Air Pollution, Avoidance Behavior, and Labor Market Outcomes: Evidence from the United States

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Abstract

I estimate the effects of exposure to ambient air pollution on daily health-related behaviors, weekly labor supply, and workplace productivity among US individuals. Using an individual fixed-effects regression approach, I examine how daily changes in outdoor air quality influence the time spent on daily health-related activities. I find that only when the air quality index becomes very unhealthy or hazardous, there is a 21% decrease in the minutes spent on outdoor sport and exercise activities, and a 260% increase in minutes spent watching TV. The increase in physical inactivity can have long-term negative health consequences. I also implement an instrumental variable (IV) strategy using wind direction and atmospheric boundary layer height as exogenous shocks to satellite-based aerosols to understand how changes in air pollution affect weekly labor supply and productivity. I find that increase in the total aerosol optical depth (AOD) leads to no overall change in labor supply decisions, both on the decision to go to work and the weekly worked hours. There are also no overall significant effects on labor productivity proxied by weekly earnings. The effects across subgroups also suggest differential effects in avoidance behaviors across the income distribution, age groups, occupations, race, and ethnicity, especially when the air quality is very unhealthy or hazardous.

JEL Codes: D24, J24, *I12*, *L66*, *Q51*, *Q53*.

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Exposure to high levels of air pollution has substantial short- and long-run negative effects on human health, leading to countries regulating the levels of air pollution (Schlenker and Walker 2016; Deryugina et al. 2019). Ground levels of particulate matter (PM) 2.5 are associated with a higher risk of mortality, and despite the significant improvements in outdoor quality in the United States, it is estimated that outdoor PM 2.5 accounts for about 320,000 premature deaths every year (Fann et al. 2012) and about 97 million U.S. residents still live in counties with pollution above the National Ambient Air Quality Standards (NAAQS) in 2020.² It is also estimated that physical inactivity is a leading cause of mortality, causing about 3.2 million deaths globally in 2016 (WHO 2019). Despite the adverse health implications that certain pollutants have, little is known about how people change their behavior when exposed to high levels of air pollution and how economic outcomes such as labor supply or productivity are affected. Studies that analyze the impacts of pollution are largely focused on health outcomes, including mortality, non-communicable diseases, hospital visits or premature deaths, partly due to data availability. A few recent studies have looked at how air quality causes avoidance behavior or affects labor market outcomes. However, these studies do not often look at avoidance behavior and may suffer from issues of external validity because they are often limited to a small geographic area or across a few years and often lack the statistical power to detect potential effects when investigating which populations are most vulnerable to increases in air pollutants.

I address this gap by exploiting daily variation in outdoor air pollution from different air pollutants and the overall air quality index (AQI), within US counties in a two-way county fixed effects linear regression, adjusting for individual and climate characteristics to examine the relationship between ambient pollution, health-related avoidance behaviors, and productivity

² <https://www.epa.gov/air-trends/air-quality-national-summary>. Last accessed on March, 9th 2022.

across U.S. respondents 2003 to 2019. I also exploit satellite-based aerosol optical depth (AOD) as a proxy for the air quality to study the effects of pollution on labor supply decisions at the extensive (i.e., decision to work in a given week) and the intensive margin (i.e., number of hours worked) as well as weekly labor productivity as proxied by weekly earnings at work.

Even though I control for multiple fixed effects, including location (i.e., county) and time (i.e., year) fixed effects, the empirical specification may still be plagued by endogeneity issues when analyzing the pollution effects on productivity. Given that individuals can also control their exposure to air pollution, this may bias the results due to endogeneity when studying health or economic outcomes including mortality or productivity. For example, exposure to extreme pollution levels can deteriorate an individual's health and may cause a reduction in productivity. To address these endogeneity concerns, I use weekly changes in wind direction and the atmospheric boundary layer height as instrumental variables (IV) or exogenous shocks to local pollution to estimate the impact of air quality or aerosols on productivity at work conditional on employment. The identifying assumption of the IV approach is that weekly changes in a county's daily wind direction or atmospheric layer height, after controlling for multiple fixed-effects, wind speed, and climatic variables, do not affect the variation in weekly earnings, except through changes in pollution levels. This approach is similar to Deryugina et al. (2019) and Khanna et al. (2021), who use changes in wind direction and atmospheric thermal inversion as instruments for pollution to analyze the causal impact of changes in air quality on mortality and migration, respectively.

The most important result is the presence of non-linear effects of air pollution on avoidance behavior. Specifically, individuals adopt defensive behaviors only at certain thresholds of air pollution. They decrease the minutes spent on outdoor sports and exercises by 24%, increase

sleeping minutes by 6.5%, and increase the minutes spent at home watching TV by 262% only when the air quality becomes very unhealthy or hazardous when compared to good levels of pollution. I also look at the effects of information on avoidance behavior by looking at the avoidance behavior around the threshold air quality index where the first air quality alert is usually issued using a regression discontinuity approach. I find no significant effects of air quality alerts on avoidance behaviors around the AQI threshold of 101. Looking at the effects on labor market outcomes (i.e., labor supply decisions and productivity), I find no effects of an increase in aerosols on both changes in decision to work (i.e., intensive margin) and the weekly worked hours (i.e., extensive margins). The null results on the overall labor supply are consistent with some studies analyzing pollution, labor supply, and productivity in the U.S. (Zivin and Neidell 2012; Chang et al. 2016) but are the opposite to other analyses of pollution impacts in different geographical contexts (Hanna and Oliva 2015). I also find no significant effects of daily and weekly pollution on daily unproductive time in the workplace and weekly earnings respectively. Finally, I investigate the presence of potential heterogeneous effects of pollution across different subgroups including age groups, race-ethnicity, and income distribution. I find that very unhealthy or hazardous levels of pollution cause individuals across different age groups and income levels to reduce their time spent on outdoor physical activities and increase time spent on physical inactivity such as sleeping or watching TV. Although the adaptation may reduce current exposure to air pollution, increase in physical inactivity is also detrimental to long-run health.

Multiple studies have documented the serious negative health effects associated with medium-run and long-run exposure to particulate matter (PM_{2.5}) and other pollutants, such as ozone, nitrogen dioxide, or carbon monoxide (CO) on mortality and infant health (Deryugina et al. 2019; Graff Zivin and Neidell 2013; Chen et al. 2013; Jayachandran 2009; Currie and Neidell

2004; Chay et al. 2003; Chay and Greenstone 2003), labor supply, productivity and investment (He, Liu, and Salvo 2019; Hanna and Oliva 2015; Schikowski et al. 2014; Zivin and Neidell 2012) and educational outcomes (Mohai et al. 2011; Stenson et al. 2021). For example, Chay and Greenstone (2003) use the exogenous variation caused by the 1980-81 recession, which caused manufacturing to slow down, to identify the effects of pollution reduction on infant health at the county level. The authors find that a reduction in the Total Suspended particles (TSPs) reduced infant mortality.

However, the evidence on individual-level avoidance behavior is often lacking (Janke 2014). Most of these quasi-experimental studies identifying the impacts of air pollution ignore behavioral confounding or avoidance behavior, which can bias the estimates (Graff Zivin and Neidell 2013; Neidell 2009). They also tend to look at the effects of a single pollutant, which might also cause an omitted variable bias problem.

There is a growing body of literature investigating the relationship between exposure to air pollution and avoidance behavior or adaptation to environmental pollution (Aguilar-Gomez 2021; Yu et al. 2019; Chang et al. 2019; Roberts et al. 2014; Janke 2014; Zivin et al. 2011; Neidell 2009; Zivin and Neidell 2009; Madajewicz et al. 2007; Friedman et al. 2001). Some studies focus on the impact of publicly and privately disclosed information about air pollution on people's behavior and others look at the relationship between ambient air pollution and health-related activities. For example, individuals reduce their exposure to risk by reducing the daily attendance at outdoor facilities in California when air quality alerts are issued (Neidell 2009) and reducing car usage when alerts are issued with driving restrictions (Aguilar-Gomez 2021). Individuals will also engage less in outdoor physical activity (e.g., walking) or engage more in physical inactivity (e.g., watching TV) during episodes of high air pollution such as smog events (Chang et al. 2019;

Roberts et al. 2014; An and Xiang 2015), which can increase the risk of diabetes and cardiovascular diseases.

This paper is closest to a study by Yu et al. (2017) that examines the relationship between annual exposure to PM_{2.5} and weekly health-related physical activities among university retirees in China. Using an individual fixed-effect regression, the authors show that an increase in PM_{2.5} is associated with a decrease in the number of minutes spent on physical activity and an increase in sleep time. Another related study is (He, Liu, and Salvo 2019a), which looks at the impact of daily fluctuation in outdoor PM_{2.5} around manufacturing sites in China on the daily output of the workers. Using atmospheric ventilation as an instrument for air quality, the authors find modest effects of prolonged exposure to PM_{2.5} on workers' labor productivity.

This paper contributes to the literature on air pollution and defensive behavior or adaptation in the U.S. using a repeated cross-sectional nationally representative survey that documents how individuals across the whole country spend time across a set of activities when exposed to increased ambient air pollution. Studies that investigate this relationship often focus on annual air pollution-level as opposed to ambient daily pollution, which individuals are most likely to respond to or focus on pollution in a smaller geographic area. In addition, they often analyze the relationship using cross-sectional data, which makes it challenging to assess behavioral response to temporal variation in air quality. Such studies are also subject to omitted time-invariant fixed differences between individuals or counties.

I also contribute to the growing literature looking at the economic impacts of air pollution. I look at how pollution affects both health-related and economic-related outcomes, which few studies do. My study provides different estimates than the current productivity literature that uses high-frequency daily worker's output.

The rest of the paper is organized as follows. Section 1 provides necessary background about the different ways air pollution levels may provoke avoidance behavior from individuals. Section 2 describes the data. Section 3 describes the empirical strategy. Section 4 presents the results, and Sections 5 and 6 present the heterogeneity analysis and limitations, respectively. Section 7 concludes.

1. Background

Both the exposure to air pollution and physical inactivity are significant risk factors for non-communicable diseases (NCDs) and for mortality. Worldwide, WHO estimated that ambient air pollution caused 4.2 million deaths in 2016. In addition, more than 25 percent of adults worldwide are physically inactive and do not meet the minimum recommended level of 150 min per week of moderate-intensity physical activity (Guthold et al. 2018), which may lead to health deterioration. Being exposed to air pollution increases the risk of cardiovascular and respiratory diseases, type-2-diabetes, cancers, and premature mortality in the long term (Beelen et al. 2014; Brook et al. 2018).

The current literature suggests that air pollution, especially exposure to PM 2.5, Ozone, or other air pollutants may decrease physical activity levels during high air pollution episodes. Some people might substitute between outdoor and indoor activities because they believe that being outdoors exposes them to more pollution and because they receive utility from spending time outside. The impact of air pollution is not limited only to highly polluted outdoor environments; outdoor air pollution also penetrates indoor environments, which may further deteriorate individuals' health and productivity.

2. Data

I use a rich set of data available on daily air pollution, weather, time spent on daily activities, as well as weekly labor supply decisions and earnings. The datasets and linkages are described below.

3.1 Air Pollution

Daily outdoor air pollution data are obtained from the United States Environmental Protection Agency's (EPA) Air Quality System database, which monitors air quality following the 1970 Clean Air Act and provides hourly and daily data on the pollution level for multiple pollutants at the pollution-monitor level. The "criteria" pollutants monitored include PM 2.5, PM 10, sulfate dioxide (SO₂), ozone (O₃), carbon monoxide (CO), nitrogen dioxide (NO₂) and lead.³ Given that a county can have more than two pollution monitors, I construct the county-level daily air pollution measure by averaging all values of a pollutant reported by all monitors within a given county. The EPA also reports the constructed Air Quality Index (AQI), which is an overall measure of outdoor air quality, taking into account all of the air pollutants measured within a county monitor. The AQI values (ranging from 0 to 500) are divided into different categories (e.g., Good, Unhealthy, Hazardous) representing different levels of health concerns, and the values are used to send out air quality warnings or alerts when a certain threshold is exceeded.

Figure 1 and Figure 2 show the spatial distribution of air pollution monitors across the U.S. in 2003 and 2019 respectively. The visual patterns in the distribution show an increase in the number of PM2.5 monitors installed across all US counties over time.

³ EPA calls these pollutants "criteria" air pollutants because they can negatively affect individuals' health and the environment, and there are permissible levels for each pollutant.

Figure 1 Spatial distribution of the PM_{2.5} monitors across US counties in 2003

Figure 2 Spatial distribution of the PM_{2.5} monitors across US counties in 2019

Figure 3 shows the aggregate yearly trends in PM_{2.5} and the AQI.⁴ The average U.S. concentration of both PM_{2.5} and the AQI has consistently decreased over the years. For example, the average value of PM_{2.5} in 2003 was 11.2 micrograms per cubic meter ($\mu\text{g}/\text{m}^3$) and is 7.2 ($\mu\text{g}/\text{m}^3$) in 2019.

⁴ Both trends in PM_{2.5} and AQI are very similar because the Air Quality Index calculated mostly uses fine particles levels.

Figure 3 Trends in PM 2.5 Concentration and Air Quality Index in the U.S., 2003-2019 using EPA Pollution data

Another measure of air pollution used to investigate the effects of pollution on labor supply and productivity at work is the fine-mode total aerosol optical depth (AOD) at 469nanometers wavelength from the ECMWF Atmospheric Composition Reanalysis 4 (EAC4), a satellite-based monitoring instrument.⁵ Although the number of pollutant monitors has increased over the years, there are still limitations in the EPA’s pollution monitor coverage for certain pollutants and years. Monitors collect filter-based samples of pollutants on a 1-in-3 day or 1-in-6-day schedule, resulting in a lack of data for the other days the air quality is not assessed. Interpolating the missing data for days where pollutants are not sampled can result in bias since air quality during unmonitored days is found to be worse than on monitored days due to strategic responses or manipulations by local governments (Chen et al. 2013; Ghanem and Zhang 2014; Greenstone et al. 2020; Zou 2021).

Many recent studies use air quality data from satellite imagery, especially aerosol optical depth either to address such concerns or due to data being sparse or unavailable in certain countries (Jayachandran 2009; Foster et al. 2009; Bombardini and Li 2016; Zou 2021). The total AOD used

⁵ See <https://ads.atmosphere.copernicus.eu/cdsapp#!/dataset/cams-global-reanalysis-eac4>. Accessed March, 8th 2021

in this study refers to the number of aerosols (e.g., smoke particles, dust, sea salt, chemicals, etc.) present within a column of air from the earth's surface to the satellite sensor and calculated from the optical depth of 469 nanometers (nm). Aerosols estimated can be used as a proxy for surface particulate matter of different sizes (e.g., PM <1mm, <2.5mm, <10mm) and shapes (Kumar et al. 2007), and are derived from the amount of light that is absorbed or reflected by the particles using radiative transfer models (Remer et al. 2005). The EAC4 is a 3-hourly data available from 2003 onward with a $0.75^\circ \times 0.75^\circ$ (approximately 81km x 81km) resolution, derived from the combination of satellite observations of atmospheric composition and detailed computer simulation of the atmosphere.

I compute the daily county-level average total AOD, PM2.5, PM10, carbon monoxide, and ozone by applying the area-weighted average of all grid-cell values overlapping each county for the years 2003-2019. While the pollution readings available from ground-based monitors reflect the air quality around that monitor and at the ground level, the satellite grid cell value represents the average amount of particle pollution in the entire atmosphere within the overall grid cell. The total AOD is a dimensionless index with theoretical values ranging from -0.05 to 5 (Remer et al. 2005). The US county-level average from EAC4 mostly ranges from 0.001 to 0.26 with a mean of 0.19 and a median of 0.15. Lower values represent clean air conditions while higher values represent hazy conditions from high pollutant concentrations.

I test the accuracy of the EAC4 satellite data by using the ground monitors' geocoordinates and computing the PM2.5 from EAC4 satellite data and comparing it with the PM2.5 reported by the ground-based monitors on the same EPA monitoring days. Figure 4 reports trends in the annual county mean from 2003 to 2019 and the visual comparison shows similar decreasing trends in PM2.5 over the years from both datasets. The most probable reason for the higher PM2.5 values

reported in the EAC4 dataset is the fact the satellite captures the PM_{2.5} particles from the ground up to the sensor location while the EPA ground-based monitors only capture PM_{2.5} at a certain height in the atmosphere.

Figure 4 Trends in PM 2.5 Concentration from EPA Ground Monitors vs CAMS Satellite daily data in the U.S., 2003-2019

3.2 Atmospheric Conditions

Daily gridded precipitation and temperature data are obtained from Schlenker and Roberts (2009), who provide complete and comprehensive weather data (i.e., daily minimum and maximum temperature, precipitation) from a Parameter Elevation Regression on Independent Slopes Model (PRISM) and weather stations. The data are available for each point of all 2.5-by-2.5 mile grid cells for the contiguous United States. Compared to the original PRISM data, the authors keep the set of weather stations constant over time and replace missing values with the distance-weighted average of the cumulative density function of all surrounding stations.

3.3 Inputs to Instrumental variables

I use two instruments for air quality, wind direction and atmospheric layer height. Although the EPA reports daily wind direction and speed, the issue of missing values motivates the use of other sources. Satellite-based wind direction and wind speed daily data at each pollution monitor are constructed from the Copernicus ERA-5 hourly reanalysis database.⁶ Wind speed and wind direction are reported on a 0.25 x 0.25 degrees grid ($\approx 27 \text{ km} * 27 \text{ km}$). Only the east-west wind direction (u-component) and north-south wind direction (v-component) are available. I construct the daily county-level u- and v-components data by averaging the hourly data, then I compute both the daily and weekly county-level wind speed and wind direction using the u- and v-components.⁷ compute Each wind direction value in degree compass corresponds to the direction from which the wind is blowing (e.g., South-East, North-West).

I also collect the boundary layer height (BLH) data from the Copernicus ERA-5 and used the hourly gridded data to construct the daily and weekly county-level boundary layer height. Numerous papers have documented Atmospheric layer height or boundary layer height (BLH) or atmospheric mixing height as one of the most important determinants of the levels of aerosols (Xiang et al. 2019; Prasad, Basha, and Ratnam 2022; Huo et al. 2021; Su, Li, and Kahn 2018; Quan et al. 2013). BLH is expressed in meters and represents the layer of the troposphere (i.e., the lowest atmospheric layer) that is directly influenced or affected by the earth's surface. The height varies spatially and temporally depending on the local weather conditions (e.g., temperature, wind speed, or moisture) and strongly affects the vertical diffusion of atmospheric pollutants (Stull 1988; Sun et al. 2013; Tang et al. 2016; Cao et al. 2020). It can go as low as a few meters when

⁶ ERA-5 is a reanalysis database for the global climate and weather since 1950. See <https://cds.climate.copernicus.eu/cdsapp#!/dataset/reanalysis-era5-single-levels>. Accessed February 14, 2022.

⁷ U-component (meters/s) represents the horizontal speed of air moving towards the East. If negative, wind moves towards the West. V-component is the speed of air moving towards the north, and a negative value represents air moving toward the South.

the air is cool at night for example, or as high as multiple kilometers in the middle of a hot and sunny day in a desert. When its depth decreases, it compresses the volume of dispersion, and pollutants that are produced from the surface are trapped locally because of lower air diffusion. This process results in deterioration of air quality or haze pollution episodes. Overall, the literature on air pollution suggests the presence of a strong negative relationship between BLH and aerosols levels.

Figure 5 visually explores the long-run relationship between BLH and aerosol levels in the US from 2003 to 2019. Panels (a) to (d) show that in counties where the long-run average BLH is lower or closer to the earth's surface (lighter areas in panel a), there is a higher concentration of aerosols, PM 2.5 and PM 10 (darker areas in panels b,c, and d). These counties with a lower boundary layer height tend to have higher levels of precipitation.

Figure 5 Long-Term County-level Distribution of the Boundary Layer Height, Pollutants, and Climatic Conditions (2003-2019)

(a) Boundary Layer Height

(b) Aerosols (469nm)

(c) PM 2.5

(d) PM 10

Note: darker colors refer to higher values and lighter shades refer to lower values.

3.4 Time Use

Time-use data are obtained from the IPUMS American Time Use Survey (ATUS), a federally-administered, nationally representative, and repeated cross-sectional survey that collects time-use diaries of United States respondents monthly since 2003⁸. The data are rich and report all the daily activities that all the respondents engaged in over 24 hours (from 4:00 a.m. of a specified day until 4:00 a.m. of the following day), allowing me to study how people spend their time in daily life activities.⁹ I use data ranging from 2003 to 2019. The information collected includes how many minutes were spent across multiple activities including personal care activities (e.g., sleeping, grooming), household activities (e.g., cooking, housework, home maintenance), sports, and exercise (e.g., walking, participating in sports, or attending sports events) and the location where the activity took place. The survey also collects socio-demographic, economic, and household-level information.

ATUS is a subcomponent of the Current Population Survey (CPS), a survey supported by the Bureau of Labor Statistics and administered by the US Census Bureau that collects monthly data on the labor force, employment and unemployment, earnings, and other individual characteristics. Individuals in the ATUS sample are randomly selected from a subset of households that completed the 8th-month interview of the CPS. There are about 400 different activities recorded, and all responses were collected using telephone interviews, which were carried out on both weekdays and weekends. In this paper, I focus on only a few categories that are more likely to respond due to changes in air quality including outdoor sports and exercise, exterior home maintenance, and

⁸ See <https://timeuse.ipums.org/>. Accessed on May 14, 2021

⁹ The very short recall period of 24 hours minimizes potential reporting biases in diaries (Hamermesh, Frazis, and Stewart 2005)

sleeping. These activities can be grouped into outdoor physical activities (e.g., sports and exercise outdoors) and indoor physical inactivity (e.g., sleeping and watching TV), and previous studies have documented the effects of increased air pollution increase on physical activity and inactivity.

I construct a daily productivity at work variable as the percent of time respondents are at work but not working following Hamermesh, Genadek, and Burda (2017). Given that ATUS provides a comprehensive list of activities carried out during the day, and their locations, I combine the reported time individuals spent on all activities at work that are not work-related (i.e., sleeping, eating or drinking, socializing or exercising) that I divide by the reported overall time spent at the workplace.¹⁰ Although this measure does not capture direct daily worker's output, as in Zivin and Neidell (2012), it serves as a good proxy for productivity in the workplace.

Using the ATUS county information and date of interview, I construct the analysis dataset by merging it with the daily county-level corresponding pollution data from the EPA, the daily county-level satellite pollution, climatic conditions, wind variables, and boundary layer height. The county identifier provided in ATUS is a five-digit numeric variable, where the first two digits represent the Federal Information Processing Standards (FIPS) state code and the last three digits are the FIPS county code. In slightly more than half of the sample, county codes are unidentified, which makes it impossible to retrieve the location of the individuals living in those counties. Overall, 44% of the observations are assigned identifiable county names. The current study only focuses on those observations with identifiable county locations, even though the remaining observations contain location information at the state level.¹¹

¹⁰ If the individual works for pay but not at the workplace, the time is not captured.

¹¹ Assigning state-level pollution to individual observations will introduce additional measurement error in the analysis.

All regressions in this study are weighted using person weights provided by the ATUS. The rationale for weighting is that it adjusts for potential selection bias and ensures that all respondent weights amount to the correct number of weekday and weekend person-days for the entire population and subpopulations.

3.5 Summary Statistics

Table 1 presents descriptive statistics for the sample for which PM 2.5 and the air quality index (AQI) are available, which has 55,219 observations.¹² The average daily concentration of PM 2.5 is 10.33 micrograms per cubic meter ($\mu\text{g}/\text{m}^3$), with a standard deviation of 6.90, PM 10 has a mean of 22.61 with a standard deviation of 14.24 while the average Air Quality Index is 43.18 with a standard deviation of 22.08. Respondents are aged from 18 to 85, 42% of individuals in the sample live in a family with less than USD 50,000.

On average, individuals in the sample reported spending 524 minutes (≈ 8.8 hours) sleeping, 159 minutes (≈ 2.8 hours) watching TV, 4 minutes on sports and exercises, and 10 minutes on exterior maintenance and gardening.¹³

Table 1 Summary statistics

	Mean	Std. Dev.	min	max	N
Panel A: EPA Air Pollutants					
PM2.5 ($\mu\text{g}/\text{m}^3$)	10.33	6.90	0	180	52673
CO (Parts per billion)	0.41	0.26	0	4	40429
Ozone (Parts per billion)	0.03	0.01	0	0	46029
Air Quality Index	43.18	22.08	0	232	52540

Panel B: Time Spent in Last

¹² The IPUMS ATUS sample for which county location information is available for the years 2003-2019 has 96,248 person-day observations. However, the EPA pollution data are not always reported for consecutive days, and some stations report pollution levels every three or six days; this monitoring issue leads to a problem where some person-day observations in the ATUS do not have a corresponding pollution day in the EPA data.

¹³ The mean values in panel B and C of Table 1a are very close to the mean values in the summary table in Appendix 2 where I use the full ATUS sample instead. Thus, the analysis sample used in this paper is still representative of the US population.

24 hours (Minutes)

Sleeping	524.07	130.92	0	927	52,673
TV Watching	159.46	163.10	0	765	52,673
Outdoor Sports & exercise	3.68	17.24	0	120	52,673
Exterior Maintenance & Lawn	10.39	41.06	0	300	52,673

Panel C: Individual-level Characteristics

Family income <\$50K	0.42	0.49	0	1	52,673
Individual has any disability	0.09	0.29	0	1	34,969
Age	44.03	18.46	15	85	52,673

Note: The Table reports weighted statistics for time use and individual-level variables using person weights provided by the ATUS. The sample is restricted to observations for which PM2.5 and AQI information is available since PM 2.5 is considered by the literature as the pollutant with the most negative effects on human health. Unit of observation is person-day (for years 2003-2019). Data for whether the respondent has any disability are available starting in 2008. Disability refers to any difficulty with vision, hearing, memory, mobility, physical difficulty, and personal care. Data for PM 10 are available starting in 2005.

3. Empirical Strategy

4.1 Fixed Effects Model

The goal is to estimate the effect of medium-run exposure to fine ambient air pollution on time spent on daily health-related activities, adjusting for any potential confounding variables. I estimate the relationship using the following form:

$$Y_{icdwm} = \beta_i P_{icdwm} + X'_{icdwm} \gamma + \alpha_c + \alpha_{wy} + \alpha_{sm} + \epsilon_{icdwm}, \quad (1)$$

where Y_{icdwm} represents the outcome of interest of individual i in county c during day d on week w month m and year y ; it is the transformed value of the self-reported amount of time in minutes an individual i spent in the last 24 hours across multiple activities, including sleeping, exercising or watching TV, using the inverse hyperbolic sine (IHS) method. The IHS transformation of the outcome allows to use the zero-valued observations in the data and corrects for skewness (Bellemare and Wichman 2020). Beta (β) is the coefficient of interest examining the effects of exposure to air pollutants on time allocation on daily activities. Two specifications are considered in this study. In the first specification, P_{icdwm} is the vector of individual-level pollutants (i.e., PM

2.5, Ozone, and CO). Given concerns about serial correlation, I also include the lag of PM 2.5, Ozone, and CO as controls in the regression. The second specification only considers the overall air quality index (AQI) as opposed to individual pollutants.

I control for a wide range of climatic variables, socio-demographic characteristics of the respondents, and fixed effects.¹⁴ Weather controls are included because of the documented effect it has on air quality (Zannetti 1990) and avoidance behavior such as outdoor exercise (Wagner et al. 2019). I consider two different sets of control variables X' . In the first specification, I control for the variables and fixed effects as specified in equation (1). The second specification includes all the fixed effects but other controls are selected using the double-selection post-LASSO method of Chernozhukov et al. (2017). Following Derksen et al. (2021), I use the **pdslasso** command in Stata and let the algorithm select important variables among the variables described in Appendix 1.¹⁵ The double LASSO selects the controls by: (i) regressing the outcome and selecting the important variables, and (ii) regressing the exogenous variable of interest on all other covariates, and selecting the relevant variables that affect the exogenous variable.¹⁶ One major advantage of this approach is that it is heteroskedastic robust, even if the controls' selection is imperfect (Belloni et al. 2014).

The fixed effects included in all specifications are county (α_c), week-by-year (α_{wy}) and state-by-month (α_{sm}) fixed effects. The county fixed effects control for any time-invariant geographic differences in observed and unobserved variables, including access to health care,

¹⁴ Climatic variables include daily maximum and minimum temperatures, daily precipitation, and wind speed.

¹⁵ In addition to linearly adding controls, I feed the algorithm quadratic terms and all possible interactions, but a higher order expansion is possible (e.g., fourth-degree polynomials) as in Derksen et al. (2021).

¹⁶ Some covariates selected by the LASSO when regressing worked hours on weekly pollution are: race-ethnicity (black dummy), interaction between black and <8th grade education, gender, interaction between gender and education level, minimum temperature, precipitations, interaction between maximum temperature and precipitation, and three state-month dummies.

county elevation, income, or education. The week-by-year fixed effects control for temporal and seasonal trends or time-varying shocks in a flexible and non-parametric way, such as shocks induced by environmental policies between 2003 and 2019.¹⁷ The state-by-month fixed effects control for state variation in the seasonal correlation between time spent on activities and air quality. I cluster the standard errors at the county level.¹⁸

An additional concern is the measurement error in the county-level air pollution data. A county may have multiple air pollution monitors that are generally geographically sparse (Figure 1.b), therefore, depending on the location of the pollution monitor in the county (e.g., North or South) and the wind direction, different levels of air pollution can be recorded by the monitors in the same county. In this study, I average the values of the pollution monitors if a county has two or more monitors; this approach assumes that the air pollution level has a uniform effect on the entire county. The OLS estimates will be biased towards zero given the presence of classical measurement error and the bias will be exacerbated by the fixed effects added. In the second part of this paper, I estimate the effects of changes in air quality on labor supply decisions (i.e., the decision to go to work, and weekly hours worked) and worker productivity. The use of satellite-based airborne pollution data will reduce the issue of measurement error for two reasons: (i) by providing a better measure of the average air quality across each county where geographically sparse ground monitors cannot correctly capture pollution levels in the whole county; and (ii) by constructing weekly pollution data by averaging daily values for all days of the week instead of using ground-pollution data and relying on interpolation techniques to fill missing values for non-

¹⁷ Controlling for month fixed effects instead of week-by-year fixed effects to account for seasonality does not significantly change the main results.

¹⁸ Ideally, I would implement the spatially adjusted standard errors accounting for spatial and serial correlation (Conley 1999; S. M. Hsiang 2010), however, I am not aware of any approach that is applicable to the instrumental variable setting.

monitoring days. Given the high spatial variation in the pollution within small areas, relying on interpolation may lead to significant measurement error (Moretti and Neidell 2011).

4.2 Pollution, Labor Supply, and Productivity: Instrumental Variable Approach

I also investigate how air pollution affects labor supply responses and productivity in the workplace. The OLS estimates looking at the impacts of air pollution on outcomes including health, crime, and labor productivity may be biased because exposure to air pollution is endogenous, even if ambient daily air pollution appears to be plausibly exogenous (Chay and Greenstone 2003b; Neidell 2009; Zivin and Neidell 2012; Deryugina et al. 2019).¹⁹ Air pollutants affect people only if they are exposed to them, and some individuals might adopt avoidance behavior such as reducing time spent on outdoor activities to reduce exposure to air pollutants, which might make them less sick and more productive. Recent studies have used different instruments for local air pollutants' concentration to examine the causal effects of increased air pollution, such as wind direction (Deryugina et al. 2019; Bondy et al. 2020; Aguilar-Gomez 2021), thermal inversion (Khanna et al. 2021), atmospheric or boundary layer height (He, Liu, and Salvo 2019a), or specific events affecting pollution levels (Hanna and Oliva 2015) to overcome the endogeneity issue. Others rely on plausibly exogenous events such as smog alerts (Neidell 2009). However, comprehensive smog alerts data for the U.S. are not easily available.

Following these papers, I use weekly changes in county-level wind direction and boundary layer height as instruments for weekly changes in county-level total aerosol optical depth (AOD).²⁰

¹⁹ For example, richer individuals may sort in less polluted areas, which in return affect their productivity (Zivin and Neidell 2012).

²⁰ For the daily AQI, I use the EPA available. For the weekly pollution, I use the weekly satellite fine-mode total aerosol optical depth (AOD) at 469nm instead of the EPA-reported AQI given that the EPA does not collect pollution samples every day of the week. leading to missing values on many days.

The impact of wind direction on pollution is caused by the fact that locally produced pollutants are redistributed depending on the wind conditions, which can increase their levels in certain places where air pollutants are not initially produced. It is also unlikely that the regular vertical increases or decreases in the boundary layer height are correlated with individual worked hours.

The conditions for the instruments to be valid are that: (i) there is enough correlation with the endogenous variable of interest; (ii) the relationship is not systematically reversed for some observations; and (iii) the instrument is not directly correlated with an unobserved determinant or the outcome of interest. The first and second stage equations to estimate the effects of daily and weekly aerosol levels on daily work productivity and weekly hours worked are expressed as:

$$AOD_{cwm_y} = \sum_{j=1}^3 \theta_j WindDirection_{cwm_y}^{90b} + X'_{cwm_y} \mu + \tau_c + \tau_{wy} + \tau_{sm} + v_{cwm_y}, \quad (2)$$

$$AOD_{cwm_y} = BLH_{cwm_y} + X'_{cwm_y} \lambda + \pi_c + \pi_{wy} + \pi_{sm} + \kappa_{cwm_y}, \quad (3)$$

$$Y_{icwm_y} = \varphi \widehat{AOD}_{cwm_y} + X'_{cwm_y} \rho + \omega_c + \omega_{wy} + \omega_{sm} + \epsilon_{cwm_y}, \quad (4)$$

where,

BLH represents the weekly boundary layer height. Y represents the outcomes, which are the inverse hyperbolic sine of weekly hours worked.²¹ For equation (2), the excluded instruments are three dummies representing the wind direction bins into which the daily or weekly value of the county falls. The original wind direction variable ranges from 0 to 360 degrees and was divided into four wind direction bins of 90-degree intervals. Each of the instrument wind direction bins has a value equal to one (1) if the weekly average wind direction falls into the interval, and zero (0) otherwise. The omitted category is the interval [0,90).

²¹ For the daily productivity at work, I use both daily wind direction and daily boundary layer height as instruments for aerosols or pollutants. For the weekly hours worked, I use weekly average wind direction and weekly boundary layer height as instruments for air quality in separate regressions.

Weak instrument bias is not a problem in this study. The first stage regression in Table 2 shows a strong correlation between both instruments (i.e., boundary layer height and wind direction) and daily AQI. For example, a decrease in the BLH is associated with a significantly higher concentration of pollutants, consistently with the air pollution literature. The first stage F-statistics in the regression results in Table 6 are also large enough to confirm the presence of strong instruments. Using wind direction bins as instruments, the F-statistic is 45, while the F-statistic using boundary layer height is 153. The latter F-stat is larger than the value of 104.7, which is for the inference to be a true 5 percent test (Lee et al. 2021).

The key identifying assumption is that after controlling for weather conditions, fixed effects, wind speed, and other control variables, the average boundary layer height or wind direction in county i on time t is unrelated to changes in worker productivity or weekly earnings by individual i in county c , except through its influence on air quality proxied by the total aerosols optical depth.

It is important to note that satellite data, especially when used as an independent variable, may provide biased estimates due to the issue of spatial dependence (i.e., correlation among nearby grid cells or units), which violates the Stable Unit Treatment Value Assumption (SUTVA) (Donaldson and Storeygard 2016). The authors also note that this issue is likely to be more acute with a higher spatial resolution of the satellite data; for example, neighboring cities or counties have lower spatial dependence than two 30 meters x 30 meters grid cells. In this study, the spatial dependence is likely low, not only because the CAMS satellite data have a resolution of 0.75×0.75 degrees ($\approx 81 \text{ km} \times 81 \text{ km}$), and the total AOD used as the independent variable is averaged at the county level.

Table 2 First Stage Regression with Weekly Wind Direction and Boundary layer Height as Instruments

	AQI	AQI
Boundary Layer Height(m)	-0.02*** (0.001)	
windspeed	-1.50*** (0.344)	-3.63*** (0.270)
Min. Temperature	-0.90*** (0.089)	-0.91*** (0.095)
Max. Temperature	1.14*** (0.114)	1.16*** (0.135)
Precipitations	-0.47*** (0.032)	-0.45*** (0.033)
90 < winddir < 180		2.79*** (0.755)
180 < winddir < 270		3.25*** (0.882)
270 < winddir < 360		-1.55*** (0.531)
Fstat	38	31
Obs.	18,013	18,013
Controls	Yes	Yes
Fixed Effects	Yes	Yes

Clustered Standard errors at the county level in parentheses

Note: Controls include rainfall, minimum and maximum temperatures, individual-level controls, and month-of-year, state-month, and county fixed effects.

4. Results

5.1 Effects on Avoidance Behavior

Effects of Air Quality Index on Time use – I explore in Table 3 the non-linear effects of AQI on the outcomes of interest at the intensive margin, controlling for covariates and fixed effects. The daily AQI provides a better representation of the overall air quality on a specific day. I analyze the possibility of a non-linear relationship between pollution and avoidance behavior by converting the continuous AQI variable into indicators for different pollution levels following the EPA categorization. The results indicate the presence of non-linear effects of pollution on avoidance behavior. For example, in panel A of Table 3, which reports pollution estimates with controls selected not using LASSO, columns 1 and 4 suggest that, on days with a very unhealthy or

hazardous AQI (i.e., AQI at 201 and above), individuals will reduce minutes spent outside on sports and exercise by 24%, increase minutes watching TV by 262% and increase sleep time by 6.5%.²² In panel B of Table 3 where controls are selected using double-LASSO, individuals also significantly reduce time spent on outdoor sports and exercises and increase in minutes sitting at home watching TV when the AQI becomes very unhealthy or hazardous. I find similar results when looking at the effects at the extensive margins (i.e., using indicators of whether an individual engages in an activity or not) in Table 1 of this paper's Appendix. These results are consistent with the idea that, given the health benefits of spending time outdoors, individuals may not decrease time spent on outdoor activities unless pollution levels are very high (Bresnahan, Dickie, and Gerking 1997).

²² The coefficients of interest in are Table 3 dummies indicating different levels of health concerns for pollution. Given that the dependent variable is transformed using IHS, the semi-elasticities can be derived by exponentiating both sides of the equations. For example, the coefficient on sports and exercises is -0.27, which is equivalent to $\exp(-0.27)-1 = -0.24$ or -24%.

Table 3 Effects of changes in Air Quality Index (AQI) on Avoidance Behavior - Non-Linear Effects

Outcome: IHS Minutes Spent on	(1) Sports & Exercises	(2) Exterior Maintenance	(3) Sleeping	(4) Watching TV
<i>Panel A: No Double LASSO</i>				
AQI - Moderate	0.006 (0.024)	0.042 (0.026)	-0.009 (0.007)	0.001 (0.054)
AQI - Unhealthy	0.066 (0.115)	0.087 (0.123)	0.023 (0.021)	-0.036 (0.249)
AQI - Hazardous	-0.270** (0.095)	0.219 (0.251)	0.063* (0.032)	1.287*** (0.256)
Observations	28,632	28,632	28,632	28,632
Dep. Var. Mean (in minutes)	4	12	532	172
Controls	Yes	Yes	Yes	Yes
<i>Panel B: Double LASSO Controls</i>				
AQI - Moderate	0.010 (0.024)	-0.010 (0.029)	-0.008 (0.007)	-0.026 (0.055)
AQI - Unhealthy	0.067 (0.119)	0.128 (0.112)	0.015 (0.019)	0.002 (0.222)
AQI - Hazardous	-0.262** (0.119)	-0.389 (0.243)	0.045 (0.040)	1.631*** (0.342)
Observations	28,648	28,648	28,648	28,648
Mean Dep. Var.	4	12	532	172
Controls	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Week of Year FE	Yes	Yes	Yes	Yes
State-Month FE	Yes	Yes	Yes	Yes

Clustered Standard errors at the county level in parentheses

Note: The reference AQI category is Good. Outcomes are transformed using the Inverse Hyperbolic Sine (IHS). The categorization of AQI into bins follows the EPA categorization for Good, moderate, and unhealthy AQI levels. Due to small sample issues, very unhealthy and hazardous categories are grouped into one. Panel A uses controls specified in Equation (1) and Panel B uses controls selected using the double LASSO approach. Besides county, week-of-year, and state-month fixed effects, the regression includes controls for minimum and maximum temperature, precipitation, wind speed, one-day lags of AQI, respondent's age, gender, education, disability status, family income, employment status, and day of the week. The LASSO estimation includes all linear, quadratic and possible interaction forms of the covariates. Estimates are weighted using the ATUS respondent weights. Semi-elasticities can be derived by exponentiating both sides of the regression equation; e.g., 1.282 effect size refers to a 262 % [$\exp(1.287)-1=2.62$] increase in time spent watching TV.

Responses to Individual Air Pollutants – Panels A and B of Table 4 present the linear relationship

between daily individual pollutants levels (PM 2.5, CO, and Ozone) and time spent across sports

and exercises, exterior maintenance, sleeping, and watching TV on a specific day. I restrict the sample to county days where data for all three pollutants are available and control for lagged values of each pollutant as well. Overall, the results suggest a positive association between the levels of Ozone in the atmosphere and physical inactivity (i.e., sleep time as well as TV watching time). The other pollutants PM 2.5 and CO do not significantly cause avoidance behavior. The effects of Ozone are consistent with previous studies suggesting that an increase in air pollution levels may increase physical inactivity by increasing sleeping time (An and Yu 2018).

Table 4 Effects of Individual Air Pollutants on Time spent on Daily Activities

Outcome: IHS Minutes Spent on	Sports & Exercises	Exterior Maintenance	Sleeping	Watching TV
PM 2.5 (mg/m3)	0.001 (0.002)	0.005 (0.003)	-0.000 (0.001)	0.007 (0.007)
CO (ppb)	-0.072 (0.118)	-0.022 (0.113)	-0.028 (0.041)	-0.318 (0.227)
Ozone (ppb)	3.373* (1.906)	1.494 (1.391)	1.313** (0.582)	6.881** (3.086)
Observations	21,637	21,637	21,637	21,637
Dep. Var. Mean (in minutes)	4	11	534	173

Clustered Standard errors at the county level in parentheses

Note: ppb= part per billion. The sample is limited to county-days where all three pollutants (PM 2.5, CO, and Ozone) are simultaneously available. Besides county, week-of-year, and state-month fixed effects, the regression includes controls for minimum and maximum temperature, precipitation, wind speed, one-day lag of pollutants, respondent's age, gender, education, disability status, family income, employment status, and day of the week. The LASSO estimation includes all linear, quadratic, and possible interaction forms of the covariates. Besides fixed effects, the regression includes controls for minimum and maximum temperature, precipitation, wind speed, one-day lags of pollutants, respondent's age, gender, education, disability status, family income, employment status, and day of the week. Estimates are weighted using the ATUS respondent weights.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Effects of Air Quality Alerts or Information on Behavior - I also analyze the effects of providing information through air quality alerts on avoidance behavior by comparing behavior on days when the Air Quality Index (AQI) is just above 101 (i.e., a threshold where a first alert is issued) to days

where the measure is below that threshold using a regression discontinuity approach.²³ The AQI is a standardized and color-coded measurement of air quality and allows individuals to understand the associated health risks. It is divided into six categories or levels of concern, including good (0 – 50), moderate (51 – 100), unhealthy for sensitive groups such as children, elderly, or people with respiratory diseases (101 – 150), unhealthy (151-200), very unhealthy (201-300), and hazardous (300 or higher). The AQI value represents the highest index value of any of the criteria pollutants. For example, if on a specific day, the constructed index of PM 10 is the highest, then the AQI takes that value.

Figure 6 presents the results of a sharp regression discontinuity (with the cutoff of AQI for alerts being 101) and suggests no effects of AQI alerts on avoidance strategies. One potential explanation for this result is the small sample size with a small number of days with AQI levels around the 101-alert threshold. Another potential explanation is that individuals respond only at very high levels of AQI as presented in the results from Table 3. However, there are not enough data around higher alert thresholds (i.e., 201 AQI for very unhealthy and 301 AQI for hazardous) to run a regression.

²³ There are few days every year where the air quality is very bad that it triggers an alert. Air quality announcements are spread through media to ensure that people stay updated on the air quality level when the AQI is 100 or higher (Wen et al. 2009). Alerts days are rare and different than other random days throughout the year because the level of pollution reverts to the mean after a spike in daily air pollution.

Figure 6 Effects of Air Quality Alerts on Avoidance Behaviors using Regression Discontinuity Approach

5.2 Effects on Labor Supply Responses

In this section, I present the impact of air pollution on labor supply responses at the extensive margin (probability of working in a week) and the intensive margin (number of hours worked in the week conditional on being employed).²⁴ Panel A of Table 5 shows the results of the OLS with controls specified in equation (1) while Panel B shows the results with the LASSO-selected controls. Column 1 of panels A and B show that a percent increase in the level of aerosols (AOD) in the atmosphere has no statistically significant effect on the decision to show up at work on a specific week. Column 2 of Panels A and B show the results for labor supply at the intensive margin. I find no effect of weekly worked hours. These results are similar to previous studies documenting how air pollution does not affect labor supply decisions, both at the extensive and intensive margins (Montt 2018; Chang et al. 2016; Zivin and Neidell 2012) but different compared

²⁴ I take the IHS of weekly hours worked to account for zero values in hours worked, given the censored dependent variable (i.e., it is impossible to work less than zero hours per week). Another estimation approach could be a Tobit model, but it will suffer from the incidental parameter problem.

to other studies showing that worked hours increase when there is improvement in air quality (Hanna and Oliva 2015).

Table 5 Effects of Air Pollution (Aerosols) on Weekly Labor Supply

	OLS		IV	
	(1)	(2)	(3)	(4)
	Absent to Work (1/0)	IHS Hours Worked Last Week	Absent to work (0/1)	IHS Hours Worked Last Week
<i>Panel A: Normal</i>				
<i>Controls</i>				
IHS Aerosols 469nm	-0.03 (0.025)	0.13 (0.073)	-0.20 (0.238)	0.21 (0.758)
F-Stat			67	67
Observations	36413	36413	36413	36413
Dep. Var. Mean (Hours)	.039	45	.036	45
Boundary Layer height Instrument			Yes	Yes
<i>Panel B: Double LASSO</i>				
<i>Controls</i>				
IHS Aerosols 469nm	-0.02 (0.024)	0.12 (0.063)	-0.02 (0.121)	0.14 (0.440)
Observations	35,639	35,639	35,639	35,639
Dep. Var. Mean (Hours)	.036	45	.036	45
LASSO-selected Instruments			Yes	Yes

Clustered Standard errors at county level in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: This regression represents a linear regression with a continuous value of Aerosols as our independent variable of interest. Panel A uses controls specified in Equation (1) and Panel B uses controls selected using the double LASSO approach. Besides county, week-of-year, and state-month fixed effects, the regression includes controls for average weekly minimum and maximum temperature, average weekly precipitation, wind speed, one-week lags of Aerosols, respondent's age, gender, education, disability status, family income, employment status. The LASSO estimation includes all linear, quadratic, and all possible interaction forms of the covariates. The last column of Panel B implements an IVLASSO approach where instruments are selected using LASSO from single and interacted variables including wind speed, four bins of wind direction, boundary layer height, and with county dummies. The F-stat reported is the Kleibergen-Paap rk Wald F statistic from a weak identification test. Estimates are weighted using the ATUS respondent weights.

5.3 Effects on Daily Labor Productivity and Weekly Earnings

In this section, I analyze the relationship between air quality and labor productivity. I use different measures of productivity at work, including the fraction of unproductive time at the workplace and weekly earnings. Using the fraction of unproductive time at the workplace as a productivity outcome, I restrict the sample to the employed individuals that worked on that day on their job. Column 1 of Table 6 presents the results of the linear regression model. Columns 2 and 3 present the results of the IV regressions using daily wind direction and BLH as instruments respectively. The results suggest no significant effect of contemporaneous daily aerosol levels on daily productivity.

Following Gibson and Shrader (2018), I use the reported “usual weekly earnings” rather than wages on the week of the interview, as an indirect measure of weekly labor productivity to also analyze the effects of pollution.²⁵ The issue using this measure is the potential timing mismatch between satellite air pollution observations and weekly earnings. However, as Gibson and Shrader (2018) noted, the issue will only result in an attenuation bias. The results in Table 7 also show no significant relationship between changes in satellite-based aerosols and weekly earnings.

These null results are different from other studies that use the high-frequency individual output to show that an increase in pollution levels leads to a significant drop in workers’ productivity (Zivin and Neidell 2012; Chang et al. 2016; Adhvaryu, Kala, and Nyshadham 2019). However, I find similar results to He, Liu, and Salvo (2019a) who show that concurrent exposure

²⁵ The weekly earnings variable is top-coded above \$2,884.61 and is for all respondents who are not self-employed with a positive labor income. Although a change in weekly earnings could be due to a change in hours worked or wages, Gibson and Shrader (2018) shows that estimates are driven mainly by wage changes.

to pollution does not affect productivity. The authors rather find that prolonged exposure affects productivity.

Table 6 Effects of Aerosols on Fraction of Unproductive Time at Work

	(1) OLS	(2) IV	(3) IV
IHS Fraction Time Not Working at Work			
IHS Aerosols (469nm)	0.01 (0.009)	-0.01 (0.053)	-0.00 (0.054)
F-Stat		43	165
Observations	14989	14989	14989
Dep. Var. Mean	0.056	0.056	0.056
Controls	Yes	Yes	Yes
County FE	Yes	Yes	Yes
Week of Year FE	Yes	Yes	Yes
State-Month FE	Yes	Yes	Yes
Wind Direction Instrument		Yes	
Boundary Layer height Instrument			Yes

Clustered Standard errors at county level in parentheses

Note: Column 1 represents a linear regression. Column 2 represents the IV approach with daily wind direction categories as the instruments, omitting the first indicator of wind direction. Column 3 represents the IV regression with daily boundary layer height as an instrument. Besides county, week-of-year, and state-month fixed effects, the regression includes controls for daily minimum and maximum temperature, precipitation, wind speed, respondent's age, gender, education, disability status, family income, employment status, and day of the week. Estimates are weighted using the ATUS respondent weights. The F-stats are Kleibergen-Paap rk Wald F statistic from weak identification tests.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7 Effects of Aerosols on Weekly Earnings

	(1) OLS	(2) IV
IHS Weekly Earnings		
IHS Aerosols 469nm	0.04 (0.116)	1.48 (1.111)
F-Stat		59
Observations	29,133	29,133
Dep. Var. Mean (\$)	943	943
Boundary Layer height Instrument		Yes

Clustered Standard errors at county level in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: Besides county, week-of-year and state-month fixed effects, the regression includes controls for average weekly minimum and maximum temperature, average weekly precipitation, wind speed, respondent's age, gender, education, disability status, family income. The F-stat reported is the Kleibergen-Paap rk Wald F statistic from a weak identification test. Estimates are weighted using the ATUS respondent weights.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

5. Treatment Effects Heterogeneity

This section examines whether the effects of air pollutants differ across subgroups of the population including age and income groups. The extent to which individuals reduce the time allocated to physical activities, miss work, or become unproductive due to high pollution levels may vary by demographics. I investigate the notion that environmental externalities may disproportionately impact groups of individuals along the income distribution (Hsiang, Oliva, and Walker 2019) given that exposure to air pollution may vary at the location where these groups reside or work; therefore, we may expect different responses to increased pollution. For example, Bondy, Roth, and Sager (2020) explore the non-linear effects of air pollution on crime and find the large effects are concentrated at the bottom of the income distribution. The rich set of socio-demographic characteristics in the ATUS data allows for exploring heterogeneity in vulnerability to air pollution.

6.1 Effects on Avoidance Behavior across Age Groups

I expect more vulnerable groups (i.e., seniors) to adopt a stronger avoidance behavior since the benefits from avoiding high outdoor pollution are larger for them. Panels in Figure 7 below report results estimated in separate regression for each outcome separately. I find that when AQI becomes very unhealthy, individuals across all age groups except 65+ significantly reduce time outdoor and exercise while increasing time spent watching TV at home. Additionally, individuals aged 25-34 and 55-64 react to hazardous AQI by increasing sleeping time.

Figure 7 Heterogeneity Effects of AQI on Avoidance Behavior across Age Groups

The categorization of AQI into bins follows the EPA categorization for Good, moderate, and unhealthy AQI levels. Very unhealthy and hazardous levels are grouped into one hazardous category. The reference category in the regression is Good. The regression includes county FE, week FE, state-by-month FE, controls for minimum and maximum temperature, precipitation, wind speed, one-day lags of AQI, climate and wind speed, respondent's age, gender, education, disability status, family income, employment status and day of the week. Estimates are weighted using the ATUS respondent weights. Semi-elasticities can be derived by applying $\exp(\text{estimate}) - 1$.

6.2 Effects on Avoidance Behavior across Income Groups

A large and growing body of evidence documents the existence of environmental inequalities and shows that the negative effects of air pollution are concentrated among low-income and racial or ethnic minority communities in the United States (Brulle and Pellow 2006). I divide the sample into three subgroups of the income distribution: (i) families with incomes less than \$50,000 (low-income); (ii) families with incomes between \$50,000 and \$100,000 (medium income); and (iii) families with incomes more than \$100,000 (high income).

Overall, the effects in Figure 8 show that individuals across the income distribution adopt different avoidance behaviors when the AQI gets hazardous. All individuals across all income groups reduce outdoor physical activity when AQI gets hazardous, while those living in medium-income families significantly spend more time sleeping. Finally, the individuals in richer families (i.e., \$100,000 and above) significantly spend more time watching TV when AQI is hazardous.

Figure 8 Heterogeneity Effects of AQI on Avoidance Behavior across Income Groups

The categorization of AQI into bins follows the EPA categorization for Good, moderate, and unhealthy AQI levels. Very unhealthy and hazardous levels are grouped into one hazardous category. The reference category in the regression is Good. The regression includes county FE, week FE, state-by-month FE, controls for minimum and maximum temperature, precipitation, wind speed, one-day lags of AQI, climate and wind speed, respondent's age, gender, education, disability status, family income, employment status and day of the week. Estimates are weighted using the ATUS respondent weights. Semi-elasticities can be derived by applying $\exp(\text{estimate}) - 1$.

6.3 Effects on Avoidance Behavior across Race and Ethnicity

I also investigate avoidance behaviors adopted in response to air quality degradation across five (5) racial or ethnic groups including non-Hispanic Whites, non-Hispanic Blacks, non-Hispanic

Asians, non-Hispanic others, and Hispanics. The results in Figure 9 below also suggest that Whites, Asians, and other racial and ethnic groups respond to very unhealthy AQI levels by reducing outdoor activities while Black respondents increase sleeping time.

Figure 9 Heterogeneity Effects of AQI on Avoidance Behavior across Racial and Ethnic Communities

The categorization of AQI into bins follows the EPA categorization for Good, moderate, and unhealthy AQI levels. Very unhealthy and hazardous levels are grouped into one hazardous category. The reference category in the regression is Good. The regression includes county FE, week FE, state-by-month FE, controls for minimum and maximum temperature, precipitation, wind speed, one-day lags of AQI, climate and wind speed, respondent's age, gender, education, disability status, family income, employment status and day of the week. Estimates are weighted using the ATUS respondent weights. Semi-elasticities can be derived by applying $\exp(\text{estimate})-1$.

6.4 Effects on Labor Supply across Gender and Occupations

Another heterogeneity analysis looks at how the effects of weekly pollution on labor supply decisions differ across gender and occupations. Figure 10 and Figure 11 also suggest no significant differential effects of aerosols across gender and occupations.

Figure 10 Heterogeneity Effects of Aerosols on Labor Supply across Gender

Figure 11 Heterogeneity Effects of Aerosols on Labor Supply across Occupations

6.5 Effects on Weekly Earnings across Occupations, Education Levels, and Gender

Lastly, I look at how the relationship between air pollution and weekly earnings from work across occupation categories, different education levels, and gender. The health of outdoor workers may be more affected by air pollution compared to other occupations, which can cause a decrease in productivity and earnings. Similarly, more educated people, who are more likely to work in white-collar jobs may be less affected. Overall, the results in Figure 12 suggest no significant relationship between aerosols and earnings across the different groups studied.

Figure 12 Heterogeneity Effects of Aerosols on Weekly Earnings across Occupations, Education Levels, and Gender

6. Robustness Checks

As a falsification test, I examine the effect of future or lead values of daily air pollution on current behavioral responses, controlling for contemporaneous and lagged values as well. Since future air pollution should not affect current outcomes, I expect an insignificant effect in a regression of the form:

$$Y_{icdmy} = \alpha_1 AQI_{cd'my} + \alpha_2 AQI_{cd''my} + X'_{cdmy} \delta + \gamma_c + \gamma_{wy} + \gamma_{sm} + \epsilon_{cd'my}, \quad (5)$$

which has the same form as equation (1) but with the coefficients α representing the effects of air pollutants (i.e., lead pollution) from one day (d') and two days (d'') after on current outcomes Y . Equation (5) also controls for contemporaneous, lagged AQI levels as well as all other controls and fixed effects specified in equation (1). Table 8 shows the results of the regression and the effects of lead linear AQI (AQI t+1 and AQI t+2) are insignificant for all outcomes.

Another important assumption for IV estimates to be interpreted as local average treatment effects (LATE) is the monotonicity assumption (Imbens and Angrist 1994). In this study, the assumption will be satisfied if all counties experience changes in pollutants in the same direction when the wind blows from a 90-degree direction bin, all will be violated if some counties experience changes in different directions than others. One way Deryugina et al. (2019) assess the validity of the assumption is by changing the sizes of the wind direction bins affecting pollution from 90-degree to 60-degree bins. I follow a similar approach and reduce the wind direction bins from 90 to 60, and then to 45 degrees in alternative specifications to test whether the estimates would change. I only focus on one productivity outcome (i.e., the fraction of unproductive time spent at work). In Table 9, column 1 uses the original 90-degree wind direction bins as instruments, column 2 decreases to 60 degrees, and column 3 decreases to 45 degrees angles. The results from columns 2 and 3 are not too different than the original insignificant estimates in column 1.

The third robustness check I implement a Tobit regression model given the presence of censoring in the data.²⁶ The issue with Tobit and fixed effects is the presence potential bias due to the incidental parameter problem (Greene 2004).²⁷ Table 10 and Table 11 show that the results are consistent with the original results, both on the avoidance behaviors, worked hours and weekly earnings.

Table 8 Robustness test: Future Pollution on Current Avoidance Behavior

Outcome: IHS Minutes Spent on	(1) Sports & Exercises	(2) Exterior Maintenance	(3) Sleeping	(4) Watching TV
AQI - Moderate	0.02 (0.033)	0.04 (0.034)	0.00 (0.008)	-0.00 (0.067)
AQI - Unhealthy	0.03 (0.089)	-0.05 (0.100)	0.05 (0.032)	-0.37 (0.280)
AQI - Hazardous	-0.18* (0.086)	-0.03 (0.146)	0.08 (0.044)	0.98*** (0.216)
AQI t+1	0.00 (0.001)	0.00 (0.001)	-0.00 (0.000)	0.00 (0.002)
AQI t+2	-0.00 (0.001)	0.00 (0.001)	-0.00 (0.000)	0.00 (0.001)
Observations	16,393	16,393	16,393	16,393
Dep. Var. Mean (in minutes)	4	12	534	175
Controls	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Week of Year FE	Yes	Yes	Yes	Yes
State-Month FE	Yes	Yes	Yes	Yes

Clustered Standard errors at county level in parentheses

* p<0.05, ** p<0.01, *** p<0.001

Note: The controls include all controls and fixed effects specified in equation 1 as well and 1 and 2-day lagged values if AQI.

²⁶ Tobit models are non-linear models usually estimated using the Maximum Likelihood (ML) method.

²⁷ The incidental parameter problem is that the estimated coefficients are inconsistent unless the number of periods in the data is close to infinity for each unit i.

Table 9 Robustness of Productivity at Work Estimates to Wind Direction Bins Choices

	(1)	(2)	(3)
IHS Fraction Time Not Working at Work	IV	IV	IV
IHS Aerosols (469nm)	-0.04 (0.064)	-0.02 (0.068)	-0.03 (0.062)
F-Stat	35	21	17
Observations	13633	13633	13633
Dep. Var. Mean	0.056	0.056	0.056
Size of wind angle bins (degrees)	90	60	45
Controls	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes

Clustered Standard errors at county level in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: The sample excludes self-employed and individuals not in the labor force. Besides county, week-of-year, and state-month fixed effects, the regression includes controls for daily minimum and maximum temperature, precipitation, wind speed, respondent's age, gender, education, disability status, family income, employment status, and day of the week. Estimates are weighted using the ATUS respondent weights. The F-stats are Kleibergen-Paap rk Wald F statistic from weak identification tests.

Table 10: Tobit Regression – Avoidance Behavior

IHS	(1) Sports & Exercises	(2) Exterior Maintenance	(3) Sleeping	(4) Watching TV
AQI - Moderate	0.00 (0.017)	0.03 (0.021)	-0.01* (0.005)	0.05 (0.048)
AQI - Unhealthy	0.02 (0.095)	0.00 (0.101)	0.01 (0.023)	-0.05 (0.208)
AQI - Hazardous	-0.27*** (0.037)	0.03 (0.166)	0.07 (0.040)	0.75** (0.289)
Observations	34191	34191	34191	34191
Dep. Var. Mean (in minutes)	4	12	532	173
Controls	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Week of Year FE	Yes	Yes	Yes	Yes
State-Month FE	Yes	Yes	Yes	Yes

Clustered Standard errors at county level in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Controls are similar to the ones in the main specification.

Table 11: Tobit Regression – Labor Supply and Productivity

IHS	(1) Hours Worked	(2) Weekly Earnings
IHS Aerosols 469nm	0.14 (0.073)	0.04 (0.114)
Observations	35639	29137
Dep. Var. Mean (in minutes)	44	1007
Controls	Yes	Yes
County FE	Yes	Yes
Week of Year FE	Yes	Yes
State-Month FE	Yes	Yes

Clustered Standard errors at county level in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The Tobit approach relies on the levels of the outcomes rather than the transformed ones using the IHS. Controls are the same as in the main specification.

7. Limitations

One limitation of the study is that due to data limitations, I do not control for whether the survey respondent has a respiratory disease. Individuals with chronic conditions, such as heart disease or chronic obstructive pulmonary disease (COPD), are more likely to adopt an avoidance behavior on days where outdoor air pollution increases to reduce mortality risk.

Another limitation is the inability to account for potential long-run adjustments made by some respondents due to a lack of data. This study focuses on daily changes in activities; however, a long-run or permanent adjustment made by an individual to reduce pollution exposure may not alter behavior when pollutant levels spike.

The last issue is the inability to rule out the presence of unobserved time-varying variables that are correlated with both air pollution and the outcomes investigated or measurement error in ground-monitor pollution or satellite pollution levels, which is an empirical concern. However, if

the source of bias is a classical measurement error in the estimates of pollution levels, then the results will only suffer from attenuation bias and thus one can obtain a lower bound of the causal effect.

Conclusion

This paper examines the relationship between exposure to outdoor air pollution, avoidance behavior through changes in time spent on daily activities, and labor supply, using a repeated cross-sectional national representative dataset of U.S. individuals. The results indicate the presence of behavioral changes or defensive responses when air quality deteriorates to very unhealthy or hazardous levels. The main mitigative actions taken by respondents include decreasing time spent outdoors on sports and exercise and increasing sleep time. The decrease in physical activity and increase in physical inactivity can be further detrimental to people's future health as low levels of physical activity constitute a major risk of mortality (World Health Organization 2010). The estimates indicating that people adopt avoidance behavior as air quality worsens are consistent with earlier studies reporting similar mitigation strategies (Bresnahan, Dickie, and Gerking 1997; Zivin and Neidell 2009; Neidell 2009; Yu et al. 2019). For some outcomes, the mitigation strategy adopted depends on age group, race, and the poverty level or income status of the respondents while individuals across all income levels spend less time on outdoor activities in a response to hazardous air quality, individuals in low-income families respond by spending more time watching TV as air quality becomes hazardous, respondents from middle-income families respond to hazardous pollution levels by sleeping more, and richer families spend more time watching TV. No heterogeneity is found across different age groups. The estimates on labor supply, on the other hand, suggest no overall effects of air pollution on the decision to miss work in a week and weekly

hours spent working. The daily productive time at work and earnings regressions show no overall significant effect of pollution on labor market outcomes.

The result that individuals adopt avoidance behavior to reduce exposure to extreme pollution has some important implications. Local agencies continue to enforce environmental regulations to keep pollution levels low and encourage outdoor physical activity, as it is estimated that up to 5 million deaths worldwide can be averted if the world's population was more active (World Health Organization 2021). In addition, some papers suggest that studies ignoring the defense actions adopted when estimating the health effects of pollution may suffer from bias (Krupnick, Harrington, and Ostro 1990; Bresnahan, Dickie, and Gerking 1997; Neidell 2009), yet other studies report that omitting defensive behavior in the specifications does not lead to an underestimation of the health effects (Janke 2014). Future research studying the health impacts of air pollution should provide estimates both with and without accounting for avoidance behavior.

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Appendix

Table 1: Control Variables and Definitions

Variable	Definition
Age	Age in years
Disability	Equal to 1 if the respondent has any difficulty of personal care, vision, hearing, physical mobility or remembering.
Race – Ethnicity	Categorical variable capturing different combinations of race and ethnicity (i.e., Hispanic, non-Hispanic white, non-Hispanic black, non-Hispanic Asian and non-Hispanic other).
Gender	Equal to 1 if respondent is a female and 0, otherwise.
Family income	Categorical variable reflecting different income bins the respondent family falls in (e.g., <\$50000, \$50000-\$100000, and > \$100,000).
Education	Categorical variable reflecting the education level of the respondent. The categories are: <=8th grade, 9th-11th grade, high-school degree, some college, bachelor's degree, Masters degree or higher.
Employment status	Categorical variable identifying the following employment statuses: not in labor force, employed-at work, employed-absent and unemployed.
Day of the week	Equal to 1 if the day of the interview is a weekday, and 0, otherwise.
Minimum Temperature	Continuous variable describing the minimum temperature of the day before the interview date
Maximum Temperature	Continuous variable describing the maximum temperature of the day before the interview date
Precipitation	Continuous variable describing the average precipitation level of the day before the interview date
Average wind speed	Continuous variable describing the average windspeed of the day before the interview date
Wind direction	Indicator taking the value =1 if the wind blows from the South-East and 0 if it blows from the North-West.

Table 2: Descriptive statistics using ATUS full survey data

Minutes Spent in last 24 hours:					
Sleeping	521.34	130.37	0	930	210,586
TV Watching	163.15	165.95	0	778	210,586
Outdoor Sports & exercise	3.65	18.15	0	135	210,586
Travel to Work	15.97	29.18	0	135	210,586
Exterior Maintenance & Lawn	13.77	49.80	0	330	210,586
Individual-level Characteristics:					
Family income <\$50K	0.44	0.50	0	1	210,586
Individual has any disability	0.10	0.30	0	1	129,151
Age	44.87	18.52	15	85	210,586

Note: The Table reports weighted statistics for time use and individual-level variables using the full 2003-2019 ATUS survey data. Unit of observation is person-day. Data for whether the respondent has any disability are available starting 2008. Disability refers to any difficulty with vision, hearing, remembering, mobility, physical difficulty, and personal care. Mean values are closer to the values from the analysis sample where PM2.5 and AQI are available.

Table 3: Effects of changes in Air Quality Index (AQI) on Avoidance Behavior - Non-Linear Effects - Extensive margin

Outcome: (0/1)	(1) Sports & Exercises	(2) Exterior Maintenance	(3) Sleeping	(4) Watching TV
AQI - Moderate	0.001 (0.005)	0.007 (0.005)	-0.001 (0.001)	0.004 (0.009)
AQI - Unhealthy	0.013 (0.025)	0.012 (0.023)	0.001 (0.001)	0.000 (0.044)
AQI - Hazardous	-0.051** (0.018)	0.038 (0.045)	-0.001 (0.001)	0.215*** (0.047)
Observations	29,144	29,144	29,144	29,144
Dep. Var. Mean (in minutes)	4	12	532	173
Controls	Yes	Yes	Yes	Yes

Clustered Standard errors at the county level in parentheses

Note: The reference AQI category is Good. Outcomes are transformed using the Inverse Hyperbolic Sine (IHS). The categorization of AQI into bins follows the EPA categorization for Good, moderate, and unhealthy AQI levels. Due to small sample issues, very unhealthy and hazardous categories are grouped into one. Panel A uses controls specified in Equation (1) and Panel B uses controls selected using the double LASSO approach. Besides county, week-of-year, and state-month fixed effects, the regression includes controls for minimum and maximum temperature, precipitation, wind speed, one-day lags of AQI, respondent's age, gender, education, disability status, family income, employment status, and day of the week. Estimates are weighted using the ATUS respondent weights.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$