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AIR POLLUTION, WILDFIRE SMOKE, AND WORKER HEALTH

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ABSTRACT

Little is known about how pollution impacts worker health and workplace safety. This paper leverages high-frequency, plausibly exogenous variation in wildfire smoke to estimate the impact of pollution on workplace injuries. Our analysis draws on unique data we construct through linking information on smoke plumes and pollution to comprehensive administrative data on workers' compensation injury claims from Texas. We first document that wildfire smoke increases ambient air pollution—with our estimates indicating that a day of smoke coverage is associated with an average increase in $PM_{2.5}$ of 18.6%. We find that an additional day of smoke coverage leads to a 2.8% increase in workplace injury claims. Similar percent increases in workplace injuries are found across different types of injuries and workers. However, because of large variation in baseline injury risk, the incidence of these pollution-induced injuries is concentrated among workers in high-risk occupations, and supplemental analysis illustrates potential opportunities for improving the targeting of costly mitigation. Our estimates indicate that pollution—and wildfire smoke in particular—substantially harms worker health, even at pollution levels well below current and proposed regulatory standards. Overall, our findings suggest workers face unique risks from pollution and provide insights for policy aiming to address these risks.

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Despite growing concerns about the impact of pollution on workers, little is known about how pollution impacts worker health and workplace safety. Workers are often exposed to substantial pollution—through both community-based sources and industrial on-site pollutants. And concerns about the impacts of pollution on workers are growing, given recent periods of very elevated pollution from wildfire smoke and projections of increases in wildfire smoke going forward due to climate change. One important way pollution has the potential to impact worker health is through increasing the likelihood of workplace injuries.[1] Many tasks workers are required to perform involve risk of injury—particularly among workers in high-risk occupations. Prior work documents that pollution leads to a deterioration of both physical and cognitive functioning (e.g., reduced worker productivity, worse student exam performance).[2] Because many workers have little margin for error in their jobs, slight changes in cognition, endurance, or focus induced by pollution could lead to injuries on the job. Workplace injuries are both common and costly. In the United States, 3 out of every 100 full-time workers experienced a workplace injury or illness in 2022,[3] and the aggregate costs of these events totaled $250 billion in 2010 (Leigh 2011).[4]

Policymakers have long been concerned about the impact of pollution on worker health and workplace safety. Understanding the impact of pollution on worker health is important for informing policy in the United States—both federal Environmental Protection Agency (EPA) policy governing acceptable levels of pollution and policy specifically governing workplace safety, which is set by federal and state Occupational Safety and Health Administration (OSHA) regulators. Federal OSHA sets national minimum standards governing workplace safety, and 22 states have state OSHAs that make additional regulations. Historically, state and federal OSHA regulators have focused on industrial on-site pollutants and provided related voluntary guidance regarding work modifications or safety measures. However, recently some state OSHA regulators have turned toward enacting enforceable regulations regarding work during periods with elevated community-wide air pollution—specifically targeting pollution from wildfire smoke.

Wildfire smoke is a major source of air pollution—with wildfires accounting for roughly a quarter of total particulate emissions since 2018. In contrast to industrial sources of air pollution, wildfire smoke is a growing source of air pollution, with the share of total particulate emissions due to wildfire smoke increasing nearly threefold over the last decade.[5] With these trends in the background, recently some state OSHA regulators have taken action to protect workers from wildfire smoke. California adopted OSHA regulations in 2019 mandating protections for outdoor workers exposed to wildfire smoke and high levels of particulate matter.[6] These protections include requiring employers to clearly communicate risks and take mitigation measures when feasible to minimize risks—for example, relocating work to other areas, shifting work to less polluted days, reducing work intensity, offering more rest periods, and providing protective equipment (such as N95 respirators). Following California's adoption of these regulations, Oregon and Washington have recently adopted similar OSHA regulations and other state OSHAs are considering

[1] This paper analyzes the impact of pollution on workplace injuries—injuries occurring during the performance of work activities—using administrative data on workers' compensation injury claims. Throughout, we use worker health and worker safety to refer to health and safety issues experienced by workers directly tied to work (e.g., directly linked to work activities and/or exposures experienced at work).

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

[3] See U.S. Bureau of Labor Statistics (2022).

[4] These aggregate costs represented roughly 1.8% of U.S. GDP in 2010. Workplace injuries and illnesses are similarly common and costly in other developed nations. Analyzing data from five large European Union countries, Tompa et al. (2021) estimate that costs from workplace injuries and illnesses represent between 2% and 4% of GDP in the Netherlands, Germany, and Finland and an even larger share of GDP in Italy and Poland.

[5] Based on data from the EPA (`https://www.epa.gov/air-emissions-inventories/air-pollutant-emissions-trends-data`), the share of total $PM_{2.5}$ emissions attributable to wildfires was 24.0% between 2018 and 2022 and this share increased from 10.7% in 2012 to 28.8% in 2022.

[6] California Code of Regulations, title 8, section 5141.

similar policies as well.[7] There is also growing pressure to enact similar regulation at the federal level—including recent calls from the National Academy of Sciences to act on this issue.[8] Despite concerns that pollution may present serious risks to worker health and the growing policy interest in addressing these risks through regulation, there is little evidence on the impact of exposure to pollution—or wildfire smoke in particular—on worker safety beyond a handful of correlational analyses and case studies.

This paper begins to fill this gap. Specifically, we leverage plausibly exogenous variation in pollution exposure arising from wildfire smoke to provide large-scale causal evidence on the impact of pollution on workplace injuries. This analysis draws on a novel dataset we constructed on workplace injuries based on comprehensive administrative workers' compensation claims data from Texas. We link these administrative data to information on wildfire smoke plumes from the National Oceanic and Atmospheric Administration Hazard Mapping System; these wildfire smoke data are based on satellite imagery of smoke plume movements, and we construct daily smoke exposure levels for each area within Texas from these data.

There are several strengths of the research design and setting. First, because both the wildfire smoke data and the workers' compensation administrative data have precise temporal and geographic information, our research design is able to isolate high-frequency, plausibly exogenous variation in daily pollution driven by the idiosyncratic movement of wildfire smoke plumes, which allows us to credibly identify the causal effect of air pollution on workplace injuries. Second, the workers' compensation administrative data cover the universe of workers' compensation injury claims in Texas, span a relatively long time period (2005-2019), and include rich information on workers and their injuries. These features of the data allow us to obtain estimates representing workers across occupations and industries and to explore heterogeneity by worker and injury characteristics. Third, in addition to providing plausibly exogenous variation in pollution exposure, wildfire smoke is an important and growing source of pollution that is at the center of current OSHA policy debates. Our study provides large-scale causal evidence of the impact of wildfire smoke on worker health, and these estimates can directly inform these ongoing policy debates.

We begin by illustrating that wildfire smoke plumes lead to a deterioration in local air quality. Specifically, we link our data on wildfire smoke plumes to EPA pollution ground monitoring data, and we use these linked data to illustrate that coverage by a smoke plume creates a sharp, temporary increase in ambient air pollution. Our estimates imply that, on average, fine particulate matter, $PM_{2.5}$, increases by 1.69 $\mu g/m^3$ on a day with smoke, representing a 0.39 standard deviation (SD) increase or an 18.6% increase beyond a non-smoke-day average of 9.06 $\mu g/m^3$. Smoke coverage is also associated with some increase in coarser particulate matter, PM_{10} (16.3% or 0.20 SD), as well as much smaller increases in ozone (8.1% or 0.22 SD) and SO_2 (4.7% or 0.03 SD). Smoke-induced increases in particulate matter are large enough that we would expect effects on physical and cognitive functioning, though changes of this magnitude are not generally perceptible to the human eye and these changes typically result in pollution levels well below current regulatory thresholds.

We then turn to investigating the impact of smoke exposure on workplace injury claims. This analysis reveals that smoke exposure leads to a significant increase in workplace injury claims. Our findings indicate that a day with smoke increases workplace injury claims by 0.165 per 100,000 workers, or a 2.8% increase

[7] For information on regulation in Oregon, see `https://osha.oregon.gov/OSHARules/adopted/2022/ao4-2022-letter-smoke-exposure.pdf`. Washington OSHA enacted emergency regulations similar to the California/Oregon regulations and is currently debating whether to make these regulations permanent (`https://lni.wa.gov/safety-health/safety-topics/topics/wildfire-smoke`). Recently, other states have debated similar legislation and put forward more informal guidance in the interim. For example, see this resource on Nevada's current guidance (`https://dir.nv.gov/uploadedFiles/dirnvgov/content/OSHA/Guidance/Wildfire%20Health%20Guidance%20for%20Nevada%20Businesses%20(5-3-2022).pdf`).

[8] See National Academies of Sciences, Engineering, and Medicine (2022).

relative to the mean daily claim rate. We present additional evidence supporting the validity of our research design and illustrating the robustness of our findings. For instance, we obtain similar estimates in alternative specifications that vary the included controls, sample restrictions, or time horizon over which impacts are measured. Further, we obtain similar patterns when investigating the impact of smoke on the subset of injuries that require urgent medical attention—those initiated with an Emergency Department visit. In addition, we present graphical evidence from a distributed lag model that illustrates that future exposure to smoke does not predict current workplace injury claims. Finally, we demonstrate our findings are similar when estimating an alternative count data model that explicitly accounts for the non-negative discrete nature of workplace injuries.

To contextualize the magnitude of our estimates, we can scale the estimated impact of smoke on injuries by the impact of smoke on ambient air pollution. For this scaling, we focus on $\mathrm{PM}_{2.5}$ because it increases sharply with smoke coverage and because it is thought to be particularly harmful for human health. Based on this scaling, our estimates imply that a 10 μg/m^3 increase in $\mathrm{PM}_{2.5}$ leads to an additional 0.98 daily injury claims per 100,000 workers or a 16.8% increase relative to the non-smoke-day mean daily claim rate. We estimate that the cost of these additional injuries is $41,079 daily per 100,000 workers, or about 0.3% of the mean daily earnings in Texas. Extrapolating from our estimates, a nationwide permanent 10 μg/m^3 increase in $\mathrm{PM}_{2.5}$ would result in an additional 850,000 injury claims annually, with an annual cost of $35.6 billion. Moreover, our estimates suggest a severe smoke day—a smoke day sufficient to meet current regulatory thresholds—would lead to a 45% increase in workplace injury claims relative to the non-smoke day mean.

Beyond estimating the overall impact of smoke on workplace injury claims, we explore how impacts may vary across different types of injuries and workers. Smoke is associated with similar percent increases in workplace injury claims across injuries with different diagnosis categories and injuries differing in severity—based on a variety of injury severity proxies we construct using the claims data. These findings suggest pollution-induced workplace injuries resemble the overall distribution of workplace injuries more generally. Further, we find smoke causes increases in workplace injuries across workers with differing characteristics. For instance, we find smoke causes broadly similar percent increases in workplace injury claims among men and women, though the increase in workplace injuries among men is nearly 2.5 times the increase among women given differences in the baseline risk of injury. We also find similar percent impacts on injuries by age among workers aged 25 to 60 years. In addition, we explore impacts by characteristics of the work setting and find that the percent increase in workplace injuries does not vary systematically by industry-occupation features such as workplace injury risk or exposure to the outdoors. Overall, this evidence suggests that the impacts of pollution on workplace injuries are near-universal.

While our estimates suggest percent impacts are similar across many types of workers, it is important to emphasize that the incidence of increased injuries is not evenly distributed across workers. Large differences in baseline injury risk imply there is large variation across workers in the overall harms of community-wide pollution. We conduct supplemental analysis aimed at characterizing the incidence of the harms of pollution and identifying potential opportunities for targeting costly mitigation efforts. The results of this analysis indicate that the pollution-induced increase in workplace injuries is highly concentrated among workers in the highest risk industry-occupations. For instance, our estimates imply that the top 5% of payroll in terms of baseline injury risk accounts for more than a quarter of the increased injuries from pollution, while the top 10% of payroll based on baseline risk accounts for 42% of the increase in workplace injuries. These findings suggest much of the benefits of mitigation could be realized through targeting mitigation toward workers in high-risk industry-occupation groups, and we conduct back-of-the-envelope counterfactuals to illustrate the gains from targeting mitigation toward high-risk groups relative to randomly allocating mitigation or targeting mitigation based on outdoor exposure—the key feature used in targeting in recently enacted and proposed state OSHA regulation.

Overall, our findings demonstrate that air pollution causes significant harms to worker health, implying large societal costs. These findings can inform ongoing policy discussions in several ways. First, our results illustrate that pollution poses unique health risks for workers—particularly those in high-risk occupations. In this way, our findings highlight the motivation for specific regulations regarding work, potentially justifying the role of OSHA regulation beyond community-wide EPA regulations. Moreover, by expanding our understanding of the harms of pollution and wildfire smoke, our estimates are also informative about the potential benefits of further EPA regulation aimed at reducing pollution and policies aimed at reducing the incidence and severity of wildfires. Second, our estimates illustrate that pollution causes increases in workplace injuries at pollution levels well below current regulatory thresholds and for workers in a wide variety of work settings. Thus, our estimates shed light on potential benefits from expanding the scope of existing OSHA and EPA regulations or adopting OSHA regulations on a wider scale. Third, our estimates are informative about the consequences of one specific mitigation strategy highlighted in recent state OSHA regulations—the re-timing of work. Our estimates indicate moving work from a severe smoke day (sufficient to meet regulatory thresholds) to a non-smoke day would reduce workplace injuries by 1.31 to 2.59 per 100,000 workers. As shifting work is costly and may be impossible for some of the workforce, our findings also highlight the need for more research on the costs of mitigation and the impacts of other mitigation strategies (e.g., reducing work intensity, offering more rest periods, providing protective equipment, scaling up safety measures aimed at avoiding injury). Finally, our findings illustrate that much of the harms of pollution are concentrated among the highest risk workers, suggesting there are gains from targeting costly mitigation toward workers in high-risk industry-occupation groups. Additionally, our findings suggest that targeting mitigation based on industry-occupation risk is more effective in reducing workplace injuries than untargeted mitigation or targeting based outdoor exposure.

Our study makes several contributions. First, our study provides large-scale causal evidence on the impact of pollution—and wildfire smoke in particular—on worker health and workplace safety. At the federal and state levels, policymakers are debating whether the government should regulate work on days affected by wildfire smoke and mandate employers implement costly mitigation measures to protect workers. Despite growing concerns among policymakers and the public, prior research on the impact of pollution on worker safety has largely been limited to case studies or correlational evidence from a particular job site or industry.[9] Our work provides large-scale causal evidence on the impact of pollution on worker health and safety through analyzing the impact of wildfire smoke on workplace injury claims. These findings inform ongoing policy debates on the impact of wildfire smoke on worker health and safety—and provide several specific insights for policy, regarding the magnitude of the harms and the scope and targeting of policy. Moreover, our estimates indicate pollution is an important determinant of workplace injuries—adding to a growing literature documenting factors that affect workplace safety more generally (e.g., Johnson 2020; Dillender 2021; Charles et al. 2022; Johnson, Levine, and Toffel 2023).

[9]Previous research about the impact of $PM_{2.5}$ on worker safety has largely consisted of case studies in the occupational health policy literature focusing on a few specific worksites where workers are exposed to worksite sources of $PM_{2.5}$ emissions, including kitchen workers (Neghab et al. 2017), aluminum workers (Brown et al. 2015), and boilermaker welders (Kile et al. 2013). Research on harms from wildfire smoke has tended to focus on case studies of the health impacts of combating fires among firefighters and other first responders (e.g., Gaughan et al. 2008, 2014). Our work also complements two contemporaneous larger-scale studies investigating the impact of nitrogen dioxide on accidents at construction sites in Isreal (Lavy, Rachkovski, and Yoresh 2023) and the impact of winter heating rule regulations on PM_{10} and work-related disabilities using data from eight Italian regions (Curci, Depalo, and Palma 2023).

Second, our study is among a handful of recent studies to investigate the impacts of wildfire smoke (e.g., Jayachandran 2009; Rangel and Vogl 2019; Borgschulte, Molitor, and Zou 2022; Arenberg and Neller 2023). Wildfire smoke is an important and growing source of pollution. Wildfire smoke accounted for nearly a third of $PM_{2.5}$ emissions in the United States in 2022. And, in contrast to pollution from industrial sources, wildfire smoke exposure is increasing over time and is expected to continue to increase with rising global temperatures. Thus, it is increasingly important to understand the harms of wildfire smoke. Our study contributes to this literature by illustrating that wildfire smoke poses unique risks for workers. Further, our results provide direct evidence on health risks workers face during wildfire smoke events, informing a major ongoing policy debate surrounding mitigating the harms from wildfire smoke.

Third, our work extends a broader literature looking at the health impacts of pollution more generally. Most of this literature estimates the impact of pollution on acute health events—such as mortality and hospital visits for respiratory illness or cardiovascular disease (e.g., Deryugina et al. 2019; Schlenker and Walker 2016; Alexander and Schwandt 2022). Because these outcomes are most relevant for the very young and old, prior work has typically focused on estimating the health impacts of pollution exposure among the elderly or among those in early childhood (or in utero). Our work extends this literature by illustrating a novel channel through which pollution can lead to acute health events and by providing direct evidence on important health consequences of pollution among the prime-aged adult population. Further, our findings highlight unique vulnerabilities that workers may face, as they are often required to perform dangerous tasks, are generally expected to work regardless of pollution levels, and have limited ability to unilaterally adjust their work activities. Moreover, our paper demonstrates that increased workplace injuries are an important adverse health impact of pollution more generally, with our findings suggesting the aggregate costs of pollution stemming from increased workplace injuries are in the same range as costs associated with impacts on other acute health outcomes previously studied in this literature.

Finally, our work complements a growing literature on how pollution impacts broader "nonhealth" outcomes. This literature studies how pollution—through causing a deterioration of physical and cognitive functioning—could impact a broad range of outcomes that go beyond acute health events. For instance, prior work documents that pollution leads to reduced worker productivity (e.g., Graff Zivin and Neidell 2012; Chang et al. 2016, 2019), worse school exam performance (e.g., Ebenstein, Lavy, and Roth 2016; Zhang, Chen, and Zhang 2018), and lower quality decision-making in a variety of contexts (e.g., Künn, Palacios, and Pestel 2023; Huang, Xu, and Yu 2020). Our findings indicate that the same underlying mechanisms—subclinical symptoms that reduce physical and cognitive functioning—lead to increased acute health events in the form of on-the-job injuries. In this way, our study connects the literatures on the health and "nonhealth" impacts of pollution by highlighting that pollution impacts a broad range of outcomes for workers. Further, our estimates suggest the costs associated with increased workplace injuries due to pollution are of the same order of magnitude as many prior estimates of the worker productivity impacts of pollution.

The remainder of the paper proceeds as follows. Section 1 provides background on the physiological impacts of pollution and on pollution's potential to impact workplace injuries. Section 2 describes the data, and Section 3 outlines the empirical strategy. Section 4 presents the main results and robustness, while Section 5 discusses magnitudes. Section 6 presents supplemental evidence on the incidence of the impacts and potential opportunities for targeting mitigation. Section 7 discusses the implications of our findings for policy, and Section 8 concludes.

1 Background

We begin by providing some background on how air pollution—and wildfire smoke exposure in particular—may impact human health and job performance. Our main focus in this discussion and throughout is on fine particulate matter, or $PM_{2.5}$, because it is strongly associated with wildfire smoke, it is widely considered to be particularly dangerous for human health, and it is difficult to avoid given that it flows easily from outdoor to indoor environments.[10] Like other forms of pollution, wildfire smoke contains $PM_{2.5}$ that enters the body through inhalation into the lungs. Exposure to this particulate matter causes inflammation of the lungs, which reduces the efficiency of oxygen intake and thus interferes with many functions throughout the body. In addition, some of this particulate matter passes into the bloodstream, where it can further interfere with cardiovascular and respiratory functions. Beyond impacting the functioning of the heart and lungs, growing evidence suggests that exposure to pollution can impair cognitive functioning and emotional regulation through reducing blood flow and cell oxygenation. While pollution exposure can cause serious acute symptoms that require immediate medical attention—such as severe respiratory distress, stroke, myocardial infarction, and heart failure—pollution exposure can also cause sub-clinical symptoms that would not typically require a visit with a health care professional (DeMeo et al. 2004). Recent evidence suggests even small increases in pollution levels can result in reduced functioning of several key body systems, resulting in an exposed individual experiencing fatigue, irritability, impatience, altered motor activity, and a lack of focus (Delgado-Saborit et al. 2021). These general symptoms may lead many affected individuals to simply feel "off" that day, without them necessarily attributing these symptoms to pollution.

In line with these physiological mechanisms, a growing literature documents adverse impacts of particulate matter on human health and performance. For instance, prior work illustrates that exposure to fine particulate matter increases the occurrence of acute health events—such as mortality and hospital utilization among children and the elderly (e.g., Deryugina et al. 2019; Alexander and Schwandt 2022).[11] Moreover, an emerging literature documents that exposure to pollution leads to physical and cognitive impairments that affect a broader range of outcomes beyond acute health or health care events.[12] For instance, a growing set of studies illustrate that elevated daily air pollution levels are associated with short-run reductions in worker productivity in a variety of specific settings—ranging from agricultural workers to factory workers to call center workers to professional athletes (e.g., Graff Zivin and Neidell 2012; Chang et al. 2016, 2019; Lichter, Pestel, and Sommer 2017). Additional research suggests that increased pollution levels lead to worse cognitive performance and impaired judgment—with studies illustrating increased pollution is associated with reductions in performance on school exams (e.g., Ebenstein, Lavy, and Roth 2016; Zhang, Chen, and Zhang 2018), increases in errors among chess players (Künn, Palacios, and Pestel 2023), and lower quality decisions among financial investors (e.g., Huang, Xu, and Yu 2020).[13] Collectively, the findings from this literature indicate that sub-clinical reductions in cognitive functioning and endurance can have important impacts on an individual's ability to perform routine tasks. These impacts have been found

[10] For evidence on the relationship between indoor and outdoor PM2.5 concentrations, see Krebs et al. (2021).

[11] Additional recent work examines the impact of other pollutants (such as total suspended particulate matter, PM_{10}, ozone, sulfur dioxide, or nitrogen oxides) on mortality or hospital utilization. For example, see Chay, Dobkin, and Greenstone (2003); Chay and Greenstone (2003); Currie, Neidell, and Schmieder (2009); Moretti and Neidell (2011); Chen et al. (2013); Schlenker and Walker (2016); Knittel, Miller, and Sanders (2016); Deschênes, Greenstone, and Shapiro (2017); Deryugina and Reif (2023).

[12] See Aguilar-Gomez et al. (2022) for a comprehensive review of this literature.

[13] Other recent work highlights the wide-ranging impacts of pollution on decision making and mental health, with recent studies finding pollution is associated with increased rates of suicides (Molitor, Mullins, and White, 2023), auto accidents (Sager, 2019) and crime (e.g., Herrnstadt et al. (2021), Burkhardt et al. (2019)).

in a wide range of environments and tasks—suggesting the impacts of pollution are widespread, affect a broad range of activities drawing on physical or cognitive skills, and affect individuals in both indoor and outdoor settings.

Many tasks workers are required to perform involve risk of injury. For workers in high-risk occupations, routine tasks require careful attention, focus, strength, and endurance, and even small impairments in physical or cognitive functioning could lead to mistakes and injuries. As fatigue, overexertion, and inattention are some of the most commonly cited drivers of workplace injuries, exposure to pollution has the potential to increase injury rates. By causing sub-clinical symptoms that impair physical and cognitive functioning, pollution exposure may hinder job performance and lead to increased injuries. The notion that subtle physiological changes could lead to increased injury rates is supported by prior work analyzing the impact of extreme heat on workplace injuries (Dillender 2021; Park, Pankratz, and Behrer 2021) and observational studies correlating workplace injuries with measures of sleep deprivation (Uehli et al. 2014). Further, federal and state OSHA regulators have long expressed concerns about the potential for exposure to air pollution to impact workplace safety. Despite these concerns, there is very limited related evidence beyond a handful of case studies or observational studies focusing on a particular worksite or industry. Our paper works toward filling this gap by estimating the causal impact of air pollution on workplace injuries—leveraging large-scale administrative data on workplace injuries and variation arising from wildfire smoke.

While wildfire smoke is thought to impact outcomes through similar channels as other sources of pollution, there is emerging evidence that suggests $PM_{2.5}$ from wildfire smoke may be more harmful to human health than particulate matter from other sources—including evidence from animal studies (Wegesser et al. 2010) and observational analyses of respiratory related hospitalizations (Aguilera et al. 2021). Moreover, recent work on the impact of wildfire smoke on quarterly labor market earnings suggests larger effects than estimated in prior work based on other sources of air pollution (Borgschulte, Molitor, and Zou 2022). Further, recent work suggests wildfire smoke exposure in utero or during early childhood is very harmful to infant health (Jayachandran 2009; Rangel and Vogl 2019) and leads to large long-run reductions in later educational attainment and labor market earnings (Arenberg and Neller 2023). This evidence suggests that particulate matter from wildfire smoke could be particularly harmful to human health, and thus, one should use appropriate caution when extrapolating from estimates of the impact of $PM_{2.5}$ based on wildfire smoke to other non-smoke based sources of $PM_{2.5}$.

In this paper, we focus on variation in pollution arising from wildfire smoke plumes. There are several strengths of this approach. First, the location of smoke plumes provides high frequency, plausibly exogenous variation in local pollution concentrations—allowing us to estimate the causal impact of air pollution on workplace injuries. See Section 3 for an in depth discussion of the key challenges in identifying the causal impacts of air pollution on workplace injuries and how focusing on wildfire smoke allows us to overcome these challenges. Second, wildfire smoke is a large and growing source of pollution. Thus, understanding the impact of wildfire smoke is increasingly important, and these estimates can inform policy aimed at both prevention and mitigation. Third, within the context of workplace injuries, wildfire smoke has received particular attention in regulatory efforts related to pollution exposure. State and federal OSHA regulators are actively debating whether and how to regulate work performed when wildfire smoke causes very high levels of ambient air pollution. Our study provides the first causal estimates to inform these debates.

2 Data

2.1 Exposure Data: Smoke Plumes, Wildfire, and Air Pollution Monitor Data

This paper leverages data on smoke plumes derived from the National Oceanic and Atmospheric Administration Hazard Mapping System (HMS). These data contain geographical shape files that outline the location of each smoke plume in the US based on satellite images. These data are intended to represent the HMS analysts' best estimates of the location of smoke plumes, where these outlines are often drawn multiple times per day—based on satellite readings during daylight hours. We use these data to construct daily measures of smoke exposure from September 2005 (the earliest month available) to December 2018. Comparing the smoke plume data to commuting zone geographic boundary files from the US Department of Agriculture, we construct our key measure of smoke exposure: the share of a commuting zone covered by a smoke plume during the indicated day.[14]

We complement these smoke plume data with data on air pollution from the Environmental Protection Agency (EPA) Air Quality System. These data are based on pollution measured through ground monitoring and include daily pollutant readings at the monitor level. While much of our discussion focuses on $PM_{2.5}$, we obtain data on a range of pollutants—on $PM_{2.5}$ and other EPA-defined "criteria air pollutants" including PM_{10}, O_3, CO, NO_2, and SO_2—to analyze the association between smoke and these pollutants. We construct daily pollution measures at the commuting zone level from September 2005 to December 2018 by averaging readings from all monitors within 150 km of the commuting zone centroid, weighting by the inverse of distance. The monitor level data used in this aggregation are the EPA's daily (24 hour) summary measures.[15] In addition, we also consider a second measure of $PM_{2.5}$ for comparison, referred to throughout as *daytime* $PM_{2.5}$, which we construct based on averaging hourly $PM_{2.5}$ monitor readings from 6am to 6pm. We view this as a natural alternative measure to consider because the period 6am to 6pm more closely aligns with daylight hours—the hours during which smoke plumes are measured—and the hours during which most people work. Because these alternative measures have advantages and disadvantages, we consider both daily and daytime $PM_{2.5}$ measures when contextualizing the magnitude of our reduced form estimates of the impact of smoke on workers' compensation claims.

Additionally, we obtain data on the location of wildfires from the Monitoring Trends in Burn Severity (MTBS) program—an interagency program under the U.S. Geological Survey Center for Earth Resources Observation and Science (EROS) and the U.S. Department of Agriculture Forest Service Geospatial Technology and Applications Center (GTAC). The MTBS program is charged with consistently mapping the location and extent of large fires across the U.S.[16] For each fire, the data include the location of the fire, the date the fire started, and the acres burned. We use these data to illustrate the robustness of our findings when excluding observations with wildfires nearby, to rule out that our estimates are driven by direct damages from fires.

In addition, we obtain county-level data on weather conditions from Schlenker (2023). These data are based on the PRISM Climate Group weather data, which contain daily information on minimum temper-

[14] For commuting zones with multiple smoke measurements on a day, our smoke measure equals the share of the commuting zone covered at the commuting zone's most covered measurement of the day. In Appendix Table A6, we show that the results are robust using an alternative smoke measure: an indicator variable for the commuting zone ever being fully covered by smoke on that day.

[15] For $PM_{2.5}$ and PM_{10}, these daily summary measures are the average of all hourly readings in a day. The EPA's daily summary measures are calculated slightly differently for other pollutants, representing: the maximum of the day's 8-hour running mean for O_3 and CO and the maximum hourly reading for SO_2 and NO_2.

[16] The MTBS program defines a large fire as a fire with more than 1,000 acres burned in the western U.S. or more than 500 acres burned in the eastern U.S.

ature, maximum temperature, and total precipitation on a 2.5 mile by 2.5 mile grid of the contiguous US. To merge these data with our analytical dataset, we aggregate these data to the commuting zone-day level focusing on the mean value of these measures within a commuting zone. These weather data are used as controls in our analysis, as weather could be correlated with pollution and may have independent impacts on workplace injuries.

2.2 Outcome Data: Workers' Compensation Administrative Data

Our analysis draws on unique administrative data on workers' compensation injury claims we have compiled through a series of open records requests to the Texas Department of Insurance. These data contain detailed records for all workers' compensation claims covered through the Texas workers' compensation insurance program, including information on the medical and cash benefits received for claims with injury dates from September 2005 to December 2018. Workers' compensation is a state-regulated insurance program that provides medical and cash benefits to covered employees who suffer a workplace injury.[17] Workers' compensation insurance provides full coverage of all injury-related medical expenditures, partial wage replacement for missed work due to injuries, and additional unconditional cash transfers for permanent impairments and workplace fatalities.

The medical benefit data contain all medical bills for care provided to workers' compensation claimants—including information on the date of service, procedures provided (CPT codes), amount paid, diagnoses (ICD-9/10 codes), place of service, and provider information. Because workers' compensation covers all injury-related medical expenses, the data include medical bills for physician care, outpatient care, inpatient care, and prescription drugs. The data also include information on claimant sex, date of birth (month-year), and zipcode. All workers' compensation injury claims involve some covered medical treatment, while roughly 22% of injuries also involve cash benefits. For claimants who receive cash benefits, the data include information on the type of cash benefits received, benefit start and end dates, total benefits received, prior average weekly wage, and industry-occupation.

Our analysis focuses on measuring the impact of smoke on air quality and claim rates, conducting analysis at the commuting zone by date level. When reporting outcomes as rates, we aggregate claims to the commuting zone level and report rates per 100,000 workers employed in the commuting zone that quarter, according to the Quarterly Census of Employed Workers (2005-2018).

We aggregate injury claims by date using the date that the injured worker first received medical treatment for their injury.[18] For many injuries—including those that require urgent medical attention—the injury date and the date of first medical treatment coincide. However, some injuries may be treated for the first time in the few days following the injury. As discussed further below, our baseline empirical approach accounts for this by analyzing impacts on three-day injury claim rates (i.e., aggregating injuries on the observation date and the following two days)—allowing workers multiple days to first report and seek treatment for their injuries. We also present two sets of supplemental analyses that illustrate the robustness of our findings with respect to the measurement of the injury date. Specifically, we illustrate our estimates are similar when focusing on the subset of claims that began with a visit to the Emergency Department—claims for which the claim start date and the injury date are very likely to align—and we illustrate that we obtain broadly similar findings if we construct our claim rate measure using alternative time horizons (e.g.,

[17] Workers' compensation insurance covers both workplace injuries and illnesses due to occupational exposure. However, in practice, nearly all claims are for workplace injuries. Thus, throughout we refer to workers' compensation claims as injury claims.

[18] The workers' compensation claims data contain administratively recorded information on the month-year of the injury—but not the exact date of injury. Thus, we use the exact date of first medical treatment received for injuries to define the claim start date.

considering claims within one day to within two weeks of the smoke day).

An advantage of focusing on commuting zones as the geographic unit of analysis is that commuting zones are small enough to allow for leveraging the meaningful within-state variation in smoke while being large enough to reflect smoke over a broader area that could be relevant to the worker—an area potentially large enough to encompass both their home and work.[19] While the workers' compensation administrative data do not contain direct information on the location of the injury, the data contain precise location information (5-digit zipcode) on the worker's residence and where the worker obtained medical care for the injury. Our baseline measure of injury claim rates assigns claims to commuting zones based on the worker's residence, though we demonstrate that our results are similar if we instead assign claims to commuting zones based on the location where the worker first obtained medical treatment for the injury.[20]

The data contain rich information about workers and their injuries. For some supplemental analysis, we leverage information on workers' compensation industry-occupation classifications—which provide a detailed characterization of industry-occupation of the worker with 334 distinct classification codes. This analysis considers two specific industry-occupation features: risk exposure and outdoor exposure. Risk exposure is measured as the workers' compensation risk of the classification—workers' compensation costs per $100 of payroll as calculated by the Texas Department of Insurance for risk adjustment purposes. Outdoor exposure is constructed based on O*NET data characterizing the frequency of outdoor work by occupation. Because industry-occupation classification information is only available for claimants with cash benefits, we impute these exposure measures for claimants with missing values by selecting the median value among claimants with non-missing values working at the same employer. After this imputation, 78% of claims have industry-occupation classification exposure measures. See Appendix Section A for more details on the construction of these exposure measures. Data on other injury and worker characteristics that we leverage are available for all claims.

The basic structure of the Texas' workers' compensation program is very similar to other state workers' compensation programs. However, there is one important exception: employers can opt out of workers' compensation coverage in Texas, whereas coverage is effectively mandatory for most employers in other states. Employers opting out of workers' compensation insurance can be sued for negligence for workplace injuries—which is costly for both employers and employees. Thus, despite the option to opt out of workers' compensation insurance, most employers opt to participate in the workers' compensation insurance system and coverage rates are very high: 87% of employees in Texas are covered by workers' compensation insurance compared to 97.5% of workers nationwide.[21] Because employers typically purchase or renew workers' compensation insurance policies on an annual basis, employer participation is very unlikely to vary with daily smoke exposure. Thus, our research design provides an unbiased estimate of the effect of smoke exposure on workers' compensation claims in Texas.

While the unique voluntary feature of the Texas workers' compensation program does not interfere

[19] As highlighted in prior work on the impact of pollution on health and "nonhealth" outcomes, the time horizon over which the impacts of pollution are fully realized is unclear. Thus, both pollution while at work and pollution before work may be an important contributor to workplace injuries, and we view it as an advantage to focus on a geographic unit of analysis that is large enough to encompass areas where the worker may spend significant amounts of time.

[20] It is not surprising that our findings are similar using these two alternative methods for assigning commuting zones, as workers typically live and work in the same commuting zone and would likely seek medical care within the same general area. In our sample, the commuting zone indicated by these two location measures perfectly aligns for 88% of injury claims.

[21] According to the Texas Department of Insurance (Texas Department of Insurance 2019), 82% of private sector workers were covered by workers' compensation insurance in 2016. In addition, public sector workers are mandated to have workers' compensation insurance. We calculate the fraction of workers covered by workers' compensation insurance in Texas is roughly 87% by combining these statistics with share of the Texas workforce in private sector employment in 2016 using data from the Bureau of Labor Statistics. The nationwide average coverage rate is obtained from McLaren, Baldwin, and Boden (2018).

with our ability to estimate the effect of smoke exposure on workers' compensation claims in Texas, it does mean that some injuries arising from smoke exposure are not reflected in our data. There are a few important related points worth noting. First, when considering effects in levels (e.g., claims per 100,000 workers), our estimates represent a lower bound on the effect of smoke exposure on workers' compensation claims if all workers in Texas were covered by workers' compensation insurance. Moreover, if smoke exposure had a similar impact on the number of workplace injuries among workers at nonparticipating employers, we could simply scale the estimates to account for the 13% of Texas workers outside of the workers' compensation insurance system. Second, it may be natural to interpret estimates in percent terms in this setting. Even if baseline injury rates are different across covered and uncovered workers, estimates in percent terms are not affected by nonparticipation if the effect of smoke exposure is similar for covered and uncovered workers in percent terms. Moreover, percent impacts are more relevant if extrapolating from our findings to broader settings beyond Texas. As discussed later in Section 4, our estimates indicate that percent impacts are similar across many different types of workers, suggesting it may be reasonable to extrapolate from our estimated percent effects to other workers. Throughout, we report estimates both in levels and as a percent of the baseline workplace injury claim rate.

More generally, differences in the composition of the workforce in Texas relative to broader populations could limit the applicability of our findings beyond Texas. We provide some context in Appendix Table A1, where we compare workers and workers' compensation claimants in Texas to those nationwide using data from the Current Population Survey (CPS) Annual Social and Economic Supplement 2006-2019 (representing years 2005-2018). Workers in Texas and nationwide appear broadly similar to one another on observable characteristics, with these similarities echoed when comparing workers' compensation claimants in Texas to those nationwide. While these similarities on observable characteristics suggest workers in Texas are similar to workers nationwide, we note that the workforce in Texas is not necessarily representative of the workforce nationwide so one should exercise appropriate caution when applying our estimates in other settings.

2.3 Descriptive Statistics

Table 1 presents some basic descriptive statistics for our commuting zone by date analytical dataset. On average, a commuting zone is covered by smoke 26 days per year, or 7% of the time. While $PM_{2.5}$ averages 9.4 $\mu g/m^3$ across all days, on smoke days $PM_{2.5}$ reaches an average level of 13.1 $\mu g/m^3$.

Table 1 also summarizes basic features of the workers' compensation claims data. On average, there are 5.8 claims daily per 100,000 workers. Of these claims, roughly 22% have both medical and cash benefits, while the remaining 78% have only medical benefits (i.e., do not involve sufficient time out of work to be eligible for cash benefits). Approximately 31% of claims are initiated with a visit to the Emergency Department, and 36% of injury claims require medical treatment for more than a month. Workers' compensation claims reflect a number of different types of injuries including, contusions (15%), fractures (6%), sprains (28%), muscle issues (18%), and other injuries (32%). Approximately 36% of claimants are female.

3 Empirical Strategy

3.1 Overview

Identifying the effect of pollution on workplace injuries is challenging. Credibly identifying the impact of pollution on any outcome often requires an instrument for pollution, because pollution variation is not generally exogenous and pollution data often suffer from issues related to data quality and coverage. Further, a key challenge in identifying the impact of pollution on workplace injuries is that the risk of workplace injury is fundamentally linked to hours worked—the more labor is supplied, the greater the chance of workplace injury—and hours worked is not typically observed on a daily level, so this is a potentially important omitted variable in any analysis of workplace injuries. Pollution may be correlated with hours worked for several reasons. For example, economic activity may cause air pollution. And, other factors—such as holidays or weather shocks—may drive changes in economic activity, workplace injuries, and air pollution. Finally, prior work has shown a small but significant impact of air pollution on productivity (in the short-run) and aggregate economic activity (in the medium-run).

In this paper, we leverage daily variation in pollution arising from wildfire smoke plumes to identify the causal effect of pollution on workplace injuries. There are several strengths of our research design which allow us to overcome the challenges outlined above.

First, leveraging high-frequency, idiosyncratic variation based on the position of wildfire smoke plumes allows us to isolate variation in pollution exposure that is plausibly exogenous to other factors that may influence workplace injuries and economic activity. Wildfire smoke plumes can travel hundreds or thousands of miles from the associated fire—providing variation that can be used to identify the effect of smoke exposure separate from any local direct damages from wildfires themselves. Further, there is substantial variation in which areas are affected, depending on both the location of fires and the wind conditions on a particular day.

We use two figures to illustrate these features. Figure 1 displays a map illustrating the distribution of the average annual number of smoke days (in Panel A) and the average annual number of large wildfires (in Panel B) across the U.S. While large wildfires are heavily concentrated in certain areas (e.g., the west), there is little correlation between areas most affected by fires and areas most affected by smoke. This reflects both the large distances smoke plumes can travel and the importance of wind patterns in determining smoke exposure. This figure also suggests the amount of smoke in Texas is similar to that observed nationwide, with Texas averaging 26.1 annual smoke days over this period and the US averaging 22.5 days.[22] Further, commuting zones in Texas have fewer wildfires than the nation as a whole—with an annual average of 0.71 within commuting zones in Texas compared to 1.08 within commuting zones nationwide. Much of the smoke exposure in Texas results from fires in neighboring states.[23] Figure 2 describes an example, illustrating the dynamics of smoke plumes in the days surrounding one large fire: the Starbuck Fire, which started near Slapout, Oklahoma on May 6, 2017 (indicated as day 0 in the figure). This was a major fire, burning 781,000 acres in Oklahoma and spilling over to Kansas as well (Frazier 2018). The figure plots smoke plumes (in orange) and the location of the Starbuck Fire (the red star). In the days leading up to the Starbuck Fire, there was no smoke in Texas. After the Starbuck Fire starts, we see smoke plumes that stretch hundreds of miles to the south and affect air quality across much of Texas. Smoke coverage peaks in the day after the fire started, before dissipating and returning to near zero levels by a few days later. Smoke from the Starbuck Fire had disparate impacts across different areas in Texas. Some major metro areas were fully covered by smoke plumes for one or more days (e.g., Dallas, Fort Worth, Austin), while other cities were completely unaffected (e.g., El Paso and Houston). Our research design leverages similar high-frequency, idiosyncratic

[22] These statistics represent a weighted average of annual smoke days (the sum of our smoke measure across a year) across commuting zones in Texas or in the U.S., weighting by the number of workers in that commuting zone. The annual average number of large wildfires is defined analogously, averaging the annual number of large wildfires across commuting zones in Texas or in the U.S., weighting by the number of workers in that commuting zone.

[23] Analyzing data from across the U.S., Wen et al. (2023) find that the majority of $PM_{2.5}$ exposure from wildfire smoke comes from sources outside of the area experiencing the smoke, with 87% coming from fires outside of the county and 60% coming from fires outside of the state.

variation in smoke coverage to identify the effect of smoke on our outcomes of interest.

Second, wildfire smoke plumes cause meaningful changes in pollution that are sufficiently large that we may expect impacts on health and cognition—and hence increased rates of workplace injuries. As we discuss further below, Table 2 illustrates that wildfire smoke causes substantial increases in $PM_{2.5}$ levels, with an average smoke day leading to a 1.7 $\mu g/m^3$ increase in $PM_{2.5}$ or more than a third of a standard deviation of the distribution of $PM_{2.5}$.

Third, our empirical strategy controls for aggregate time-varying factors that may influence work or workplace injuries. Specifically, our regression specifications include exact date fixed effects, which allow us to flexibly control for other factors—such as holidays, statewide weather conditions, and other aggregate shocks—that could impact workplace injuries and economic activity statewide. In addition, we demonstrate the robustness of our findings when including additional controls or focusing on subsamples.

Fourth, by focusing on high-frequency daily variation in smoke exposure, our research design sidesteps many ways pollution could impact local labor supply (or labor demand)—and hence the overall population at risk of workplace injuries. Many factors influencing the size and composition of the workforce—such as hiring decisions and work schedules—are often determined days (or months) in advance, and workers often have limited flexibility to adjust daily work or working hours in real time. We also might expect little or no adjustment of work in response to smoke in our setting because nearly all wildfire smoke events during our analysis sample cause a moderate deterioration of air quality that is not visible to the human eye.[24] As we demonstrate, our estimates are not driven by extreme periods of intense smoke exposure—events that may be associated with extensive news coverage and could potentially be more likely to cause changes in behavior (of employers or employees) not present with more moderate levels of pollution exposure. While one might expect limited or no adjustment of work hours in the range of pollution in our analysis, we also empirically assess the relationship between smoke exposure and hours worked nationwide using Basic Monthly Current Population Survey data.[25] Appendix Table A2 describes the details of this analysis and reports the results. This analysis suggests there is no evidence that weekly smoke exposure is associated with changes in weekly hours worked.

Finally, if employers or employees change their behavior in response to daily variation in smoke exposure in a way that reduces the likelihood of workplace injuries (e.g., working reduced schedules, using sick days, taking more breaks), our estimates of the change in workplace injuries are net of these changes in behavior and may understate the increase in workplace injuries that would have occurred in the absence of these behavioral responses. Importantly, any behavioral responses on the part of employers or employees in our setting occur in the absence of regulation—as Texas has no regulations regarding smoke exposure at work.[26] Thus, our estimates—which are net of any behavioral adjustments in the absence of regulation—directly inform current policy debates surrounding the enactment and expansion of regulations related to worker exposure to wildfire smoke.

[24] Only 0.4% of smoke days across our analysis period have recorded ambient $PM_{2.5}$ in excess of 35 $\mu g/m^3$, and air quality on a typical smoke day in our sample is within the "good" to "moderate" ranges defined by the EPA. When analyzing smoke events associated with pollution levels observed in our sample, Heft-Neal et al. (2023) find no evidence of decreased mobility among individuals in general in response to smoke, through analyzing park visits, vehicle traffic, and ED visits related to accidents.

[25] This analysis takes advantage of the fact that the Current Population Survey asks about weekly hours worked for the same week in most months. County identifiers are suppressed for small counties in the Current Population Survey. For our analysis of hours worked, we focus on counties identifiable in the Current Population Survey across the United States and conduct the analysis at the county level. See Appendix Table A2 for more details on this analysis.

[26] During our analysis period (and currently), there are no regulations requiring employers in Texas to adjust work schedules in response to pollution levels or smoke exposure.

3.2 Econometric Specification

Our goal is to identify the effect of wildfire smoke on air quality and workplace injuries. We estimate the reduced form impact of smoke using the following regression specification:

$$y_{jt} = \gamma smoke_{jt} + \tau_t + \phi_{jq(t)} + X_{jt}\Theta + \epsilon_{jt}, \tag{1}$$

where j indexes the commuting zone and t indexes the date. The key smoke exposure measure, $smoke_{jt}$, is the share of the commuting zone covered by wildfire smoke on the observation date. By including date fixed effects (τ_t), this specification accounts for statewide time-varying factors that could impact wildfire smoke, pollution, or workplace injuries. This specification also includes commuting zone by quarter fixed effects ($\phi_{jq(t)}$) to flexibly control for area-specific factors and time trends. We include additional controls (X_{jt}) for weather and leads and lags of smoke and weather, as described further below.

We begin by using this estimating equation to examine the impact of smoke exposure on ambient air pollution—$PM_{2.5}$ and other pollutants—as measured through pollution ground monitoring. We then use this estimating equation to examine the effect of smoke on injury claim rates, measured as injury claims per 100,000 workers. We analyze claim rates for all workers' compensation claims and for subsets of claims (e.g., claims initiated with a visit to the Emergency Department, claims with specific injury or worker characteristics). When analyzing impacts on workplace injury claim rates, the dependent variable (y_{jt}) is the three-day total—based on the observation date t and the following two days—per 100,000 workers. To ensure that γ is not confounded by weather or smoke on the two days following the observation date, we include two leads of the weather controls and the smoke indicators.[27] We also include three lags of the weather controls and smoke indicators, to minimize concerns about auto-correlation.

The identification assumption behind this specification is that smoke coverage is orthogonal to other determinants of workplace injuries, conditional on the included controls for time varying and time invariant factors. Though it is not possible to directly test this assumption, both intuition and additional empirical evidence provide support for this assumption. Features of smoke transport suggest this assumption is broadly plausible. Smoke can travel long distances and wind conditions on a particular day influence the location of smoke plumes and local smoke exposure. Further, we illustrate the robustness of the results through estimating alternative specifications varying the set of included controls or the definition of key variables. In addition, we present estimates from a distributed lag model that demonstrate future smoke does not impact today's injury claims.

3.3 Identifying Variation

We provide further description of the variation in smoke coverage. Figure 3 displays yearly plots of the number of smoke days by commuting zone in Texas from 2006 to 2018, where areas are shaded based on quintiles of the distribution of average annual smoke days over the entire period.[28] This figure illustrates that areas with high smoke exposure in some years have low smoke exposure in other years, suggesting that there may be substantial idiosyncratic variation in smoke across areas and over time. Importantly, our empirical specification leverages much more granular variation in smoke, as Equation (1) controls for exact date fixed effects and commuting zone by quarter fixed effects.

[27] The baseline specification controls for daily maximum temperature and for daily precipitation in quintile bins. In Table 3, we verify the robustness of the results to including additional weather controls.

[28] While our sample period begins in September 2005, these annual maps focus on years for which we have complete data—2006 to 2018.

To more directly visualize the identifying variation underlying the baseline specification, we consider the distribution of residuals from a regression of our measure of smoke, $smoke_{jt}$, on the full set of controls included in Equation (1) above. Smoke exhibits substantial residual variation, with an interquartile range of 0.028—representing 0.12 of the standard deviation or 10.5 smoke days if aggregated over a year. The interdecile range is 0.13, which is 0.55 of the standard deviation and represents roughly 47.8 smoke days if aggregated over a year.

Figure 4 describes this residual variation by year (in Panel A) and by commuting zone (in Panel B)—displaying the interquartile range and the interdecile range of the residuals. This figure illustrates there is substantial variation in smoke coverage both within each year and within each commuting zone. This suggests the estimates are not driven solely by variation within a particular year or commuting zone and the estimates are broadly representative of the state over the analysis period.

4 Results

4.1 Impact on Ambient Air Pollution

We begin by examining the impact of smoke coverage on ambient air pollution measured through ground monitors. Table 2 displays the results of estimating Equation (1) with the dependent variable representing the air pollution concentration on the observation date for the indicated pollutants.

Table 2 indicates that smoke coverage on a given day increases average daily $PM_{2.5}$ by 1.69 $\mu g/m^3$, which is a 0.39 standard deviation (SD) increase or an 18.6% increase above the non-smoke-day mean of 9.06 $\mu g/m^3$. We observe similar increases when measuring $PM_{2.5}$ during daytime hours—with the estimates indicating smoke increases average daytime $PM_{2.5}$ by 1.89 $\mu g/m^3$, representing a 0.40 SD increase or a 21.7% increase beyond a non-smoke-day mean of 8.71 $\mu g/m^3$. Smoke coverage also causes a smaller increase in PM_{10}—a 0.20 SD increase or a 16.3% increase beyond the non-smoke-day mean. The estimates also suggest smoke coverage is associated with elevated O_3 and SO_2 levels, though the magnitudes of these associations are much smaller with implied impacts of 8.1% (0.22 SD) and 4.7% (0.03 SD) respectively.[29] We find smoke coverage is not associated with elevated levels of CO or NO_2.

To provide some context, we can compare these magnitudes to standards for ambient air pollution set by the EPA and pollution thresholds in recent state OSHA regulations. The EPA sets an annual standard for ambient $PM_{2.5}$ of 15 $\mu g/m^3$ and a daily standard of 35 $\mu g/m^3$, well above the level of ambient air pollution on a typical smoke day. In addition, a typical smoke day results in ambient air pollution far below the $PM_{2.5}$ concentration thresholds outlined in recent state OSHA regulations—55.5 $\mu g/m^3$ in California and 35.5 $\mu g/m^3$ in Oregon and Washington. Most smoke events cause a moderate deterioration of air quality that is not discernible to the naked eye, and our estimates are identified by these moderate smoke events.[30] Only 0.4% of smoke days across our analysis period have recorded ambient $PM_{2.5}$ in excess of 35 $\mu g/m^3$, and our findings are virtually unchanged when excluding these events.

[29] These findings are broadly consistent with other work on the relationship between smoke and pollution. For example, Borgschulte, Molitor, and Zou (2022) find that smoke primarily affects particulate matter, leading to sizable increases in both $PM_{2.5}$ and PM_{10}, with notably smaller impacts on other pollutants including O_3 and SO_2. This evidence also aligns with recent scientific reports which indicate wildfire smoke is complex and contains particulate matter, as well as O_3 precursors and SO_2 (U.S. Environmental Protection Agency 2022; Rickly et al. 2022).

[30] Air quality on a typical smoke day is within the “good” to “moderate” range of the EPA-defined Air Quality Index.

4.2 Impact on Workers' Compensation Injury Claims

Next, we examine the impact of smoke on workplace injury claims. We present estimates of the overall impact of smoke on injury claim rates, as well as estimated impacts by injury and worker characteristics.

Overall Impact on Injury Claim Rate Table 3 displays results from our main reduced form specification described in Equation (1). This table displays estimates for the key coefficient of interest (γ), along with the associated standard errors and p-values. The bottom row reports the magnitude of the impacts as a percent of the mean daily claim rate. Column 1 reports the baseline estimates, while the remaining columns report estimates from alternative specifications assessing the robustness of our findings.

Our baseline specification indicates that a smoke day causes a 0.165 increase in workplace injury claims per 100,000 workers, with a 95% confidence interval spanning 0.07 to 0.26. This represents a 2.8% increase over the mean daily claim rate of 5.8 injuries per 100,000 workers. The remaining columns in Table 3 demonstrate the robustness of these findings when varying the included controls, sample restrictions, and definition of the dependent variable. Columns 2 and 3 illustrate that we obtain similar estimates when including an expended set of weather controls or additional commuting zone by month-of-the-year fixed effects. Column 4 indicates the estimates are very similar when restricting our sample to exclude observations for days with large wildfires within 200 kilometers of the commuting zone, providing reassurance that the results are driven by smoke rather than direct damages from wildfires.[31] Column 5 illustrates that our findings are similar—and if anything the magnitude is slightly larger—when excluding weekends. Column 6 probes the robustness of our findings by analyzing an alternative dependent variable: claims originating with an Emergency Department visit per 100,000 workers. These claims are less discretionary and represent injuries requiring urgent medical treatment. We find a slightly larger increase in percent terms when investigating claims initiated with an Emergency Department visit than found with claims overall (4.3% vs. 2.8%).

The estimated increase in workplace injury claims is substantial. To further contextualize magnitudes, we can scale the reduced form estimates by the impact of smoke on ambient air pollution. For this scaling exercise, we focus on $PM_{2.5}$ as a summary measure of the impact of smoke on ambient air pollution, given $PM_{2.5}$ increases sharply on smoke days (see Table 2) and is thought to be particularly harmful to human health. We note that other compounds (either measured or unmeasured) contained in smoke may also contribute to the estimated increase in injuries. Thus, the resulting scaled estimates are most informative about the impacts of $PM_{2.5}$ from wildfire smoke, and more caution is warranted when extrapolating to $PM_{2.5}$ from non-smoke-based sources.

Scaling the baseline estimated increase in injury claims (from Table 3 column 1) by the estimated increase in $PM_{2.5}$ (from Table 2 column 1) indicates that a 10 $\mu g/m^3$ increase in daily $PM_{2.5}$ leads to an additional 0.98 injury claims per 100,000 workers or a 16.9% increase relative to the mean daily claim rate.[32] Alternatively, scaling the reduced form increase in injury claims by the estimated increase daytime $PM_{2.5}$ (from Table 2 column 2) suggests that a 10 $\mu g/m^3$ increase in $PM_{2.5}$ leads to an additional 0.87 injury claims per 100,000 workers or a 15.1% increase relative to the mean daily claim rate. Section 5 provides a more in depth discussion of the magnitude of the estimates and the relation to other impacts of pollution.

[31] Appendix Table A7 further verifies the robustness of the results to excluding observations that could potentially experience direct damages from wildfires by using the Global Fire Emissions Database (Randerson et al. 2018), which uses a more comprehensive fire definition that includes smaller fires. Appendix Table A7 indicates that the estimated effects are similar to the baseline estimates regardless of which dataset we use to identify observations with nearby fires.

[32] The implied impact of $PM_{2.5}$ is very similar when estimating an analogous instrumental variables specification which focuses on the subset of observations for which $PM_{2.5}$ data are available. See Appendix Table A3 for these estimates.

Impacts by Injury and Worker Characteristics Next, we turn to examining heterogeneity by injury and worker characteristics. In this analysis, we continue to analyze claims per 100,000 workers, where workers are defined as all workers in the indicated commuting zone and quarter. We note mean claim rates vary substantially by injury characteristics (as some types of injuries are more common than others) and worker characteristics (due to differences in both the share of the workforce these workers comprise and the likelihood of injury for these workers conditional on working). Thus, while we report estimates both in levels and as percents, our discussion below often focuses on comparing percent effects.

We investigate how the impact of smoke varies by type of injury. Table 4 presents results from estimating Equation (1) examining claim rates separately for different injury categories: muscle injuries, sprains, contusions, fractures, and other injuries. The estimated percent impacts are similar to the overall impact for the largest injury categories (muscle issues, sprains, and other). There are no significant impacts of smoke on the smallest injury categories (contusions or fractures), though the percent effects are statistically indistinguishable from the overall impact on all injuries in percent terms.[33]

Table 5 examines the impact of smoke on claims by injury claim severity, drawing on several proxies for injury severity that we construct using the administrative claims data. This analysis suggests similar percent impacts for claims that are more or less severe. For instance, our estimates indicate similar increases in claims with above or below median total workers' compensation claim costs (2.6% vs. 3.1%). Further, we find similar increases for claims needing medical treatment for less than a month and those needing medical treatment for more than one month (2.6% vs. 3.4%). In addition, we observe broadly similar increases for claims with income and medical benefits compared to those with only medical benefits (2.1% vs. 3.1%).[34] Finally, we find increases among both claims initiated with a visit to the Emergency Department (4.3%) and claims initiated with other medical care (2.2%). These findings suggest that the additional injury claims induced by smoke are broadly similar to workers' compensation injury claims more generally.

Next, we examine the impact of smoke on injury claims among workers with differing characteristics. Table 6 presents results focusing on basic characteristics observed for all workers: sex and age.[35] There are a few patterns worth noting. First, much of the increase in injuries on smoke days is driven by an increase in injuries among men—as the increase in injuries among men is 2.5 times larger than the increase in injuries among women. However, because men are injured more often than women, the increase in injuries for men and women is more similar in percent terms (3.1% vs. 2.1%). Second, smoke induces similar percent increases in injuries among workers aged 25 to 60. There is no detectable impact of smoke on injuries among workers younger than 25 years of age, and we can reject that the effect in percent terms for workers younger than 25 is the same as the percent effect for the full sample at the one-percent level.

Table 7 displays estimates of impacts on injuries classified by job characteristics of the injured worker. This analysis draws on workers' compensation industry-occupation classification information and focuses on two features of industry-occupations: risk exposure and outdoor exposure. See Section 2 for more detail on how these measures are constructed. Comparing estimates in columns 1 and 2, we see that the overall im-

[33]To assess the statistical significance of the differences, we first create a stacked dataset with separate observations for rates of all injuries and of each subcategory of injuries. We next estimate a version of Equation (1) with all regressors interacted with an indicator variable for the dependent variable being for the subcategory of injuries. We then test for the statistical significance of the difference between the implied percent impacts from the coefficient on the smoke measure and from the coefficient on the smoke measure interacted with the indicator variable for the subcategory of injuries.

[34]We note the effects are naturally more precise for claims without cash benefits (i.e., those with only medical benefits) as these make up three quarters of claims.

[35]Note that this analysis holds the denominator fixed as the total workers in the community zone that quarter. In Appendix Table A4, we repeat this analysis using group-specific denominators by scaling the total number of workers by the share of workers in the indicated group, where this share is calculated using the American Community Survey. As expected, while the point estimates change when the denominator is group-specific, the estimates in percent terms are very similar to the percent estimates shown in Table 6.

pact of smoke on claims is similar when focusing on all claims or on the subset of claims for which industry-occupation measures are available. The remaining columns consider differences by industry-occupation exposure measures—separately considering claims by tercile of risk exposure (columns 3-5) and outdoor exposure (columns 6-8). These estimates suggest there is no systematic relationship between either risk or outdoor exposure and the percent impact of smoke on claims.

Overall, the estimates investigating impacts by worker characteristics suggest the impacts are near-universal—affecting workers with varying demographic and job characteristics. It is worth emphasizing that even if percent impacts are similar across workers, the overall distribution of the harms of smoke may vary substantially across workers due to differences in their baseline injury risk. Section 6 discusses this point further and conducts related back-of-the-envelope calculations exploring the incidence of these impacts.

4.3 Additional Robustness

In addition to the primary robustness analysis reported in Table 3, below we present additional analysis illustrating the robustness of our findings.

Dynamic Effects: Alternative Estimation Strategies and Graphical Evidence Our baseline estimates capture the impact of smoke on claims initiated on the smoke day or within the following two days. Our focus on claim outcomes aggregated over three days is motivated by the fact that smoke has the potential to affect injury claims over multiple days for two reasons. First, as discussed in Section 2, the claim initiation date is measured using the date the worker first obtained medical care for their injury. Since workers sometimes first obtain medical care in the days following the injury, it may be important to include some follow-up period to fully capture the effect of pollution exposure on injuries occurring on the observation date. Second, the full impact of smoke exposure on injuries may take a few days to be realized, if pollution on the observation date affects injuries in the days directly following exposure.[36] Below, we present additional robustness analysis exploring the dynamics of the impacts and demonstrating the robustness of our findings when considering alternative horizons.

Table 9 Panel A reports the results from estimating Equation (1) using alternative measures of claims aggregated over different horizons, ranging from one day to 14 days. There are a few patterns in this table worth noting. First, the impact of smoke on claims is positive and statistically significant, regardless of the horizon over which claims are measured. This highlights the robustness of our main findings. Second, the estimates suggest it is important to include claims in the days immediately following smoke to capture the full impact. While smoke has the largest impact on claims initiated on the smoke day itself, this same-day increase accounts for roughly half of the estimated impact measured over three days. At the same time, the effects begin to level off quickly after including the days immediately following the smoke day, suggesting the baseline three-day aggregation window is sufficiently long to capture the near complete impact of smoke on workplace injuries. For example, the estimated impact over three days is the same as the estimated impact over a week.[37]

To provide additional evidence on the dynamics of the effects, we estimate a distributed lag model

[36] As emphasized in prior work estimating the impact of pollution on broader "nonhealth" outcomes, the time horizon over which pollution can impact physical and cognitive functioning is unclear (Aguilar-Gomez et al., 2022). Smoke may have instantaneous effects on physical and cognitive functioning, though smoke may also impact physical and cognitive functioning in the hours and days following exposure.

[37] As we would expect, precision declines as the horizon extends. This highlights a key trade-off when selecting the time horizon to consider: longer horizons may capture more complete effects of smoke but lengthening the horizon can decrease the precision to detect these effects.

using the following dynamic specification:

$$y_{jt} = \sum_{k \in K} \beta_k smoke_{j,t-k} + \sum_{k \in K} X_{j,t-k}\Omega_k + \nu_{jq(t)} + \sigma_t + \epsilon_{jt}, \tag{2}$$

where j indexes the commuting zone and t indexes the date. The dependent variable, y_{jt}, represents daily air pollution levels or claim rates, and we model the effect of wildfire smoke as a series of variables, $smoke_{j,t-k}$, equal to the share of the commuting zone covered by smoke k days before the observation date for all $k \in K$. As in Equation (1), the commuting zone by quarter fixed effects ($\nu_{jq(t)}$) and date fixed effects (σ_t) in Equation (2) account for flexible commuting-zone-level time trends and statewide time-varying factors that could impact wildfire smoke, pollution, or workplace injuries. We include additional controls ($X_{j,t-k}$) for weather on the observation day and the surrounding days in K. This analysis considers the impact of smoke exposure within two weeks of the observation date (setting $K = [-14, 13]$), though our estimates are similar if we consider shorter or longer windows. In this estimation, the coefficients of interest are the vector of β_k coefficients—which measure the impact of smoke exposure k days before the day of observation on the commuting zone's daily claim initiation rate relative to days outside of this window (i.e., effectively normalizing $\beta_k \equiv 0$ for all $k \notin K$).

Figure 5 displays estimates from this specification analyzing both air pollution (Panel A) and injury claim rates (Panel B). In line with the estimates in Table 2, Panel A indicates that smoke on the observation date is associated with an approximately 1.7 μg/m^3 increase in daily PM$_{2.5}$ and a 1.9 μg/m^3 increase in daytime PM$_{2.5}$. We note this plot also illustrates that smoke can affect air quality for multiple days—though the impacts are concentrated on the same day, with much smaller impacts on the day directly preceding and following that day. This suggests smoke may affect air quality when the associated plume is no longer (or not yet) detectable through satellite imagery and may be in part due to differences in measurement timing between smoke and PM$_{2.5}$ (as smoke plumes are only measured during daylight hours).[38] This evidence supports our inclusion of leads and lags of smoke in the baseline regression analysis. Turning to the analysis of injury claim rates, Panel B suggests there is no systematic relationship between smoke in the future and claims on the index day. In contrast, we see that smoke on the index day causes a sharp increase in same-day injury claims—with estimates indicating the increase in same-day claims is 0.066 per 100,000 workers, or a 1.1% increase relative to the daily claim rate. Additionally, this plot suggests that smoke yesterday has an almost equally large impact on today's injury claims, while smoke in days before yesterday has little impact on today's claims. This graphical evidence aligns with the findings from Table 9 Panel A and further supports our baseline regression analysis which aims to capture both the instantaneous and delayed effects of smoke on workplace injuries.

Beyond the approach leveraged in our baseline regressions, an alternative way to characterize the immediate and delayed effects of smoke exposure would be to simply aggregate coefficients from the distributed lag model depicted in Figure 5 Panel B. For example, one can represent the impact of smoke on the index day on claims over the next three days as either: δ from our baseline regression analysis (in Equation 1) or $\sum_{k \in [-2,0]} \beta_k$ from the distributed lag model (in Equation 2). These two approaches are methodologically very similar and, in our setting, deliver almost identical empirical estimates. Appendix Table A5

[38] There are two pieces of evidence consistent with this latter explanation. First, the impact on PM$_{2.5}$ of smoke in the day before or after the observation date is smaller (relative to the same-day impact) with the daytime measure of PM$_{2.5}$. This is consistent with smoke tomorrow (yesterday) affecting today's PM$_{2.5}$ in the evening after daylight hours (morning before daylight hours). Second, if smoke tomorrow primarily affects today's PM$_{2.5}$ in the evening—after work is complete for most people—we may expect little to no impact of smoke tomorrow on today's injuries. Consistent with this, the estimates in Panel B indicate no impact of smoke tomorrow on today's claims.

displays estimates from the alternative approach for each horizon considered, with Table 9 Panel B summarizing the estimates from this alternative approach. Comparing Panels A and B of Table 9, we see that these approaches yield very similar estimates.

Count Model The baseline analysis relates claim rates to smoke through an OLS regression. We explore the robustness of our findings when estimating a Poisson model for injury claims that explicitly accounts for the non-negative, discrete nature of workers' compensation claims. For this Poisson regression analysis, the dependent variable is claims aggregated over three days (i.e., the index day and the following two days). Table 8 reports these estimates. As with the baseline OLS analysis on claim rates, the estimates from the Poisson model indicate that smoke increases injury claims. The magnitudes are also comparable, with estimates from the Poisson model with the baseline controls implying that smoke causes a 2.2% increase in claims relative to the mean daily claim rate.

Other Robustness Appendix Table A6 presents additional analysis demonstrating the robustness of our findings when considering alternative variable definitions or sample restrictions. For instance, we obtain similar estimates using an alternative measure of smoke coverage—a binary variable indicating the commuting zone was fully covered by smoke—instead of the baseline continuous measure. In addition, the estimates are similar when employing an alternative way to define claim location—aggregating claims to commuting zones using the location where the claimant first obtained medical care rather than their residential location. Further, we obtain similar estimates to the baseline estimates when excluding the top 1% of smoke days with respect to daily $PM_{2.5}$, which excludes smoke days with $PM_{2.5}$ exceeding 23.9 $\mu g/m^3$.

5 Discussion of Magnitudes

Next, we provide further discussion of the magnitude of our estimates—in terms of additional injury claims and the costs associated with these injuries. We then compare our estimated impacts to those in prior work on other impacts of pollution.

Interpreting Magnitudes To assess the costs associated with increased workplace injury claims, we draw on estimates from the National Safety Council, which estimates the average societal cost of workplace injuries is $42,000 per medically consulted injury (National Safety Council 2023).[39] This estimate aims to be a comprehensive measure of injury costs by including wage and productivity losses, medical expenses, administrative expenses, and employer uninsured costs; notably, this estimate excludes property damage costs and thus may represent an underestimate of the total costs of these injuries. To explore the costs associated with increased injury claims, we apply this National Safety Council cost estimate to our estimated increase in injuries under the assumption that the marginal injuries induced by smoke are as costly as the average injury. We view this assumption as broadly plausible, given that our analysis indicates that smoke induces similar increases in claims for more and less severe injuries.

As discussed earlier, we find that an additional day of smoke coverage leads to 0.165 additional injury claims per 100,000 workers, a 2.8% increase over the mean daily claim rate. To assess the magnitude of the estimates, we scale our estimated increase in injury claims by the impact of smoke on ambient $PM_{2.5}$. Based on this scaling, our estimates imply that a 10 $\mu g/m^3$ increase in $PM_{2.5}$ leads to an additional 0.98 injury claims per 100,000 workers or a 16.9% increase relative to the mean daily claim rate. The cost of these additional injuries is $41,139 daily per 100,000 workers, or about 0.3% of the mean daily earnings in Texas.[40]

[39] All calculations in this section are reported in 2021 dollars, as the National Safety Council estimate is for 2021 injuries.

[40] We calculate the costs as a percent of daily earnings in Texas by scaling the cost of these injuries by the mean daily earnings of Texas workers from Appendix Table A1 (adjusted to 2021 dollars using the CPI-U).

Extrapolating from these estimates, we can consider the impact of other pollution shocks, such as a permanent increase in $PM_{2.5}$ or a smoke day severe enough to reach regulatory thresholds. Considering these shocks requires substantial extrapolation beyond the identifying variation, therefore appropriate caution should be used when interpreting these results. With these caveats in mind, our estimates imply that a permanent 10 $\mu g/m^3$ increase in $PM_{2.5}$ would lead to an additional 358 injury claims annually per 100,000 workers, with these injuries costing $15.0 million per 100,000 workers. Aggregating across workers, a statewide change of this magnitude would result in an additional 47,368 injury claims annually in Texas, with these injuries costing $2.0 billion annually in Texas.

In our sample, a 10 $\mu g/m^3$ increase in $PM_{2.5}$ would typically result in pollution levels well below current regulatory thresholds—both in federal EPA regulations and in recently adopted state OSHA regulations in California, Oregon, and Washington. So, it may also be natural to consider the impact of a severe smoke day—one sufficient to reach current regulatory thresholds. To do this, we consider a 26.44 $\mu g/m^3$ increase in $PM_{2.5}$—an increase equal to the difference between the mean pollution level on a non-smoke day in our sample (9.06 $\mu g/m^3$) and 35.5 $\mu g/m^3$ (the threshold Oregon and Washington OSHAs adopted and close to the 35 $\mu g/m^3$ EPA daily standard for $PM_{2.5}$). Extrapolating from our estimates, a severe smoke day would lead to an additional 2.59 injury claims per 100,000 workers, representing a 45% increase in daily claim rate. This increase in injuries would lead to additional costs of $108,604 per 100,000 workers, representing 0.8% of daily earnings. A smoke day this severe that spanned the state of Texas would lead to an additional 343 injury claims in Texas, with these injuries costing $14.4 million.

While the magnitudes discussed above are substantial, these calculations may understate some impacts that may be of interest in this setting. For example, while these calculations capture the impact of smoke on workers' compensation injury claims in Texas, not all workplace injuries are associated with a workers' compensation claim and thus the impact on all workplace injuries is likely meaningfully larger than the magnitudes discussed above. Moreover, the impact of smoke on the workers' compensation claim rate nationwide is likely substantially larger than the estimated impact within Texas, as workers' compensation claims per worker are lower in Texas than nationwide.[41] If we wanted to approximate the nationwide impact, we could scale up our estimates by estimates of the nationwide claim rate, assuming the percent impacts we estimate from Texas apply across the U.S. This scaling suggests a permanent 10 $\mu g/m^3$ increase in $PM_{2.5}$ would lead to an additional 565 annual injury claims per 100,000 workers nationwide—with these injuries costing $24 million per 100,000 workers or about 0.5% of mean annual earnings. Aggregating across workers, this would represent an additional 850,000 injuries annually nationwide, with an annual cost of $35.6 billion.

Comparison to Other Impacts of Pollution We can compare our estimates to other impacts of pollution estimated in prior work. We begin by comparing our estimates to estimates of the impact of pollution on worker productivity. Most studies in this literature relate ambient air pollution levels to worker productivity at a particular worksite where workers are paid by piece rate (and thus it is straightforward to measure worker productivity). Our estimates are most comparable to the subset of these studies investigating impacts of $PM_{2.5}$. For instance, Chang et al. (2016) find a 10 $\mu g/m^3$ increase in $PM_{2.5}$ (measured as a six-day average) leads to a 6% decline in productivity among piece-rate pear packers at a Northern California fac-

[41] Based on data in a National Academy of Social Insurance report, workers' compensation claims averaged 9.4 injuries per 100,000 covered workers from 2005 to 2018 based on data from 38 states whose claims are aggregated by the National Council on Compensation Insurance (Murphy and Wolf 2022). While this estimate does not represent all 50 states, it is the most comprehensive estimate available based on administrative claims data. If scaled by the share of workers covered by workers' compensation insurance nationwide (approximately 97.5%), the estimated claim rate for these states is 9.16 injuries per 100,000 workers. We use this estimated broader claim rate as the estimated nationwide claim rate in the scaling exercise described in the text below.

tory. Adhvaryu, Kala, and Nyshadham (2022) estimate that a 10 $\mu g/m^3$ hourly increase in $PM_{2.5}$ leads to a 0.6% decline in productivity among workers at an Indian garment factory. He, Liu, and Salvo (2019) find $PM_{2.5}$ has no short-term impact on productivity among manufacturing workers in two Chinese towns, though prolonged exposure to a 10 $\mu g/m^3$ increase in $PM_{2.5}$ is associated with a 1% decline in productivity. We note that the context of these estimates is quite different than ours. For instance, these studies focus on impacts at particular job sites, while our estimates consider workers across Texas spanning all industries and occupations. Despite the differences in context, our estimates of the costs of pollution stemming from increased workplace injuries are in the same range as many of the prior estimates of the productivity effects of air pollution—both overall and within the specific industry-occupations that are closest to those studied in these worker productivity papers.[42]

We can also compare our estimates to other impacts of pollution on health. Prior work characterizing the impacts of pollution on health largely focuses on impacts on mortality and hospital utilization—particularly among children and the elderly. We can compare the implied aggregate nationwide costs from increased workplace injuries to the aggregate nationwide costs implied by other impacts documented in this literature. See Appendix Table A8 for more details on these calculations. Some estimates in prior work suggest a permanent 10 $\mu g/m^3$ increase in $PM_{2.5}$ would result in a $4.1 billion annual increase in inpatient spending among the elderly (based on estimates in Deryugina et al. 2019) and a $1.1 billion annual increase in spending on respiratory-related ED visits among children 0–4 years of age (based on estimates in Alexander and Schwandt 2022). The total costs from increased workplace injuries are much larger—nine times the increase in inpatient spending among the elderly and 32 times the increase in spending for respiratory-related ED visits among young children.[43] We can also compare the aggregate costs from increased workplace injuries to the implied value of life years lost based on estimated mortality impacts among the elderly. Estimates in Deryugina et al. (2019) imply that a permanent a 10 $\mu g/m^3$ increase in $PM_{2.5}$ would lead to $62.8 billion in life years lost annually among the elderly due to increases in mortality. Comparing this to our estimates, the aggregate costs of increased workplace injuries are 57% of the value of life years lost among the elderly.

Overall, our findings indicate that pollution can have large and important consequences on worker health through increasing workplace injuries. These increased injuries impose costs on firms and workers—through increased medical spending, earnings reductions, work disruptions, reduced worker productivity, and administrative expenses. And the costs associated with increased workplace injuries are substantial and in the same range as many other important negative consequences of pollution.

6 Supplemental Evidence: Incidence of Impacts

Pollution-induced increases in workplace injuries are not borne equally by all individuals—or all workers. While we find similar percent impacts across different types of workers, the baseline injury rate varies dramatically across different types of workers. Thus, the overall costs of (community-based) pollution vary dramatically across workers.

[42]Overall, we find that a 10 $\mu g/m^3$ increase in $PM_{2.5}$ leads to costs that represent 0.3% of Texas payroll due to increased workplace injuries. In Section 6, we calculate industry-occupation-specific costs relative to payroll, by combining our estimates with information on baseline industry-occupation workers' compensation injury risk for 334 distinct industry-occupation classification codes. We can compare the industry-occupation-specific implied impacts from this analysis for occupations studied in the literature examining worker productivity impacts. This analysis suggests that a 10 $\mu g/m^3$ increase in $PM_{2.5}$ would lead to costs from increased injuries that amount to 1.3% of payroll among fruit packers, 1.5% of payroll among clothing manufacturing workers, and 0.6% of payroll among yarn or thread manufacturing workers.

[43]Our measure of costs associated with workplace injuries goes beyond medical costs (e.g., including work disruptions, productivity losses, uninsured employer costs, etc.). If we focus more narrowly on injury-related medical spending, our estimates imply that a permanent 10 $\mu g/m^3$ increase in $PM_{2.5}$ would cost $3.0 billion in medical spending on workplace injuries per year, or about 73% the impact on inpatient spending among the elderly and three times the impact on ED spending among young children.

To illustrate this point, we conduct back-of-the-envelope calculations that illustrate how the costs of pollution-induced workplace injuries vary by industry and occupation. For this analysis, we draw on workers' compensation industry-occupation classification codes, which represent a detailed characterization of the nature of work covering 334 unique codes. We begin by calculating costs (as a percent of payroll) for a 10 $\mu g/m^3$ increase in $PM_{2.5}$ by industry-occupation. For this calculation, we assume constant percent impacts across classifications, consistent with the evidence in Section 4 which illustrates no systematic relationship between percent impacts and key industry-occupation characteristics such as workplace injury risk or outdoor exposure. Under this assumption, we can obtain classification-specific impacts by scaling the mean impact of this increase in pollution as a percent of payroll (0.3% statewide) by an industry-occupation classification's risk. Classification risk is measured as workers' compensation costs per $100 of payroll (as calculated by the Texas Department of Insurance for risk adjustment purposes) normalized to have mean one across workers' compensation covered payroll.

Figure 6 displays a histogram with the resulting industry-occupation impacts, where each observation underlying this histogram represents an industry-occupation classification. While the costs of a 10 $\mu g/m^3$ increase in $PM_{2.5}$ represent 0.3% of payroll statewide, we see that the impacts are much larger in high-risk occupations—representing between 1% and 3% of payroll or more among the highest risk industry-occupations. To provide context, Appendix Table A9 lists industry-occupation impacts for the largest classifications at the extremes of the risk distribution: in the top 5% of risk (Panel A) and the bottom 5% of risk (Panel D). This table also provides industry-occupation impacts for the largest classifications in the middle of the risk distribution—those between the median and top 5% of risk (Panel B) and those between the bottom 5% of risk and the median (Panel C).

Some of the largest industry-occupation classifications in the top of the risk distribution are oil and gas well workers, roofing employees, car manufacturing workers, storage warehouse workers, and poultry workers. Among these high-risk workers, the costs of a 10 $\mu g/m^3$ increase in $PM_{2.5}$ represent between 2.0% and 3.7% of payroll. Clerical office workers, salespeople, architects, attorneys, and telephone company workers are some of the largest very low-risk classifications—for which the costs of a 10 $\mu g/m^3$ increase in $PM_{2.5}$ represent 0.1% of payroll or less. Among industry-occupations that are in the bottom half of the risk distribution but outside the bottom 5%, some of the largest classifications are retail workers, college professional employees, and auto repair shop workers—with impacts among these workers representing between 0.1% and 0.6% of payroll. Some of the largest classifications that are above the median but outside the top 5% of risk are trucking employees, plumbers, electricians, hotel employees, and concrete/cement workers. For these employees, costs associated with a 10 $\mu g/m^3$ increase in $PM_{2.5}$ represent between 0.8% and 1.8% of payroll.

There is substantial variation in industry-occupation classification size, with the largest classification—clerical office workers—representing roughly 40% of payroll statewide. Thus, a natural follow-up question is: What is the distribution of the harms of pollution across workers after accounting for the share of payroll in each classification? The answer to this question is important both for characterizing the incidence of the harms of pollution and for identifying potential opportunities for targeting costly mitigation efforts. Motivated by this, we present back-of-the-envelope counterfactuals describing the distribution of harms (or the potential benefits of targeting) based on industry-occupation classification workplace injury risk. We then compare the potential benefits of targeting based on risk exposure to: (i) untargeted (random) mitigation efforts or (ii) targeting based on outdoor exposure.

Figure 7 Panel A displays the marginal cost of a 10 $\mu g/m^3$ increase in $PM_{2.5}$, where classifications are ordered according to either their risk exposure ("risk index"; represented by blue circles) or outdoor exposure ("outdoor index"; represented by gray diamonds). The horizontal axis represents the share of payroll that is at or above the indicated percentile of the relevant index, while the vertical axis displays the costs associated with increased workplace injuries from a 10 $\mu g/m^3$ increase in $PM_{2.5}$ (as a percent of payroll) in that marginal classification. Figure 7 Panel B displays a parallel plot for average rather than marginal costs—where we calculate the average impact among classifications at or above the indicated percentile of the risk or outdoor index. There are a few important take-aways from this figure. First, the harms of pollution are highly concentrated among high-risk industry-occupations. While a 10 $\mu g/m^3$ increase in $PM_{2.5}$ generates costs representing 0.3% of payroll overall, the marginal impact at the 95th percentile is 1.1% of payroll, at the 90th percentile is 0.88% of payroll, and at the 75th percentile is 0.48% of payroll, while the median impact is 0.09% of payroll—less than a third of the overall average. Second, while outdoor exposure is positively correlated with risk exposure, the two are not perfectly correlated. As a result, the harms of pollution are more concentrated among workers with high risk exposure than they are concentrated among workers who are highly exposed to the outdoors.

This final point can be seen more directly in Figure 8. This figure plots the share of aggregate costs from pollution-induced increases in workplace injury claims among workers at or above the indicated percentile of the risk index (in blue) or the outdoor index (in gray). This figure illustrates that the top 5% of payroll based on risk exposure accounts for 26% of the total aggregate costs of pollution from increased workplace injury claims, while the top 5% of payroll based on outdoor exposure accounts for 22% of the aggregate costs of pollution. Similarly, the figure indicates the top 10% of payroll based on risk exposure bears 42% of the aggregate costs of pollution, whereas the top 10% of payroll based on outdoor exposure bears 33% of the aggregate costs. Note these shares are much larger than 5% or 10% respectively—indicating the harms of pollution are far from evenly distributed across the workforce. Instead, this analysis indicates the harms of pollution are highly concentrated within a relatively small share of the workforce—with much of the costs attributable to high-risk industry-occupations. Moreover, while exposure to the outdoors is positively correlated with workplace injury risk, these harms are much more concentrated among workers in high-risk industry-occupations than they are concentrated among workers in industry-occupations highly exposed to the outdoors.

These findings have natural implications for the targeting of mitigation. Specifically, the fact that harms are quite concentrated within a small share of the workforce suggests there are potential benefits from targeting costly mitigation toward the segment of the workforce most likely to benefit from such efforts. Suppose there exists a feasible mitigation strategy that reduces the harms of pollution proportionally across the workforce. Based on Figure 8, targeting this mitigation toward the top 10% of payroll based on risk exposure would yield more than four times the reduction in workplace injuries and associated costs than would be obtained from untargeted mitigation aimed at a random 10% of payroll. Moreover, targeting such mitigation based on risk exposure would yield higher benefits than targeting based on outdoor exposure. For example, targeting mitigation toward the top 10% of payroll defined based on risk exposure would result in a 25% larger reduction in workplace injuries (and associated costs) than targeting mitigation toward the top 10% of payroll based on outdoor exposure. If the costs of mitigation are proportional to the payroll targeted, this analysis suggests that it would be more efficient to target mitigation based on risk exposure rather than outdoor exposure.

7 Policy Implications

Our estimates illustrate that air pollution adversely impacts the health of workers through increasing the rate of workplace injury, leading to substantial societal costs. We turn to discussing some implications of our results.

Our findings provide several important insights that can inform policy. First, our results highlight that pollution presents unique health risks for workers. In this way, our findings suggest a motivation for specific regulation addressing worker exposure to pollution, providing a potential rationale for OSHA regulation alongside broader environmental policy. Our estimates inform ongoing policy debates regarding design and scope of OSHA regulations—for example, debates about adopting federal OSHA regulation regarding smoke. Additionally, by enhancing our understanding of the negative impacts of pollution and wildfire smoke, our estimates shed light on potential benefits of expanding efforts to reduce pollution exposure through EPA regulations targeting pollution reduction and policies aimed at reducing the occurrence and severity of wildfires (e.g., forest management, fire prevention, slowing/reversing rising temperatures). Moreover, our findings highlight the importance of considering harms for worker health when evaluating polices related to pollution or management of wildfire risks.

Second, our results shed light on potential benefits from broadening the scope of regulation. Our findings indicate that wildfire smoke increases workplace injuries at pollution levels well below current regulatory thresholds. Further, we document these harms extend to workers working in a variety of settings, including workers more and less exposed to the outdoors. The widespread nature of the harms is potentially consistent with different possibilities—for example, worker exposure to community-based pollution may be similar across different work settings or exposure to pollution outside of work may impact subsequent workplace injuries. While our analysis cannot separately identify the role of these possibilities, our estimates suggest the impacts are primarily driven by pollution on the smoke day itself, though pollution experienced over the previous two days may also contribute to increased injury claims. Overall, our findings shed light on potential benefits from expanding the scope of current regulation—for example, through lowering pollution thresholds in EPA and OSHA regulation or expanding OSHA regulation to cover workers less exposed to the outdoors. Moreover, our findings suggest it is important to consider how pollution is specified within OSHA regulations—for instance, there could be a rationale to consider pollution during the period directly preceding work in addition to pollution during work hours.

Third, our estimates can be used to assess the impact of one specific mitigation strategy included in recent state OSHA regulations: rescheduling work to less polluted days. Based on our estimates, shifting work from a severe smoke day (sufficient to meet regulatory thresholds) to a non-smoke day would reduce workplace injuries by 1.31 to 2.59 per 100,000 workers.[44] This suggests that one potentially feasible mitigation strategy can substantially offset the harms of pollution. However, because shifting work is generally costly and could be impossible for some of the workforce, these benefits need to be weighed against the costs. Thus, our findings also highlight the need for more research on the costs of mitigation and more research on the impacts of other mitigation strategies. For example, future research should explore other mitigation

[44] This interval is obtained through considering two alternative ways to interpret impacts on injury claims initiated in the days following the smoke day. It could be that excess injury claims in the days following the smoke day are for injuries that occurred on the smoke day itself (e.g,. because of delays in obtaining medical care for these injuries). In this scenario, moving work from a severe smoke day to a non-smoke day would reduce workplace injuries by the entire three-day decrease in workplace injury claims. On the other hand, it could be that excess injury claims in the days following the smoke day are because of delayed impacts of smoke (i.e., injuries occurring in the days following the smoke day), in which case we would not want to attribute these injury claims to work on the smoke day itself. In that case, moving work from a severe smoke day to a non-smoke day would lead to a decline in workplace injuries of 1.31 per 100,000 workers based on the one-day claim rate impacts in Table 9.

strategies highlighted in recent OSHA regulations—including reducing work intensity, offering more rest periods, providing protective equipment. Moreover, our findings highlight the importance of exploring the impact of alternative strategies to limit increases in injuries on polluted days, like implementing enhanced injury prevention safety practices on polluted days or rescheduling high-risk tasks to less polluted days.

Finally, our findings can inform us about the potential gains from targeting costly mitigation. While our estimates suggest percent effects are similar across workers, the incidence of increased injuries varies dramatically by industry-occupation because of differing baseline injury risk. Our analysis suggests that harms of pollution are concentrated among the highest risk workers—26% (42%) of the costs are among the top 5% (10%) of payroll in terms of risk. Given that mitigation is typically costly, this implies that there are likely substantial gains from targeting costly mitigation toward workers in high-risk industry-occupation groups. For example, our back-of-the-envelope counterfactual analysis illustrates targeting mitigation toward the top 10% of payroll in terms of industry-occupation workers' compensation risk would yield more than four times the reduction in workplace injuries that would be obtain through randomly allocated mitigation. Moreover, our analysis suggests targeting mitigation based on industry-occupation risk is substantially more effective in reducing workplace injuries than targeting based outdoor exposure—the key feature used for targeting in recent state OSHA regulations. More broadly, our results highlight the wide-reaching impacts of community based pollution across workers—suggesting a rationale to shift the focus of targeting within OSHA regulation from workers often assumed to have greater exposure to pollution while at work (e.g., outdoor workers) toward workers most sensitive to pollution exposure due to the inherent risks involved in their work activities (e.g., workers in high-risk industry-occupations).

8 Conclusion

This paper investigates the impact of pollution on worker health and safety, leveraging plausibly exogenous variation in the timing and location of wildfire smoke plumes and comprehensive administrative data on workers' compensation injury claims from Texas. We find that smoke increases ambient air pollution and causes substantial increases in the rate of workplace injury claims. These impacts appear near-universal, with similar percent impacts across different types of injuries and workers. However, because there is large variation in baseline injury risk by industry-occupation, the costs of increased injuries are highly concentrated among workers in high-risk industry-occupations. Our results indicate that more than a quarter of the costs of pollution are borne by the top 5% of payroll in terms of industry-occupation workers' compensation risk, suggesting potential benefits of targeting costly mitigation. Our estimates indicate that pollution substantially harms worker health, even at pollution levels well below thresholds used in current and proposed regulations. Moreover, the implied cost of pollution-induced workplace injuries is the same order of magnitude as the cost of many other important previously documented impacts of pollution.

Our study provides large-scale causal evidence on the effect of air pollution—and wildfire smoke—on worker health and safety. These results have broad implications for policy. By highlighting that pollution poses unique risks for workers, our findings provide a motivation for policies specifically addressing worker exposure to pollution, potentially justifying recent OSHA regulatory efforts pertaining to work during periods of elevated pollution due to wildfire smoke. Moreover, our findings provide several specific insights related to the impact of mitigation and targeting of OSHA regulation—informing ongoing policy debates surrounding recently enacted and proposed state-level OSHA regulation and proposals for OSHA regulation at the federal level. Further, our evidence adds to growing evidence on the wide-ranging harms of pollution, and thus can inform broader environmental policy aimed at reducing pollution exposure, such as EPA policy and policies aimed at reducing the prevalence and severity of wildfires.

Our work also connects to policy discussions surrounding occupational health and workplace safety more generally. Engaging in work inherently involves risk of injury, particularly in high-risk occupations. Regulation and guidance regarding workplace safety explicitly recognize trade-offs between work and safety—often focusing on risk mitigation rather than complete elimination of risks and offering a sliding scale of mitigation measures that could be implemented depending on feasibility and costs. Our findings provide some broader insights regarding the regulation of workplace risks. First, our results highlight how workplace safety is influenced by community-wide conditions—such as pollution and smoke. In this way, our findings provide a potential justification for expanding the scope of OSHA regulations to consider factors beyond those directly controlled by firms—supporting the rationale behind recent state OSHA policies regulating work in areas experiencing smoke. Second, our analysis highlights some important considerations in the design of regulation addressing workplace safety hazards stemming from temporary shocks that affect the broader community. Unlike much of the regulation and guidance from OSHA focusing on consistent everyday workplace hazards, policies addressing temporary community-wide shocks may require safety protocols centered around dynamic real-time adjustment in response to prevailing community-wide conditions—e.g., scaling up injury prevention measures on days with elevated pollution levels. Furthermore, while community-wide events may impact workers across all work settings, the consequences for workplace safety may be disproportionately borne by those in high-risk occupations and there may be benefits of targeting regulation toward this segment of the workforce.

Beyond informing policy, our work also complements and extends broader literatures analyzing the impacts of pollution and the determinants of workplace safety. While there is growing causal evidence documenting the acute health impacts of pollution, existing evidence largely focuses on impacts on young children and the elderly, and there is limited direct evidence on how pollution impacts the health of prime-aged adults. Prior work on the impact of pollution on non-elderly adults has primarily focused on broader "nonhealth" outcomes—for example, demonstrating that pollution leads to reductions in worker productivity and lower quality decision-making. Our results complement this literature by illustrating that the same mechanisms underlying broader "nonhealth" impacts of pollution—sub-clinical symptoms that reduce physical and cognitive functioning—lead to increased acute health events (on-the-job injuries) among adults and these impacts result in aggregate costs comparable to many other previously documented health and broader impacts of pollution. Moreover, our findings extend an emerging literature on workplace safety by demonstrating that air pollution is an important determinant of workplace safety, expanding our knowledge of what factors influence workplace safety more generally.

References

Adhvaryu, Achyuta, Namrata Kala, and Anant Nyshadham. 2022. "Management and Shocks to Worker Productivity." *Journal of Political Economy*, 130(1): 1–47.

Aguilar-Gomez, Sandra, Holt Dwyer, Joshua Graff Zivin, and Matthew Neidell. 2022. "This Is Air: The "Nonhealth" Effects of Air Pollution." *Annual Review of Resource Economics*, 14(1): 403–425.

Aguilera, Rosana, Thomas Corringham, Alexander Gershunov, and Tarik Benmarhnia. 2021. "Wildfire smoke impacts respiratory health more than fine particles from other sources: observational evidence from Southern California." *Nature Communications*, 12(1): 1493.

Alexander, Diane and Hannes Schwandt. 2022. "The Impact of Car Pollution on Infant and Child Health: Evidence from Emissions Cheating." *The Review of Economic Studies*, 89(6): 2872–2910.

Arenberg, Samuel and Seth Neller. 2023. "Ashes to Ashes: The Lifelong Consequences of Early-Life Wildfire Exposure." Working Paper.

Borgschulte, Mark, David Molitor, and Eric Yongchen Zou. 2022. "Air Pollution and the Labor Market: Evidence from Wildfire Smoke." *The Review of Economics and Statistics*, 1–46.

Brown, Daniel M, Maya Petersen, Sadie Costello, Elizabeth M Noth, Katherine Hammond, Mark Cullen, Mark van der Laan, and Ellen Eisen. 2015. "Occupational Exposure to PM2.5 and Incidence of Ischemic Heart Disease: Longitudinal Targeted Minimum Loss-based Estimation." *Epidemiology (Cambridge, Mass.)*, 26(6): 806—814.

Burkhardt, Jesse, Jude Bayham, Ander Wilson, Ellison Carter, Jesse D. Berman, Katelyn O'Dell, Bonne Ford, Emily V. Fischer, and Jeffrey R. Pierce. 2019. "The Effect of Pollution on Crime: Evidence from Data on Particulate Matter and Ozone." *Journal of Environmental Economics and Management*, 98: 102267.

Chang, Tom, Joshua Graff Zivin, Tal Gross, and Matthew Neidell. 2016. "Particulate Pollution and the Productivity of Pear Packers." *American Economic Journal: Economic Policy*, 8(3): 141–169.

Chang, Tom Y., Joshua Graff Zivin, Tal Gross, and Matthew Neidell. 2019. "The Effect of Pollution on Worker Productivity: Evidence from Call Center Workers in China." *American Economic Journal: Applied Economics*, 11(1): 151–172.

Charles, Kerwin Kofi, Matthew S. Johnson, Melvin Stephens, and Do Q. Lee. 2022. "Demand Conditions and Worker Safety: Evidence from Price Shocks in Mining." *Journal of Labor Economics*, 40(1): 47–94.

Chay, Kenneth, Carlos Dobkin, and Michael Greenstone. 2003. "The Clean Air Act of 1970 and Adult Mortality." *Journal of Risk and Uncertainty*, 27(3): 279–300.

Chay, Kenneth Y. and Michael Greenstone. 2003. "The Impact of Air Pollution on Infant Mortality: Evidence from Geographic Variation in Pollution Shocks Induced by a Recession*." *The Quarterly Journal of Economics*, 118(3): 1121–1167.

Chen, Yuyu, Avraham Ebenstein, Michael Greenstone, and Hongbin Li. 2013. "Evidence on the Impact of Sustained Exposure to Air Pollution on Life Expectancy from China's Huai River Policy." *Proceedings of the National Academy of Sciences*, 110(32): 12936–12941.

Curci, Gabriele, Domenico Depalo, and Alessandro Palma. 2023. "The Dirtier You Breathe,The Less Safe You Are.The Effect of Air Pollutionon Work Accidents." CEIS Working Paper No. 554.

Currie, Janet, Matthew Neidell, and Johannes F. Schmieder. 2009. "Air Pollution and Infant Health: Lessons from New Jersey." *Journal of Health Economics*, 28(3): 688–703.

Delgado-Saborit, Juana Maria, Valentina Guercio, Alison M. Gowers, Gavin Shaddick, Nick C. Fox, and Seth Love. 2021. "A Critical Review of the Epidemiological Evidence of Effects of Air Pollution on Dementia, Cognitive Function and Cognitive Decline in Adult Population." *Science of The Total Environment*, 757: 143734.

DeMeo, Dawn L., Antonella Zanobetti, Augusto A. Litonjua, Brent A. Coull, Joel Schwartz, and Diane R. Gold. 2004. "Ambient Air Pollution and Oxygen Saturation." *American Journal of Respiratory and Critical Care Medicine*, 170(4): 383–387.

Deryugina, Tatyana and Julian Reif. 2023. "The Long-run Effect of Air Pollution on Survival." National Bureau of Economic Research Working Paper 31858.

Deryugina, Tatyana, Garth Heutel, Nolan H. Miller, David Molitor, and Julian Reif. 2019. "The Mortality and Medical Costs of Air Pollution: Evidence from Changes in Wind Direction." *American Economic Review*, 109(12): 4178–4219.

Deschênes, Olivier, Michael Greenstone, and Joseph S. Shapiro. 2017. "Defensive Investments and the Demand for Air Quality: Evidence from the NOx Budget Program." *American Economic Review*, 107(10): 2958–2989.

Dillender, Marcus. 2021. "Climate Change and Occupational Health: Are There Limits to Our Ability to Adapt?" *Journal of Human Resources*, 56(1): 184–224.

Ebenstein, Avraham, Victor Lavy, and Sefi Roth. 2016. "The Long-Run Economic Consequences of High-Stakes Examinations: Evidence from Transitory Variation in Pollution." *American Economic Journal: Applied Economics*, 8(4): 36–65.

Flood, Sarah, Miriam King, Renae Rodgers, Steven Ruggles, J. Robert Warren, and Michael Westberry. 2022. "Integrated Public Use Microdata Series, Current Population Survey: Version 10.0 [dataset]." IPUMS, Minneapolis, MN.

Frazier, Ian. 2018. "The Day the Great Plains Burned." *The New Yorker*.

Gaughan, Denise M., Jean M. Cox-Ganser, Paul L. Enright, Robert M. Castellan, Gregory R. Wagner, Gerald R. Hobbs, Toni A. Bledsoe, Paul D. Siegel, Kathleen Kreiss, and David N. Weissman. 2008. "Acute Upper and Lower Respiratory Effects in Wildland Firefighters." *Journal of Occupational and Environmental Medicine*, 50(9): 1019–1028.

Gaughan, Denise M., Paul D. Siegel, Michael D. Hughes, Chiung-Yu Chang, Brandon F. Law, Corey R. Campbell, Jennifer C. Richards, Stefanos F. Kales, Marcia Chertok, Lester Kobzik, Phuong-son Nguyen, Carl R. O'Donnell, Max Kiefer, Gregory R. Wagner, and David C. Christiani. 2014. "Arterial stiffness, oxidative stress, and smoke exposure in wildland firefighters." *American Journal of Industrial Medicine*, 57(7): 748–756.

Graff Zivin, Joshua and Matthew Neidell. 2012. "The Impact of Pollution on Worker Productivity." *American Economic Review*, 102(7): 3652–3673.

Heft-Neal, Sam, Carlos F. Gould, Marissa L. Childs, Mathew V. Kiang, Kari C. Nadeau, Mark Duggan, Eran Bendavid, and Marshall Burke. 2023. "Emergency department visits respond nonlinearly to wildfire smoke." *Proceedings of the National Academy of Sciences*, 120(39).

He, Jiaxiu, Haoming Liu, and Alberto Salvo. 2019. "Severe Air Pollution and Labor Productivity: Evidence from Industrial Towns in China." *American Economic Journal: Applied Economics*, 11(1): 173–201.

Herrnstadt, Evan, Anthony Heyes, Erich Muehlegger, and Soodeh Saberian. 2021. "Air Pollution and Criminal Activity: Microgeographic Evidence from Chicago." *American Economic Journal: Applied Economics*, 13(4): 70–100.

Huang, Jiekun, Nianhang Xu, and Honghai Yu. 2020. "Pollution and Performance: Do Investors Make Worse Trades on Hazy Days?" *Management Science*, 66(10): 4455–4476.

Jayachandran, Seema. 2009. "Air Quality and Early-Life Mortality." *Journal of Human Resources*, 44(4): 916–954.

Johnson, Matthew S. 2020. "Regulation by Shaming: Deterrence Effects of Publicizing Violations of Workplace Safety and Health Laws." *American Economic Review*, 110(6): 1866–1904.

Johnson, Matthew S., David I. Levine, and Michael W. Toffel. 2023. "Improving Regulatory Effectiveness through Better Targeting: Evidence from OSHA." *American Economic Journal: Applied Economics*, 15(4): 30–67.

Kile, Molly L., Shona Fang, Andrea A. Baccarelli, Letizia Tarantini, Jennifer Cavallari, and David C. Christiani. 2013. "A panel study of occupational exposure to fine particulate matter and changes in DNA methylation over a single workday and years worked in boilermaker welders." *Environmental Health*, 12(1): 47.

Knittel, Christopher R., Douglas L. Miller, and Nicholas J. Sanders. 2016. “Caution, Drivers! Children Present: Traffic, Pollution, and Infant Health.” *Review of Economics and Statistics*, 98(2): 350–366.

Krebs, Benjamin, Jennifer Burney, Joshua Graff Zivin, and Matthew Neidell. 2021. “Using Crowd-Sourced Data to Assess the Temporal and Spatial Relationship between Indoor and Outdoor Particulate Matter.” *Environmental Science & Technology*, 55(9): 6107–6115.

Künn, Steffen, Juan Palacios, and Nico Pestel. 2023. “Indoor Air Quality and Strategic Decision Making.” *Management Science*, 69(9): 4973–5693.

Lavy, Victor, Genia Rachkovski, and Omry Yoresh. 2023. “Heads Up: Does Air Pollution Cause Workplace Accidents?” National Bureau of Economic Research Working Paper 30715.

Leigh, J. Paul. 2011. “Economic Burden of Occupational Injury and Illness in the United States.” *The Milbank Quarterly*, 89(4): 728–772.

Lichter, Andreas, Nico Pestel, and Eric Sommer. 2017. “Productivity Effects of Air Pollution: Evidence from Professional Soccer.” *Labour Economics*, 48: 54–66.

Manson, Steven, Tracy A. Kugler, Kathryn Grace, Jonathan Schroeder, David Van Riper, and Steven Ruggles. 2023. “IPUMS International Historical Geographic Information System: Version 2 [dataset].” IPUMS, Minneapolis, MN.

McLaren, Christopher F., Marjorie L. Baldwin, and Leslie I. Boden. 2018. “Workers’ Compensation: Benefits, Costs, and Coverage (2016 data).” National Academy of Social Insurance.

Molitor, David, Jamie T. Mullins, and Corey White. 2023. “Air pollution and suicide in rural and urban America: Evidence from wildfire smoke.” *Proceedings of the National Academy of Sciences*, 120(38): e2221621120.

Moretti, Enrico and Matthew Neidell. 2011. “Pollution, Health, and Avoidance Behavior: Evidence from the Ports of Los Angeles.” *Journal of Human Resources*, 46(1): 154–175.

Murphy, Griffin T. and Jennifer Wolf. 2022. “Workers’ Compensation:Benefits, Costs, and Coverage (2020 data).” National Academy of Social Insurance.

National Academies of Sciences, Engineering, and Medicine. 2022. “Frameworks for Protecting Workers and the Public from Inhalation Hazards.” Washington, DC: The National Academies Press.

National Center for O*NET Development. 2023. “Work Context — Outdoors, Under Cover.” *O*NET OnLine*, `https://www.onetonline.org/find/descriptor/result/4.C.2.a.1.d`. Date Accessed: November 2023. .

National Safety Council. 2023. “Injury Facts: Work Injury Costs, 2021.” `https://injuryfacts.nsc.org/work/costs/work-injury-costs/`. Date Accessed: October 2023.

Neghab, Masoud, Mahdieh Delikhoon, Abbas Norouzian Baghani, and Jafar Hassanzadeh. 2017. “Exposure to Cooking Fumes and Acute Reversible Decrement in Lung Functional Capacity.” *The international journal of occupational and environmental medicine*, 8: 207–216.

Park, Jisung, Nora M. C. Pankratz, and A. Behrer. 2021. “Temperature, Workplace Safety, and Labor Market Inequality.” *SSRN Electronic Journal*.

Randerson, JT, GR Van Der Werf, L Giglio, GJ Collatz, and PS Kasibhatla. 2018. “Global Fire Emissions Database, Version 4.1 (GFEDv4).” `https://doi.org/10.3334/ORNLDAAC/1293`. Date Accessed: November 2023.

Rangel, Marcos A. and Tom S. Vogl. 2019. “Agricultural Fires and Health at Birth.” *The Review of Economics and Statistics*, 101(4): 616–630.

Rickly, P. S., H. Guo, P. Campuzano-Jost, J. L. Jimenez, G. M. Wolfe, R. Bennett, I. Bourgeois, J. D. Crounse, J. E. Dibb, J. P. DiGangi, G. S. Diskin, M. Dollner, E. M. Gargulinski, S. R. Hall, H. S. Halliday, T. F. Hanisco, R. A. Hannun, J. Liao, R. Moore, B. A. Nault, J. B. Nowak, J. Peischl, C. E. Robinson, T. Ryerson, K. J. Sanchez, M. Schöberl, A. J. Soja, J. M. St. Clair, K. L. Thornhill, K. Ullmann, P. O. Wennberg, B. Weinzierl, E. B. Wiggins, E. L. Winstead, and A. W. Rollins. 2022. "Emission factors and evolution of SO_2 measured from biomass burning in wildfires and agricultural fires." *Atmospheric Chemistry and Physics*, 22(23): 15603–15620.

Sager, Lutz. 2019. "Estimating the Effect of Air Pollution on Road Safety Using Atmospheric Temperature Inversions." *Journal of Environmental Economics and Management*, 98.

Schlenker, Wolfram. 2023. "Data Sources and Links." *http://www.columbia.edu/ ws2162/links.html*.

Schlenker, Wolfram and W. Reed Walker. 2016. "Airports, Air Pollution, and Contemporaneous Health." *The Review of Economic Studies*, 83(2): 768–809.

Texas Department of Insurance. 2019. "Employer Participation in the Texas Workers' Compensation System: 2018 Estimates."

Texas Department of Insurance (TDI). 2005. "Workers' Compensation Relativities Study." (Date accessed: 9/2016).

Tompa, Emile, Amirabbas Mofidi, Swenneke van den Heuvel, Thijmen van Bree, Frithjof Michaelsen, Young Jung, Lukas Porsch, and Martijn van Emmerik. 2021. "Economic burden of work injuries and diseases: a framework and application in five European Union countries." *BMC Public Health*, 21(1): 49.

Uehli, Katrin, Amar J. Mehta, David Miedinger, Kerstin Hug, Christian Schindler, Edith Holsboer-Trachsler, Jörg D. Leuppi, and Nino Künzli. 2014. "Sleep problems and work injuries: A systematic review and meta-analysis." *Sleep Medicine Reviews*, 18(1): 61–73.

U.S. Bureau of Labor Statistics. 2022. "Incidence rates of nonfatal occupational injuries and illnesses by industry and case types, 2022." `https://www.bls.gov/iif/nonfatal-injuries-and-illnesses-tables/table-1-injury-and-illness-rates-by-industry-2022-national.htm` (Date Accessed:03/2024).

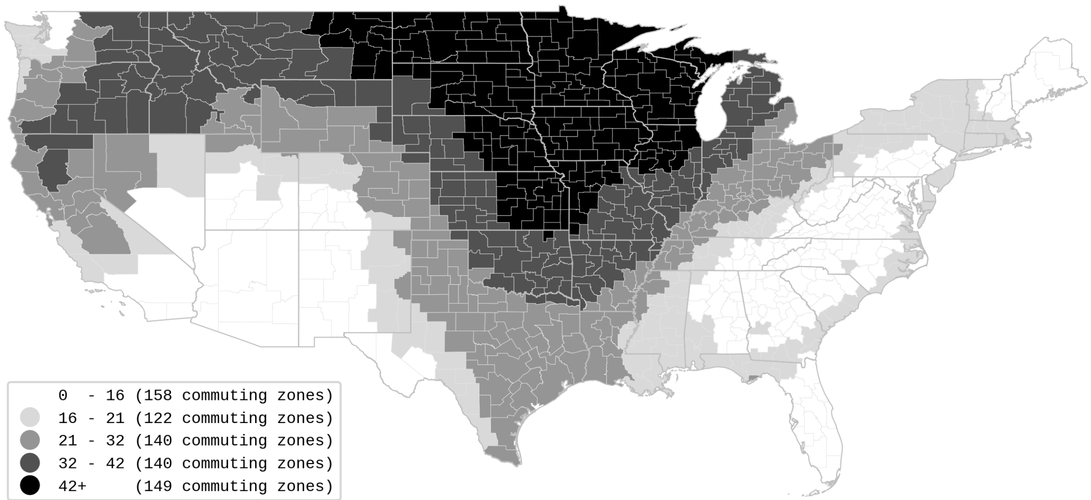
U.S. Environmental Protection Agency. 2022. "Wildland Fire Activty and Modeled Impacts on O3 and PM2.5." U.S. Environmental Protection Agency, Office of Air Quality Planning and Standards, Air Quality Assessment Division.

Wegesser, Teresa C., Lisa M. Franzi, Frank M. Mitloehner, Arantza Eiguren-Fernandez, and Jerold A. Last. 2010. "Lung antioxidant and cytokine responses to coarse and fine particulate matter from the great California wildfires of 2008." *Inhalation Toxicology*, 22(7): 561–570. PMID: 20388000.

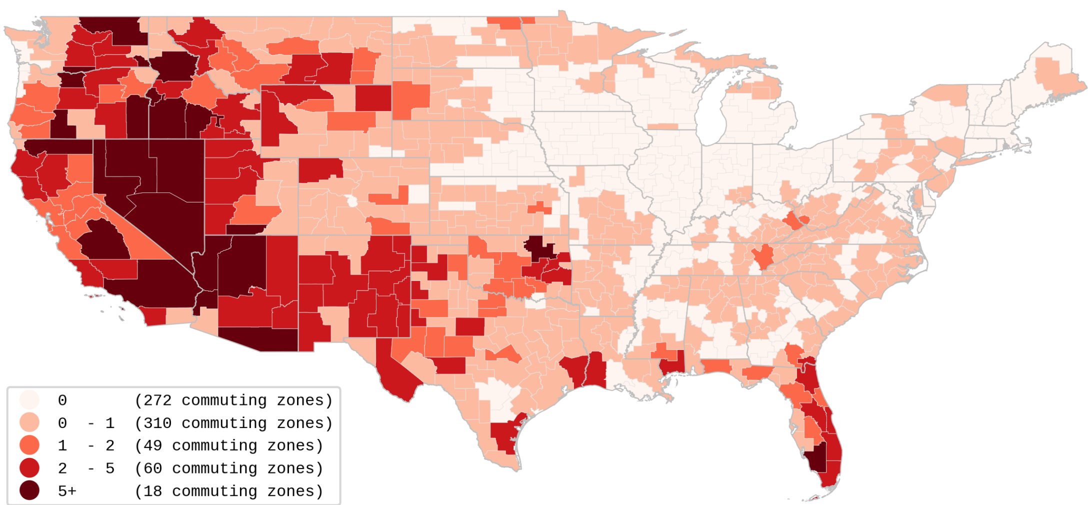
Wen, Jeff, Patrick Baylis, Judson Boomhower, and Marshall Burke. 2023. "Quantifying Fire-Specific Smoke Severity." EarthArXiv preprint.

Zhang, Xin, Xi Chen, and Xiaobo Zhang. 2018. "The Impact of Exposure to Air Pollution on Cognitive Performance." *Proceedings of the National Academy of Sciences*, 115(37): 9193–9197.

Figure 1: Average Annual Smoke Coverage and Fires Across US



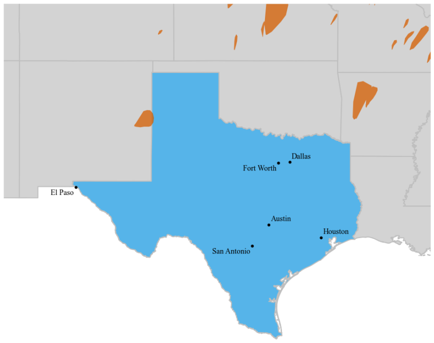
(a) Average Annual Number of Smoke Days



(b) Average Annual Number of Wildfires

Notes: This figure shows means of annual smoke exposure and the number of large wildfires for commuting zones across the United States from 2006 to 2018.

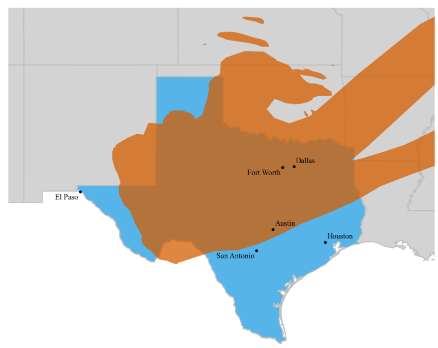
Figure 2: Smoke Plume Dynamics Example: Starbuck Fire (March 6, 2017)



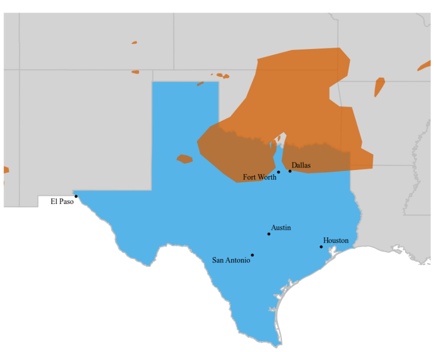
(a) Day -2

(b) Day -1

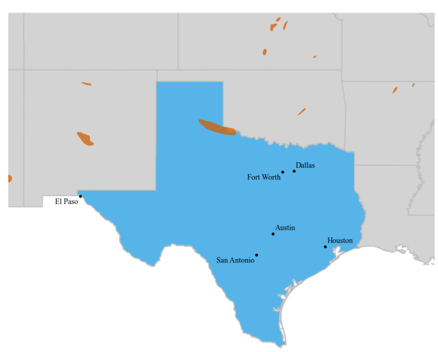
(c) Day 0



(d) Day 1



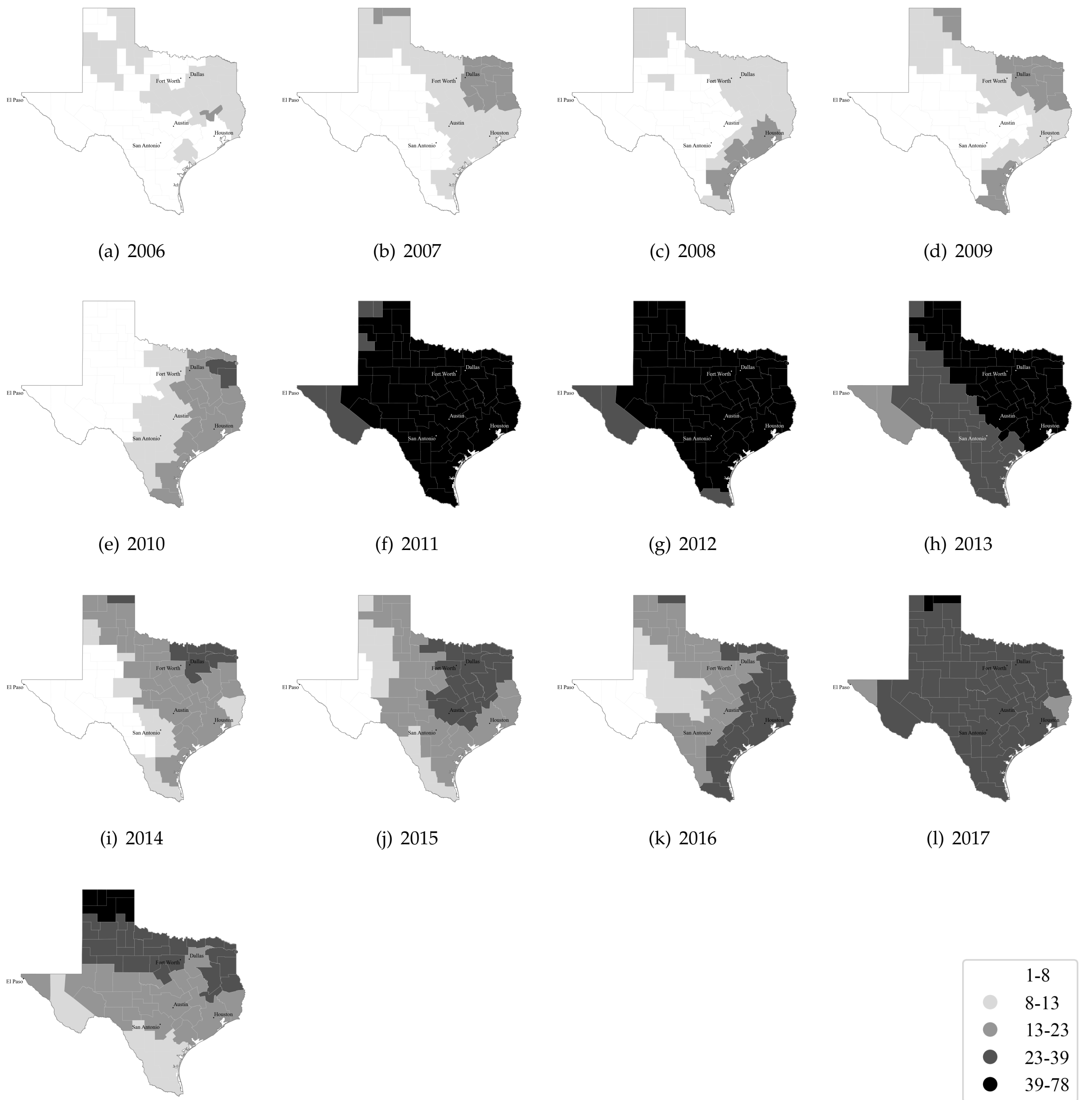
(e) Day 2



(f) Day 3

Notes: This figure displays smoke plume dynamics for smoke in the days surrounding the Starbuck Fire. The labels represent days relative to the start of the fire, with the day the fire broke out labeled as day 0 (March 6, 2017). In this figure, the location of the Starbuck fire is indicated with a red star, and smoke plumes are depicted in orange.

Figure 3: Smoke Days in Texas by Year



(a) 2006 (b) 2007 (c) 2008 (d) 2009

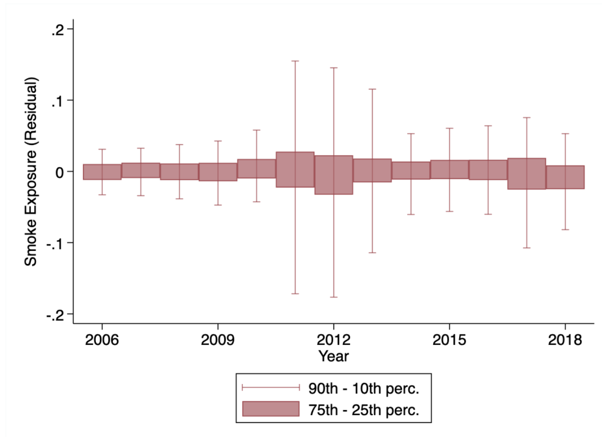
(e) 2010 (f) 2011 (g) 2012 (h) 2013

(i) 2014 (j) 2015 (k) 2016 (l) 2017

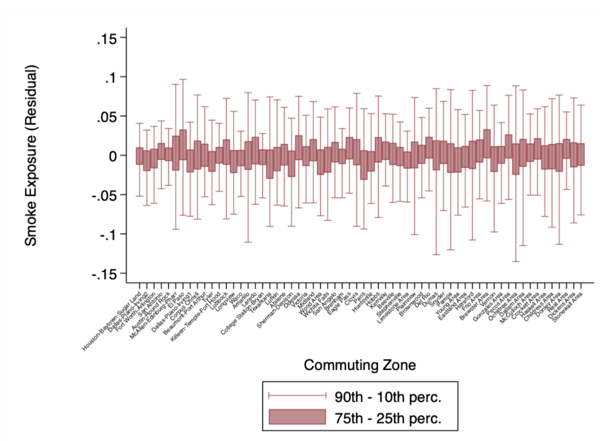
(m) 2018

Notes: This figure illustrates the year by year variation in the number of smoke days across Texas commuting zones, where we measure the total number of smoke days by aggregating our smoke measure to the annual level. The coloring scheme is held fixed across the panels above, where the colors represent quintiles of the annual smoke day distribution pooling across all years.

Figure 4: Identifying Variation



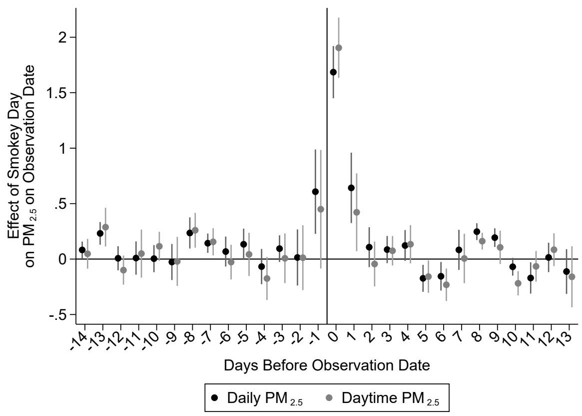
(a) Residual Variation in Smoke, by Year



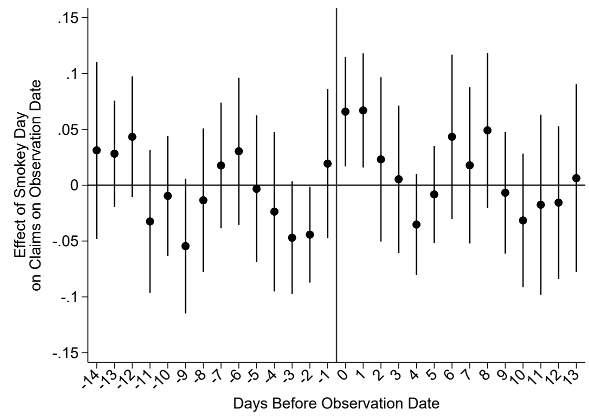
(b) Residual Variation in Smoke, by Commuting Zone

Notes: This figure shows means of the residual variation in smoke by year and by commuting zone. The residuals are calculated after first regressing the day's smoke on all of the controls in Equation (1), including the commuting-zone-by-quarter-by-year fixed effects, date fixed effects, indicator variables for the quintile of the day's maximum temperature, indicator variables for the quintile of the day's precipitation, and indicator variables for the quintiles of the maximum temperature and precipitation and controls for smoke on the three days before and two days after the observation date.

Figure 5: Distributed Lag Model: Impact of Smoke on Ambient Air Pollution and Injury Claims



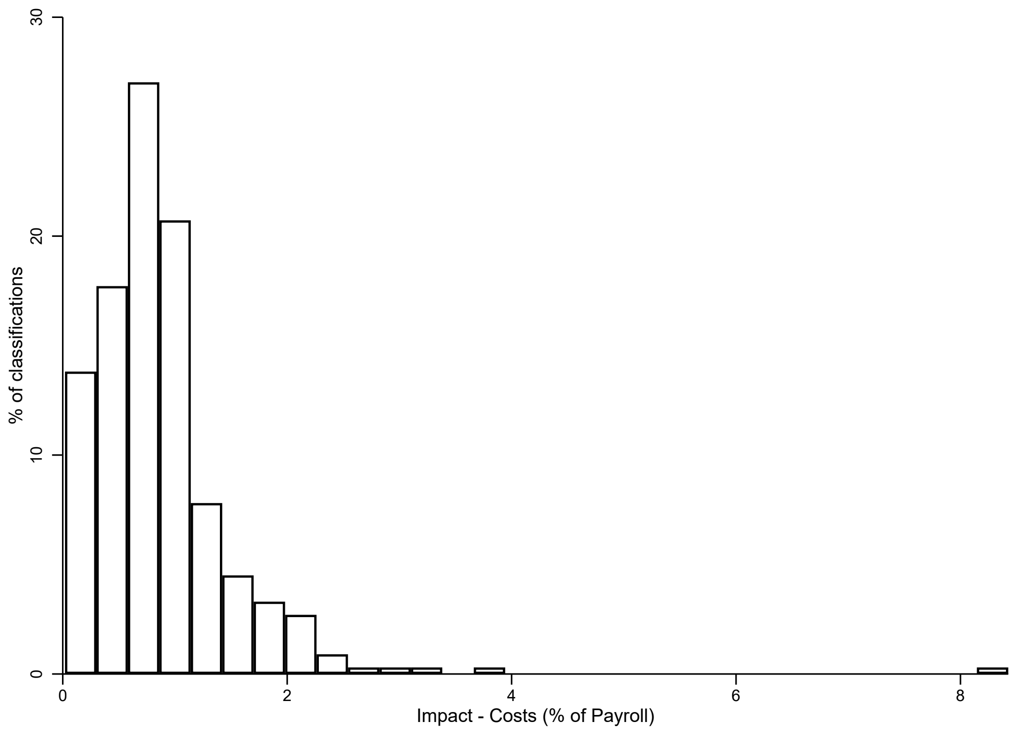
(a) $PM_{2.5}$



(b) Daily Claim Rates

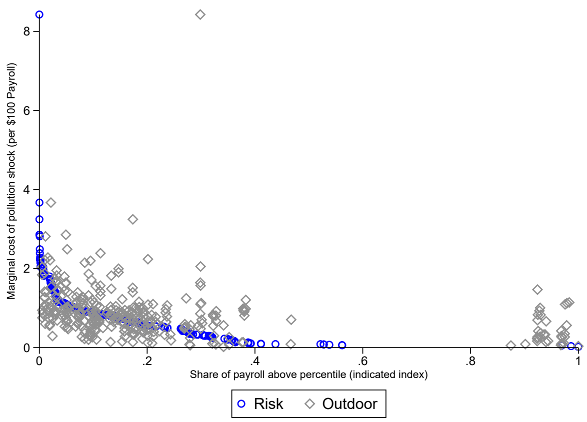
Notes: This figure displays estimates of the impact of smoke from estimating Equation (2) for the indicated dependent variable. The regression controls include commuting-zone-by-quarter-by-year fixed effects, date fixed effects, indicator variables for the quintile of the day's maximum temperature, indicator variables for the quintile of the day's precipitation, and indicator variables for the quintiles of the maximum temperature and precipitation and controls for smoke on the 14 days before and 13 days after the observation date. The sample includes observations from September 2005 through 2018 for all 62 commuting zones in Texas. The regression is weighted by commuting zones' mean employment during the sample period calculated from the Quarterly Census of Employment and Wages. In addition to the point estimates, the figure also displays the associated 95% confidence intervals calculated from standard errors clustered at the commuting zone level.

Figure 6: Distribution of Impacts of 10 $\mu g/m^3$ Increase in $PM_{2.5}$ by Industry-Occupation Classification

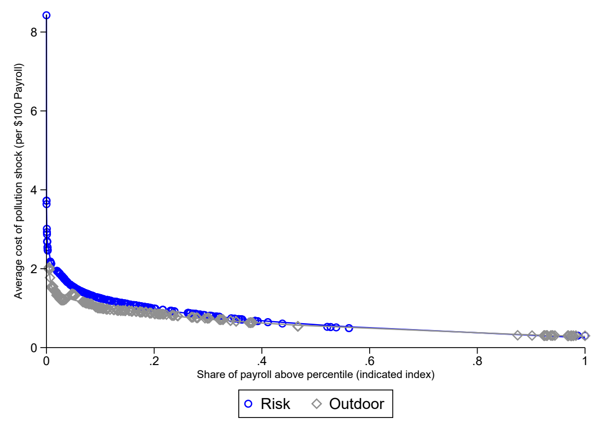


Notes: This figure displays a histogram of the distribution of the impact of a 10 $\mu g/m^3$ increase in $PM_{2.5}$ by industry-occupation as a percent of covered payroll. Each observation represented in this histogram is a workers' compensation industry-occupation classification (of which there are 334 unique classification codes). This impact is calculated assuming constant percent effects across industry-occupation classifications. Specifically, we use the overall impact implied by the baseline estimates (as a percent of payroll) and scale this by the relative risk of in the classification. A classification's relative risk is simply workers compensation costs/payroll (as calculated by the Texas Department of Insurance for the purpose of risk adjustment) normalized so to have a mean of one across all covered payroll.

Figure 7: Marginal and Average Impacts of 10 μg/m^3 Increase in PM$_{2.5}$ by Exposure Index



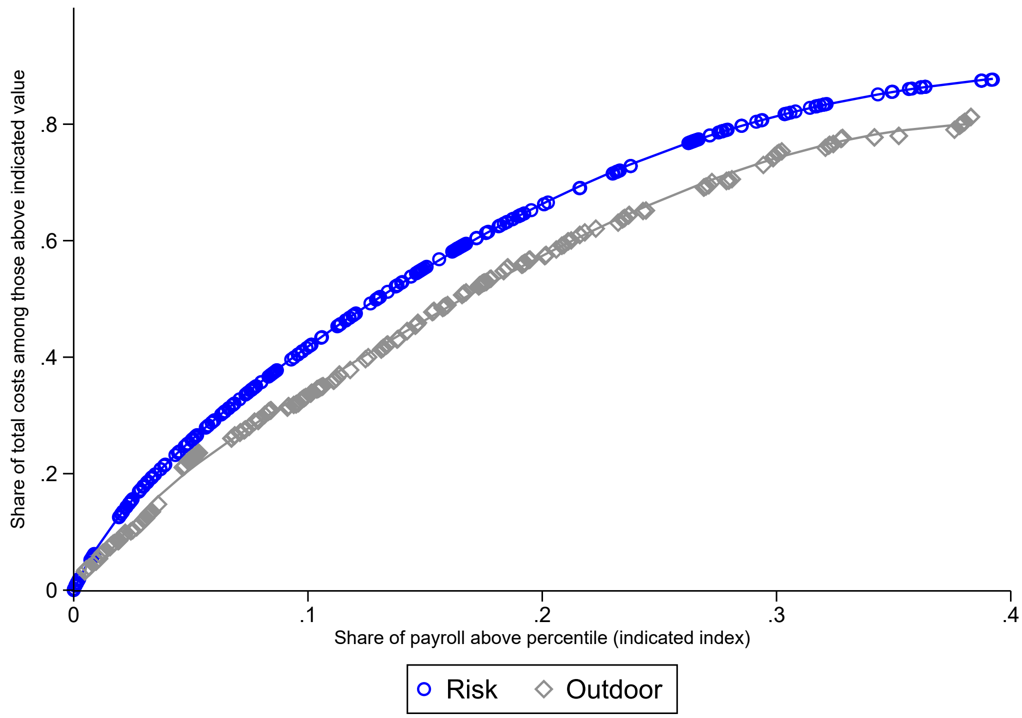
(a) Marginal Impact by Indicated Index



(b) Average Impact by Indicated Index

Notes: This figure displays the marginal impact (in Panel A) and average impact (in Panel B) of a 10 μg/m^3 increase in PM$_{2.5}$ by industry-occupation as a percent of covered payroll, where classifications are ordered from highest to lowest according to either their risk exposure ("risk index"; represented by blue circles) or outdoor exposure ("outdoor index"; represented by gray diamonds). In both panels, the horizontal axis represents the share of covered payroll that is at or above the indicated percentile of the relevant index. In Panel A, the vertical axis displays the costs associated with increased workplace injuries from a 10 μg/m^3 increase in PM$_{2.5}$ (as a percent of payroll) in that marginal classification. Panel B shows the parallel plot for average rather than marginal costs—where we calculate the average impact "from the left" among classifications with index values greater than or equal to the marginal classification at the indicated percentile.

Figure 8: Share of Aggregate Costs Borne by Those with Index Above Indicated Value



Notes: This figure plots the share of aggregate costs from pollution-induced increases in workplace injuries that is borne by workers at or above the indicated percentile of the risk index (in blue) or the outdoor index (in gray). For this plot, classifications are ordered from highest to lowest according to their risk or outdoor index, and the horizontal axis represents the share of covered payroll that is at or above the indicated percentile of the relevant index. The vertical axis displays the share of aggregate costs from pollution-induced increases in workplace injuries that is borne by workers at or above the indicated percentile of the relevant index. Note that this share is invariant to the magnitude of the pollution shock considered under linear extrapolation.

Table 1: Descriptive Statistics

	Mean	Standard Deviatio
Panel A: Exposure		
Smoke Event (%)	0.07	0.24
$PM_{2.5}$, all days	9.4	4.5
$PM_{2.5}$, on days with smoke	13.1	5.1
Panel B: Workers' Compensation Claims (rates per 100,000 workers)		
Total Claims	5.8	3.9
By Claim Characteristics		
Received Only Medical Benefits	4.6	3.2
Received Both Medical and Cash Benefits	1.3	1.2
Total Workers' Compensation Benefits ≥ Median	2.9	2.2
Total Workers' Compensation Benefits < Median	2.9	2.3
Claims initiated with an ED visit	1.8	1.7
Claims not initiated with an ED visit	4.0	3.2
Needed medical treatment < 1 month	3.8	2.7
Needed medical treatment ≥ 1 month	2.1	1.7
By Injury Type		
Muscle Issue	1.0	1.2
Sprain	1.6	1.4
Contusion	0.9	0.9
Fracture	0.3	0.6
Other	1.8	1.5
By Worker Characteristics		
Male	3.5	2.6
Female	2.1	1.7
Age <25	0.7	0.8
Age 25-35	1.4	1.2
Age 35-45	1.3	1.2
Age 45-60	1.4	1.3
Panel C: Population at risk		
Number of Workers	1,314,389	1,021,973

Notes: This table describes the analytical dataset. The dataset includes all date and commuting zones pairings from September 2005 through 2018 for all 62 commuting zones in Texas and has 301,940 observations in total. The means and standard deviations are weighted by commuting zones' mean employment during the sample period calculated from the Quarterly Census of Employment and Wages.

Table 2: Impact of Smoke on Ambient Air Pollution

	(1) $PM_{2.5}$	(2) $PM_{2.5}$ day time	(3) PM_{10}	(4) O_3	(5) CO	(6) NO_2	(7) SO_2
Smoke	1.687	1.888	3.911	0.0023	0.000	-0.191	0.031
	(0.122)	(0.139)	(0.619)	(0.0002)	(0.002)	(0.074)	(0.010)
	[<0.001]	[<0.001]	[<0.001]	[0.0000]	[0.999]	[0.014]	[0.004]
Daily Levels							
Mean	9.06	8.71	24.05	0.028	0.25	7.20	0.66
Standard deviation	4.34	4.72	19.64	0.011	0.12	4.40	1.00
N	252,950	249,801	60,640	218,919	112,040	160,128	137,689

Notes: This table displays estimates of the impact of smoke on ambient air pollution from estimating Equation (1). Each column displays estimates from a separate regression, where the dependent variable is indicated in the column heading. The dependent variable in column 2 is $PM_{2.5}$ averaged over "daytime" hours (6am-6pm), while all other columns consider daily (24-hour) measures of the indicated pollutants. Each regression includes controls for commuting-zone-by-quarter-by-year fixed effects, date fixed effects, indicator variables for the quintile of the day's maximum temperature, indicator variables for the quintile of the day's precipitation, and indicator variables for the quintiles of the maximum temperature and precipitation and controls for smoke on the three days before and two days after the observation date. The sample for each regression includes all observations with non-missing pollution measures from September 2005 through 2018 for all 62 commuting zones in Texas. All regressions are weighted by commuting zones' mean employment during the sample period calculated from the Quarterly Census of Employment and Wages. Standard errors clustered at the commuting zone level are reported in parentheses, and p-values are reported in brackets.

Table 3: Impact of Smoke on Injury Claims

	(1) Claims	(2) Claims	(3) Claims	(4) Claims	(5) Claims	(6) ED Claims
Smoke	0.165	0.143	0.166	0.178	0.220	0.077
	(0.048)	(0.047)	(0.043)	(0.045)	(0.053)	(0.024)
	[0.001]	[0.004]	[<0.001]	[<0.001]	[<0.001]	[0.002]
Controls						
Set of weather controls	Baseline	Expanded	Baseline	Baseline	Baseline	Baseline
Commuting zone X quarter X year f.e.	x	x	x	x	x	x
Exact date f.e.	x	x	x	x	x	x
Commuting zone X month-of-the-year f.e.			x			
Sample Restrictions						
Excluding commuting zone obs within 200 km of wildfires				x		
Excluding weekends					x	
Daily Claims						
Mean daily claims	5.8	5.8	5.8	5.8	7.5	1.8
Standard deviation	4.0	4.0	4.0	4.0	3.4	1.7
N	301,816	301,816	301,816	280,508	215,512	301,816
Implied % impact relative to mean daily claims	2.8	2.5	2.9	3.1	2.9	4.3

Notes: This table displays estimates of the impact of smoke on workers' compensation injury claims from estimating Equation (1). Each column displays estimates from a separate regression, where the dependent variable is the three-day claim rate in columns 1 through 5 and the three-day claim rate of injuries originating in the ED for column 6. The regression for column 1 includes the baseline controls as described in the notes in Table 2. The regression for column 2 replaces the quintile controls for the day's maximum temperature and precipitation with decile controls and also adds controls for the decile of the day's minimum temperature and for the decile of the minimum temperature three days before and two days after the observation date. The regression for column 3 supplements the baseline controls with commuting-zone-by-month-of-year fixed effects. The sample includes observations from September 2005 through 2018 for all 62 commuting zones in Texas. Column 4 excludes observations for commuting zones with wildfires occurring within a day of the observation date, while column 5 excludes weekends. All regressions are weighted by commuting zones' mean employment during the sample period calculated from the Quarterly Census of Employment and Wages. Standard errors clustered at the commuting zone level are reported in parentheses, and p-values are reported in brackets.

Table 4: Impact of Smoke Injury Claims by Injury Type

	(1)	(2)	(3)	(4)	(5)	(6)
	All Claims	Claims by Injury Type				
		Muscle Issue	Sprain	Contusion	Fracture	Other
Smoke	0.165	0.065	0.042	0.008	-0.015	0.059
	(0.048)	(0.021)	(0.021)	(0.019)	(0.013)	(0.024)
	[0.001]	[0.003]	[0.047]	[0.668]	[0.251]	[0.019]
Daily Claim Rate per 100,000 Workers						
Mean	5.8	1.0	1.6	0.9	0.3	1.8
Standard deviation	4.0	1.2	1.4	0.9	0.6	1.5
N	301,816	301,816	301,816	301,816	301,816	301,816
Implied % impact relative to mean daily claim rate	2.8	6.3	2.6	1.0	-4.3	3.2

Notes: This table displays estimates of the impact of smoke on workers' compensation injury claims from estimating Equation (1). Each column displays estimates from a separate regression, where the dependent variable is the three-day claim rate for the injury type indicated in the column heading. Refer to the notes in Table 2 for a description of the baseline controls included in each regression. The sample includes observations from September 2005 through 2018 for all 62 commuting zones in Texas. All regressions are weighted by commuting zones' mean employment during the sample period calculated from the Quarterly Census of Employment and Wages. Standard errors clustered at the commuting zone level are reported in parentheses, and p-values are reported in brackets.

Table 5: Impact of Smoke on Injury Claims by Injury Severity

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	All Claims	Claims by Claim Attributes							
		Received Only Medical Benefits	Received Both Medical and Cash Benefits	Total Workers' Compensation Benefits ≥ Median	Total Workers' Compensation Benefits < Median	Claims initiated with an ED visit	Claims not initiated with an ED visit	Needed medical treatment < 1 month	Needed medical treatment ≥ 1 month
Smoke	0.165	0.139	0.026	0.076	0.090	0.077	0.088	0.096	0.069
	(0.048)	(0.050)	(0.023)	(0.038)	(0.045)	(0.024)	(0.042)	(0.049)	(0.035)
	[0.001]	[0.007]	[0.262]	[0.051]	[0.049]	[0.002]	[0.041]	[0.056]	[0.052]
Daily Claim Rate per 100,000 Workers									
Mean	5.8	4.5	1.3	2.9	2.9	1.8	4.0	3.7	2.1
Standard deviation	4.0	3.2	1.2	2.2	2.3	1.7	3.2	2.7	1.8
N	301,816	301,816	301,816	301,816	301,816	301,816	301,816	301,816	301,816
Implied % impact relative to mean daily claim rate	2.8	3.1	2.1	2.6	3.1	4.3	2.2	2.6	3.4

Notes: This table displays estimates of the impact of smoke on workers' compensation injury claims from estimating Equation (1). Each column displays estimates from a separate regression, where the dependent variable is the three-day claim rate for the measure indicated in the column heading. Refer to the notes in Table 2 for a description of the baseline controls included in each regression. The sample includes observations from September 2005 through 2018 for all 62 commuting zones in Texas. All regressions are weighted by commuting zones' mean employment during the sample period calculated from the Quarterly Census of Employment and Wages. Standard errors clustered at the commuting zone level are reported in parentheses, and p-values are reported in brackets.

Table 6: Heterogeneity: Impact of Smoke on Injury Claims by Worker Characteristics

	(1) All	(2) Male	(3) Female	(4) Age <25	(5) Age 25-35	(6) Age 35-45	(7) Age 45-60
Smoke	0.165	0.111	0.044	-0.023	0.059	0.046	0.083
	(0.048)	(0.039)	(0.019)	(0.018)	(0.020)	(0.014)	(0.026)
	[0.001]	[0.006]	[0.021]	[0.209]	[0.004]	[0.002]	[0.002]
Daily Claim Rate per 100,000 Workers							
Mean	5.8	3.5	2.1	0.7	1.4	1.3	1.9
Standard deviation	4.0	2.7	1.7	0.9	1.2	1.3	1.6
N	301,816	301,816	301,816	301,816	301,816	301,816	301,816
Implied % impact relative to mean daily claim rate	2.8	3.1	2.1	-3.1	4.3	3.4	4.5

Notes: This table displays estimates of the impact of smoke on workers' compensation injury claims from estimating Equation (1). Each column displays estimates from a separate regression, where the dependent variable is the three-day claim rate for the group indicated in the column heading. Refer to the notes in Table 2 for a description of the baseline controls included in each regression. The sample includes observations from September 2005 through 2018 for all 62 commuting zones in Texas. All regressions are weighted by commuting zones' mean employment during the sample period calculated from the Quarterly Census of Employment and Wages. Standard errors clustered at the commuting zone level are reported in parentheses, and p-values are reported in brackets.

Table 7: Impact of Smoke on Injury Claims by Job Characteristics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	All Claims	Claims by Class Code						
		Non-Missing Class Codes	Risk, Top Tercile	Risk, Middle Tercile	Risk, Bottom Tercile	Outdoor, Top Tercile	Outdoor, Middle	Outdoor, Bottom
Smoke	0.165	0.135	0.042	0.079	0.014	0.072	0.022	0.040
	(0.048)	(0.046)	(0.025)	(0.021)	(0.027)	(0.017)	(0.027)	(0.019)
	[0.001]	[0.005]	[0.099]	[<0.001]	[0.600]	[<0.001]	[0.406]	[0.042]
Daily Claim Rate per 100,000 Workers								
Mean	5.8	4.5	1.5	1.5	1.6	1.5	1.4	1.6
Standard deviation	4.0	3.5	1.5	1.5	1.4	1.5	1.3	1.6
N	301,816	301,816	301,816	301,816	301,816	301,816	301,816	301,816
Implied % impact relative to mean daily claim rate	2.8	3.0	2.8	5.3	0.9	4.8	1.6	2.5

Notes: This table displays estimates of the impact of smoke on workers' compensation injury claims from estimating Equation (1). Each column displays estimates from a separate regression, where the dependent variable is the three-day claim rate for the measure indicated in the column heading. Refer to the notes in Table 2 for a description of the baseline controls included in each regression. The sample includes observations from September 2005 through 2018 for all 62 commuting zones in Texas. All regressions are weighted by commuting zones' mean employment during the sample period calculated from the Quarterly Census of Employment and Wages. Standard errors clustered at the commuting zone level are reported in parentheses, and p-values are reported in brackets.

Table 8: Robustness: Count Models

	(1) Claims	(2) Claims	(3) Claims	(4) Claims	(5) Claims	(6) ED Claims
Smoke	0.007	0.006	0.007	0.007	0.008	0.011
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.004)
	[0.002]	[0.006]	[<0.001]	[0.001]	[<0.001]	[0.004]
Controls						
Set of weather controls	Baseline	Expanded	Baseline	Baseline	Baseline	Baseline
Commuting zone X quarter X year f.e.	x	x	x	x	x	x
Exact date f.e.	x	x	x	x	x	x
Commuting zone X month-of-the-year f.e.			x			
Sample Restrictions						
Excluding commuting zone obs within 200 km of wildfires				x		
Excluding weekends					x	
Daily Claims						
Mean daily claims	63.9	63.9	63.9	63.4	83.2	18.3
Standard deviation	60.9	60.9	60.9	60.5	62.5	16.8
N	301,816	301,816	301,816	280,508	215,512	301,816
Implied impact on number of claims	1.4	1.2	1.3	1.3	1.8	0.6
Implied % impact relative to mean daily claims	2.2	1.9	2.1	2.0	2.1	3.4

Notes: This table displays estimates of the impact of smoke on workers' compensation injury claims from estimating Equation (1). Each column displays estimates from a separate Poisson regression, where the dependent variable is the three-day count of claims in columns 1 through 5 and the three-day count of claims for injuries originating in the ED for column 6. The regression for column 1 includes the baseline controls as described in the notes in Table 2. The regression for column 2 replaces the quintile controls for the day's maximum temperature and precipitation with decile controls and also adds controls for the decile of the day's minimum temperature and for the decile of the minimum temperature three days before and two days after the observation date. The regression for column 3 supplements the baseline controls with commuting-zone-by-month-of-year fixed effects. The sample includes observations from September 2005 through 2018 for all 62 commuting zones in Texas. Column 4 excludes observations for commuting zones with wildfires occurring within a day of the observation date, while column 5 excludes weekends. Standard errors clustered at the commuting zone level are reported in parentheses, and p-values are reported in brackets.

Table 9: Robustness: Impact of Smoke Injury Claims Across Different Follow-up Windows

Panel A: Varying Window for Definition of Claim Rate							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Claims	Claims	Claims	Claims	Claims	Claims	Claims
	1-day	2-day	3-day	5-day	7-day	10-day	14-day
Smoke	0.084	0.144	0.165	0.134	0.165	0.240	0.167
	(0.026)	(0.037)	(0.048)	(0.064)	(0.047)	(0.072)	(0.087)
	[0.002]	[<0.001]	[0.001]	[0.040]	[0.001]	[0.001]	[0.061]
Implied % impact relative to mean daily claim rate	1.4	2.5	2.8	2.3	2.8	4.1	2.9

Panel B: Varying Window for Sum of Coefficients in Distributed Lag Model							
	1-day	2-day	3-day	5-day	7-day	10-day	14-day
Effect of Smoke on Claims from	0.084	0.148	0.160	0.130	0.158	0.191	0.162
Adding Coefficients in Window, ΣB_k	0.026	0.035	0.049	0.058	0.049	0.073	0.086
	[0.002]	[0.000]	[0.002]	[0.030]	[0.002]	[0.012]	[0.062]
Implied % impact relative to mean daily claim rate	1.4	2.6	2.8	2.2	2.7	3.3	2.8

Notes: Each column displays estimates from a separate regression. Panel A displays estimates of the impact of smoke on workers' compensation injury claims from estimating Equation (1), where the dependent variable is the rate of claims aggregated over the window indicated in the column heading. Panel B displays the sum of coefficient estimates over the indicated time horizon from estimating the distributed lag model described in Equation 2. See the text for more details on this specification, and refer to Appendix Table A5 for the full set of estimated coefficients for the specification underlying Panel B. Each regression includes controls for commuting-zone-by-quarter-by-year fixed effects, date fixed effects, indicator variables for the quintile of the day's maximum temperature, and indicator variables for the quintile of the day's precipitation. In addition, regressions include indicator variables for the quintiles of the maximum temperature and precipitation and indicators for smoke on the days before and after the observation date for days within the indicated time horizon. The sample includes observations from September 2005 through 2018 for all 62 commuting zones in Texas. All regressions are weighted by commuting zones' mean employment during the sample period calculated from the Quarterly Census of Employment and Wages. Standard errors clustered at the commuting zone level are reported in parentheses, and p-values are reported in brackets.

APPENDIX

A Data Construction

Classifying injury type We classify claims as muscle issues, sprains, contusions, or fractures using ICD-9 diagnosis codes from medical care received on the first day of injuries. For bills that identify ICD-10 codes, we convert ICD-10 codes to ICD-9 codes using a crosswalk from the Centers for Medicare & Medicaid Services so that we have consistent definitions of injuries over time. We classify claims based on their most frequently listed ICD-9 codes from among the above injury types with ties broken randomly. Claims are classified as being "Other" if they have at least one ICD-9 code listed and do not have an ICD-9 code for a muscle issue, sprain, contusion, or fracture.

Measuring outdoor and risk exposure In supplemental analysis, we use information on workers' compensation industry-occupation classifications—which provide a detailed characterization of industry-occupation of the worker with 334 distinct classification codes. For this analysis, we consider two specific industry-occupation features: risk exposure and outdoor exposure. Risk exposure is measured as the relative risk of the classification. This relative risk is calculated by the Texas Department of Insurance (TDI) for risk adjustment purposes and measures workers' compensation costs relative to payroll. Specifically, these are the industry-occupation classification relativities reported in the 2005 TDI Workers' Compensation Relativities Study (Texas Department of Insurance TDI).

We construct a measure of outdoor exposure based on O*NET data characterizing the frequency of outdoor work by occupation. To construct this measure, we first created a crosswalk mapping each workers' compensation industry-occupation classification code to the closest matching occupation code within the O*NET data based on occupation titles and descriptions. We then measure the outdoor exposure of the industry-occupation as the outdoor exposure of the associated O*NET occupation—which measures the frequency that workers are required to work outdoors fully exposed to weather (National Center for O*NET Development 2023).

Since industry-occupation classification is only available for claimants with cash benefits, we impute these industry-occupation exposure measures for claimants with missing values by selecting the median value among claimants with non-missing values working at the same employer.[1] After this imputation process, 78% of claims have industry-occupation classification exposure measures.

[1] We identify workers at the same employer through an encrypted employer ID, which is non-missing for 40% of claims. In cases when the encrypted employer ID is missing, we construct proxies for the employer based on the combination of employer zip codes and the insurer IDs.

Table A1: Comparison of Injured Workers in Texas and All States

	Texas, All Workers	All States, All Workers	Texas, Workers' Compensation Claimants	All States, Workers' Compensation Claimants
Age	40.9	41.8	44.9	47.6
% Male	54.6%	52.9%	67.8%	60.6%
% White	81.0%	80.2%	81.9%	80.4%
% Married	56.1%	54.8%	58.5%	57.3%
% Worked last year	100.0%	100.0%	74.9%	67.1%
% Worked full time last year	82.6%	79.5%	67.1%	57.8%
Family income	$94,246	$100,880	$79,222	$78,297
Individual earnings	$46,143	$47,823	$30,675	$25,792
Weekly earnings (for weeks worked last year)	$962	$1,000	$1,071	$977
Industry Last Year (%)				
Agriculture/Forestry/Fishing/Hunting	2.4%	2.7%	0.8%	2.1%
Arts/Entertainment/Accommodation/Food Services	10.4%	11.2%	8.5%	7.4%
Finance/Real Estate/Professional Services	20.0%	20.1%	15.1%	11.4%
Health Care/Educational Services	20.8%	22.1%	13.0%	18.4%
Manufacturing	9.1%	10.7%	11.0%	15.4%
Mining/Utilities/Construction	13.2%	9.6%	17.2%	13.2%
Public Administration/Other Services	4.4%	4.7%	7.3%	7.5%
Wholesale Trade/Retail Trade/Transportation	19.8%	19.0%	27.2%	24.6%

Notes: This table compares workers and workers' compensation claimants in Texas and the entire United States using data from the IPUMS Current Population Survey Annual Social and Economic Supplement 2006 to 2019 (representing years 2005 to 2018) (Flood et al. 2022). The table displays summary statistics for all workers in Texas in column 1, for all workers in all states in column 2, for workers' compensation claimants in Texas in column 3, and for workers' compensation claimants in all states in column 4. All dollar values are CPI-U adjusted to 2018 dollars.

Table A2: Impact of Smoke on Weekly Hours Worked

	(1) Weekly Hours Worked	(2) Weekly Hours Worked
Smoke	0.020	0.003
	(0.015)	(0.010)
	[0.171]	[0.768]
Controls		
Worker demographics	x	
Individual fixed effects		x
Mean Weekly Hours Worked	38.5	38.5
N	3,180,184	3,180,184

Notes: This table displays estimates of the impact of smoke on weekly hours worked. The data on hours worked come from the September 2005 to December 2018 Basic Monthly Current Population Survey. During January through October, the Current Population Survey asks about weekly hours worked during the week containing the 12th day of the month. The worker demographic characteristics included in the regressions for column 1 include fixed effects for age and race and an indicator variable for workers being male. In addition to the controls indicated in the table, each regression also controls for year-week fixed effects, county fixed effects, and quintiles of the mean daily maximum temperature and the mean daily precipitation for the week. The smoke measure is the total number of days of smoke coverage during the week. Regressions are weighted by the Basic Monthly Current Population Survey weights. Standard errors clustered at the county level are reported in parentheses, and p-values are reported in brackets.

Table A3: Instrumental Variables Estimates of the Impact of $PM_{2.5}$ on Injury Claims

	(1) Claims	(2) Claims	(3) Claims	(4) Claims	(5) Claims	(6) ED Claims
$PM_{2.5}$	0.109	0.102	0.110	0.120	0.153	0.047
	(0.028)	(0.028)	(0.026)	(0.027)	(0.038)	(0.013)
	[<0.001]	[0.001]	[<0.001]	[<0.001]	[<0.001]	[0.001]
Controls						
Set of weather controls	Baseline	Expanded	Baseline	Baseline	Baseline	Baseline
Commuting zone X quarter X year f.e.	x	x	x	x	x	x
Exact date f.e.	x	x	x	x	x	x
Commuting zone X month-of-the-year f.e.			x			
Sample Restrictions						
Excluding commuting zone obs within 200 km of wildfires				x		
Excluding weekends					x	
Daily Claim Rate per 100,000 Workers						
Mean	5.8	5.8	5.8	5.8	7.5	1.8
Standard deviation	3.8	3.8	3.8	3.8	3.1	1.6
F-Stat on First Stage	191	217	220	163	207	220
N	252,950	252,950	252,950	235,288	180,658	252,950

Notes: This table displays estimates of the impact of $PM_{2.5}$ on workers' compensation injury claims from an analogous instrumental variables regression, instrumenting for a commuting zone's daily $PM_{2.5}$ level using smoke. Each column displays estimates from a separate regression, where the dependent variable is the three-day claim rate in columns 1 through 5 and the three-day claim rate of injuries originating in the ED for column 6. The regression for column 1 includes the baseline controls as described in the notes in Table 2. The regression for column 2 replaces the quintile controls for the day's maximum temperature and precipitation with decile controls and also adds controls for the decile of the day's minimum temperature. The regression for column 3 supplements the baseline controls with commuting-zone-by-month-of-year fixed effects. The regression for column 2 replaces the quintile controls for the day's maximum temperature and precipitation with decile controls and also adds controls for the decile of the day's minimum temperature and for the decile of the minimum temperature three days before and two days after the observation date. The sample includes observations from September 2005 through 2018 for all 62 commuting zones in Texas. Column 4 excludes observations for commuting zones with wildfires occurring within a day of the observation date, while column 5 excludes weekends. All regressions are weighted by commuting zones' mean employment during the sample period calculated from the Quarterly Census of Employment and Wages. Standard errors clustered at the commuting zone level are reported in parentheses, and p-values are reported in brackets.

Table A4: Robustness: Impact of Smoke by Worker Characteristics, Adjusting Rates to Reflect Group-Specific Denominators

	(1) All	(2) Male	(3) Female	(4) Age <25	(5) Age 25-35	(6) Age 35-45	(7) Age 45-60
Smoke	0.165	0.207	0.097	-0.195	0.269	0.209	0.275
	(0.048)	(0.072)	(0.040)	(0.123)	(0.086)	(0.059)	(0.089)
	[0.001]	[0.006]	[0.019]	[0.117]	[0.003]	[0.001]	[0.003]
Daily Claim Rate per 100,000 Workers							
Mean	5.8	6.5	4.6	5.3	6.0	5.7	6.1
Standard deviation	4.0	4.9	3.7	6.2	6.2	5.8	5.2
N	301,816	301,816	301,816	301,816	301,816	301,816	301,816
Implied % impact relative to mean daily claim rate	2.8	3.2	2.1	-3.7	4.5	3.6	4.5

Notes: This table displays estimates of the impact of smoke on workers' compensation injury claims from estimating Equation (1). Each column displays estimates from a separate regression, where the dependent variable is the three-day claim rate for the group indicated in the column heading. The difference between the analysis in this table and the analysis reported in Table 6 is that the analysis in this table considers dependent variables where the denominator has been scaled to reflect the group-specific denominator using data from the IPUMS American Community Survey five-year summary files (Manson et al. 2023) to calculate the share of the workforce in the indicated group. Refer to the notes in Table 2 for a description of the baseline controls included in each regression. The sample includes observations from September 2005 through 2018 for all 62 commuting zones in Texas. All regressions are weighted by commuting zones' mean employment during the sample period calculated from the Quarterly Census of Employment and Wages. Standard errors clustered at the commuting zone level are reported in parentheses, and p-values are reported in brackets.

Table A5: Additional Robustness: Alternative Approach to Aggregate Impacts Over Time

	(1) 1-day	(2) 2-day	(3) 3-day	(4) 5-day	(5) 7-day	(6) 10-day	(7) 14-day
Effect of Smoke (on Indicated Day before Observation Date) on Claims							
0	0.084	0.076	0.075	0.071	0.069	0.068	0.066
	(0.026)	(0.025)	(0.026)	(0.026)	(0.026)	(0.026)	(0.025)
	[0.002]	[0.004]	[0.005]	[0.008]	[0.011]	[0.011]	[0.009]
1		0.072	0.070	0.070	0.069	0.068	0.067
		(0.025)	(0.024)	(0.025)	(0.025)	(0.025)	(0.026)
		[0.006]	[0.006]	[0.007]	[0.009]	[0.009]	[0.011]
2			0.016	0.019	0.021	0.020	0.023
			(0.040)	(0.037)	(0.038)	(0.037)	(0.037)
			[0.700]	[0.612]	[0.583]	[0.584]	[0.533]
3				0.002	0.000	0.001	0.005
				(0.032)	(0.033)	(0.033)	(0.033)
				[0.941]	[0.990]	[0.974]	[0.873]
4				-0.033	-0.036	-0.036	-0.035
				(0.021)	(0.023)	(0.022)	(0.023)
				[0.131]	[0.110]	[0.114]	[0.123]
5					-0.010	-0.011	-0.008
					(0.022)	(0.022)	(0.022)
					[0.641]	[0.628]	[0.704]
6					0.046	0.040	0.043
					(0.035)	(0.037)	(0.037)
					[0.193]	[0.286]	[0.243]
7						0.015	0.018
						(0.037)	(0.035)
						[0.675]	[0.613]
8						0.043	0.049
						(0.036)	(0.035)
						[0.240]	[0.162]
9						-0.018	-0.007
						(0.026)	(0.027)
						[0.487]	[0.805]
10							-0.032
							(0.030)
							[0.295]
11							-0.018
							(0.040)
							[0.665]
12							-0.016
							(0.034)
							[0.649]
13							0.006
							(0.042)
							[0.882]
Effect of Smoke on Claims from Adding Coefficients in Window, ΣB_k	0.084	0.148	0.160	0.130	0.158	0.191	0.162
	(0.026)	(0.035)	(0.049)	(0.058)	(0.049)	(0.073)	(0.086)
	[0.002]	[0.000]	[0.002]	[0.030]	[0.002]	[0.012]	[0.062]
Daily Claim Rate per 100,000 Workers							
Mean	5.8	5.8	5.8	5.8	5.8	5.8	5.8
Standard deviation	4.0	4.0	4.0	4.0	4.0	4.0	4.0
N	301,940	301,878	301,816	301,692	301,568	301,382	301,134
Implied % impact relative to mean daily claim rate	1.4	2.6	2.8	2.2	2.7	3.3	2.8

Notes: This table displays estimates of the impact of smoke on workers' compensation injury claims from estimating Equation (1). Each column displays estimates from a separate regression, where the dependent variable is the daily rate of claims. Each regression includes controls for commuting-zone-by-quarter-by-year fixed effects, date fixed effects, indicator variables for the quintile of the day's maximum temperature, and indicator variables for the quintile of the day's precipitation. In addition, regressions include controls for indicator variables for the quintiles of the maximum temperature and precipitation and controls for smoke on the days before and after the observation date for the number of days included in the window for calculating the claim rates. The coefficients for the smoke days in the aggregation window are shown in the table. The sample includes observations from September 2005 through 2018 for all 62 commuting zones in Texas. All regressions are weighted by commuting zones' mean employment during the sample period calculated from the Quarterly Census of Employment and Wages. Standard errors clustered at the commuting zone level are reported in parentheses, and p-values are reported in brackets.

Table A6: Additional Robustness: Varying Definition of Smoke or Sample Restrictions

	(1)	(2)	(3)	(4)	(5)	(6)
				Robustness to Excluding 99th Percentile of PM2.5 (99th percentile = 23.9)		
	Claims	Claims	Claims	Claims	$PM_{2.5}$	Claims
Smoke	0.165		0.127	0.184	1.419	0.182
	(0.048)		(0.056)	(0.050)	(0.074)	(0.061)
	[0.001]		[0.026]	[0.001]	[<0.001]	[0.004]
Full Smoke Coverage Indicator		0.167				
		(0.044)				
		[<0.001]				
Method Used to Identify Commuting Zone	Baseline	Baseline	Alternative	Baseline	Baseline	Baseline
Exclude Days with Missing $PM_{2.5}$				x	x	x
Excluding Smoke Exposure with $PM_{2.5}$ > 99th Percentile					x	x
Daily Claim Rate per 100,000 Workers						
Mean	5.8	5.8	5.9	5.8	n/a	5.8
Standard deviation	4.0	3.9	3.9	3.9	n/a	3.9
N	301,816	301,816	301,816	252,950	252,167	252,167
Implied % impact relative to mean daily claim rate	2.8	2.9	2.1	3.2	n/a	3.2

Notes: This table displays estimates of the impact of smoke on workers' compensation injury claims from estimating Equation (1). Each column displays estimates from a separate regression, where the dependent variable is the three-day claim rate in columns 1 through 4 and in column 6 and is $PM_{2.5}$ levels in column 5. The regression for column 1 includes the baseline controls as described in the notes in Table 2. In column 2, the baseline smoke measure is replaced with an indicator variable for the commuting zone being fully covered by smoke. In column 3, the location of claims is based on the location of first medical treatment for claims with non-missing location information for the first medical treatment. The baseline sample includes observations from September 2005 through 2018 for all 62 commuting zones in Texas. Columns 4 through 6 exclude observations with missing $PM_{2.5}$ information, while columns 5 and 6 further exclude observations with $PM_{2.5}$ above the 99th percentile of $PM_{2.5}$ levels across the sample. All regressions are weighted by commuting zones' mean employment during the sample period calculated from the Quarterly Census of Employment and Wages. Standard errors clustered at the commuting zone level are reported in parentheses, and p-values are reported in brackets.

Table A7: Additional Robustness: Excluding Observations with Nearby Fires

	(1) Claims	(2) Claims	(3) Claims
Smoke	0.165	0.178	0.168
	(0.048)	(0.045)	(0.060)
	[0.001]	[<0.001]	[0.007]
Excluding commuting zone obs within 200 km of wildfires			
Using Monitoring Trends in Burn Severity Data		x	
Using Global Fire Emissions Data			x
Daily Claims			
Mean daily claims	5.8	5.8	5.8
Standard deviation	4.0	4.0	4.0
N	301,816	280,508	184,261
Implied % impact relative to mean daily claims	2.8	3.1	2.9

Notes: This table displays estimates of the impact of smoke on workers' compensation injury claims from estimating Equation (1). Each column displays estimates from a separate regression, where the dependent variable is the three-day claim rate for the injury type indicated in the column heading. Refer to the notes in Table 2 for a description of the baseline controls included in each regression. The sample includes observations from September 2005 through 2018 for all 62 commuting zones in Texas. All regressions are weighted by commuting zones' mean employment during the sample period calculated from the Quarterly Census of Employment and Wages. Standard errors clustered at the commuting zone level are reported in parentheses, and p-values are reported in brackets.

Table A8: Aggregate Cost Associated with Other Health Impacts of Pollution Based on Prior Estimates

Paper	Reported findings	Additional information used	National Impact of a 10 $\mu g/m^3$ increase in $PM_{2.5}$
Alexander and Schwandt (2022)	From Table 6: An additional cheating diesel car (per 1000 cars): -increases $PM_{2.5}$ by 0.60 $\mu g/m^3$ -increases ED visits (per quarter per 1,000 children 0-4 years of age) by 0.24 visits	Number of children 0-4 years of age:18.5 million (from US Census Quick Facts, 2020) Cost of ED visit for respiratory condition: \$2,702 (from Schlenker and Walker (2016))	Number of annual ED visits: 297,600 Annual cost: \$1.0 billion
Deryugina et al. (2019)	From Table 3: Instrumental Variables estimate: 1 $\mu g/m3$ increase in $PM_{2.5}$ for one day leads to an extra \$19,339 in patient spending per 1 million fee-for-service Medicare benficiaries.	-Number of Medicare Beneficiaries: 44 million (from pg. 4203, footnote 36)	Number of annual inpatient admissions: 354,444 Annual cost: \$3.1 billion
Deryugina et al. (2019)	-From Table 4 column 6: 1 $\mu g/m3$ increase in $PM_{2.5}$ for one day leads to 2.991 life years lost per million Medicare beneficiaries.	-Value of each life year lost: \$100,000 (from pg. 4203) -Number of Medicare Beneficiaries: 44 million (from pg. 4203, footnote 36)	Annual cost of life years lost: \$48.0 billion

Notes: This table provides more detail on the calculations of the aggregate costs of pollution on outcomes analyzed in prior work, focusing on the indicated estimates. In calculating aggregate costs reported in column (4), dollar values in columns (2) and (3) are adjusted to 2021 dollars using the CPI-U based on comparing 2021 to the year representing the mid-point of the sample underlying the indicated value.

Table A9: Largest Classifications by Segment of Risk Distribution

Classification Number	Classification Name	Share covered payroll in Texas	Relative Risk (exp costs/ payroll, normalized mean 1)	Impact of a 10 μg/m3 increase in $PM_{2.5}$ Costs (% relative to daily payroll)
	Panel A: Largest Among Top 5% of Relative Risk			
6202	OIL OR GAS WELL & DRIVERS	0.47%	6.79	2.04%
3881	CAR MFG - RAILROAD - & DRIVERS	0.06%	7.35	2.21%
7538	ELECTRIC LIGHT OR POWER LINE CONSTRUCTION & DRIVERS	0.06%	9.37	2.81%
5551	ROOFING - ALL KINDS - & YARD EMPLOYEES, DRIVERS	0.04%	7.59	2.28%
8293	STORAGE WAREHOUSE - FURNITURE - & DRIVERS	0.02%	6.83	2.05%
5040	IRON OR STEEL: ERECTION: FRAME - STRUCTURES	0.02%	12.21	3.67%
6238	CASING INSTALLATION - OIL WELL - & DRIVERS	0.01%	8.28	2.49%
3081	FOUNDRY - FERROUS - NOC	0.01%	6.79	2.04%
6400	CHAIN LINK FENCE CONSTRUCTION; FENCE ERECTION - ALL TYPES; MOBILE HOME - WINDSTORM TIE-DOWN INSTALLATION: BY SPECIALTY CONTRACTOR; PLAYGROUND EQUIPMENT INSTALLATION	0.01%	7.95	2.39%
0034	HATCHERY - POULTRY - STORE OPERATIONS ONLY & DRIVERS	0.00%	7.39	2.22%
	Panel B: Largest Among Classifications Between Median and Top 5% of Relative Risk			
7219	TRUCKING: NOC - ALL EMPLOYEES & DRIVERS	1.05%	5.99	1.80%
5183	PLUMBING NOC & DRIVERS	0.65%	2.85	0.86%
3724	MACHINERY OR EQUIPMENT ERECTION OR REPAIR NOC & DRIVERS	0.62%	2.76	0.83%
5190	ELECTRICAL WIRING & DRIVERS	0.61%	3.01	0.90%
8018	STORE: WHOLESALE, OR COMBINED WHOLESALE AND RETAIL NOC & DRIVERS	0.43%	3.81	1.14%
9014	BUILDINGS - OPERATION BY CONTRACTORS	0.41%	2.85	0.86%
7380	CHAUFFEURS, DRIVERS & THEIR HELPERS NOC - COMMERCIAL	0.37%	3.49	1.05%
3066	SHEET METAL WORK - SHOP	0.34%	2.69	0.81%
9052	HOTEL: ALL OTHER EMPLOYEES & SALESPERSONS, DRIVERS	0.32%	2.70	0.81%
5200	CONCRETE OR CEMENT WORK	0.31%	3.10	0.93%
	Panel C: Largest Among Classifications Between Bottom 5% and Median of Relative Risk			
8017	STORE: RETAIL NOC & DRIVERS	2.46%	1.60	0.48%
8868	COLLEGE: PROFESSIONAL EMPLOYEES & CLERICAL	2.38%	0.44	0.13%
8833	HOSPITAL: PROFESSIONAL EMPLOYEES	2.19%	0.76	0.23%
8391	AUTOMOBILE REPAIR SHOP & PARTS DEPARTMENT EMPLOYEES, DRIVERS	1.38%	1.77	0.53%
9079	RESTAURANT NOC	1.34%	1.82	0.55%
5606	CONTRACTOR - EXECUTIVE SUPERVISOR OR CONSTRUCTION SUPERINTENDENT	0.95%	1.08	0.32%
5191	OFFICE MACHINE OR APPLIANCE INSTALLATION, INSPECTION, ADJUSTMENT OR REPAIR	0.70%	0.67	0.20%
3681	TELEVISION, RADIO OR TELECOMMUNICATION DEVICE MFG	0.62%	1.10	0.33%
4740	OIL REFINING - PETROLEUM - & DRIVERS	0.62%	0.99	0.30%
7405	AIRCRAFT OR HELICOPTER OPERATION: AIR CARRIER - FLYING CREW	0.59%	0.73	0.22%
	Panel D: Largest Among Classifications in Bottom 5% of Relative Risk			
8810	CLERICAL OFFICE EMPLOYEES NOC	40.76%	0.18	0.05%
8742	SALESPERSONS, COLLECTORS OR MESSENGERS - OUTSIDE	8.34%	0.29	0.09%
8832	PHYSICIAN & CLERICAL	2.67%	0.30	0.09%
8809	EXECUTIVE OFFICERS NOC - PERFORMING CLERICAL OR OUTSIDE SALESPERSONS DUTIES ONLY	2.36%	0.21	0.06%
8601	ARCHITECT OR ENGINEER - CONSULTING	1.86%	0.33	0.10%
8820	ATTORNEY - ALL EMPLOYEES & CLERICAL, MESSENGERS, DRIVERS	1.70%	0.13	0.04%
8803	AUDITOR, ACCOUNTANT OR FACTORY COST OR OFFICE SYSTEMATIZER - TRAVELING	1.35%	0.07	0.02%
8901	TELEPHONE OR TELEGRAPH CO: OFFICE OR EXCHANGE EMPLOYEES & CLERICAL	1.04%	0.24	0.07%
8748	AUTOMOBILE SALESPERSONS	0.62%	0.27	0.08%
7610	RADIO OR TELEVISION BROADCASTING STATION - ALL EMPLOYEES & CLERICAL, DRIVERS	0.40%	0.36	0.11%

Notes: This table lists the top ten classifications in the indicated segment of the risk distribution, where percentiles are taken with respect to (unweighted) industry-occupation workers' compensation classification codes. The table displays the workers' compensation classification number, the classification name, the share of covered payroll in Texas represented by the classification, and the normalized relative risk of the classification (=expected costs/payroll, normalized to have mean of one across all workers' compensation covered payroll).