Air Pollution and Health at Work

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Abstract

Despite pathophysiological evidence linking pollution to human physical and cognitive functioning, little is known about the economic consequences of such impacts. This paper fills this gap by investigating the causal effect of air pollution on worker health and workplace safety. Using a novel dataset combining high-frequency air pollution and meteorological data with workplace injury records from Florida and leveraging exogenous variations in pollution caused by temperature inversions, I find that PM2.5 significantly increases workplace injuries. The effect is nonlinear, increasing with rising pollution levels, and shows a non-negligible impact even at mild pollution levels below the current regulatory standards.

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JEL Classification: Q53, Q51, J28, J24

1 Introduction

Air pollution is a global environmental problem with far-reaching impacts on human health and economic development in both developing and developed countries. While low- and middle-income countries like India and China bear a disproportionate burden of such pollution, in the era of global warming, extreme weather events such as wildfires and droughts have been increasing both the frequency and extent of air pollution in high-income countries, presenting new challenges for air pollution control.

As a result, there is a growing interest among the public and economists in the impact of air pollution. While the adverse effects of air pollution on mortality and public health are well-documented (Deryugina et al. 2019; Anderson 2020, among others), relatively little is known about its impact beyond the direct health implications, especially on the labor market and labor productivity. A growing body of research is shifting its focus from the general health impacts to a wide range of "non-health" outcomes (see Aguilar-Gomez et al. 2022, for a detailed review), studying outcomes such as labor supply (Hanna and Oliva 2015), game performance and decision-making (e.g., Künn, Palacios, and Pestel 2023; Huang, Xu, and Yu 2020), as well as academic performance (e.g., Bharadwaj et al. 2017; Ebenstein, Lavy, and Roth 2016; Heissel, Persico, and Simon 2022). Among these studies, a few have investigated worker productivity, including Graff Zivin and Neidell (2012), Chang et al. (2019), and He, Liu, and Salvo (2019). However, these studies primarily measure worker productivity by wages and piece-rate outputs, and mainly focus on the agricultural and manufacturing sectors in developing countries.

In this paper, I construct a novel panel dataset from the United States to investigate the causal impact of air pollution on worker health and workplace safety, key aspects of labor productivity. The dataset combines administrative workers' compensation (WC) data from Florida, which contains precise information on the location and date of workplace injuries, with high-resolution data on air pollution and meteorological variables. Workplace safety and worker health are important yet surprisingly understudied factors in labor productivity. While early studies, such as Hausman, Ostro, and Wise (1984), Ostro (1983), Pönkä (1990), and Hansen and Selte (2000), have found positive correlation between air pollution and sick leave and work loss, a causal link is yet to be established. Moreover, workplace injuries are costly and can lead to significant productivity losses. Severe injuries that involve hospitalization and amputation often result in work absences lasting from days to weeks. Productivity losses, along with workers' compensation payments and medical expenses incurred because of work-related deaths and injuries, cost the U.S. more than $234 billion in 2018 (National Safety Council; Weiss, Murphy, and Boden 2020).

Fine particulate matter, known as PM2.5, and ozone have been found to be linked with various acute health events, such as respiratory and cardiovascular conditions, due to their ability to penetrate deep into the lungs, bloodstream, and brain. Depending on the level of exposure, PM2.5 and ozone can also lead to a number of subclinical symptoms that do not necessitate health care visits but may result in reduced cognitive and physical functioning. Typical symptoms include fatigue, impatience, irritability, altered motor activity, inattention, and distraction (Delgado-Saborit et al. 2021; Chang et al. 2016). Job tasks, especially in high-risk occupations, demand attention, resilience, mental stability, physical strength, and endurance. Therefore, in addition to affecting visibility, air pollution—particularly PM2.5 and ozone—can influence workplace injuries and health by reducing physical and cognitive abilities through biological channels.

Pinning down the causal effect of air pollution is challenging, because it is not randomly assigned across space or workplaces. Air pollution is likely endogenous, and standard estimates may suffer from omitted variable bias and selection bias. A typical solution is to apply the instrumental variable (IV) method. For an IV to be valid, it must be relevant to the treatment variable, affecting air pollution in a nonnegligible way, and satisfy the exclusion restriction—meaning it should be uncorrelated with workplace injuries except through its effect on air pollution. This paper employs an arguably valid instrument, leveraging plausibly exogenous variations in air pollution driven by atmospheric temperature inversion episodes to identify the causal impact of general air pollution—pollution caused by various reasons, including but not limited to wildfires. Temperature inversion is a canonical instrument for air pollution in environmental economics studies (Sager 2019; Jans, Johansson, and Nilsson 2018; Arceo, Hanna, and Oliva 2016). It refers to a natural phenomenon where warmer air at higher altitudes traps cooler air near the surface, preventing pollutants from rising and keeping them close to the ground. Since temperature inversion episodes occur at high altitudes and are generally invisible to individuals, they are unlikely to affect economic activities or workplace injuries, making them a valid instrumental variable.

This paper provides rigorous causal evidence that PM2.5 and ozone pollution significantly impact workplace injuries in Florida. The estimated effects of PM2.5 exhibit a non-linear pattern, with the impact increasing with rising pollution levels. Specifically, a one-unit increase in PM2.5 at 12 $\mu g/m^3$ is associated with an increase in WC claims per 1 million population by 0.8 percentage points (equivalent to a 2% increase relative to the sample mean claim rate). This effect is significantly greater for PM2.5 at 30 $\mu g/m^3$, to be approximately 8 percentage points and equivalent to a 21% increase. In comparison, the effect of ozone pollution is linear and relatively smaller compared to the effect of PM2.5. A 10-ppb increase in ozone is found to increase WC claims per 1 million population by 0.7 percentage points, equivalent to an increase of around 2% relative to the baseline sample mean. Including additional controls for air pollution lags, I find no evidence of lagged or cumulative impacts, indicating that the estimated effects are primarily driven by acute exposure.

By analyzing the impacts across different injury categories defined by their nature and cause, I find that the effect of PM2.5 and ozone is primarily driven by increases in traumatic injuries rather than in respiratory, cardiovascular, or mental conditions. Additionally, these pollutants are more strongly associated with injuries resulting from cognitive-related issues, such as falls, slips, cuts, and being caught in machinery, rather than with injuries from other causes, such as heat or cold exposure, gunshots, or natural disasters. These findings support the hypothesis that reductions in physical and cognitive functions associated with air pollution are likely the driving force behind increased injury risks.

Based on these results, I evaluate the monetary costs associated with workplace injuries caused by air pollution, focusing on its impact on workers' compensation costs. A back-of-the-envelope calculation suggests a substantial increase in WC payments due to air pollution. For instance, a single day of a 10-$\mu g/m^3$ increase in PM2.5 across Florida is estimated to cause 247 additional workplace injuries per 1 million population and result in an increase in WC costs by more than $200 million.

This paper contributes to the literature in several ways. First, this work links air pollution and worker health and workplace safety, documenting a significant impact of air pollution on workplace injuries in Florida. It broadly enriches research on environmental hazards and workplace safety by revealing the impact of a new crucial risk factor for workplace safety and an additional outcome where air pollution has significant adverse effects.

In addition, this paper explores a channel through which air pollution affects labor productivity: by increasing workplace injuries. In this way, it contributes to the emerging literature on the so-called "non-health" effects of environmental hazards (such as, Chang et al. 2016; Graff Zivin and Neidell 2012; Park, Pankratz, and Behrer 2021, among others) by demonstrating that, beyond affecting worker productivity—typically measured by wages and piece-rate outputs—as well as academic and game performance as previously reported, air pollution can also influence workers' on-the-job performance and increase the risk of workplace injuries.

Furthermore, most prior works provided evidence based on case studies, restricting the sample to a single firm or a small geographical area. Analyses in this paper are based on comprehensive workers' compensation claims data, which includes precise temporal and geographic information on workplace accidents and injuries from a universe of claim records in Florida spanning an 18-year period (2002–2019). It provides rigorous evidence from a large-scale representative sample within the state. This work complements three contemporaneous studies on air pollution and workplace safety in different contexts:

Lavy, Rachkovski, and Yoresh (2022), who examine the impact of NO_2 on accidents at construction sites in Israel; Curci, Depalo, and Palma (2023), who analyze the impact of PM10 on work-related disabilities in eight regions of Italy, using winter heating regulations as an IV; and Cabral and Dillender (2024), who explore the effect of PM2.5 from wildfire smoke on workplace injuries in Texas.

Lastly, this study has important implications for informing policymaking. First, by linking air pollution and workplace safety, this paper suggests that improving air quality can potentially benefit both employers and employees. Ignoring the effect of air pollution on workplace safety likely underestimates these benefits of air quality improvement. Additionally, echoing policy discussions on whether to strengthen the EPA's National Ambient Air Quality Standards (NAAQS) for Particulate Matter (PM), the substantial impacts of daily ambient PM2.5 at levels below the EPA's regulatory standards found in this study support the suggestion to further reduce the 24-hour NAAQS standards. Furthermore, this paper provides robust evidence of the adverse impacts of PM2.5 and ozone on worker health and workplace safety. By highlighting the significant harms caused by air pollution, it informs OSHA in shaping policies to address workers' exposure to air pollution and encourages a thorough evaluation of optimal regulatory measures to mitigate associated risks. Specifically, the greater impacts found at higher PM2.5 levels and in poorer neighborhoods, along with the heterogeneous effects across PM2.5 and ozone, imply potential benefits in allocating limited regulatory resources towards these hot-spot regions and specific air pollutants, such as PM2.5.

The rest of the paper is organized as follows. In Section 2, I introduce fine particulate matter and ozone, discuss the biological mechanisms through which air pollution impacts workplace injuries, and review existing literature on the health and productivity effects of air pollution. Section 3 describes the data. Section 4 illustrates the empirical strategy. Primary results are presented in Section 5. In Section 6, based on the main results, I evaluate the economic cost of air pollution, focusing on the costs associated with workers' compensation. Section 7 concludes.

2 Background

In this section, I start by discussing how air pollution—especially fine particulate matter and ozone pollution—impacts job performance and workplace safety through biological mechanisms. Next, I summarize existing literature on the effects of air pollution on health and labor productivity.

Fine particulate matter and ground-level ozone are two major global air pollutants in modern society. Particulate matter (PM) is a mixture of solid particles and liquid droplets found in ambient air, which varies greatly in size and composition. Fine particulate matter (PM2.5) refers to particles with a nominal mean aerodynamic diameter of up to 2.5 micrometers. Thus, PM2.5 is typically invisible and can easily infiltrate indoor environments through ventilation systems and by penetrating the building envelope. Ground-level ozone (O_3) is the major component of haze and smog, and is formed primarily from photochemical reactions between two air pollutants — volatile organic compounds (VOC) and nitrogen oxides (NO_x).

PM2.5 and ozone are found to have serious adverse health effects due to its ability to penetrate deep into the lungs, blood streams and brain. PM2.5 and ozone can damage the tissues of the respiratory tract, irritate and corrode the walls of the alveoli (tiny air sacs), resulting in decreased lung function, aggravated asthma, and inflammation of the airways. Apart from contributing to respiratory conditions, PM2.5 and ozone are linked to cardiovascular diseases. When translocating into systemic circulation, PM2.5 and ozone can trigger systemic inflammation, impair the coagulation process, damage blood vessels, and lead to metabolic disorders.[1]

Depending on the level of exposure, PM2.5 and ozone can also lead to more subtle effects, such as changes in blood pressure, irritation in the eyes, ear, nose, throat, and skin, and mild headaches (Pope 2000; Auchincloss et al. 2008). These milder effects, resulting from exposure to lower levels of pollution, typically do not necessitate health care visits but

[1]For a comprehensive review on the adverse health effects of PM2.5 and ozone and their pathophysiological mechanisms, see EPA (2009, 2019), Kim, Kim, and Kim (2020), Zhang, Wei, and Fang (2019), Hua et al. (2024), and Feng et al. (2023).

may be linked to reduced functioning in several key body systems. Affected individuals might experience fatigue, impatience, irritability, altered motor activity, inattention, and distraction (Delgado-Saborit et al. 2021; Chang et al. 2016).

Moreover, epidemiologists have found growing evidence documenting the impacts of PM2.5 and ozone on human cognitive ability. These pollutants, through both chronic and acute exposure, have been shown to impair cognitive functions, including memory, attention, and fluid reasoning (e.g., Guxens et al. 2018; Peters et al. 2000; La Nauze and Severnini 2021; Bedi et al. 2021; Singh et al. 2022; Schikowski and Altuğ 2020; Shehab and Pope 2019) and affect mental well-being and regulation (Weuve et al. 2012; Prado Bert et al. 2018; Bernardini et al. 2020; Zhao et al. 2018; Zhao et al. 2020; Nguyen, Malig, and Basu 2021).

The decline in physical and cognitive functions is likely linked to a higher risk of workplace accidents and injuries. Job tasks, especially in high-risk occupations, demand attention, focus, resilience, mental stability, physical strength, and endurance. Even minor faults and misjudgments caused by inattention, fatigue, distraction, or overexertion can result in accidents and injuries. A similar link between environment-driven cognitive and physical impairment and an increased risk of injuries has been found in previous studies examining the impact of heat on workplace injuries (e.g., Park, Pankratz, and Behrer 2021; Dillender 2021) and the effect of PM2.5 on road accidents (Sager 2019).

Mounting research has investigated the adverse impacts of air pollution on health and labor productivity, providing evidence from various contexts. First, there is extensive evidence indicates that air pollution raises mortality and hospitalization rates, especially among children and the elderly (see, for example, Deryugina et al. 2019; Anderson 2020; Alexander and Schwandt 2022; Moretti and Neidell 2011). The available evidence is based on a variety of air pollutants, not limited to PM2.5 and ozone, but extending to carbon monoxide (Currie, Neidell, and Schmieder 2009; Currie and Neidell 2005; Schlenker and Walker 2016; Knittel, Miller, and Sanders 2016), total suspended particulates (Chay and Greenstone 2003; Chay, Dobkin, and Greenstone 2003), nitrogen oxides (Deschenes, Greenstone, and Shapiro 2017), and sulfur dioxide (Deryugina and Reif 2023). Beyond the impact on population health, a growing body of research is shifting its focus from the general health impact to a wide range of "non-health" outcomes.[2] These "non-health" outcomes include: worker productivity of agricultural workers (Graff Zivin and Neidell 2012), call center workers (Chang et al. 2019), and manufacturing workers (He, Liu, and Salvo 2019), labor supply (Hanna and Oliva 2015), school performance (Bharadwaj et al. 2017; Zhang, Chen, and Zhang 2018; Ebenstein, Lavy, and Roth 2016; Heissel, Persico, and Simon 2022), game performance (Künn, Palacios, and Pestel 2023) and decision making (Huang, Xu, and Yu 2020), mental health (Persico and Marcotte 2022; Molitor, Mullins, and White 2023), and crime (Burkhardt et al. 2019; Herrnstadt et al. 2021). In these studies, reductions in cognitive and physical function are identified as the primary mechanisms contributing to the effect of air pollution.

Taken together, existing literature has demonstrated that air pollution has significant effects on human health, leading to both acute health events and subclinical symptoms. Especially, declines in cognitive and physical functioning resulting from air pollution have been shown to impact individual performance across various scenarios, which plays a crucial role in shaping worker productivity. The evidence comes from various occupations spanning manufacturing, services, and agricultural sectors, across multiple regions covering developed and developing economies, and both indoor and outdoor environments, suggesting a widespread impact.

3 Data

In this paper, I measure workplace safety and health at work by the workplace injury rate, established from a longitudinal panel drawing on unique administrative data on workers' compensation (WC) claims for Florida. The WC claim data is acquired through open data requests from Florida's Department of Financial Services, Division of Workers' Compensation. Each WC claim record consists of information collected on the DWC-1

[2]See Aguilar-Gomez et al. (2022) for a comprehensive review.

form, also known as the First Report of Injury or Illness (FROI) Form, which reports the date of the accident associated with the claim, county and ZIP code of the accident, and injury characteristics, such as cause of injury, nature of injury, and the injured body codes. I collected claim records from January 2001 (the earliest available year) to December 2019 (the latest pre-COVID year).[3]

Workers' compensation offers cash benefits and/or medical care to employees who are injured or become ill "in the course and scope" of their job. Available benefits include medical treatment and full coverage of medical expenses, partial reimbursement of lost wages, compensation for temporary and permanent disability, and compensation to beneficiaries in case of a workplace fatality. The WC insurance is mandatory for employers conducting work in Florida.[4]

Based on the claim data, I create two outcome variables. The WC claim rate is constructed by aggregating the claims by ZIP code and date, and calculating the rate per 1,000,000 population.[5] Alternatively, I define a binary variable indicating the occurrence of workplace accident associated with WC claims at the ZIP code and date level and create the accident rate variable per 1,000,000 population. The empirical analyses are therefore conducted at the ZIP code by date level. One benefit of using the Florida WC claim data is that it consists of the exact geographical and temporal information of the accidents associated with the claims, which allows researchers to link the claim data to air pollution and weather data. Moreover, analyzing data at the ZIP code level rather than larger units such as commuting zones or counties allows for a more accurate assessment of ambient air pollution and local climate conditions at the locations where accidents occur, thereby reducing measurement errors.

[3]Additionally, I restrict the analysis to accidents that occurred within Florida. There is a small share of claims (less than 1%) involving accidents overseas or in unincorporated organized territories such as Puerto Rico and the Virgin Islands. Excluding these accidents may underestimate the impact of air pollution.

[4]Employers with one or more employees in the construction industry, with four or more employees in non-construction industries, and with six regular employees; and/or twelve seasonal workers who work more than 30 days during a season and/or more than a total of 45 days in the same calendar year must provide workers' compensation insurance for their employees. Source: https://www.myfloridacfo.com/division/wc/employer/coverage-requirements.

[5]Population counts are based on the 2000 and 2010 U.S. Census, downloaded from https://www.census.gov/en.html.

Next, I combine the WC claim data with high-resolution air pollution data and consider two major air pollutants, PM2.5 and ozone. Daily air pollution data for PM2.5 and ozone are retrieved from EPA's Fused Air Quality Surface Using Downscaling (FAQSD) dataset.[6] FAQSD is a scientific re-analysis dataset based on the EPA's Bayesian space-time downscaler model that projects station-based atmospheric variables to outputs at a finer scale. The model leverages air monitoring data from national, state, and local stations, along with emission and meteorological data from the Community Multiscale Air Quality (CMAQ) model. It incorporates meteorological conditions, such as wind, temperature, pressure, humidity, cloud formation, and precipitation rates and emissions, including aerosols and volatile organic compounds (VOCs).[7]

FAQSD provides a daily measure of ambient PM2.5 and ozone gridded on 12 km grids. The earliest available year is 2002. I collect PM2.5 and ozone data from 2002 to 2019 and aggregate them to the ZIP code and date level by taking the average over all grids lying within each ZIP code boundary.

In addition, I control for time-varying near-surface meteorological conditions by extracting daily climate data, including total precipitation (rain and melted snow), maximum, minimum, and average air temperatures, as well as dew point temperature, from the PRISM spatial climate datasets (Daly et al. 2008).[8] The PRISM data are measured at 4 km grids. Similar to the air pollution data, I aggregate the 4-km resolution daily weather covariates to the ZIP code-day level.

Air pollution is not randomly assigned across space or workplaces, rendering it endogenous for the workplace safety outcome. To address the issue of potential endogeneity of air pollution variables, I follow the environmental economics literature and adopt an

[6]FAQSD output files are downloaded via EPA RSIG website https://www.epa.gov/hesc/rsig-related-downloadable-data-files.

[7]The CMAQ is designed to manage multipollutant interactions simultaneously and simulate a wide range of chemical reactions, including the catalytic cycling of nitrogen oxides (NO_x) and VOCs in the formation and breakdown of ozone.

[8]PRISM data is downloaded from the portal of Northwest Alliance for Computational Science & Engineering (https://prism.oregonstate.edu/recent/. The PRISM datasets are developed by the PRISM climate group based on climate observations from a wide range of monitoring networks, applying the Parameter-elevation Relationships on Independent Slopes Model (PRISM) with sophisticated quality control measures. See https://prism.oregonstate.edu for more information.

instrumental variable strategy. The atmospheric temperature inversion is a canonical instrument for air pollution in environmental economics studies. For example, Sager (2019), Jans, Johansson, and Nilsson (2018), and Arceo, Hanna, and Oliva (2016), among others, use the temperature inversion as an instrument for air pollutants such as PM10, PM2.5, and CO. In general, temperature tends to decrease with altitude. However, it increases with altitude during inversion episodes because warmer air at higher altitudes confines cooler air near the surface. As a consequence, this prevents pollutants from rising and dispersing, trapping them close to the ground. This type of instrument produces arguably exogenous variations in air pollution.

I follow Sager (2019) and collect air temperatures at the 925hPa and 950hPa pressure levels and the surface level at 3 am local time for Florida from NASA's MERRA-2 climate reanalysis product (Global Modeling and Assimilation Office 2015).[9] The temperature inversion IVs are then defined similarly as those in Sager (2019) as continuous variables equal to the difference in air temperature between a certain pressure level (925hPa or 950hPa) and the surface level. As shown in the summary statistics Table 1, the propensity of temperature inversion episodes in Florida at the 925hPa or 950hPa pressure level is approximately 4%.

The final use data covers 1506 ZIP code zones in Florida spanning years 2002 to 2019. Table 1 reports the summary statistics. The sample average of WC claims per 1 million population is about 0.39, with the average workplace accident rate per 1 million population at around a similar level at 0.34. Figure 1 presents the distribution of the total number of WC claims across ZIP code zones from 2001 to 2019. The darker the color, the greater the number of claims. In total, there are 1,036,999 claims reported. Clearly, these claims are not evenly distributed: they are more prevalent in densely populated areas with greater economic activity. For air pollution, the sample mean PM2.5 level is approximately 8 $\mu g/m^3$, ranging from 0 $\mu g/m^3$ to as high as 125 $\mu g/m^3$, while for ozone pollution, the

[9] Therefore, the temperature inversion variable essentially captures "night-time" inversion episodes. The advantage of using the night-time temperature inversion variable, a lagged measure, is that it helps to avoid the potential direct impact of temperature inversions on economic activities during the day, which could threaten the exclusion restriction. Moreover, temperature inversions are more frequent at night.

sample mean level is at about 38 parts per billion (ppb) with the highest level at around 102 ppb.

4 Research Design

Pinning down the causal effect of air pollution is challenging because air pollution is likely endogenous, and a simple OLS model may suffer from omitted variable bias and selection bias. For instance, the intensity of economic activities are correlated with both pollution and workplace accidents, raising concerns of omitted variable bias. Workers and employers can adjust the extent of exposure to pollution by, for example, changing the work schedule, calling in sick, or taking a longer lunch break. Such responses affect the incidence of workplace injuries, assuming the likelihood of workplace accidents is correlated with the length of time workers spend at work. Moreover, if the responses of workers and employers differ across locations due to unobserved factors, e.g., workers are more cautious in polluted places and thus their labor supply is more sensitive to air quality deterioration, then standard estimates may suffer from selection bias.

A typical solution is to apply the instrumental variable (IV) method. For an instrumental variable to be a valid instrument, it must be relevant to the treatment variable, i.e., it must affect the endogenous variable—in this setting, air pollution—in a nonnegligible way. Moreover, a valid IV must satisfy the exclusion restriction, i.e., the instrument must be uncorrelated with workplace safety except through its effect on air pollution.

This paper adopts the IV strategy and leverages exogenous variations of PM2.5 and ozone driven by atmospheric temperature inversions. As previously discussed, atmospheric temperature inversion is a commonly-used IV for air pollution in the environmental literature. It is an arguably plausible IV for the workplace accident outcomes for several reasons. First, there is a strong correlation between temperature inversion episodes and air pollution. To illustrate that temperature inversion episodes are correlated to PM2.5 and ozone pollution, I conduct a first-stage analysis, separately regressing the two air pollution variables, PM2.5 and ozone, on temperature inversions measured at 925hPa and

950hPa pressure levels. The estimation model consists of a full set of controls and fixed effects (as fully described below), accounting for time- and location-specific confounding factors and the impact of other weather conditions. Table 2 presents the estimation results. It shows that there is a strong and statistically significant correlation between temperature inversions and PM2.5 (which are positively correlated), and between temperature inversions and ozone (a negative correlation).[10] For instance, a one degree Celsius temperature difference at the 950 hPa pressure level is estimated to increase the daily PM2.5 level by 0.83 $\mu g/m^3$, which is equivalent to a 10% increase relative to the sample mean. In addition, given the sizable F statistics, I conclude that there is no evidence of weak instruments. Second, the atmospheric temperature inversion is a meteorological phenomenon occurred in the high altitude, and hence unlikely to directly affect economic activities and workplace safety. Moreover, since temperature inversion episodes are not near-surface phenomena, they are generally invisible to individuals who live and work on the Earth's surface. Consequently, employers and employees will not respond to temperature inversions by adjusting work schedules and intertemporal labor supply, which can indirectly affect workplace accidents and injuries. Hence, it is plausible to assume that the temperature inversion can only affect workplace accidents through its effect on air pollution, and the exclusion restriction is satisfied. Taken together, this paper leverages the exogenous and sizable—large enough to induce subclinical symptoms affecting physical and cognitive functioning—daily variations of PM2.5 and ozone driven by temperature inversion episodes to identify the causal impact of air pollution on workplace accident and injury rates.

Given that the temperature inversion can serve as a valid IV, I adopt a two-stage least squares (2SLS) model, employing the two continuous temperature inversion variables, as

[10]The negative correlation between temperature inversions and ozone is not an uncommon finding in the related literature. For example, Sager (2019) finds a negative correlation between temperature inversions and ozone levels using data from the United Kingdom.

described in Section 3, as IVs for air pollution. Specifically, I estimate the following model:

$$Y_{zdy} = \beta f(X_{zdy}) + \tau W_{zdy} + \sigma_z + \delta_{cy} + \rho_{ym} + \zeta_{zy} + \psi_k + \varepsilon_{zdy} \quad (1)$$

where z, c, d, and y denote ZIP-code, county, day, and year, respectively. m and k represent month and day of week, respectively. Y_{zdy} represents either the WC claim rate per 1,000,000 population or the accident rate per 1,000,000 population measured at the ZIP-code z, day d, and year y level. Considering that the impact of air pollution may exhibit a non-linear feature, I specify the air pollution variable X_{zdy} (PM2.5 or ozone) in polynomial form.[11] W_{zdy} denotes a vector of weather covariates. For contemporaneous weather conditions, I control for daily maximum, minimum, and mean temperatures, a binary indicator of precipitation, and the polynomials of daily accumulative precipitation. To further account for time- and location-specific confounding factors, I control for a rich set of fixed effect in Equation (1). The preferred model includes 5-digit ZIP code (σ_z), county by year (δ_{cy}), ZIP-code by year (ζ_{zy}, month by year (ρ_{ym}), and day of week (ψ_k) fixed effects. The day of week and month by year fixed effects partial out seasonal variations of workplace injury rates, differences in rates between weekdays and weekend, and other aggregate statewide shocks. ZIP code fixed effects controls for time-invariant confounding factors that are specific to ZIP code zones. The county by year and ZIP code by year fixed effects further absorb time-varying (at the year level) county- and ZIP code-specific unobservables that may affect workplace injuries.

The coefficient of interest is β. It identifies the causal effect of air pollution on workplace injuries (measured by the WC claim rate) and accidents (measured by the accident rate), given that the temperature inversion IVs induce exogenous (and monotonic) variations in PM2.5 or ozone conditional on the controlled covariates and fixed effects (Imbens and Angrist 1994).

[11]The results presented in the main text are based on models that use the quadratic polynomials of the air pollution variable. It relaxes the constant effect assumption and permits the effect to vary, either increasing or decreasing, with the level of air pollution.

5 Empirical Results

5.1 Main Results

Based on the two temperature inversion IVs, I conduct the 2SLS estimations separately for the PM2.5 and ozone variables. The estimation results are summarized in Table 3. Column (1) shows that the effect of PM2.5 is not statistically distinguishable from zero when the PM2.5 variable is specified linearly. However, after accounting for the potential non-linear feature of the PM2.5 effect, Column (2) show a statistically significant positive and increasing effect of PM2.5. Figure 2 presents the marginal effects of PM2.5 at 10 $\mu g/m^3$ to 36 $\mu g/m^3$. The estimated effect increases from approximately 0.8 percentage points when PM2.5 is 12 $\mu g/m^3$ to more than 8 percentage points when PM2.5 is above 30 $\mu g/m^3$. An effect of 8 percentage points suggests that increasing PM2.5 by 1 $\mu g/m^3$ when the PM2.5 level is at 30 $\mu g/m^3$ would increase the total WC claims per 1,000,000 population by 0.08, which is equivalent to a 21% increase relative to the sample mean. This impact is smaller at around 2% when PM2.5 pollution is at a lower level, e.g., 12 $\mu g/m^3$.

In contrast, the effect of ozone on WC claims is likely linear. Column (3) implies a statistically positive impact of ozone. A increase of ozone by 10 ppb is found to increase the WC claims by about 0.7 percentage points, equivalent to an increase of 1.8% relative to the sample mean WC claims per 1 million population. Column (4) suggests that the estimated effect does not follow a non-linear pattern.

We can interpret the estimated effects in Table 3 as the "intensive" margin impact, i.e., the effect of PM2.5 and ozone on the number of workplace injuries conditional on the occurrence of workplace accidents. Another dimension that is of interest is the "extensive" margin impact, which captures how air pollution influences the likelihood of workplace incidence. To examine the extensive margin effect, I create a binary indicator of workplace accident that equals one if the daily number of WC claims are non-zero for each ZIP-code zone, and reproduce Table 3 using this accident indicator. The second stage 2SLS results are reported in Table 4. Columns (2) shows a similar non-linear impact for PM2.5. As shown in Figure 3, PM2.5 is estimated to increase the rate of workplace accidents by about 1.1 percentage points even when exposing to a small level of PM2.5 at 12 $\mu g/m^3$. This effect is equivalent to a relative increase of 3% compared to the sample mean accident rate. The effect increases substantially to 6.1 percentage points for a larger level of PM2.5 at 30 $\mu g/m^3$, which is equivalent to a percentage change of 18% relative to the sample mean rate. Unlike the effect of PM2.5, the effect of ozone on the accident rate presents a linear feature. Column (3) implies that increasing the ozone level by 10 ppb increases the workplace accident rate per 1 million population by 0.5 percentage point, equivalent to an increase of 2%.

To benchmark these estimates, we can compare them with findings from the prior work. For example, Cabral and Dillender (2024), a contemporary work investigating the impact of wildfire-driven PM2.5 pollution on workplace injuries using data from Texas, found that, on average, one day of smoke coverage is associated with an increase in daily PM2.5 level by 1.69 $\mu g/m^3$, which consequently leads to 0.165 additional injuries per 100,000 workers. This is equivalent to an effect of 0.098 additional injuries per 100,000 workers—a 17% increase relative to the sample mean rate—resulting from a 1 $\mu g/m^3$ increase in PM2.5. In this paper, the range of estimated percentage effects of general PM2.5 pollution at different levels (i.e., pollution caused by various reasons, including but not limited to wildfires) encompasses the estimates in Cabral and Dillender (2024). Specifically, a 1-$\mu g/m^3$ increase in PM2.5 is found to increase the WC claim rates by 3% - 28%, depending on the PM2.5 level. Furthermore, the findings in this paper indicate that PM2.5 and ozone, can have a similar, if not greater, impact on workplace health and safety compared to other environmental hazards, such as heat or NO_2 pollution, as well as on safety outcomes in other settings, such as road safety. For instance, Lavy, Rachkovski, and Yoresh (2022) found that a 10-ppb increase in NO_2 pollution is associated with a 0.00004 percentage point increase in the probability of workplace accidents at construction sites in Israel (a 25% increase relative to the sample mean rate) and a 0.03 increase in accidents per 100,000 workers each year. Beyond that, using data from California, Park, Pankratz, and Behrer (2021) provided evidence that hotter temperature significantly affect health at work: A high temperature day increases the same-day injury risk by 5%-7% relative to the baseline mean. Additionally, Sager (2019) studied the impact of PM2.5 on road accidents in the UK, adopting the temperature inversion IV, and found that a 1 $\mu g/m^3$ increase in PM2.5 would increase the number of vehicles involved in road accidents by 0.8%. This effect is evaluated at the mean with average PM2.5 level at 13.2 $\mu g/m^2$. Despite the different research settings and environmental hazards under study, which complicates direct comparison, the estimated impacts of PM2.5 and ozone pollution in this paper generally show similar, and even greater in certain cases, magnitudes compared to estimates found in the literature.

Lastly, air pollution from previous days might affect today's workplace injuries, as its impact can last for more than a day or take time to manifest. To examine the cumulative and lagged effects, I estimate an additional model that incorporates air pollution variables from the previous four days and the following four days into Equation (1). Figure 4 presents the estimated marginal effects for PM2.5 and ozone. Similar to Cabral and Dillender (2024) and Sager (2019), I do not find evidence of lagged or cumulative impact of PM2.5 and ozone pollution.[12]

5.2 Heterogeneity Results

There is comprehensive evidence documenting reductions in human cognitive ability due to exposure to air pollution. In addition, air pollution is found to be associated

[12] An alternative way to measure the cumulative pollution is counting the number of days with air pollution for a certain time period. For example, I calculate the number of days when the PM2.5 level was greater than 15 $\mu g/m^3$ and the number of days when the ozone level was greater than 100 $\mu g/m^3$ (equivalent to approximately 51 ppb), under the WHO standard (WHO 2021), in the past 5 days and use them as the cumulative pollution variables. I further calculate the number of days occurring temperature inversion episodes in the past five days at pressure levels 925hPa and 950hPa as two measures of the cumulative temperature inversion. Estimating Equation 1 including the cumulative pollution variable as an additional treatment variable and the cumulative temperature inversion variables as additional IVs, I find a sizable impact of the cumulative PM2.5 pollution (see Table B.1). As shown in Figure A.1, having one additional day of PM2.5 pollution is estimated to significantly increase the claim rate, and this impact is expected to grow as the number of pollution days increases. There is no statistically significant evidence of cumulative or lagged effect for ozone pollution.

with respiratory conditions, mental stress, depression, and cardiovascular conditions. Symptoms of these conditions in the workplace qualifies for workers' compensation and would be recorded in the WC claim. On the other hand, injuries associated with cognitive decline would be classified under different injury categories. Therefore, analyzing how air pollution affects injuries of different natures can shed light on the underlying causes of these effects. Based on the nature of injury codes in the data, I categorize claims into five groups: 1) traumatic injuries involving amputation, fracture, crushing, etc; 2) respiratory conditions including asthma and other respiratory disorders; 3) cardiovascular conditions such as heart attack and vascular; 4) mental conditions including mental disorders and mental stress; 5) other injuries. Estimating the preferred model Equation (1) separately for claims within each group, I present in Figures 5 and 6 the estimated effects for PM2.5 and ozone, respectively. The effects on claims of respiratory conditions, mental conditions, and cardiovascular conditions are small and indistinguishable from zero. In contrast, there is a significant effect on traumatic injuries and other injuries. This suggests that air pollution influences workplace injuries primarily via its impact on cognitive ability, rather than directly causing adverse health effects.

Using the information from WC claim records regarding the cause of injury, I further examine whether the impact of air pollution varies across injuries caused by different reasons Echoing the previous finding on the heterogeneous impact by the nature of the injury, I find that the impact of air pollution is mainly driven by cognition-related causes, such as being caught in, under, or between machinery, and fall, slip, or trip injuries, compared to other reasons such as heat or cold exposures. Specifically, I classify the causes of injury into three categories: 1) cognition-related self-caused injuries which are caused by reasons such as "Caught In, Under or Between", "Cut, Puncture, Scrape Injured By", "Fall, Slip or Trip", and "Striking Against or Stepping On"; 2) cognition-related injuries caused by others, including injuries caused by "Crash of Motor Vehicle", "Struck or Injured By Fellow Worker". These are cognition-related injuries because the decline in cognitive functions such as attention, memory, and fluid reasoning is closely associated with these types of accidents and injuries. For example, fall, slip, or trip injuries are likely to caused by lack of attention, while crashes of motor vehicle are likely due to inattention and reckless behaviors of the driver. Other causes such as "Burn or Scald – Heat or Cold Exposures" and "Miscellaneous Causes" including gunshots and natural disasters are classified as the third category. Figure 7 illustrates the results of PM2.5 for these three groups. For injuries associated with cognitive-related causes (both self-caused and caused by others), the effect of PM2.5 at 10 $\mu g/m^3$ is small and statistically indistinguishable from zero. This effect gradually increases to around 5 percentage points at 30 $\mu g/m^3$. In contrast, for injuries caused by non-cognitive-related reasons, such as heat or cold exposure, the estimated impact remains small and not statistically different from zero at all PM2.5 levels. For ozone pollution, a similar pattern is found where the effect emerges for injuries caused by cognition-related factors. As shown in Columns (1) - (3) of Table 5, the marginal effect of ozone pollution is estimated to increase injuries caused by cognition-related reasons by 0.03-0.04 percentage points. The corresponding effect is essentially zero for injuries driven by other causes.

The reported claims include various types, such as those involving medical treatment and time loss, as well as those with neither time loss nor medical treatment. Examining the impact of air pollution by claim type sheds light on how the effects of pollution on worker health translate into reduced productivity and economic losses. The threat of air pollution on workplace safety would be much less concerning if the impact were concentrated on claims without time loss. Figure 8 presents the estimated effect of PM2.5 on the two types of claims: those with medical treatment and time loss, and those without time loss. I find that the impact of PM2.5 is concentrated on claims with medical treatment and time loss, while no statistically significant impact is found on claims without time loss. Table 5 exhibits a similar pattern for ozone pollution: the effect of ozone is estimated at around 0.04 percentage points on claims with medical treatment and time loss and zero on claims with no time loss. The estimation results by claims type imply potential economic losses in labor productivity resulting from air pollution. I attempt to quantify the monetary losses from increased workplace injuries associated with air pollution in Section 6.

Furthermore, to examine the spatial distribution of air pollution impacts and identify which neighborhoods are more affected in terms of workplace safety, I categorize WC claim injury sites into four groups based on the quartiles of the median household income distribution. I estimate the effect of air pollution separately for each of the four groups. Figures 9 and 10 suggest that the effects of PM2.5 and ozone decrease with increasing income, showing no influence on workplaces in wealthier neighborhoods but significantly higher impacts on those in poorer communities. This trend is likely influenced by the sorting of industries that are dirtier and/or more hazardous in poorer neighborhoods. It highlights another aspect of environmental justice: individuals are adversely affected by environmental hazards not only depending on where they live but also where they work.

5.3 Robustness Exercises

The following section presents a number of exercises evaluating the robustness of the main results. First, to further control for unobserved confounding factors that vary across both counties and time (month-year), I experiment with adding county by month-year fixed effects to the model of Equation (1). Results are reported in Table B.2 Columns (3) and (4). Compared to the main results reported in Columns (1) and (2), controlling for this much richer set of fixed effects produces similar estimates for both PM2.5 and ozone. Although the estimates become marginally significant in this specification, which adds more than 14,472 fixed effects, the results remain significant at conventional levels. Second, in the main analyses, the robust standard errors allowing heteroskedasticity are reported. These results are robust to different choices of standard error options. For example, I show in Columns (5) and (6) that when standard errors are clustered at the ZIP-code and year level, the estimates remain significant at the 1% level. In addition to the continuous temperature inversion IV, as in Sager (2019), binary IVs that indicate the occurrence of temperature inversion episodes at various pressure levels are employed in the existing literature, e.g., Jans, Johansson, and Nilsson (2018) and Arceo, Hanna, and

Oliva (2016). Following this strand of literature, I adopt alternative temperature inversion IVs , represented by two binary indicators signifying temperature inversion episodes at 925 hPa and 950 hPa pressure levels, and reproduce Table 3. As shown in Columns (7) and (8), the estimation results employing the alternative IVs for PM2.5 and ozone resemble the original estimates in the main analyses. This implies that the estimates reported in the main text are not sensitive to the choice of IVs.

Moreover, a few studies measure WC claim rates relative to local employment.[13] Here, to gauge whether previous findings are robust to this alternative outcome variable definition, I gather county-level annual employment data from the Quarterly Census of Employment and Wages (QCEW) and construct the rate of WC claims per 1 million employees as a new outcome variable. Columns (1) and (2) in Table B.3 present the estimation results, regressing the new WC claim rate on PM2.5 and ozone, using the preferred model and the two continuous temperature inversion IVs (see Table 3). I find that the estimated impacts are of similar magnitudes in term of the percentage effect compared to those in the main finding. For instance, Column (1) reports that the marginal effect of PM2.5 measured at 12 $\mu g/m^2$ is estimated at 1.5 percentage points, equivalent to a 1% increase relative to the corresponding sample mean.[14] The estimated impact is approximately 17 percentage points, equivalent to a 13% increase for a higher level of PM2.5 at 30 $\mu g/m^3$. In comparison, the estimated percentage effects are about 2% at 12 $\mu g/m^3$ and 21% at 30 $\mu g/m^3$ in the previous findings.[15] For ozone, the estimated percentage effects are relatively smaller and at around 0.1% for both outcome variables.

Next, since WC claims (and claim rates) are count variables that are always above zero, it is natural to consider a Poisson model. Columns (3) and (4) in Table B.3 report estimates from a Poisson IV model using the same two temperature inversion IVs as in the main analyses. Column (3) shows that based on the Poisson IV model, the estimated incidence

[13] For example, Cabral and Dillender (2024) studied an outcome variable defined as the WC claims per 100,000 employees, and Lavy, Rachkovski, and Yoresh (2022) examined the number of accident per 100,000 workers.

[14] The sample mean of WC claims per 1 million employment is 1.38.

[15] The 8% difference in the estimated percentage effect for PM2.5 at 30 $\mu g/m^3$ is not statistically different from zero.

rate ratio is 1.0011 at 12 $\mu g/m^3$. It indicates that a one unit increase in PM2.5 at 12 $\mu g/m^3$ is associated with a 0.11 percentage points increase in the WC claim rate, which is slightly smaller than the number in the previous finding. The effect becomes greater at around 21% (8 percentage points) for a higher level of PM2.5 (30 $\mu g/m^3$), essentially the same as the previous estimate. As shown in Column (4), the Poisson IV model finds a greater effect compared to the result in Table 3. The estimate is around 0.4 percentage points, which is equivalent to a percentage impact of 1%. The difference between the estimates from the Poisson IV model and the 2SLS is statistically different from zero. This suggests that the 2SLS model may underestimate the impact of ozone pollution, providing a lower bound of the effect.

Furthermore, by adding PM2.5 or ozone observed 1 to 4 days ahead of the corresponding WC claim day to control for future air pollution, I show in Figure 4 that there is no effect of future air pollution (lead 1-4 days) on WC claims. Beyond that, I conduct a placebo test, randomly shuffling either the outcome variable or the air pollution variables separately and re-estimating Equation (1). Table B.4 reports the estimation results. In general, the estimates are statistically indistinguishable from zero, reinforcing the conclusion that the main findings of this paper imply causality and are not due to coincidence.

6 The Cost of Air Pollution

Workplace injuries are costly to not only injured workers and their families, but also employers and the society. The direct costs of workplace accidents and injuries include workers' compensation payments and medical expenses. In addition to these direct costs, employers also incur indirect expenses, such as repairing damaged equipment and property, training replacement employees, and conducting accident investigation and implementing of corrective measures. Serious, nonfatal workplace injuries are estimated to cost U.S. businesses more than one billion dollars a week for medical and lost-wage expenses in 2018 (Workplace Safety Index 2021). Workers' compensation benefits paid, along with the productivity loss and medical expenses incurred because of work-related deaths and injuries cost the American society more than 234 billion dollars in 2018 (National Safety Council; Weiss, Murphy, and Boden 2020). For workers, severe injuries that involve hospitalization and amputation usually result in work loss that ranges from days to weeks and even cause disabilities that would limit workers' ability to work in the future.

To quantify the monetary cost of the effect of air pollution on workplace injuries, I provide a back-of-the-envelope calculation of the air-pollution-driven changes in workers' compensation benefits paid based on the estimated effects. Specifically, previous analyses show that a 10-ppb increase in ozone is associated with an increase in WC claims per 1 million population by 0.007, while the effect of a 10-$\mu g/m^3$ increase in PM2.5 ranges from 0.08 (at 12 $\mu g/m^3$) to 1.10 (at 36 $\mu g/m^3$) per 1 million population. According to the assessment of the National Safety Council, the average cost of workers' compensation claims was $42,008 in 2018-2019.[16] Based on this statistics, the impact of a single-day 1-$\mu g/m^3$ increase of PM2.5 on workers' compensation costs per claim ranges from $330 to $4616 per 1 million population (See Table 6). The impact resulting from ozone pollution is similar to the effect of one unit increase of PM2.5, with a single-day increase of 10-ppb associated with an increase in WC costs of about $300 per 1 million population.

Furthermore, consider a scenario where a ZIP code zone experiences permanent air quality deterioration, such as the daily PM2.5 level increasing by 1 $\mu g/m^3$ throughout the year. This marginal change in PM2.5 pollution can lead to substantial costs for workers' compensation, ranging from around 0.1 million dollars per 1 million population for a region with mild PM2.5 pollution (12 $\mu g/m^3$) to more than 1.6 million dollars per 1 million population for a region with more severe PM2.5 level (36 $\mu g/m^3$). This assessment can be easily extended to the whole state of Florida and extrapolate to pollution at greater levels. For instance, consider a statewide shock that leads to a sharp increase in the daily air pollution level by, for example, 10 $\mu g/m^3$.[17] Such uniform single-day increases in PM2.5 pollution across the state are estimated to result in 247 additional injuries per 1 million population and cost workers' compensation more than $0.2 billion dollars in

[16]Source: NSC Injury Facts, https://injuryfacts.nsc.org/work/costs/workers-compensation-costs/.
[17]This could be driven by catastrophic natural disasters such as wildfire.

total.[18] The actual impact on workers' compensation associated with air pollution can be significantly higher than the above assessment due to several reasons. First, although the WC insurance program is mandatory in Florida, WC claims do not necessarily cover all workplace injuries. Therefore, the estimated impact on workplace injuries may be understated. Second, air quality deterioration episodes usually occur periodically and last for multiple days. Evaluations based on a single-day air quality change likely underestimate the impact. Lastly, in some hot-spot regions, where higher PM2.5 levels have been observed, the impact of PM2.5 is significantly higher than the estimate used in the previous assessments. Thus, these regions should anticipate a considerably greater increase in workers' compensation costs. In summary, the previously discussed estimates of the costs of air pollution on workers' compensation should be interpreted with caution and can be recognized as the lower bound of the actual impact.

7 Conclusion

This paper investigates whether air pollution, in particular, PM2.5 and ozone, impairs worker health and workplace safety, using comprehensive administrative data on workers' compensation claims from Florida. Containing the precise information on location and date of occurred workplace injuries, the WC claim data allows researchers to link it to air pollution and climate data measured at a finer geographical area, reducing the measurement error. Adopt an instrumental variable method and an arguably valid instrument that satisfies both the exclusion restriction and the monotonicity assumption, I leverage plausibly exogenous variations in air pollution driven by atmospheric temperature inversion episodes to identify the causal impact. A rich set of fixed effects is included in the preferred model to absorb location-specific and temporal variations and further control

[18]Costs = $0.0164 \times 10\ \mu g/m^3 \times \$42008 \times 1506$ ZIP code zones $\times 21.73 = \$225,455,353.14$. This assessment is based on the estimate measured at 14 $\mu g/m^3$ and Florida's total population (21.73 million) from the 2020 Census. As shown in the Appendix Figure A.2 which presents the share of days with PM2.5 above 15 $\mu g/m^2$ from 2002 to 2019, each ZIP code zone has been observed to experience at least 6% of days (394 days) with PM2.5 levels above $\mu g/m^2$. Therefore, I adopt the effect evaluated at 14 $\mu g/m^2$ as a proxy. Intuitively, one can imagine the increase of 10 $\mu g/m^2$ occurring on a day with a PM2.5 level of 14 $\mu g/m^2$.

for time-varying unobservables.

I find that air pollution, especially PM2.5, significantly increase workplace injuries. The estimated effects exhibit a non-linear pattern, with the impact increasing with rising pollution levels. Specifically, a one-unit increase in PM2.5 at 12 $\mu g/m^3$ is associated with an increase in WC claims per 1 million population by 0.8 percentage points (equivalent to a 2% increase relative to the sample mean claim rate), while this effect is estimated to be approximately 8 percentage points, equivalent to a 21% increase, when PM2.5 at 30 $\mu g/m^3$. The effect of ozone pollution is linear and relatively smaller compared to the effect of PM2.5. A 10-ppb increase in ozone is found to increase WC claims per 1 million population by 0.7 percentage points, equivalent to an increase of around 2% relative to the baseline sample mean. Including additional controls for air pollution lags, I find no evidence of lagged or cumulative impacts, indicating that the estimated effects are primarily driven by acute exposure.

These findings add to the emerging literature on the so-called "non-health" effects of environmental hazards and studies on air pollution and workplace safety broadly. This study demonstrates that, beyond affecting worker productivity—typically measured by wages and piece-rate outputs—and game performance as previously reported, air pollution can also influence workers' on-the-job performance and increase the risk of workplace injuries. These contemporaneous effects on injury risk can be far-reaching, with prolonged or long-term implications for lifetime productivity and future work capacity.

Pathophysiological studies show strong evidence that PM2.5 and ozone exposures affect human physical and cognitive functioning and lead to acute health events or subclinical symptoms, depending on the extent of exposure. Consequently, declines in physical and cognitive ability likely affect workers' on-the-job performance, thus increasing the risk of workplace injuries. In line with this hypothesis, by analyzing the different impacts across injury categories defined by their nature and cause, I find that the impact of PM2.5 and ozone is concentrated on traumatic injuries rather than respiratory, cardiovascular, or mental conditions. Additionally, these pollutants are more associated with injuries caused by cognitive-related issues such as falls, slips, cuts, and being caught in machinery, rather than other causes such as burns, scalds, gunshots, or natural disasters. These findings shed important light on the mechanisms behind the estimated effects: air pollution-associated reductions in physical and cognitive functions are likely the driving force contributing to the increased injury risks. This is the same force behind the impacts of environmental hazards on various "non-health" outcomes, as documented in prior work. This paper thus illustrates that the same biological channel also influences workplace injuries and worker productivity.

Furthermore, the back-of-the-envelope calculation in Section 6 suggests a sizable impact on workers' compensation costs associated with even a one-unit increase in ambient air pollution. The induced costs are particularly greater for PM2.5 compared to ozone pollution, and are sizable even for pollution levels below the current regulatory standards.

Taken together, the above findings have important policy implications. First, these findings suggest that improving air quality can potentially benefit both employers and employees, likely reducing labor productivity loss and both the direct and indirect costs of work-related injuries. It calls for caution in the benefit and cost evaluation of environmental policies. Without considering the likely gains from improving workplace safety, the benefits of environmental policies that intend to improve air quality, whether outdoor or indoor, are likely to be underestimated. Second, echoing policy discussions on whether to strengthen the EPA's National Ambient Air Quality Standards (NAAQS) for Particulate Matter (PM), the substantial impacts of daily ambient PM2.5 at levels below the EPA's regulatory standards found in this study support the suggestion to further reduce the 24-hour NAAQS standards.[19] Lastly, this paper provides rigorous evidence of the adverse impacts of PM2.5 and ozone on worker health and workplace safety. By demonstrating the extensive harms of air pollution, it informs OSHA's policies targeting worker exposure to air pollution and promotes a thorough evaluation of optimal regulatory measures to

[19] On February 7, 2024, EPA changed the annual PM2.5 standard from 12 $\mu g/m^3$ to 9 $\mu g/m^3$, while retained the 24-hour PM2.5 standard at 35 $\mu g/m^3$. Source: https://www.epa.gov/pm-pollution/final-reconsideration-national-ambient-air-quality-standards-particulate-matter-pm.

mitigate associated risks. In particular, the greater impacts found at higher PM2.5 levels and in poorer neighborhoods, along with the heterogeneous effects across PM2.5 and ozone, imply potential benefits in allocating limited regulatory resources towards these hot-spot regions and specific air pollutants, such as PM2.5.

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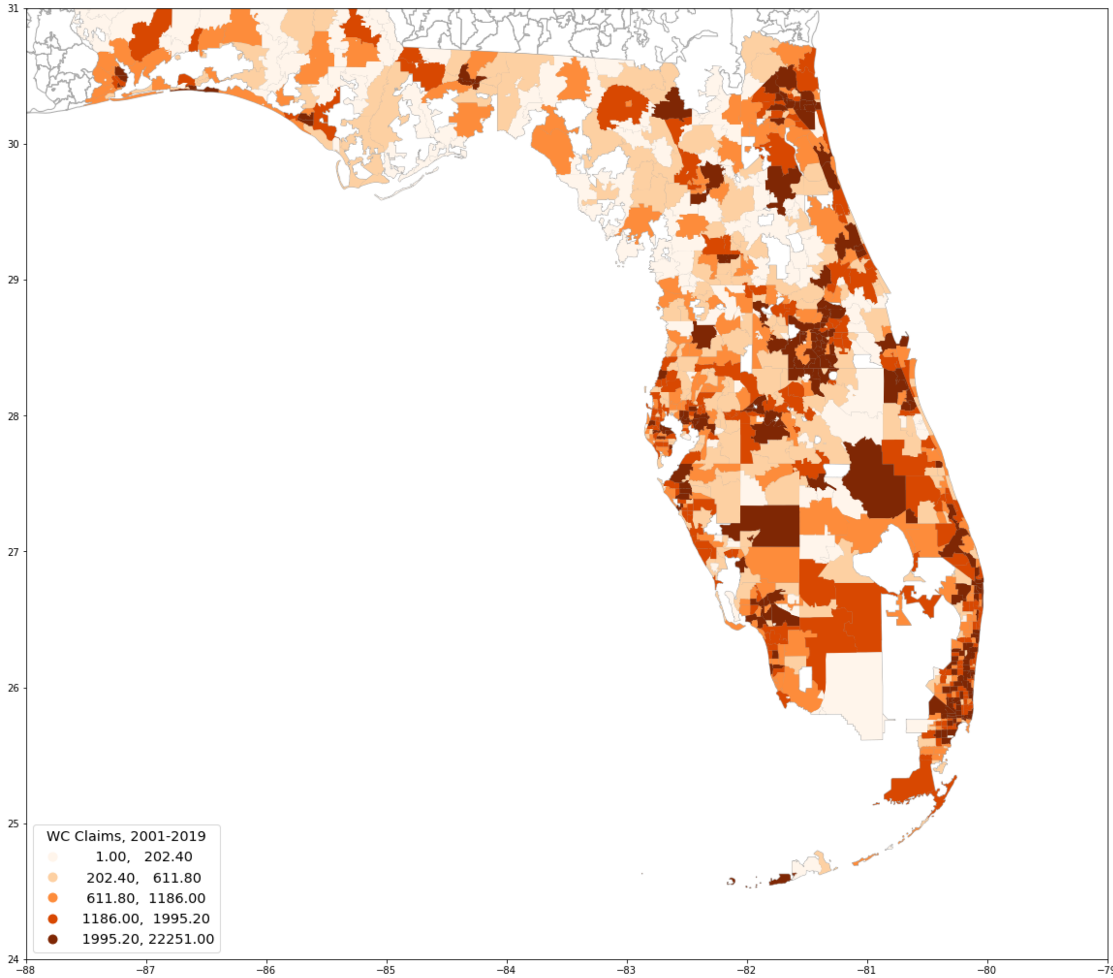


Figure 1: WC Claims, 2001-2019

Notes: This figure plots the total number of workers' compensation claims from 2001 to 2019 across Florida's 5-digit ZIP code zones.

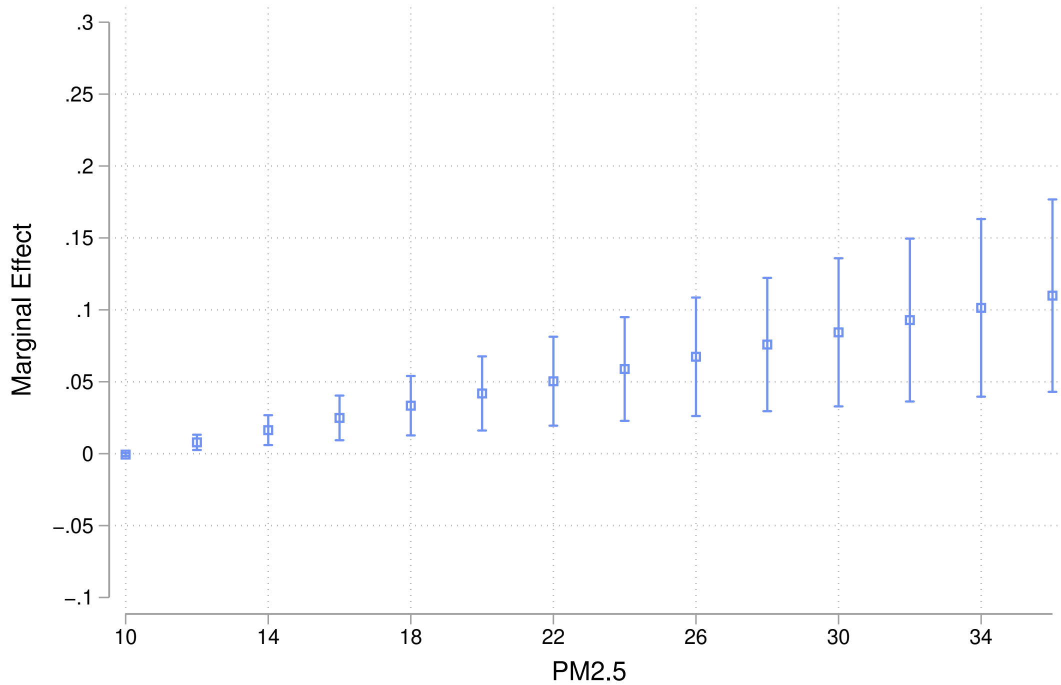


Figure 2: 2SLS Intensive Margin Effects, PM2.5

Notes: This figure reports the estimated marginal effect and its 95% confidence intervals for PM2.5 levels spanning from 10 $\mu g/m^3$ to 36 $\mu g/m^3$ on the WC claim rate. The estimation model includes controls for ZIP code, county-year, ZIP code-year, year-month, and day of week fixed effects, as well as time-varying weather covariates.

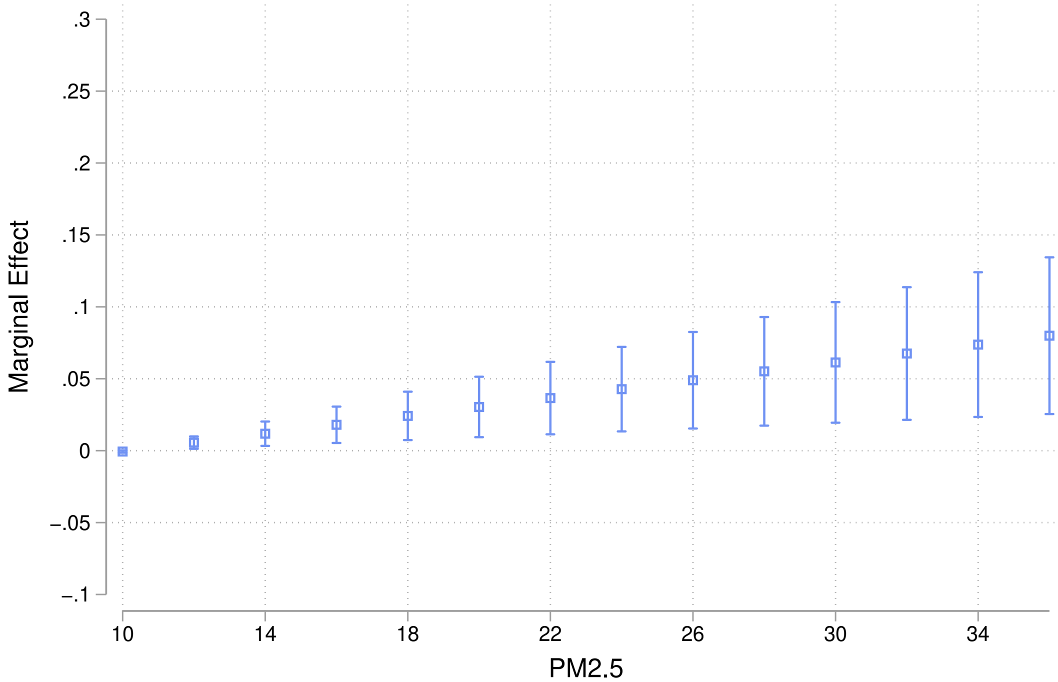


Figure 3: 2SLS Extensive Margin Effects, PM2.5

Notes: This figure reports the estimated marginal effect and its 95% confidence intervals for PM2.5 levels spanning from 10 $\mu g/m^3$ to 36 $\mu g/m^3$ on the binary variable indicating workplace injuries. The estimation model includes controls for ZIP code, county-year, ZIP code-year, year-month, and day of week fixed effects, as well as time-varying weather covariates.

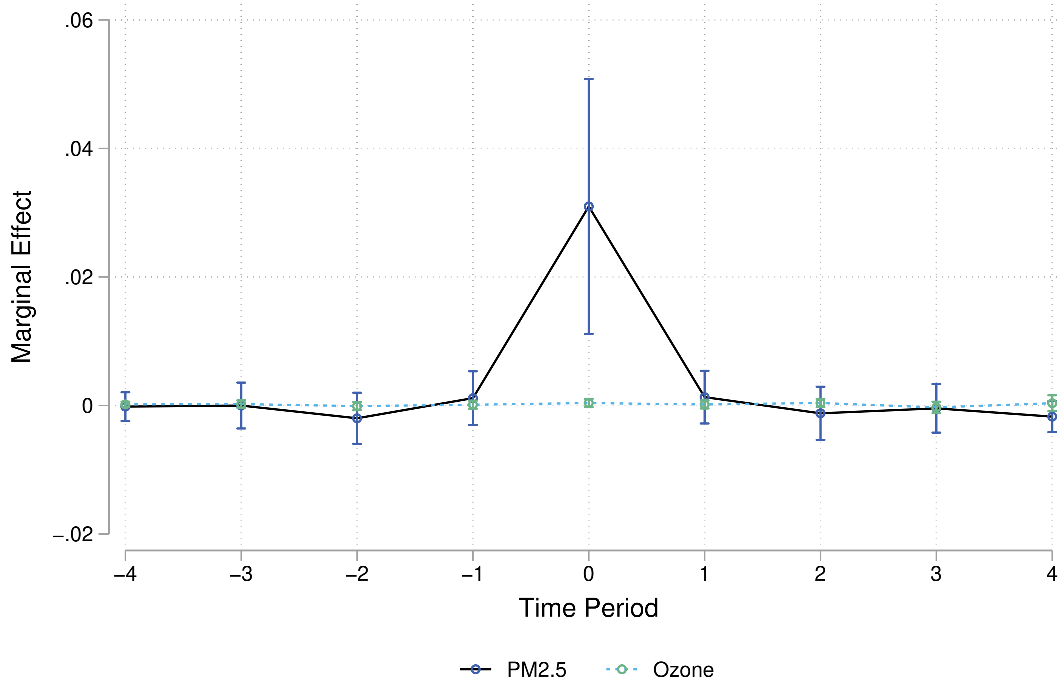


Figure 4: 2SLS Lagged Effects

Notes: This figure presents the estimated marginal effects of PM2.5 and ozone on the WC claim rate, along with their 95% confidence intervals. The estimation model incorporates air pollution variables measured over four lag periods and four lead periods. The marginal effect of PM2.5 during the zero period is evaluated at 30 $\mu g/m^3$. The model accounts for fixed effects by ZIP code, county-year, ZIP code-year, year-month, and day of the week, as well as time-varying weather covariates.

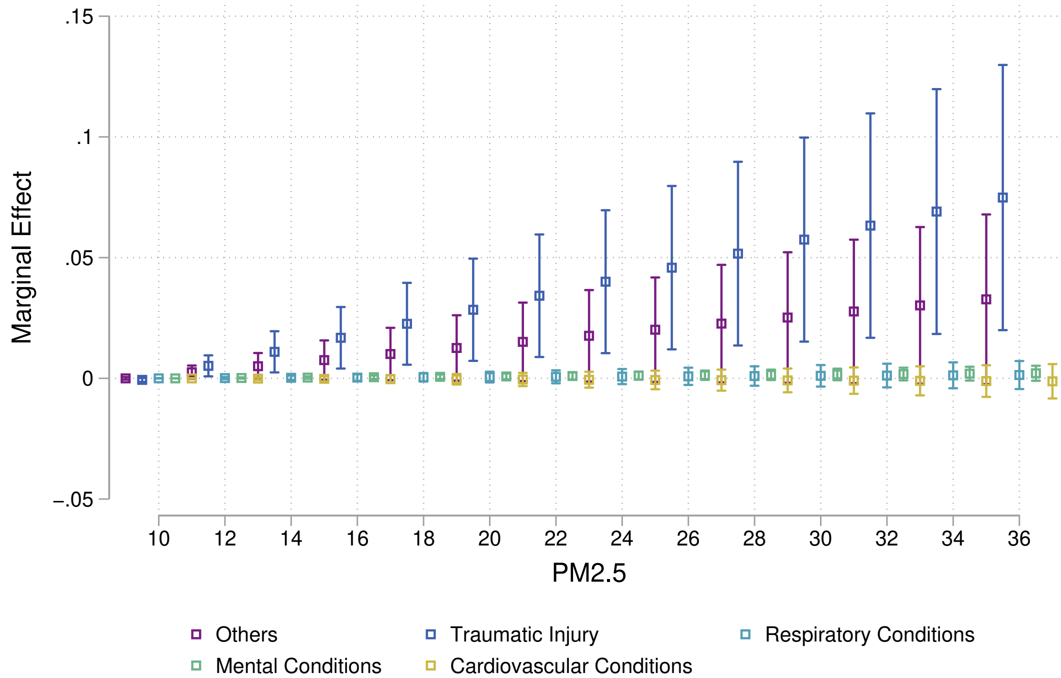


Figure 5: Heterogeneity by Nature of Injury, PM2.5

Notes: This figure reports the estimated marginal effect and its 95% confidence intervals for PM2.5 levels spanning from 10 $\mu g/m^3$ to 36 $\mu g/m^3$ on the WC claim rate by the nature of injury. WC claims are categorized into five groups based on the nature of injury codes: 1) traumatic injuries involving amputation, fracture, crushing, etc; 2) respiratory conditions including asthma and other respiratory disorders; 3) cardiovascular conditions such as heart attack and vascular; 4) mental conditions including mental disorders and mental stress; 5) other injuries.

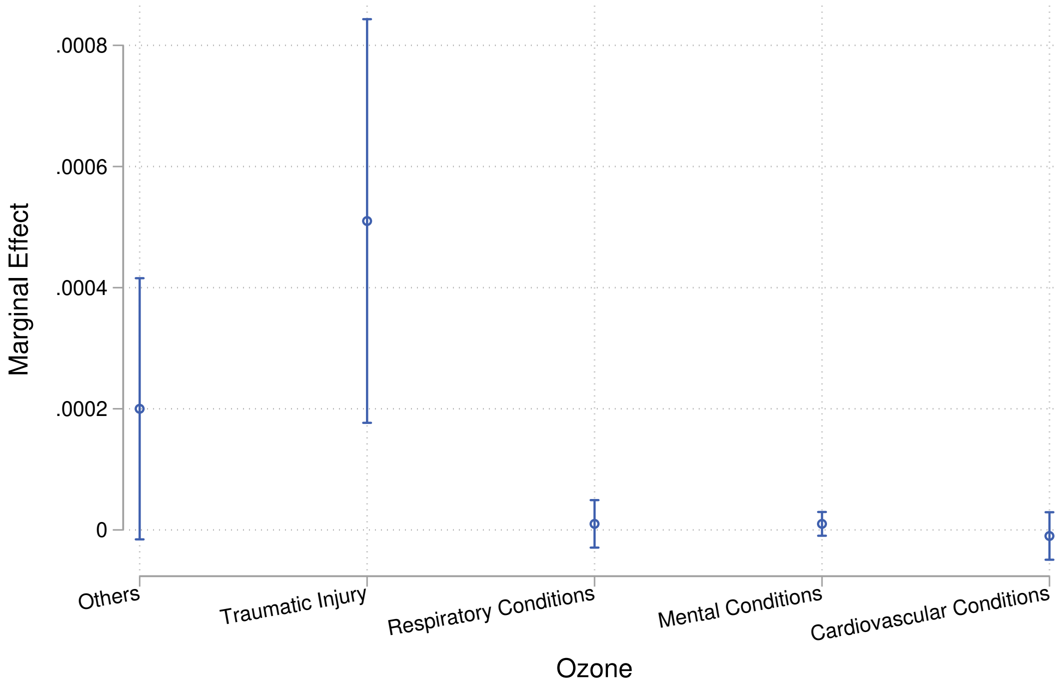


Figure 6: Heterogeneity by Nature of Injury, Ozone

Notes: This figure reports the estimated marginal effect and its 95% confidence intervals for ozone pollution on the WC claim rate by the nature of injury. WC claims are categorized into five groups based on the nature of injury codes: 1) traumatic injuries involving amputation, fracture, crushing, etc; 2) respiratory conditions including asthma and other respiratory disorders; 3) cardiovascular conditions such as heart attack and vascular; 4) mental conditions including mental disorders and mental stress; 5) other injuries.

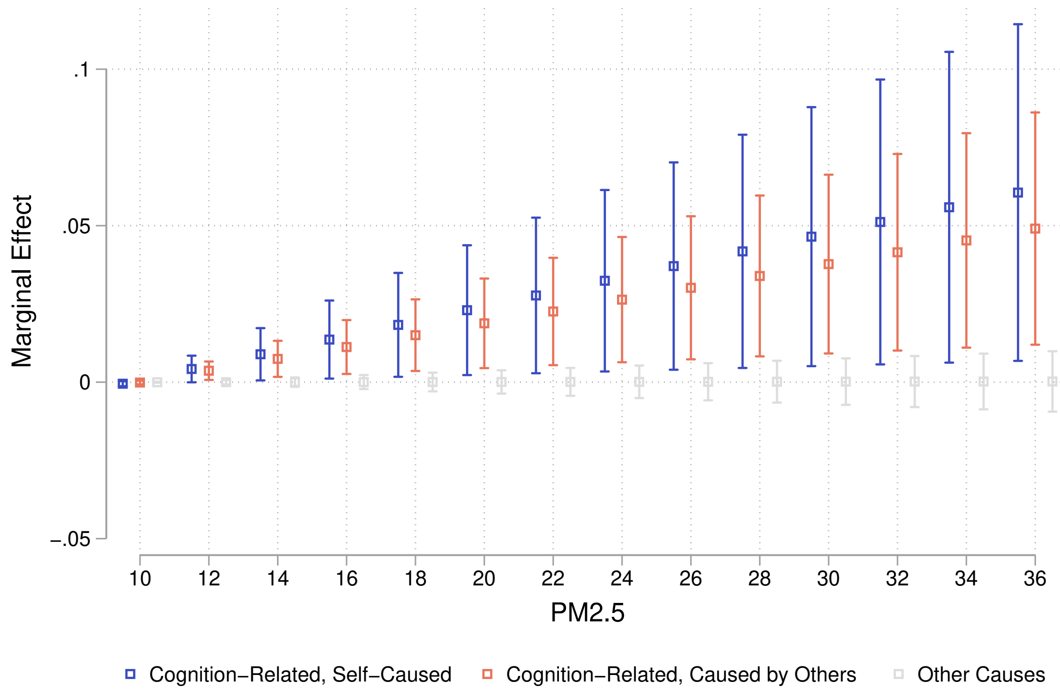


Figure 7: Heterogeneity by Cause of Injury, PM2.5

Notes: This figure reports the estimated marginal effect and its 95% confidence intervals for PM2.5 levels spanning from 10 $\mu g/m^3$ to 36 $\mu g/m^3$ on the WC claim rate by the cause of injury. I classify the causes of injury into three categories: 1) Cognition-related self-caused injuries which are caused by reasons such as “Caught In, Under or Between”, “Cut, Puncture, Scrape Injured By”, “Fall, Slip or Trip”, and “Striking Against or Stepping On”. 2) Cognition-related injuries caused by others, including injuries caused by “Crash of Motor Vehicle”, “Struck or Injured By Fellow Worker”. These are cognition-related injuries because the decline in cognitive functions such as attention, memory, and fluid reasoning is closely associated with these types of accidents and injuries. For example, fall, slip, or trip injuries are likely to caused by lack of attention, while crashes of motor vehicle are likely due to inattention and reckless behaviors of the driver. 3) Other causes such as “Burn or Scald – Heat or Cold Exposures” and “Miscellaneous Causes” including gunshots and natural disasters are classified as the third category.

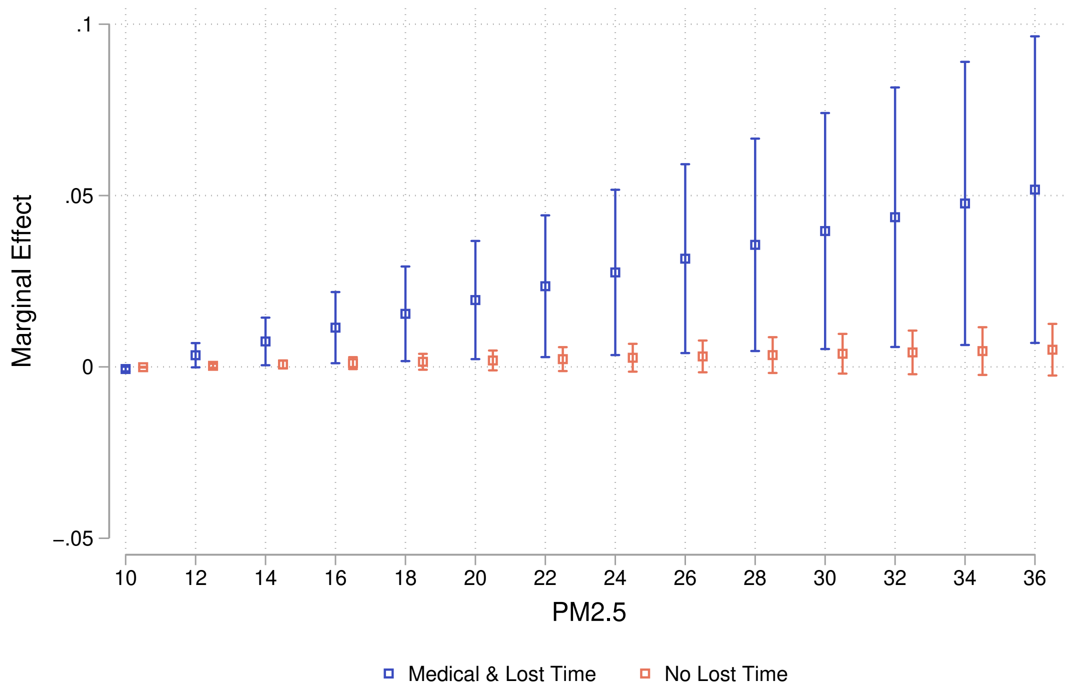


Figure 8: Heterogeneity by Claim Type, PM2.5

Notes: This figure reports the estimated marginal effect and its 95% confidence intervals for PM2.5 levels spanning from 10 $\mu g/m^3$ to 36 $\mu g/m^3$ on the WC claim rate by the claim type. WC claims are grouped into two categories: 1) claims with medical treatment and time loss, and 2) claims without medical treatment or time loss.

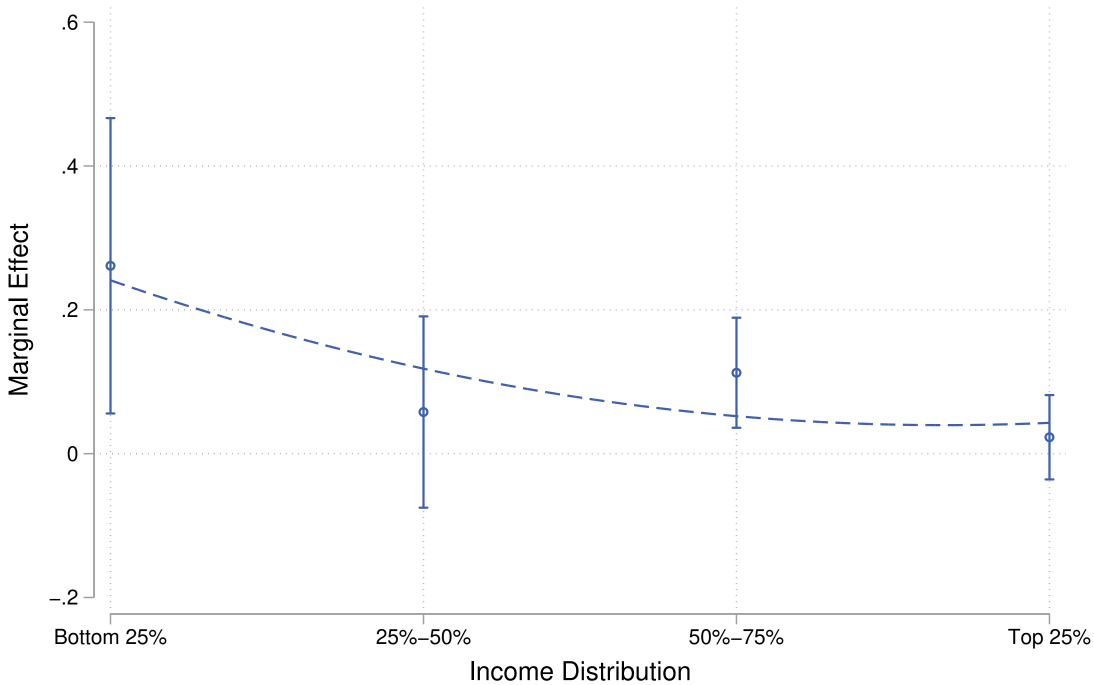


Figure 9: Heterogeneity by Spatial Income Distribution, PM2.5

Notes: This figure illustrates the estimated marginal effect of PM2.5, evaluated at 30 $\mu g/m^3$, along with its 95% confidence intervals, on the WC claim rate across neighborhood groups classified by income distribution. WC claim injury sites are divided into four groups based on quartiles of the median household income distribution.

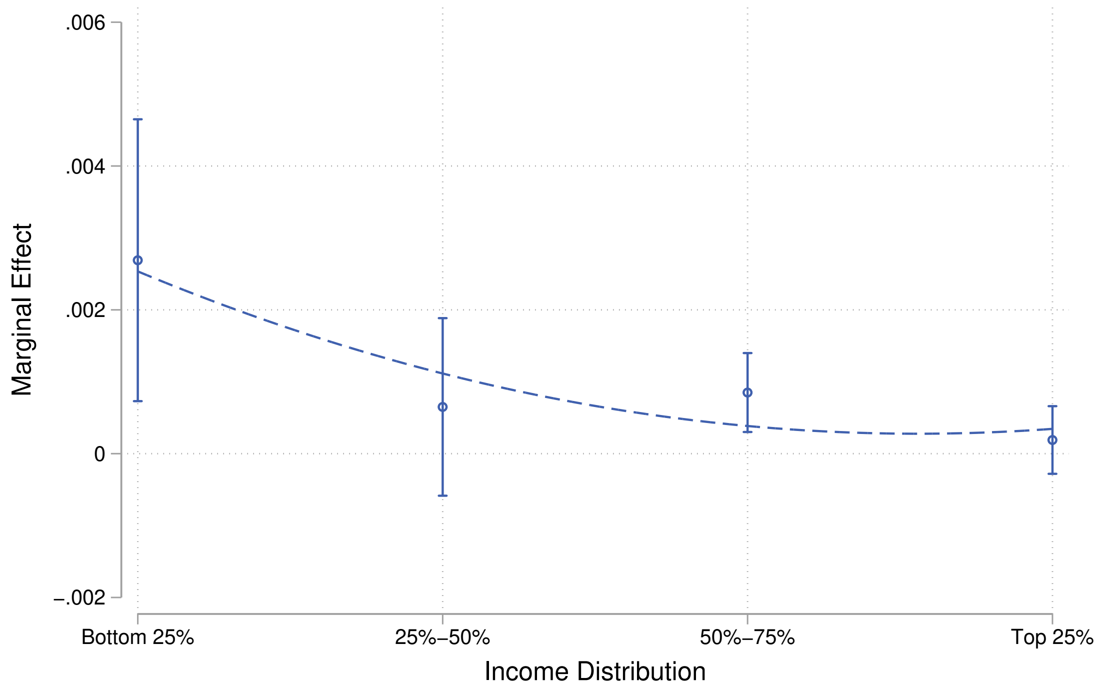


Figure 10: Heterogeneity by Spatial Income Distribution, Ozone

Notes: This figure illustrates the estimated marginal effect of ozone, along with its 95% confidence intervals, on the WC claim rate across neighborhood groups classified by income distribution. WC claim injury sites are divided into four groups based on quartiles of the median household income distribution.

Table 1: Summary Statistics

	(1)	(2)	(3)	(4)	(5)
	N	Mean	Std.	Min	Max
Workplace Safety					
WC Total Claims	10450134	0.12	0.42	0	96
WC Total Claims per 1,000,000 Population	10450134	0.39	3.24	0	886
Any Accident	10450134	0.10	0.30	0	1
Any Accident per 1,000,000 Population	10450134	0.34	2.85	0	142
Air Pollution					
Ozone (ppb)	9900444	37.63	11.13	2	102
PM2.5 ($\mu g/m^3$)	9900444	8.14	3.75	0	125
Weather					
Daily Precipitation (mm/day)	10450134	3.93	9.84	0	446
Any Precipitation	10450134	0.55	0.50	0	1
Maximum Temperature (°C)	10450134	27.87	5.31	-3	41
Minimum Temperature (°C)	10450134	17.01	6.83	-10	32
Mean Temperature (°C)	10450134	22.55	5.80	-6	33
Temperature Inversion (@925hPa)	9964021	-2.58	1.28	-5	11
Temperature Inversion (@950hPa)	9964021	-1.33	0.70	-3	7
Any Temperature Inversion (@925hPa)	9964021	0.04	0.20	0	1
Any Temperature Inversion (@950hPa)	9964021	0.04	0.20	0	1

Notes: This table reports the summary statistics for the analysis sample.

Table 2: First Stage Results

	(1)	(2)	(3)	(4)
	PM2.5		*Ozone*	
Temperature Inversions (@925hPa)	0.3344***		-0.8618***	
	(0.0009)		(0.0025)	
Temperature Inversions (@950hPa)		0.8304***		-0.7619***
		(0.0017)		(0.0048)
N	9439881	9439881	9439881	9439881
F-Stats	121733	265	96755	14406
R^2	0.31	0.32	0.48	0.47

Notes: Robust standard errors in parentheses. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$. The estimation adopts the preferred model with ZIP code, county-year, ZIP code-year, year-month, and day of week fixed effects, as well as weather covariates. First-stage Kleibergen-Paap F statistics are reported.

Table 3: Second Stage 2SLS Regression Results, Intensive Margin

	(1)	(2)	(3)	(4)
	Outcome: WC Total Claims per 1,000,000 Population			
PM2.5	-0.0007	-0.0432***		
	(0.0005)	(0.0131)		
$PM2.5^2$		0.0021***		
		(0.0007)		
Ozone			0.0007***	0.0025
			(0.0002)	(0.0020)
$Ozone^2$				-0.00002
				(0.00003)
N	9439881	9439881	9439881	9439881
First Stage F-Stats	121733	265	96755	14406

Notes: Robust standard errors in parentheses. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$. Standard errors are weighted by population. The estimation adopts the preferred model with ZIP code, county-year, ZIP code-year, year-month, and day of week fixed effects, as well as weather covariates. First-stage Kleibergen-Paap F statistics are reported.

Table 4: Second Stage 2SLS Regression Results, Extensive Margin

	(1)	(2)	(3)	(4)
	Outcome: Any Accident per 1,000,000 Population			
PM2.5	-0.0007	-0.0316***		
	(0.0004)	(0.0107)		
$PM2.5^2$		0.0016***		
		(0.0005)		
Ozone			0.0005***	0.0023
			(0.0002)	(0.0016)
$Ozone^2$				-0.00002
				(0.00002)
N	9439881	9439881	9439881	9439881
First Stage F-Stats	121733	265	96755	14406

Notes: Robust standard errors in parentheses. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$. Standard errors are weighted by population. The estimation adopts the preferred model with ZIP code, county-year, ZIP code-year, year-month, and day of week fixed effects, as well as weather covariates. First-stage Kleibergen-Paap F statistics are reported.

Table 5: Heterogeneity Results, Ozone

	(1)	(2)	(3)	(4)	(5)
	Outcome: WC Total Claims per 1,000,000 Population				
	By Cause of Injury			By Claim Type	
	Cognition-Related		Other Causes	Medical+	No Time Loss
	Self-Caused	Caused By Others			
Ozone	0.0004**	0.0003***	0.0000	0.0004**	0.0000
	(0.0002)	(0.0001)	(0.00003)	(0.0002)	(0.0000)
N	9439881	9439881	9439881	9439881	9439881

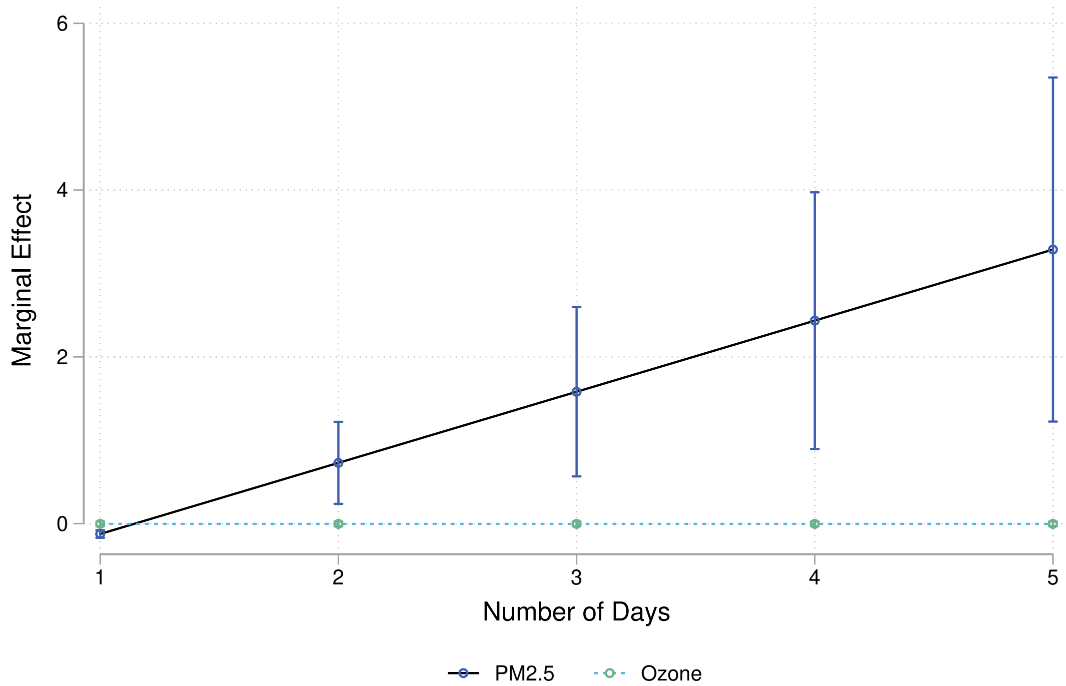
Notes: Robust standard errors in parentheses. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$. Standard errors are weighted by population. The estimation adopts the preferred model with ZIP code, county-year, ZIP code-year, year-month, and day of week fixed effects, as well as weather covariates. First-stage Kleibergen-Paap F statistics are reported. "Medical+" denotes claims involving medical treatment and time loss.

Table 6: Estimation of Workers' Compensation Costs

	(1)	(2)	(3)	(4)
Pollutant Type	Estimates	Unit(s) of Change	Expenses per Claim	Increased Costs per Claim
PM2.5 ($\mu g/m^3$) @				
12	0.00786	1	42008	330.18288
14	0.01636	1	42008	687.25088
16	0.02486	1	42008	1044.31888
18	0.03336	1	42008	1401.38688
20	0.04187	1	42008	1758.87496
22	0.05037	1	42008	2115.94296
24	0.05887	1	42008	2473.01096
26	0.06737	1	42008	2830.07896
28	0.07587	1	42008	3187.14696
30	0.08437	1	42008	3544.21496
32	0.09288	1	42008	3901.70304
34	0.10138	1	42008	4258.77104
36	0.10988	1	42008	4615.83904
Ozone (ppb)				
-	0.00073	10	42008	306.6584

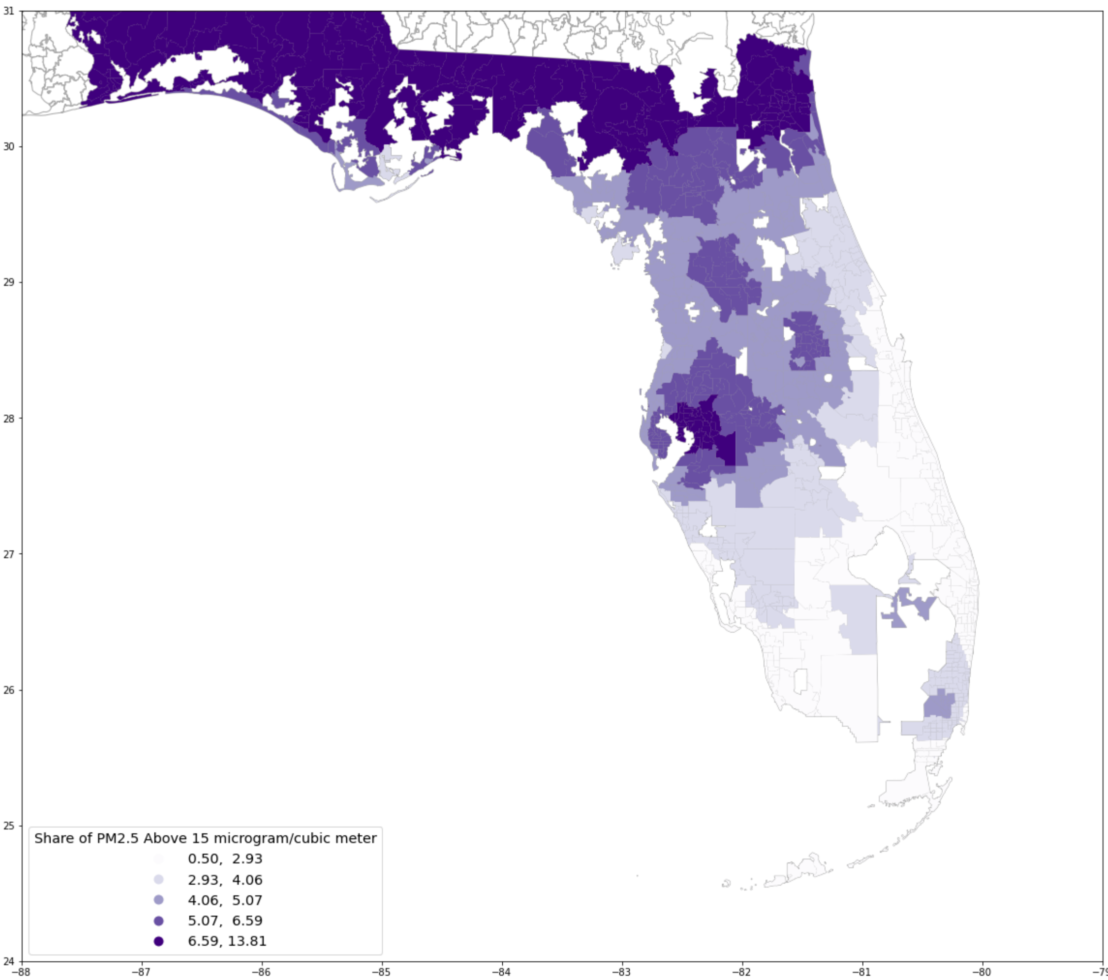
Notes: This table presents a back-of-the-envelope calculation of the impact of a single-day increase in PM2.5 (by 1 $\mu g/m^3$) and ozone (by 10 ppb) on workers' compensation costs per claim. The cost per claim is derived from the National Safety Council's evaluation of the average workers' compensation claim expenses for 2018-2019. Estimates of the marginal effect of PM2.5 and ozone are based on the results in Table 3 Columns (2) and (3), respectively.

A Figures



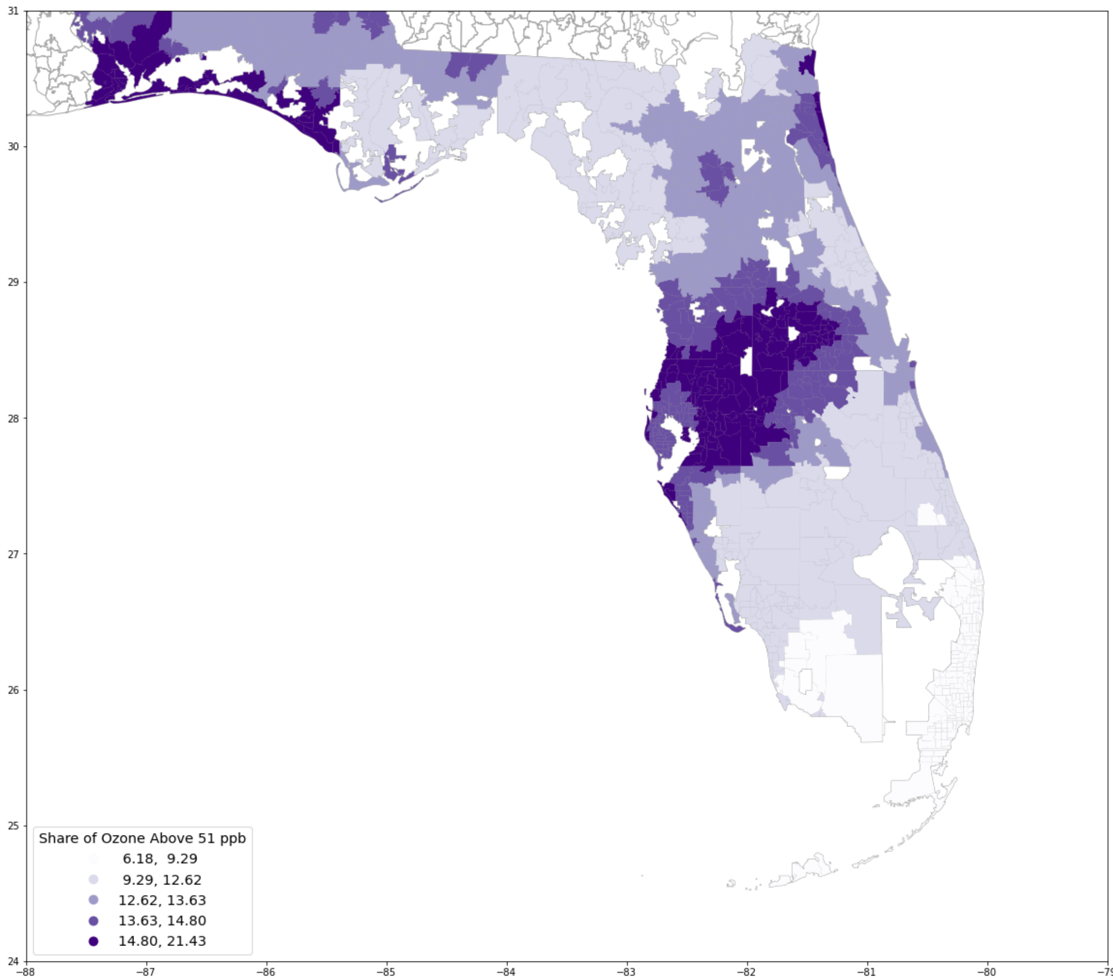
A.1: 2SLS Cumulative Effects

Notes: This figure reports the estimated marginal effects and their 95% confidence intervals for the number of PM2.5 and ozone pollution days over the past five days on the WC claim rate, based on the estimates in Appendix Table B.1.



A.2: The Share of PM2.5 Pollution Days, 2002-2019

Notes: This figure displays the spatial distribution of the share of PM2.5 pollution days from 2001 to 2019 across Florida's 5-digit ZIP code zones, based on the WHO standard where PM2.5 levels exceed 15 $\mu g/m^3$. The darker the color, the higher the frequency of PM2.5 pollution days.



A.3: The Share of Ozone Pollution Days, 2002-2019

Notes: This figure displays the spatial distribution of the share of ozone pollution days from 2001 to 2019 across Florida's 5-digit ZIP code zones, based on the WHO standard where ozone levels exceed 51 ppb. The darker the color, the higher the frequency of ozone pollution days.

B Tables

B.1: Cumulative Exposure Results

	(1)	(2)
	Outcome: WC Total Claims per 1,000,000 Population	
PM2.5	-0.03900***	
	(0.01490)	
PM2.5^2	0.00185**	
	(0.00075)	
# of PM2.5 Exposure Past 5 Days	-0.97681***	
	(0.28486)	
# of PM2.5 Exposure Past 5 Days^2	0.42639***	
	(0.13370)	
Ozone		0.00105***
		(0.00032)
# of Ozone Exposure Past 5 Days		-0.00285
		(0.01461)
N	9439881	9439881

Notes: Robust standard errors in parentheses. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$. Standard errors are weighted by population. This table presents the estimation results using an alternative method to measure cumulative pollution, specifically by counting the number of days with air pollution over the past five days. A PM2.5 pollution day is defined as a day when the PM2.5 level exceeds 15 $\mu g/m^3$, while an ozone pollution day is defined as a day when the ozone level exceeds 100 $\mu g/m^3$ (approximately 51 ppb), according to the WHO standard (WHO 2021). The model incorporates fixed effects for ZIP code, county-year, ZIP code-year, year-month, and day of the week. It also accounts for spontaneous air pollution and time-varying weather covariates.

B.2: Robustness Results (1/3)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Outcome: WC Total Claims per 100,000 Employment							
	Original Results		*Additional FEs*		*Alternative Clustering Level*		*Alternative IVs*	
PM2.5	-0.0316***		-0.0227*		-0.0432***		-0.0363***	
	(0.0107)		(0.0134)		(0.0084)		(0.0071)	
$PM2.5^2$	0.0016***		0.0011*		0.0021***		0.0018***	
	(0.0005)		(0.0007)		(0.0004)		(0.0004)	
Ozone		0.0005***		0.0004*		0.0007***		0.0008***
		(0.0002)		(0.0002)		(0.0001)		(0.0001)
First Stage F-Stats	265	96755	269.05	85869.18	265.84	97006.13	196.03	49939.56
N	9439881	9439881	9439881	9439881	9439881	9439881	9439881	9439881
Cty-Month-Year FE			✓	✓				
Two-way Clustering					✓	✓		
Binary IVs							✓	✓

Notes: Robust standard errors in parentheses. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$. Standard errors are weighted by population. This table summarizes the results of the robustness check. Columns (1) and (2) display the original results from the main text for comparison. Columns (3) and (4) provide estimates from a model that adds county-by-month-year fixed effects to the model in Equation (1). Columns (5) and (6) present standard errors clustered at the ZIP code and year levels. The final two columns report estimates using two binary indicators for temperature inversion episodes at the 925 hPa and 950 hPa pressure levels as alternative instrumental variables for PM2.5 and ozone.

B.3: Robustness Results (2/3)

	(1)	(2)	(3)	(4)
	Outcome: WC Total Claims per 1,000,000 Employment		*Outcome: WC Total Claims per 1,000,000 Population*	
	2SLS Model		Poisson IV Model	
PM2.5	-0.0909**		-0.0507***	
	(0.0357)		(0.0143)	
$PM2.5^2$	0.0044**		0.0022***	
	(0.0018)		(0.0008)	
Ozone		0.0016***		0.0043***
		(0.0006)		(0.0010)
First Stage F-Stats	274.45	94878.28	274.45	94878.28
N	9439881	9439881	9439881	9439881
Incidence Rate Ratio			1.0011(@12), 1.0836(@30)	1.0043

Notes: Robust standard errors in parentheses. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$. The estimation adopts the preferred model with ZIP code, county-year, ZIP code-year, year-month, and day of week fixed effects, as well as weather covariates. Columns (1) and (2) display the estimation results using the workers' compensation claim rate relative to local employment as the outcome. County-level annual employment data is collected from the Quarterly Census of Employment and Wages (QCEW). Columns (3) and (4) report the estimates and the incidence rate ratios from a Poisson IV model.

B.4: Robustness Results (3/3)

	(1)	(2)	(3)	(4)
	Shuffled Outcome		Shuffled Treatment	
PM2.5	0.03623		-0.03058	
	(0.05667)		(0.05026)	
PM2.5^2	-0.00182		0.00138	
	(0.00284)		(0.00252)	
Ozone		-0.00057		0.00066
		(0.00091)		(0.00081)
N	9439881	9439881	9439881	9439881

Notes: Robust standard errors in parentheses. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$. This table presents the results of a placebo test, randomly shuffling either the outcome variable (as shown in Columns 1 and 2) or the air pollution variables (see Columns 3 and 4) separately and re-estimating Equation (1). The estimation adopts the preferred model with ZIP code, county-year, ZIP code-year, year-month, and day of week fixed effects, as well as weather covariates.