline model in Table 2. Column (3) adds the state-by-month fixed effects. Column (4) considers the state-specific linear time trend. Column (5) employs a two-way cluster at the county and state-year levels. Standard errors, shown in parentheses, are clustered at the county level by default. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A3: Effects of Thermal Inversion on Health Behaviors

	Current Smoker	Binge Drinking	Not Doing Exercise	Exercise Time	Sleeping Time	Leisure Time
	(1)	(2)	(3)	(4)	(5)	(6)
Thermal Inversion	-0.0000	0.0004	-0.0005	-0.2417	-0.2243	0.5572
	(0.0009)	(0.0008)	(0.0007)	(0.6527)	(1.2693)	(1.8196)
Observations	1,159,109	1,140,124	1,158,833	21,798	21,798	21,798

Notes: This table gives circumstantial evidence on the validity of exclusion restriction by showing that our IV is orthogonal to health-related behaviors. All regressions control for demographics, weather variables, year, month, weekend, and county fixed effects. The first three outcome variables come from BRFSS (2001-2012), while the last three variables are from ATUS (2004-2012). Standard errors, shown in parentheses, are clustered at the county level. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A4: Balance Test

	(1) Male	(2) Age	(3) White	(4) Black	(5) Hispanic	(6) Other Races	(7) <High School	(8) High School
Thermal Inversion	0.0008	0.0210	-0.0007	-0.0008	0.0006	0.0009	0.0007	0.0009
	(0.0010)	(0.0212)	(0.0007)	(0.0005)	(0.0007)	(0.0007)	(0.0010)	(0.0009)
Observations	1,176,774	1,176,774	1,176,774	1,176,774	1,176,774	1,176,774	1,176,774	1,176,774
	(9) College but No Degree	(10) College Degree or Above	(11) Married	(12) Never Married	(13) Other Marital Status	(14) Income <15k	(15) Income 15k-25k	(16) Income 25k-35k
Thermal Inversion	-0.0014	-0.0002	-0.0009	0.0006	0.0002	0.0002	-0.0001	0.0001
	(0.0009)	(0.0008)	(0.0009)	(0.0006)	(0.0007)	(0.0004)	(0.0007)	(0.0005)
Observations	1,176,774	1,176,774	1,176,774	1,176,774	1,176,774	1,176,774	1,176,774	1,176,774
	(17) Income 35k-50k	(18) Income 50k+	(19) Any Health Insurance	(20) Self Employed	(21) Employed for Wages	(22) Unemployed for >1 year	(23) Unemployed for <1 year	(24) Homemaker
Thermal Inversion	-0.0004	0.0003	0.0012*	0.0004	-0.0004	0.0001	-0.0001	0.0001
	(0.0007)	(0.0007)	(0.0006)	(0.0006)	(0.0010)	(0.0004)	(0.0004)	(0.0005)
Observations	1,176,774	1,176,774	1,176,774	1,176,774	1,176,774	1,176,774	1,176,774	1,176,774

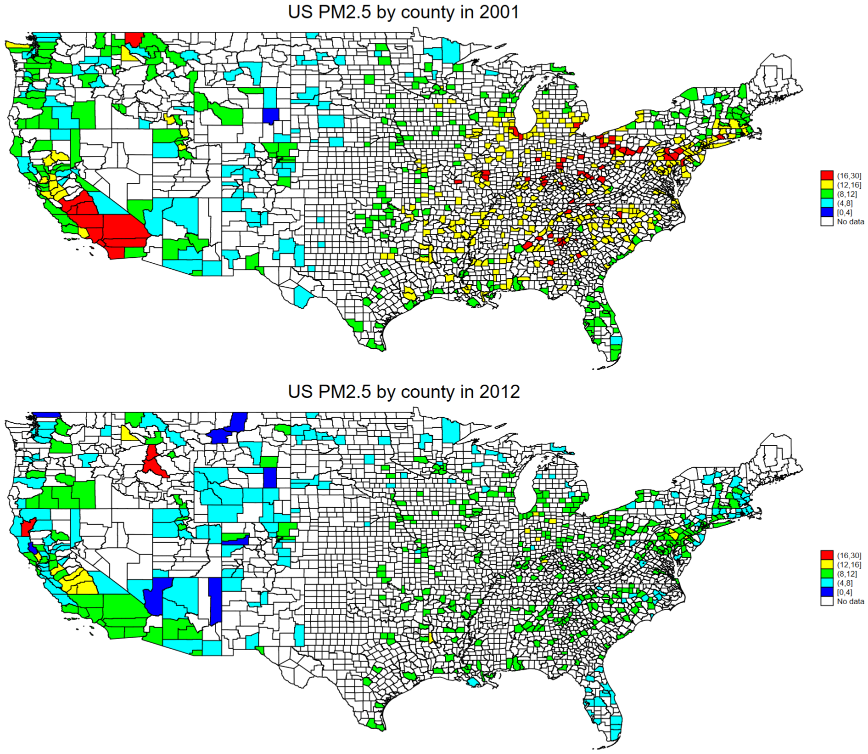
Notes: This table reports the results of balance tests using demographics as the outcome variable. The sample is restricted to adults aged 25-64. All regressions control for weather variables, year, month, weekend, county fixed effects, and demographics, with the exception of the one used as the outcome. Standard errors are reported in parentheses and are clustered at the county level. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A5: The Impact on Indicators for Different Mentally Unhealthy Days

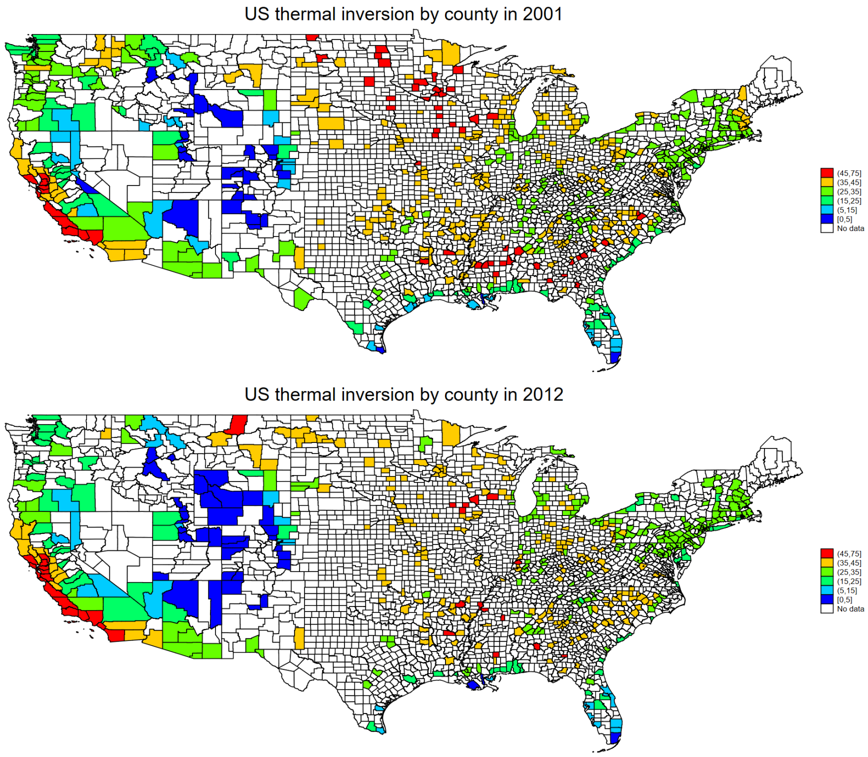
	Mentally Unwell Days				
	$\geq$ 5 days	$\geq$ 10 days	$\geq$ 15 days	$\geq$ 20 days	$\geq$ 25 days
	(1)	(2)	(3)	(4)	(5)
PM2.5	0.0036*	0.0042*	0.0038**	0.0054**	0.0035
	(0.0020)	(0.0023)	(0.0017)	(0.0023)	(0.0024)
Observations	398,213	398,213	398,213	398,213	398,213

Notes: The outcome variables are five indicators for the number of days that the respondent felt mentally unwell: $\geq$5, $\geq$10, $\geq$15, $\geq$20, and $\geq$25. All regressions control for demographics, weather variables, year, month, weekend, and county fixed effects. Standard errors are reported in parentheses and are clustered at the county level. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Figure A.1: Geographic Variation for PM2.5 and Thermal Inversion



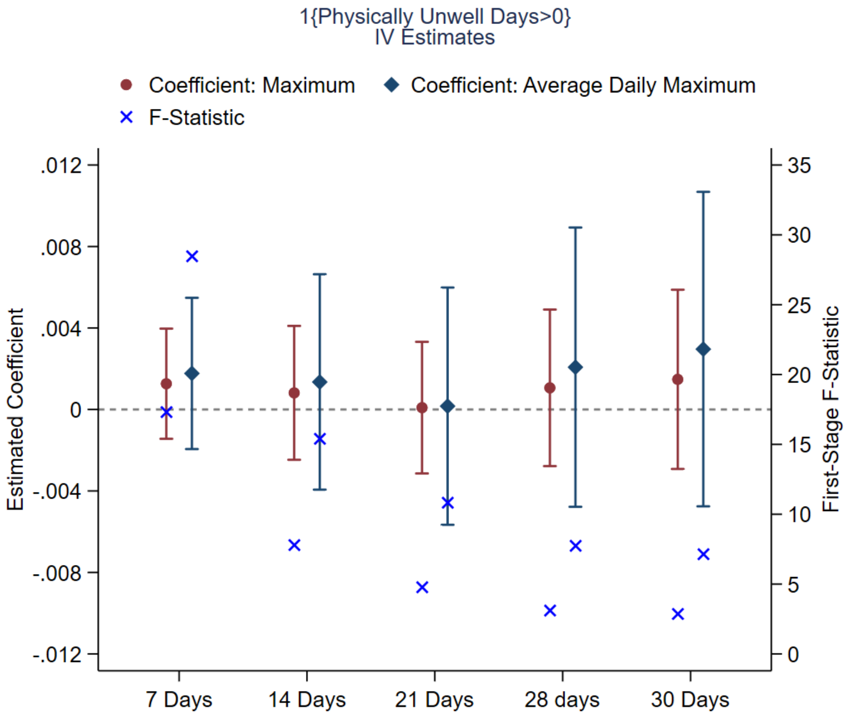
(a) County-level PM2.5

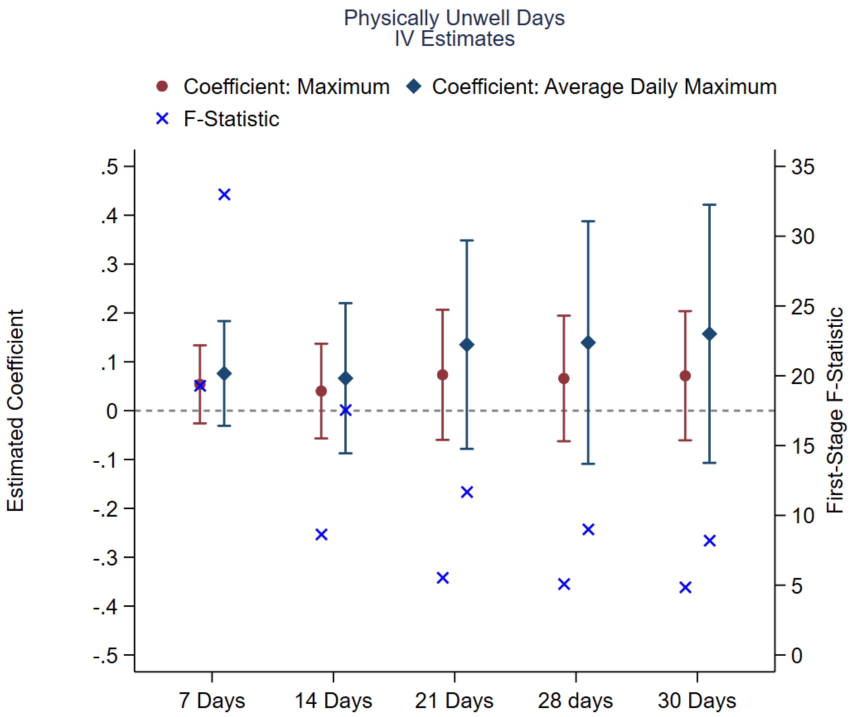


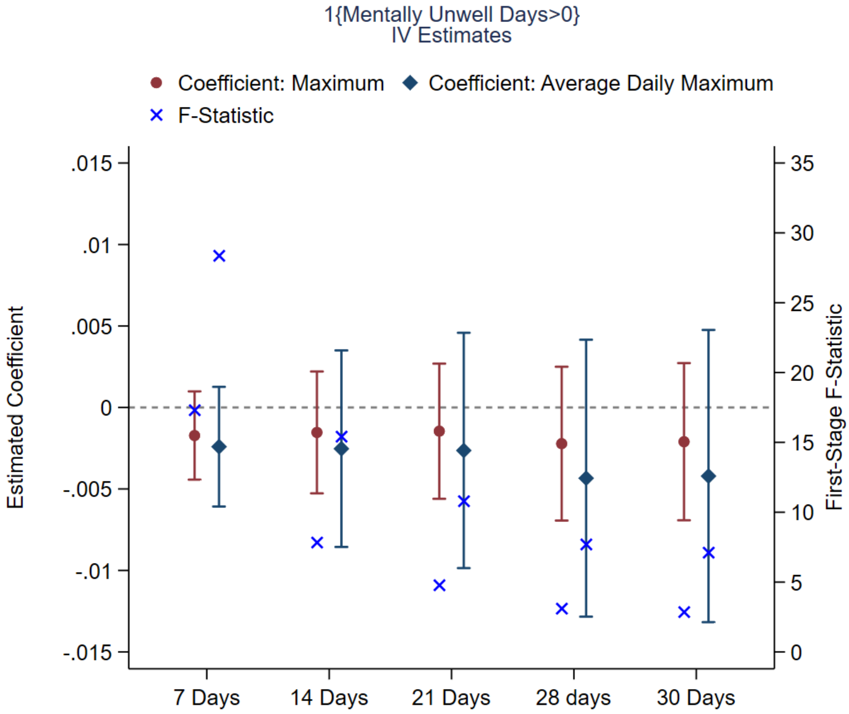
(b) County-level Thermal Inversion Count

Notes: The upper panel displays the maps depicting the monthly average of PM2.5 by county in 2001 and 2012. The bottom panel illustrates the monthly count of thermal inversions by county in 2001 and 2012.

Figure A.2: Recall Error and Alternative Measures of PM2.5



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IV Estimates
Coefficient: Maximum
Coefficient: Average Daily Maximum
F-Statistic
Estimated Coefficient
First-Stage F-Statistic
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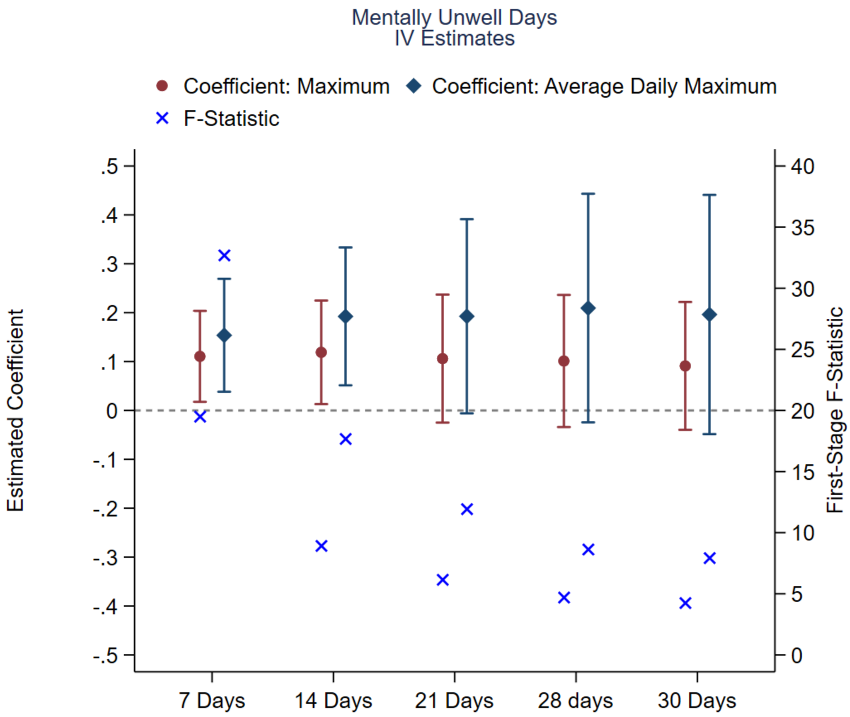
.01
.005
0
-.005
-.01
-.015
35
30
25
20
15
10
5
0
7 Days
14 Days
21 Days
28 days
30 Days


Mentally Unwell Days
IV Estimates
Coefficient: Maximum
Coefficient: Average Daily Maximum
F-Statistic
Estimated Coefficient
First-Stage F-Statistic
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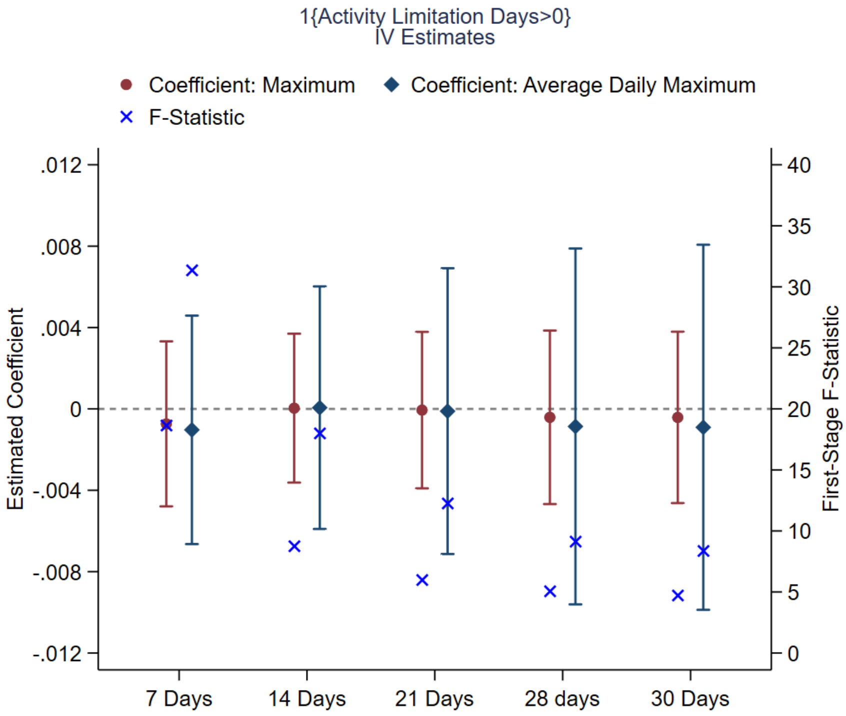
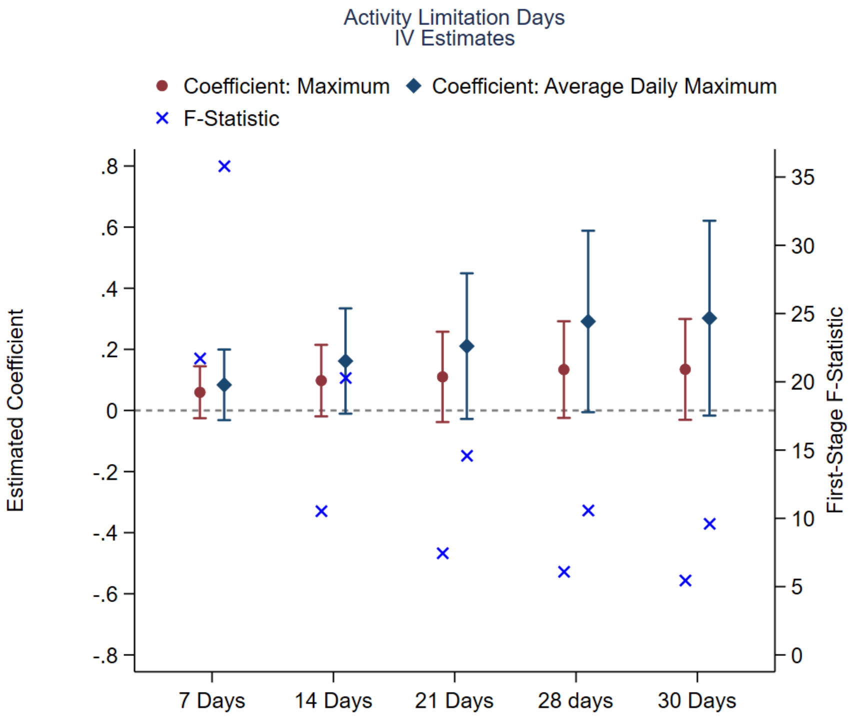
.4
.3
.2
.1
0
-.1
-.2
-.3
-.4
-.5
40
35
30
25
20
15
10
5
0
7 Days
14 Days
21 Days
28 days
30 Days





Notes: These figures exhibit the IV estimates along with the 95% confidence interval using different measures of PM2.5. For each graph, circle markers report IV estimates using maximum PM2.5 over the past 7-30 days, while diamond markers show IV estimates using average daily maximum PM2.5 over the past 7-30 days. The instrument is the total count of thermal inversions for the corresponding periods. Cross marks indicate the F-statistic of the first-stage equation with the null hypothesis that thermal inversion has no effect on PM2.5. All regressions control for demographics, weather variables, year, month, weekend, and county fixed effects. Standard errors in parentheses are clustered at the county level.