

NBER WORKING PAPER SERIES

AIR POLLUTION, WILDFIRE SMOKE, AND WORKER HEALTH

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Working Paper 32232
<http://www.nber.org/papers/w32232>

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
March 2024, Revised June 2026

For outstanding research assistance, we thank Daniel Jordan Alvarez, Mu Yang Shin, and Kai Wu. For providing helpful comments and feedback, we thank Judson Boomhower, Jackson Dorsey, Mary Evans, David Molitor, Matthew Neidell, and seminar participants at BU-Harvard-MIT Health Economics Seminar, Corvinus University of Budapest, George Washington University, Georgetown University McDonough School of Business, Northwestern University Kellogg School of Management, Triangle Health Economics Seminar at Duke University, the University of California San Diego, the University of Chicago, the University of Pennsylvania Wharton Business School, the University of Rochester Simon School of Business, Vanderbilt University, the University of New Hampshire, the University of Georgia, and the University of Texas at Austin. Cabral gratefully acknowledges financial support from the National Science Foundation CAREER Award (1845190). The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

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NBER Working Paper No. 32232
March 2024, Revised June 2026
JEL No. I18, J28, J3, Q53

ABSTRACT

Little is known about how pollution impacts worker health and safety. This paper leverages high-frequency, plausibly exogenous variation in wildfire smoke exposure 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. The incidence of these pollution-induced injuries is unevenly distributed across workers, and supplemental analysis reveals potential opportunities for targeting costly mitigation. Our estimates suggest that pollution—and wildfire smoke in particular—substantially harms worker health, even at pollution levels well below current and proposed regulatory standards. Further, the magnitude of our estimated impacts is sizable relative to prior estimates of other impacts of pollution. Overall, our findings suggest workers face unique risks from pollution and provide insights for policy aiming to address these risks.

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Many workers face serious health risks at work due to the nature of their job or the conditions under which they perform work activities. Policymakers have long been concerned that pollution and environmental hazards pose unique risks for workers, with occupational health regulators worldwide issuing related guidance and policy. Workers are often exposed to substantial pollution—through both community-based sources and industrial on-site pollutants. And concerns about the impact of pollution on worker health and safety are growing, given recent periods of very elevated air pollution from wildfire smoke and projections of increases in wildfire smoke going forward due to climate change. But despite these growing concerns, little is known about how pollution impacts worker health and workplace safety. 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 Workers may be particularly vulnerable to pollution exposure because they often have limited ability to adjust their activities on the job compared to non-work settings. 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. And understanding the impact of pollution on workplace injuries is important, as 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 (U.S. Bureau of Labor Statistics 2023a), and the aggregate costs of these events totaled \$250 billion in 2010 (Leigh 2011).³ Moreover, the costs associated with workplace injuries are sizable relative to other work-related risks. For example, the nationwide cost of workers’ compensation insurance is nearly twice the aggregate cost of unemployment insurance in a typical non-recessionary year.⁴

Policymakers in many countries have expressed concerns about the impact of air pollution and particulate matter on worker health and safety,⁵ and occupational health and safety regulators are actively designing and revising policies governing work during periods with elevated air pollution. Thus, understanding the impact of pollution on worker health and safety is important for informing related policy worldwide. In the United States, the impact of pollution on worker safety is relevant to both 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 enforce-

¹This paper analyzes the impact of pollution on workers’ compensation 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). While our data include both worker injuries and illnesses due to occupational exposure, in practice, the overwhelming majority of claims reflect worker injuries and we refer to these as worker injuries throughout.

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

³These 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.

⁴For example, based on McLaren, Baldwin, and Boden (2018) and U.S. Department of Labor (2020), the nationwide costs of workers’ compensation were 1.9 times the nationwide costs of unemployment insurance in 2016.

⁵In the United States, federal and state Occupational Safety and Health Administration (OSHA) regulators have issued guidance and regulations to employers about managing workplace risk related to worker exposure to particulate matter (e.g., OSHA 2011, Cal/OSHA 2023). Workplace safety regulators in other countries have issued similar guidance, including regulators in the European Union (EU-OSHA, 2012), Canada (Canadian Centre for Occupational Health and Safety, 2024), and Australia (Safe Work Australia, 2024).

able 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 in the U.S. 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.⁶ 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 workers exposed to wildfire smoke and high levels of particulate matter. These regulations require employers to clearly communicate risks and implement 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 similar policies as well.⁷ Industry groups and lobbyists have pushed back against these regulatory efforts, voicing concerns that the required mitigation measures are extremely costly for employers to implement. At the same time, there is growing pressure from groups concerned about worker safety to enact similar regulation at the federal level—including recent calls from the National Academy of Sciences to act on this issue (e.g., National Academies of Sciences, Engineering, and Medicine 2022). Despite concerns that pollution may present serious risks to worker health and the growing policy debate about whether and how to address 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. In doing so, our analysis illustrates that increased workplace injuries is a first-order harm of pollution, with estimates suggesting the costs from increased workplace injuries are in the same range as the estimated costs of other important impacts of pollution—such as reduced worker productivity and increased medical spending among children and the elderly. Our approach leverages 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

⁶Based on EPA 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.

⁷For information on California’s wildfire smoke regulation, see Cal. Code Regs. tit. 8, § 5141.1 (“Protection from Wildfire Smoke”). Oregon adopted similar permanent rules under OAR 437-002-1081 (“Protection from Wildfire Smoke”). Washington subsequently adopted permanent wildfire smoke regulations codified in WAC Chapter 296-820 (“Wildfire Smoke”). Other states have also considered related legislation or issued guidance regarding workplace exposure to wildfire smoke.

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 the 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 $1.69 \mu\text{g}/\text{m}^3$ 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 $9.06 \mu\text{g}/\text{m}^3$. 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 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 relative to the non-smoke-day 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 $PM_{2.5}$ because it increases sharply with smoke coverage and because it is thought to be particularly harmful for human health. Nonetheless, we note that wildfire smoke causes a broad deterioration of air quality by elevating multiple pollutants and appropriate caution is warranted when extrapolating to other non-smoke-based sources of $PM_{2.5}$. Based on this scaling, our estimates imply that a $1 \mu\text{g}/\text{m}^3$ increase in $PM_{2.5}$ leads to an additional 0.098 daily injury claims per 100,000 workers or a 1.7% increase relative to the mean daily claim rate. We estimate that the cost of these additional injuries is \$4,114 daily per 100,000 workers, or about 0.03% of the mean daily earnings in Texas. Extrapolating from our estimates, a nationwide permanent $1 \mu\text{g}/\text{m}^3$ increase in $PM_{2.5}$ would result in an additional 85,000 injury claims annually, with an annual cost of \$3.6 billion. Moreover, extrapolation from our estimates suggests 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 mean daily claim rate.

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 in-

creases 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 find similar percent impacts across industries, suggesting that the impacts of pollution on workplace injuries are near-universal.

While our estimates suggest percent impacts are similar across many types of workers, the incidence of increased injuries is not evenly distributed across workers. Large differences in baseline injury risk imply there is substantial 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. This analysis indicates 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. Further, back-of-the-envelope calculations suggest there may be large gains from targeting costly mitigation toward workers in high-risk industry-occupations and suggest a rationale for shifting the focus of targeting in recent related occupational health and safety regulations.

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 increases the risk of injury during everyday work activities and generates substantial health risks for workers—particularly those in high-risk occupations. In this way, our findings highlight a rationale for occupational health and safety regulation related to pollution exposure, complementing broader environmental regulation. Moreover, by expanding our understanding of the harms of pollution and wildfire smoke, our estimates also inform discussions about the potential benefits of policies aimed at reducing pollution and limiting the incidence and severity of wildfires. Second, our estimates indicate that pollution increases workplace injuries at pollution levels well below current regulatory thresholds and across a wide range of work settings. Thus, our findings shed light on the potential benefits of expanding the scope of existing occupational health and safety and environmental regulations or adopting related protections more broadly. Third, our findings have implications for the design of mitigation policy. Recent state OSHA regulations have largely focused on reducing exposure to wildfire smoke—for example, through respirators or the re-timing of work. Our estimates suggest that 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. At the same time, because wildfire smoke is a community-wide exposure that affects workers across many work environments, our findings suggest there may also be value in complementary mitigation strategies aimed at reducing injury risk conditional on exposure, such as reducing work intensity, increasing rest periods, or strengthening workplace safety practices on polluted days. As shifting work is costly and may be infeasible for some of the workforce, our findings also highlight the need for additional research on the costs and effectiveness of alternative mitigation strategies. Finally, while wildfire smoke causes a broad deterioration in air quality with widespread impacts on workplace injuries, much of

the increase in injuries is concentrated among workers in high-risk occupations. This suggests there may be important gains from targeting costly mitigation toward workers facing the greatest baseline workplace risks.

Related Literature Our study contributes to several strands of the academic literature. First, it adds to a growing body of work on the causal determinants of workplace safety. Understanding these determinants is important given the large aggregate costs of workplace injuries and the prevalence of hazardous working conditions (Maestas et al. 2017). Prior research has primarily focused on the role of regulation and market forces in shaping workplace safety (e.g., Johnson 2020; Johnson, Schwab, and Koval 2022; Hummels, Munch, and Xiang 2016; Charles et al. 2022; Johnson, Levine, and Toffel 2023) and the costs of workplace injuries (e.g., Krueger 1990; Powell and Seabury 2018; Cabral and Dillender 2024). We extend this literature by providing large-scale causal evidence on the impact of pollution on worker safety. Despite increasing policy concern, existing research is largely limited to case studies or correlational analyses within specific industries or worksites.⁸ Our study offers novel causal evidence on the effects of community-wide pollution on workers' compensation claims, informing ongoing policy debates. More broadly, our findings identify pollution as an important determinant of worker safety and a contributing factor to recent trends in workplace injuries.

Second, our study contributes to a growing literature on the impacts of wildfire smoke (e.g., Jayachandran 2009; Rangel and Vogl 2019; Borgschulte, Molitor, and Zou 2024; Arenberg and Neller 2023). Wildfire smoke is an increasingly important source of pollution, accounting for nearly one-third of U.S. PM_{2.5} emissions in 2022, and is expected to rise with global temperatures. Understanding its harms is therefore critical. We add to this literature by showing that wildfire smoke poses distinct health risks for workers. As discussions of occupational health and safety policy related to wildfire smoke often focus on mitigating harms during smoke events, our findings provide direct evidence on worker health risks and inform these debates.

Third, our work extends the broader literature on the health impacts of pollution. Most studies focus on acute outcomes such as mortality and hospitalizations (e.g., Deryugina et al. 2019; Schlenker and Walker 2016) and typically examine impacts among children or older adults. We contribute by identifying a novel channel through which pollution affects health and by providing direct evidence on impacts among prime-aged adults. We further show that increases in workplace injuries are concentrated in high-risk occupations, highlighting the particular vulnerability of workers who perform dangerous tasks, have limited flexibility, and cannot easily adjust their activities in response to pollution. Finally, we demonstrate that the aggregate costs of pollution through increased workplace injuries are substantial and comparable in magnitude to several other acute health impacts of pollution.

Finally, our work complements a growing literature on the “nonhealth” impacts of pollution. This literature shows that pollution, by impairing physical and cognitive functioning, affects outcomes such as worker productivity (e.g., Graff Zivin and Neidell 2012), exam performance (e.g., La Nauze and Severnini 2025), and decision-making (e.g., Künn, Palacios, and Pestel 2023). Our findings indicate that the same un-

⁸Previous research about the impact of PM_{2.5} on worker health 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 three contemporaneous larger-scale studies investigating the impact of nitrogen dioxide on accidents at construction sites in Israel (Lavy, Rachkovski, and Yoresch 2024); the impact of winter heating rule regulations on PM₁₀ and work-related disabilities using data from eight Italian regions (Curci, Depalo, and Palma 2023); and the impact of dust precipitation on the rate of taking sick-leave for work accidents drawing on data from Spain (Hattemer and Moreno-Martinez 2024).

derlying mechanisms—subclinical symptoms that impair physical and cognitive functioning—also increase acute health events in the form of on-the-job injuries. In doing so, we connect the health and “nonhealth” literatures by showing that pollution affects a broad range of worker outcomes. Unlike prior work, however, our outcome captures a serious, work-related health risk, informing occupational health and safety policy debates. We further show that these harms are widespread across industries and occupations and entail substantial costs comparable to productivity losses from pollution.

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.⁹ 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).^{10,11} 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 across workers in a variety of specific work settings—ranging from California fruit farmworkers to Indian garment factory workers to California pear packing workers to Chinese call center workers (e.g., Graff Zivin and Neidell 2012; Adhvaryu, Kala, and Nyshadham 2022; Chang et al.

⁹For evidence on the relationship between indoor and outdoor $PM_{2.5}$ concentrations, see Krebs et al. (2021).

¹⁰Additional 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).

¹¹While there is limited evidence about mortality impacts among prime-aged adults, recent work by Finkelstein et al. (2024) documents that the Great Recession induced similar proportional declines in mortality across all age groups and provides suggestive evidence that reductions in pollution may explain roughly a third of this decline in aggregate.

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

2016, 2019; Archsmith, Heyes, and Saberian 2018). 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 among children (e.g., Ebenstein, Lavy, and Roth 2016; Zhang, Chen, and Zhang 2018) and brain training games among adults (La Nauze and Severnini 2025), 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 pollution can cause sub-clinical symptoms—such as impairments in physical and cognitive functioning—that can have important impacts on an individual’s ability to perform routine tasks. These impacts have been found 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.¹⁴

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. While the circumstances of injuries vary, according to the Bureau of Labor Statistics (U.S. Bureau of Labor Statistics 2020), the vast majority of workplace injuries are attributable to three types of injuries: 27% of workplace injuries are from falls, trips or slips; 26% are from contact with equipment; and 29% are from non-impact causes—resulting from physical force directed at an outside object, often occurring during activities such as lifting, pushing, turning, holding, carrying, or throwing.¹⁵ 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 workers to do their work activities with less attention and focus—e.g., lifting boxes with slightly worse form, being distracted while using dangerous equipment, or paying less attention when climbing a ladder—which can lead to increased workplace 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 (e.g., Dillender 2021; Park, Pankratz, and Behrer 2021; Drescher and Janzen 2025; Ireland, Johnston, and Knott 2023) 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 air pollution to impact worker safety and, more generally, about the potential for adverse working conditions to increase the likelihood of workplace accidents and injuries. 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.

Wildfire smoke affects human outcomes through many of the same channels as other forms of air pollution, and a growing body of work documents its impacts across a range of domains (see Gellman and Wibbenmeyer 2025; Gould et al. 2024 for reviews). Evidence from toxicological studies highlights the bi-

¹³Other 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., Herrnsstadt et al. 2021, Burkhardt et al. 2019).

¹⁴While our focus is on short-run impacts, a growing literature also documents important long-run consequences of pollution exposure, including effects on cognitive decline and survival (e.g., Bishop, Ketcham, and Kuminoff 2023; Deryugina and Reif 2023).

¹⁵While other sources of workplace injuries are less common, 6% of workplace injuries are from transportation incidents, 5% are from violence, and 5% are from occupational exposure to harmful substances or circumstances (e.g., electricity, radiation, traumatic events). The remaining injuries are from other causes, including fires, explosions, and repetitive motion. This information is from 2018 injuries that involve missed work and comes from the Bureau of Labor Statistics website.

ological effects of wildfire smoke exposure (Wegesser et al. 2010). More broadly, epidemiological and economic studies document substantial impacts of wildfire smoke on mortality and morbidity (e.g., Reid et al. 2016; Cascio 2018; Aguilera et al. 2021a; Qiu et al. 2025). Recent work also suggests that health responses may vary with behavioral adaptation at high exposure levels (Heft-Neal et al. 2023; Miller, Molitor, and Zou 2024; Burke et al. 2022). In addition, there is evidence of meaningful effects on economic outcomes: for example, exposure to wildfire smoke has been shown to reduce labor market earnings (Borgschulte, Molitor, and Zou 2024). A related literature links early-life exposure to air pollution from wildfire smoke to adverse birth outcomes and longer-run reductions in human capital (e.g., Jayachandran 2009; Rangel and Vogl 2019; Arenberg and Neller 2023; Heft-Neal et al. 2022; Holstius et al. 2012).

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, wildfire smoke has received particular attention from occupational health and safety regulators. State and federal occupational health and safety regulators are actively debating whether and how to regulate work performed when wildfire smoke causes high levels of ambient air pollution. Our study provides the first causal estimates to inform these debates.

2 Data

2.1 Pollution 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) (National Oceanic and Atmospheric Administration 2021). These data contain geographical shape files that outline the location of each smoke plume in the U.S. 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 U.S. Department of Agriculture,¹⁶ we construct our key measure of smoke exposure: the share of a commuting zone covered by a smoke plume during the indicated day.¹⁷

We complement these smoke plume data with data on air pollution from the Environmental Protection Agency (EPA) Air Quality System (U.S. Environmental Protection Agency 2020). 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 PM₁₀, O₃, CO, NO₂, and SO₂—to analyze the associ-

¹⁶The geographic shape files used for this project come from the following sources: U.S. Department of Agriculture, Economic Research Service (2000); U.S. Census Bureau (2010a, 2018); Esri (2018). In addition, we use geographic crosswalks from zipcode to county and from county to commuting zone from the following sources: U.S. Census Bureau (2010b); U.S. Department of Agriculture (2023).

¹⁷For 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 A11, we show that the results are robust to using an alternative smoke measure: an indicator variable for the commuting zone ever being fully covered by smoke on that day. Further, Appendix Table A12 illustrates our results are similar if we instead define smoke at the county level.

ation 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.¹⁸ 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 (Monitoring Trends in Burn Severity 2023)—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.¹⁹ 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 (2024). These data are based on the PRISM Climate Group weather data, which contain daily information on minimum temperature, maximum temperature, and total precipitation on a 2.5 mile by 2.5 mile grid of the contiguous U.S. 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 (Texas Department of Insurance 2018*b,c,d*). 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.²⁰ 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.²¹

¹⁸For PM_{2.5} and PM₁₀, 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 O₃ and CO and the maximum hourly reading for SO₂ and NO₂.

¹⁹The 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.

²⁰Workers’ 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.

²¹Workplace injuries are also associated with substantial costs not covered by workers’ compensation insurance, including costs borne by employers (e.g., productivity losses, disruption costs, property damage, and other unreimbursed costs) and by employees

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 by date level and report rates per 100,000 workers employed in the commuting zone that quarter, according to the 2005-2018 Quarterly Census of Employment and Wages (U.S. Bureau of Labor Statistics 2023b). Throughout the analysis, commuting zone by date observations are weighted by the commuting zone's mean quarterly employment during the sample period, based on data from the Quarterly Census of Employment and Wages.

We aggregate injury claims by date using the date that the injured worker first received medical treatment for their injury.²² 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., 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.²³ 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.²⁴ While our

(e.g., uninsured earnings losses, and other non-monetized health costs). Section 5 discusses costs of workplace injuries further when providing context for the estimates.

²²The 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.

²³As 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.

²⁴It is not surprising that our findings are similar using these two alternative methods for assigning commuting zones, as workers

baseline specification defines smoke at the commuting zone level, Appendix Table A12 shows we obtain similar estimates in specifications with smoke defined at the county level.

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 (Texas Department of Insurance 2009). Outdoor exposure is constructed based on O*NET occupation-level data (O*NET 2023), where we measure outdoor exposure of an occupation as the inverse of the reported frequency of work performed in indoor environmentally-controlled settings.²⁵ 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 Texas's 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.²⁶ 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 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 up 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

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 zones indicated by these two location measures perfectly align for 88% of injury claims.

²⁵We note this measure of outdoor exposure closely aligns with the definition of outdoor exposure in recent state OSHA regulations.

²⁶According 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 the 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).

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.²⁷

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 (Flood et al. 2025) 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.

Based on our data, there was an average of 2.4 workplace injuries for every 100 covered workers over our 2006-2018 analysis period. Appendix Section B provides additional background information on workplace injuries that is useful for interpreting our findings. For example, Appendix Figure A1 presents several benchmarks for the injury data used in this study. Workers' compensation claim rates calculated from our administrative microdata closely match aggregate rates reported by the Texas Department of Insurance, supporting the validity of the data. In addition, workers' compensation claim rates in our data track broader workplace injury patterns in Texas measured by the Bureau of Labor Statistics, and all series exhibit the gradual decline in workplace injuries observed nationally over time.

Beyond being relatively common, workplace injuries are also economically consequential. They generate substantial costs through medical spending, productivity disruptions, and persistent earnings losses for injured workers. The National Safety Council estimates that the average medically consulted workplace injury costs approximately \$42,000. Because workers' compensation claims largely reflect injuries requiring medical attention, this benchmark maps closely to the types of workplace injuries observed in our data. We draw on this estimate in our discussion of magnitudes and provide additional context for this figure in Appendix Section B.

2.3 Descriptive Statistics

Table 1 presents the mean and standard deviation of key measures in 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.²⁸ 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

²⁷Even among participating employers, workers' compensation claims data may not cover the universe of workplace injuries if workers choose not to report their injuries or choose not to seek treatment for their injuries. While our estimates are directly informative about workplace injuries covered by workers' compensation insurance, our estimates in percent terms are useful for extrapolating to predict impacts on workplace injuries more broadly if reporting conditional on injury is unrelated to the presence of wildfire smoke. Table 5 illustrates the effects are similar across more and less severe injuries, consistent with reporting conditional on injury being unrelated to smoke.

²⁸The baseline model is a linear regression with claim rates as the dependent variable and therefore includes observations with zero claims; however, 97% of observations have at least one associated injury claim.

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. There are 301,816 commuting zone–date observations.

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 U.S. averaging 22.5 days.²⁹ 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.³⁰ Figure 2 describes an example, illustrat-

²⁹These 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.

³⁰Analyzing data from across the U.S., Wen et al. (2023) find that the majority of PM_{2.5} exposure from wildfire smoke comes from

ing the dynamics of smoke plumes in the days surrounding one large fire: the Starbuck Fire, which started near Slapout, Oklahoma on March 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 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 on 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 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 the potential for increased risk 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.³¹ 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. Appendix Table A3 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.³²

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.

³¹Only 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.

³²Appendix Table A3 reports an analogous instrumental variables specification. These results suggest there is no association between smoke coverage and hours worked on a weekly level, with the associated 95% confidence interval allowing us to rule out that a $1 \mu g/m^3$ increase in pollution leads to more than a 0.05% decline in weekly hours worked. This null result for the impact of pollution on hours worked is in line with similar findings from several studies leveraging high-frequency variation to analyze the impacts of pollution on worker productivity (e.g., Graff Zivin and Neidell 2012; Chang et al. 2016, 2019), though other studies find evidence that

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 inclusive 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. Thus, our estimates—which are inclusive of any behavioral adjustments in the absence of regulation—directly inform current policy debates surrounding the enactment and expansion of regulations related to work during periods with elevated pollution due to wildfire smoke.

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:

$$y_{jt} = \gamma \text{smoke}_{jt} + \tau_t + \phi_{jq(t)} + X_{jt}\Theta + \epsilon_{jt}, \quad (1)$$

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.³³ 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 by year 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.³⁴ We also include three lags of the weather controls and smoke indicators, to minimize concerns about auto-correlation. Given the included controls, the estimated γ should be interpreted as the impact of one day of smoke on claims, holding constant whether smoke was present in the days directly preceding or following that day.³⁵ We calculate standard errors clustered at the

air pollution reduces hours worked (e.g., Aragón, Miranda, and Oliva 2017). When investigating long-run impacts of pollution, some prior work has found significant negative impacts of pollution on earnings and employment (e.g., Borgschulte, Molitor, and Zou 2024; Hanna and Oliva 2015; Isen, Rossin-Slater, and Walker 2017).

³³Appendix Table A11 illustrates that our findings are very similar when using an alternative smoke measure: an indicator that the commuting zone is fully covered by smoke on the observation date.

³⁴The baseline specification controls for daily maximum temperature and for daily precipitation in quintile bins. While the main tables report the coefficient of interest on the smoke measure, Appendix Table A4 also reports the coefficients on the temperature controls for reference. In Table 3, we verify the robustness of the results to including additional weather controls.

³⁵The impact of a smoke day has the potential to have differential impacts based on the duration of the smoke event if the impact of smoke is related to the accumulated duration of exposure to smoke. Appendix Table A2 reports supplemental analysis that tests for heterogeneity in the impacts of a smoke day depending on the duration of the smoke event by estimating a distributed lag model with interaction terms between smoke on the reference day and lagged values of smoke in the days directly before the reference day. The estimated coefficients on the interaction terms from this model indicate that the impact of smoke today on today’s claims does not depend on whether the individual was also exposed to smoke in the directly preceding days.

commuting zone level to account for serially correlated shocks within commuting zones.³⁶

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. Appendix Figure A2 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. 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 by year fixed effects.

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 3 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. For Panel B, commuting zones are ordered from largest to smallest, with the largest commuting zones in Texas being Houston, Dallas, and Fort Worth. 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 $\mu\text{g}/\text{m}^3$,

³⁶In Appendix Table A6, we verify the results are robust to clustering standard errors at both the commuting zone level and the region by quarter by year level. Adding the second level of clustering at the region by quarter by year level allows for serial correlation of smoke exposure across broader regions within year-quarters to reflect the fact that there is spatial correlation in commuting zones' smoke exposure from smoke plumes covering multiple commuting zones at the same time. For region definition, we use the 11 health regions as determined by the Texas Department of State Health Services (Texas Department of State Health Services 2024).

which is a 0.39 standard deviation (SD) increase or an 18.6% increase above the non-smoke-day mean of $9.06 \mu\text{g}/\text{m}^3$. We observe similar increases when measuring $\text{PM}_{2.5}$ during daytime hours—with the estimates indicating smoke increases average daytime $\text{PM}_{2.5}$ by $1.89 \mu\text{g}/\text{m}^3$, representing a 0.40 SD increase or a 21.7% increase beyond a non-smoke-day mean of $8.71 \mu\text{g}/\text{m}^3$. 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.³⁷ 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 the standard for ambient air pollution set by the EPA and pollution thresholds embedded in recent state OSHA regulations. The EPA sets a daily standard for ambient $\text{PM}_{2.5}$ of $35 \mu\text{g}/\text{m}^3$, which is well above the level of ambient air pollution on a typical smoke day. In addition, a typical smoke day in our data results in ambient air pollution well below the $\text{PM}_{2.5}$ thresholds at which recent state OSHA regulations begin requiring enhanced workplace protections.³⁸ 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.³⁹ Only 0.4% of smoke days across our analysis period have recorded ambient $\text{PM}_{2.5}$ in excess of $35 \mu\text{g}/\text{m}^3$, and we show that our findings are virtually unchanged when excluding these events.

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 non-smoke-day 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 expanded 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.⁴⁰ Column 5 illustrates that our findings are

³⁷These findings are broadly consistent with existing evidence on the relationship between wildfire smoke and air pollution. For example, Borgschulte, Molitor, and Zou (2024) find that smoke primarily affects particulate matter, leading to sizable increases in both $\text{PM}_{2.5}$ and PM_{10} , with notably smaller impacts on other pollutants, including O_3 and SO_2 . This is also consistent with government reports and the atmospheric science literature, which shows that wildfire smoke is a complex mixture dominated by particulate matter but also associated with measurable increases in O_3 precursors and SO_2 (U.S. Environmental Protection Agency 2022; Rickly et al. 2022; Akagi et al. 2011; Andreae 2019).

³⁸Recent wildfire smoke regulations in California, Oregon, and Washington generally require enhanced workplace protections once $\text{PM}_{2.5}$ concentrations reach approximately $35.5 \mu\text{g}/\text{m}^3$ (AQI 101), including measures such as voluntary respirator access, communication requirements, and exposure mitigation practices. Washington's regulations also include some lower-threshold administrative requirements beginning at approximately $20.5 \mu\text{g}/\text{m}^3$ of $\text{PM}_{2.5}$, including training and communication provisions.

³⁹Air quality on a typical smoke day is within the "good to moderate" range of the EPA-defined Air Quality Index.

⁴⁰Appendix Table A13 further verifies the robustness of the results to excluding observations that could potentially experience direct

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 smoke causes a broad deterioration in air quality that goes beyond impacts captured by $PM_{2.5}$ measures, and 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.⁴¹

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 $1 \mu g/m^3$ increase in daily $PM_{2.5}$ leads to an additional 0.098 injury claims per 100,000 workers or a 1.7% increase relative to the mean daily claim rate. Appendix Table A5 illustrates the implied impact of $PM_{2.5}$ is very similar when estimating an analogous instrumental variables (IV) specification which focuses on the subset of observations for which $PM_{2.5}$ data are available. Based on the analogous IV specification, a $1 \mu g/m^3$ increase in daily $PM_{2.5}$ leads to an additional 0.109 injury claims per 100,000 workers (a 1.9% increase relative to the mean daily claim rate), with a 95% confidence interval spanning 0.054 to 0.164. Instead of scaling by the daily measure of $PM_{2.5}$, we could scale the reduced form increase in injury claims by the estimated increase in daytime $PM_{2.5}$ (from Table 2 column 2). Doing this suggests that a $1 \mu g/m^3$ increase in daytime $PM_{2.5}$ leads to an additional 0.087 injury claims per 100,000 workers or a 1.5% increase relative to the mean daily claim rate. Appendix Table A5 illustrates the implied impact is similar in an analogous IV specification estimated on the subset with available $PM_{2.5}$ data. Section 5 provides a more in-depth discussion of the magnitude of the estimates and the relation to other impacts of pollution.

Impacts by Injury and Worker Characteristics Next, we turn to examining heterogeneity by injury and worker characteristics. In this analysis, we analyze claims in the indicated subset 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,

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 A13 indicates that the estimated effects are similar to the baseline estimates regardless of which dataset we use to identify observations with nearby fires.

⁴¹One reason why this scaling exercise is useful is that it allows us to quantify the magnitudes of the estimated impacts in a way that is comparable to other studies looking at the impacts of $PM_{2.5}$ from wildfire smoke. Not all smoke events are equally severe, and we would expect impacts on injuries to be larger when the smoke event causes a greater deterioration in local air quality. To the extent that $PM_{2.5}$ is a useful summary measure, scaling the impacts on injuries by the impacts on $PM_{2.5}$ allows us to recover the estimated impact on injuries per unit of $PM_{2.5}$ produced by wildfire smoke.

contusions, fractures, and other injuries. These different injury types may occur during the course of similar activities and reflect the nature of workplace injuries, which are primarily driven by falls/trips, contact with equipment, and non-impact causes (e.g., injuries while lifting, pushing, turning, holding, carrying, or throwing). The estimated percent impacts are similar to the overall impact for the largest injury categories (muscle issues, sprains, and other). While estimated impacts are noisier for the smallest injury categories (contusions or fractures), the implied percent impacts are statistically indistinguishable from the overall impact on injuries.⁴²

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%). 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.⁴³ 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.

Relative to other work examining the impacts of pollution on workers, a strength of our setting is that the data and variation span workers in all industries and occupations and the data contain detailed information on worker industry-occupation. Leveraging this feature, we examine the impact of pollution on workplace injuries by job characteristics of the injured worker. Table 7 presents these estimates. 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 impact 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

⁴²To 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.

⁴³Note that this analysis holds the denominator fixed as the total workers in the commuting zone that quarter. In Appendix Table A7, we repeat this analysis using group-specific denominators calculated by scaling the total number of workers in the QCEW each quarter by each group's share of all workers in Texas, where groups' shares of all workers in Texas are calculated using the IPUMS American Community Survey five-year summary files (Schroeder et al. 2025). 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.

exposure (columns 6-8). The estimated impacts do not vary monotonically with either risk or outdoor exposure of the industry-occupation, and the estimates are not statistically distinguishable across terciles for either feature. Thus, this analysis suggests there is no evidence of a systematic relationship between either risk or outdoor exposure and the percent impact of smoke on claims. We extend this analysis using O*NET-based indices of occupational physical and cognitive requirements and similarly find no systematic differences in the estimated impacts across these dimensions (see Appendix Table A8). Taken together, these results are consistent with the effects of smoke exposure being broadly distributed across occupations and roughly proportional to baseline risk.

Note that these estimates represent heterogeneity by industry-occupation features—and do not represent the causal effect of these features.⁴⁴ Nevertheless, these estimates are useful for informing the targeting of policy aimed at mitigating these impacts. For example, while some recent state OSHA regulations regarding smoke have focused on risks among outdoor workers, this evidence suggests that the percent impact of smoke on workplace injuries does not vary systematically with industry-occupation outdoor exposure, and there could be a rationale for considering broadening the scope (or altering the targeting) of related guidance and regulations.

An implication of these estimates is that the impacts of pollution from wildfire smoke appear near universal, affecting workers in different types of work contexts and environments.⁴⁵ We might expect wide-reaching impacts of pollution from wildfire smoke on workplace injuries for a few reasons. First, wildfire smoke raises community-wide pollution levels and causes a deterioration of air quality across all work settings. Recent evidence shows that PM_{2.5} passes easily and quickly from outdoor to indoor environments (Krebs et al. 2021), and indoor workers often work in establishments that are partially open to the outdoors (e.g., warehouses, manufacturing plants)—particularly among workers in occupations with substantial risk of workplace injury. Moreover, many workers are required to perform some activities outdoors even if they primarily work indoors.⁴⁶ Second, because workers generally live and work in the same broader community and wildfire smoke causes a community-wide increase in pollution, pollution exposure during non-working hours (in the hours before work or during breaks) may contribute to the estimated impacts on workplace injuries.⁴⁷ The broader literature on the impacts of pollution on health and related outcomes provides unclear guidance on the expected timing of the impacts of pollution, with evidence documenting the importance of contemporaneous exposure as well as exposure in the last few hours or days. While we cannot precisely identify how the timing of exposure matters in our setting, the distributed lag model estimates presented below suggest there could be some scope for exposure outside of work (in the hours

⁴⁴For instance, other relevant industry-occupation features may be correlated with industry-occupation outdoor exposure (e.g., features of the jobs or the workers who perform these jobs), and thus this evidence cannot be used to infer how the work setting in isolation—indoor versus outdoor—affects the impacts of pollution on workplace injuries. One would need plausibly exogenous variation in whether a given set of work activities were conducted in an indoor versus outdoor setting to identify the effect of the setting itself.

⁴⁵In this way, our study provides novel (indirect) evidence on the short-run consequences of pollution on workers' physical and cognitive functioning using data and variation spanning all industries and occupations. While prior work examining other related outcomes (e.g., worker productivity) has documented effects of pollution among both indoor and outdoor workers, studies in this literature tend to use data from one particular jobsite or industry, meaning that within study there is little or no variation in the work setting. This analysis also complements related evidence from Borgschulte, Molitor, and Zou (2024), who document near-universal long-run impacts of pollution on labor market outcomes across all industries.

⁴⁶Using O*NET data on the frequency of outdoor work by occupation, we can evaluate the frequency of outdoor work among workers in industry-occupations least exposed to the outdoors. Among workers in industry-occupations in the lowest tercile of outdoor exposure in the heterogeneity analysis, O*NET data indicates 7 percent of workers in these industry-occupations report working outdoors every day and 13 percent report working outdoors at least once a week.

⁴⁷While workers' compensation insurance covers injuries that occur at work, pollution exposure outside of work—in the hours (or days) before work or during breaks—could potentially contribute to the impacts on workplace injuries. And there is no a priori reason to expect pollution exposure outside of work to systematically vary across workers by industry-occupation.

before work) to contribute to the impacts on workplace injuries.

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.⁴⁸ Below, we present additional robustness analysis exploring the dynamics of the impacts and demonstrating the robustness of our findings when considering alternative horizons.

Table 8 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.⁴⁹

To provide additional evidence on the dynamics of the effects, we estimate a distributed lag model using the following dynamic specification:

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

⁴⁸As 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.

⁴⁹As 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.

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 by year 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 4 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 $1.7 \mu\text{g}/\text{m}^3$ increase in daily $\text{PM}_{2.5}$ and a $1.9 \mu\text{g}/\text{m}^3$ increase in daytime $\text{PM}_{2.5}$. 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 $\text{PM}_{2.5}$ (as smoke plumes are only measured during daylight hours).⁵⁰ 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. 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 8 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 4 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 A9 displays estimates from the alternative approach for each horizon considered, with Table 8 Panel B summarizing the estimates from this alternative approach. Comparing Panels A and B of Table 8, 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

⁵⁰There are two pieces of evidence consistent with this latter explanation. First, the impact on $\text{PM}_{2.5}$ of smoke in the day before or after the observation date is smaller (relative to the same-day impact) with the daytime measure of $\text{PM}_{2.5}$. This is consistent with smoke tomorrow (yesterday) affecting today’s $\text{PM}_{2.5}$ in the evening after daylight hours (morning before daylight hours). Second, if smoke tomorrow primarily affects today’s $\text{PM}_{2.5}$ 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.

for the 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). Appendix Table A10 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 A11 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. Scaling the estimated impact of this alternative smoke measure on claims by the estimated impact of this measure on $PM_{2.5}$ implies a $1 \mu g/m^3$ increase in $PM_{2.5}$ leads to 0.105 injury claims per 100,000 workers, which is very similar to 0.098 injury claim per 100,000 workers implied by the baseline estimates. 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 $23.9 \mu g/m^3$. In addition, Appendix Table A12 demonstrates that our results are similar if we define smoke at the county level instead of at the commuting zone level. For example, scaling the estimated impact of a smoke day on claims at the county level by the estimated impact of a smoke day on $PM_{2.5}$ at the county level implies that a $1 \mu g/m^3$ increase in $PM_{2.5}$ leads to an additional 0.100 injury claims per 100,000 workers, which is very similar to the analogous figure implied by the baseline estimates.

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).⁵¹ 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, any health costs borne by the worker beyond medical expenses and productivity losses (e.g., pain and suffering), or any broader costs from workplace injuries borne by the government (e.g., lost tax revenue, increases in transfers). Thus, this figure 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.

⁵¹ All calculations in this section are reported in 2021 dollars, as the National Safety Council estimate is for 2021 injuries. An alternative to a cost-based measure for assessing societal costs would be a measure based on willingness to pay. While economists often use contingent valuation methods to assess workers' willingness to pay to avoid (have) negative (positive) job amenities (e.g., Lavetti 2023), we are not aware of any broadly applicable and well-identified contingent-valuation-based estimates of workers' willingness to pay to avoid typical (nonfatal) workplace 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 1 $\mu\text{g}/\text{m}^3$ increase in PM_{2.5} leads to an additional 0.098 injury claims per 100,000 workers or a 1.7% increase relative to the mean daily claim rate. The cost of these additional injuries is \$4,114 daily per 100,000 workers, or about 0.03% of the mean daily earnings in Texas.⁵²

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. First, we consider a permanent change in air pollution, allowing us to compare magnitudes to other studies that similarly extrapolate from estimates based on high-frequency variation to consider the impacts of a permanent change in ambient air pollution. Our estimates imply that a permanent 1 $\mu\text{g}/\text{m}^3$ increase in PM_{2.5} would lead to an additional 36 injury claims annually per 100,000 workers, with these injuries costing \$1.5 million per 100,000 workers. Aggregating across workers, a statewide change of this magnitude would result in an additional 4,737 injury claims annually in Texas, with these injuries costing \$200 million annually in Texas.

In our sample, a 1 $\mu\text{g}/\text{m}^3$ increase in PM_{2.5} would typically result in pollution levels well below current regulatory thresholds—both in federal EPA regulations and in recent state OSHA wildfire smoke regulations. So, it may also be natural to consider the impact of a severe smoke day—one sufficient to reach the thresholds at which recent state OSHA regulations begin requiring enhanced workplace protections. To do this, we consider a 26.44 $\mu\text{g}/\text{m}^3$ 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 $\mu\text{g}/\text{m}^3$) and 35.5 $\mu\text{g}/\text{m}^3$ (the PM_{2.5} threshold at which recent state OSHA regulations in California, Oregon, and Washington begin requiring substantive workplace protections, and a level very close to the EPA daily PM_{2.5} standard of 35 $\mu\text{g}/\text{m}^3$). Considering these shocks requires substantial linear extrapolation beyond the range of the identifying variation, so these estimates should be interpreted with appropriate caution. With these caveats in mind, 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 the 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 spanning the state of Texas would lead to an additional 343 injury claims, with associated costs of approximately \$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.⁵³ 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 1 $\mu\text{g}/\text{m}^3$ increase

⁵²We 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, U.S. Bureau of Labor Statistics 2021).

⁵³Based 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.

in PM_{2.5} would lead to an additional 56 annual injury claims per 100,000 workers nationwide—with these injuries costing \$2.4 million per 100,000 workers or about 0.05% of mean annual earnings. Aggregating across workers, this would represent an additional 85,000 injuries annually nationwide, with an annual cost of \$3.6 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 1 $\mu\text{g}/\text{m}^3$ increase in PM_{2.5} (measured as a six-day average) leads to a 0.6% decline in productivity among piece-rate pear packers at a Northern California factory. Adhvaryu, Kala, and Nyshadham (2022) estimate that a 1 $\mu\text{g}/\text{m}^3$ hourly increase in PM_{2.5} leads to a 0.06% 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 1 $\mu\text{g}/\text{m}^3$ increase in PM_{2.5} is associated with a 0.1% 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.⁵⁴

We can also compare our estimates to other impacts of pollution on healthcare utilization. See Appendix Table A14 for more details on these calculations. Prior work finds that a permanent 1 $\mu\text{g}/\text{m}^3$ increase in PM_{2.5} would result in a \$406 million annual increase in inpatient spending among the elderly (based on Deryugina et al. 2019) and a \$12 million annual increase in spending on respiratory-related emergency department visits among children ages 0–4 (based on Alexander and Schwandt 2022). Based on related work examining the impacts of wildfire smoke, a comparable increase in PM_{2.5} from smoke would lead to a \$92 million annual increase in respiratory-related emergency department spending among individuals under age 19 (Aguilera et al. 2021b). Compared to these estimates, the implied aggregate costs from increased workplace injuries are substantially larger, exceeding the estimated increases in healthcare spending from these other impacts by an order of magnitude.⁵⁵

We can also compare our estimates to the mortality impacts of pollution.⁵⁶ Estimates in Deryugina et al. (2019) imply that a permanent 1 $\mu\text{g}/\text{m}^3$ increase in PM_{2.5} would lead to approximately \$6.3 billion

⁵⁴Overall, we find that a 1 $\mu\text{g}/\text{m}^3$ increase in PM_{2.5} leads to costs that represent 0.03% 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 1 $\mu\text{g}/\text{m}^3$ increase in PM_{2.5} would lead to costs from increased injuries that amount to 0.13% of payroll among fruit packers, 0.15% of payroll among clothing manufacturing workers, and 0.06% of payroll among yarn or thread manufacturing workers.

⁵⁵Our measure of costs associated with workplace injuries goes beyond medical costs (e.g., including work disruptions, productivity losses, and uninsured employer costs). If we focus more narrowly on injury-related medical spending, our estimates imply that a permanent 1 $\mu\text{g}/\text{m}^3$ increase in PM_{2.5} would result in approximately \$300 million in annual medical spending on workplace injuries, or about 74% of the impact on inpatient spending among the elderly and roughly three times the impact on emergency department spending among individuals aged 19 and younger.

⁵⁶Our benchmarking focuses on studies that, like ours, identify impacts using high-frequency variation in pollution exposure. We note that some studies that estimate effects using year-to-year variation report larger estimated impacts of pollution on mortality (e.g., Qiu et al. 2025).

in life years lost annually among the elderly. Relative to this benchmark, the aggregate costs of increased workplace injuries are about 57% as large. Some recent estimates focusing on wildfire smoke suggest that a similar increase in PM_{2.5} would result in approximately \$3.7 billion in life years lost annually among the elderly (based on Miller, Molitor, and Zou 2024). Our estimated workplace injury costs of \$3.6 billion are similar in magnitude to the costs associated with elderly mortality based on these smoke-based estimates.

In addition to benchmarking our findings against prior estimates of the impact of pollution on other outcomes, we can also use our estimates to assess the importance of air pollution as a potential explanation for recent trends in workplace injuries. Over the period 2002-2022, PM_{2.5} levels nationally fell on average by 5.3 $\mu\text{g}/\text{m}^3$, largely due to a decline in industrial pollutants. Over the same period, workers' compensation claims per worker declined 49% nationally. While many factors have contributed to the decline in workplace injuries including fundamental changes in workplace safety, management practices, and industry composition, our estimates suggest improvements in air quality over the last two decades can explain nearly 20% of the decline in workplace injuries over this period.

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. Moreover, our estimates suggest pollution is a quantitatively important factor behind recent trends in workplace injuries.

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. While in many ways this point is simple and intuitive, it has important potential implications for the targeting of policy and suggests potential improvements are possible with the targeting of current and proposed occupational health and safety policy.

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 1 $\mu\text{g}/\text{m}^3$ 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 (0.03% 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 5 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 1 $\mu\text{g}/\text{m}^3$ increase in PM_{2.5} represent 0.03% of payroll statewide, we see that the impacts are much larger in high-risk occupations—representing between 0.1% and 0.3% of payroll or more among the highest risk industry-

occupations. To provide context, Appendix Table A16 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 $1 \mu\text{g}/\text{m}^3$ increase in $\text{PM}_{2.5}$ represent between 0.2% and 0.4% 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 $1 \mu\text{g}/\text{m}^3$ increase in $\text{PM}_{2.5}$ represent 0.01% 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 0.01% and 0.06% 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 $1 \mu\text{g}/\text{m}^3$ increase in $\text{PM}_{2.5}$ represent between 0.08% and 0.18% 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 calculations 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 6 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), where classifications are ordered on the horizontal axis according to the percentile of the indicated index. This figure illustrates that the top 5% of payroll based on industry-occupation 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 industry-occupation 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 tar-

getting 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 6, 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 targeting mitigation based on risk exposure would be more efficient in reducing workplace injuries than targeting based on 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 meaningful risks for worker health and safety, providing a rationale for occupational health and safety regulation alongside broader environmental policy. Recent state OSHA regulatory efforts addressing wildfire smoke have largely been motivated by concerns about respiratory and cardiovascular health risks from exposure to particulate matter. Our findings suggest that the consequences of wildfire smoke for workers may be broader than previously emphasized, extending to increased risk of workplace injuries. Importantly, this risk arises from the interaction between community-wide pollution exposure and the risks inherent in work activities, rather than from exposure that is necessarily specific to the workplace itself. In this way, the risks of pollution for workers are shaped not only by exposure, but also by the nature of work performed. Our estimates inform multiple policy debates, including the design and scope of occupational safety regulations (e.g., OSHA regulations), environmental policy governing pollution exposure (e.g., EPA standards), and policies aimed at reducing the occurrence and severity of wildfires.

Second, our results shed light on the potential benefits of broadening the scope of regulation. We find that wildfire smoke increases workplace injuries at pollution levels well below current regulatory thresholds and across a wide range of work settings, including workers more and less exposed to the outdoors. The widespread nature of these harms is consistent with several mechanisms—for example, exposure to community-based pollution may be similar across work settings, or exposure outside of work may affect subsequent workplace injuries. While our analysis cannot separately identify these channels, the estimates suggest that much of the effect is driven by pollution on the smoke day itself, though exposure on the following day may also contribute. Overall, these findings point to potential gains from expanding the scope of existing regulation—for example, by lowering pollution thresholds or extending protections to workers less exposed to the outdoors. They also highlight the importance of how pollution is specified within occupational health and safety regulations, including the potential relevance of exposure in the period directly preceding work.

Third, our estimates are important for informing firm, worker, and policymaker decisions regarding worker safety during periods with elevated pollution. Recent state OSHA regulations include a range of measures to mitigate risks from wildfire smoke. Some provisions focus on reducing exposure—such as

respirator use and work rescheduling—while others emphasize communication and worker awareness. Our results provide evidence on the potential benefits of one such strategy: 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.⁵⁷ While this suggests that rescheduling work can meaningfully mitigate the harms of pollution, such adjustments are often costly and may be infeasible in many settings.⁵⁸ More broadly, our findings highlight that pollution affects worker safety not only through acute respiratory or cardiovascular effects, but also by increasing the likelihood of workplace injuries. This implies that policies focused solely on reducing exposure at the worksite may miss an important margin for mitigation. In light of this, there may be value in complementary mitigation strategies aimed at reducing injury risk conditional on exposure. For example, during periods with elevated pollution employers could adjust job tasks (e.g., scaling back particularly high-risk activities such as working at heights or operating heavy machinery, or restricting lifting loads), modify work intensity (e.g., increasing rest periods or limiting physically demanding tasks), or strengthen safety protocols (e.g., additional supervision or safety checks when workers may be experiencing fatigue or reduced attention).

Finally, our findings can inform the potential gains from targeting costly mitigation. While percent effects are similar across workers, the incidence of increased injuries varies substantially by industry-occupation due to differences in baseline injury risk. Our analysis suggests that harms are concentrated among the highest-risk workers—26% (42%) of the costs are borne by the top 5% (10%) of payroll in terms of risk. Given that mitigation is typically costly, this implies substantial gains from targeting efforts toward high-risk industry-occupation groups. For example, our back-of-the-envelope counterfactual analysis indicates that targeting mitigation toward the top 10% of payroll in terms of workers' compensation risk would yield more than four times the reduction in workplace injuries relative to randomly allocated mitigation. Moreover, targeting based on industry-occupation risk appears substantially more effective than targeting based on outdoor exposure—the primary feature used in recent state OSHA regulations. These results highlight the broad reach of community-based pollution across workers and suggest a potential rationale to shift the focus of targeting within OSHA regulation toward workers most sensitive to pollution due to the inherent risks of their work activities.

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

⁵⁷This 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 8.

⁵⁸A complete assessment of the benefits and costs of shifting work would also consider effects on outcomes outside of work. Because wildfire smoke causes a community-wide deterioration in air quality, shifting work to less polluted days could plausibly increase injuries that occur outside of work (for example, during recreational activities). Although our analysis cannot assess potential impacts on non-work injuries, two related points are worth noting. First, if pollution increases injury risk outside of work, this may lead policymakers to favor mitigation strategies that do not involve shifting work, such as reducing work intensity, increasing rest periods, providing protective equipment, or strengthening injury-prevention measures. Second, while injury risk may be similar on and off the job for some low-risk workers (e.g., clerical occupations), this is unlikely to hold for high-risk workers, who account for the majority of workplace injuries. For these workers, job-related activities are likely substantially more hazardous than typical activities outside of work. As a result, if pollution also increases injury risk outside of work, this would further support targeting work-shifting policies toward high-risk occupations, where workplace risks far exceed baseline non-work risks.

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 current regulatory thresholds. Moreover, the implied cost of pollution-induced workplace injuries is the same order of magnitude as the cost of many other previously documented impacts of pollution on other outcomes.

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, suggesting a potential rationale for recent OSHA regulatory efforts in the U.S. 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 occupational health and safety regulation—informing ongoing policy debates surrounding recently enacted and proposed OSHA regulation in the U.S. and similar policy debates worldwide concerning the regulation of work during periods of elevated pollution. Further, our evidence adds to the growing evidence on the wide-ranging harms of pollution, and thus can inform broader environmental policy aimed at reducing pollution exposure 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 related occupational health and safety 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 occupational health and safety regulators 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 costly mitigation 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 and an important factor contributing to recent trends in workplace injuries, expanding our knowledge of what influences worker safety more generally.

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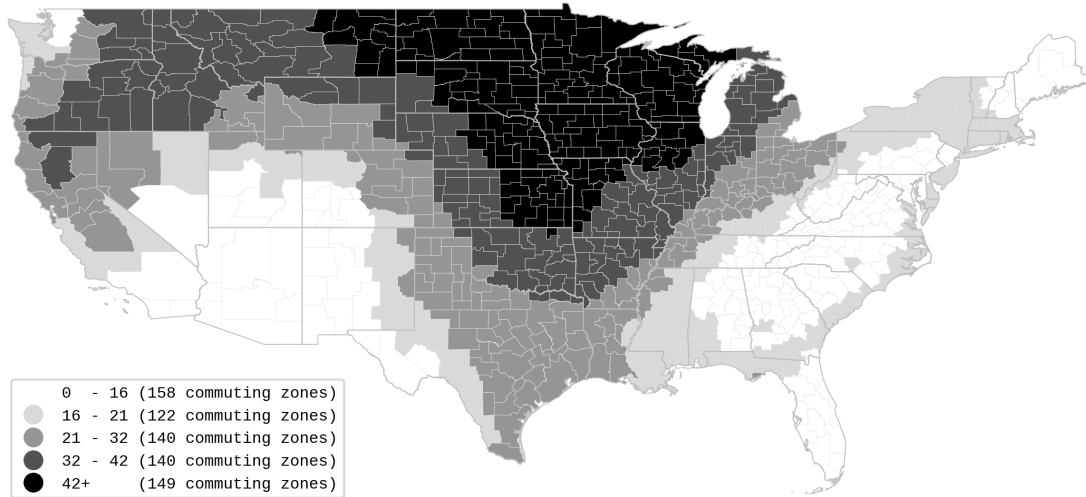
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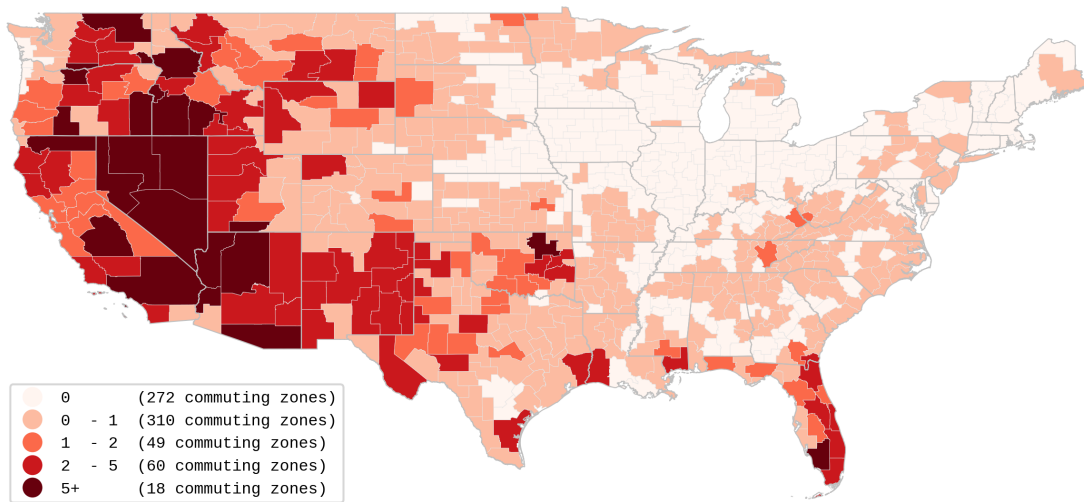
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Figure 1: Average Annual Smoke Coverage and Fires Across U.S.



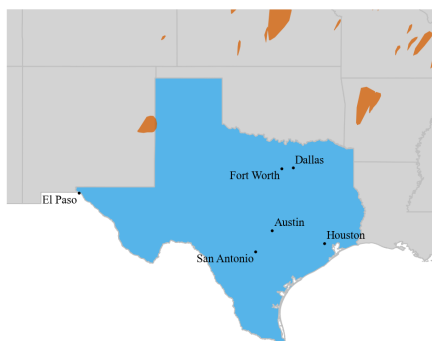
(a) Average Annual Number of Smoke Days



(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)



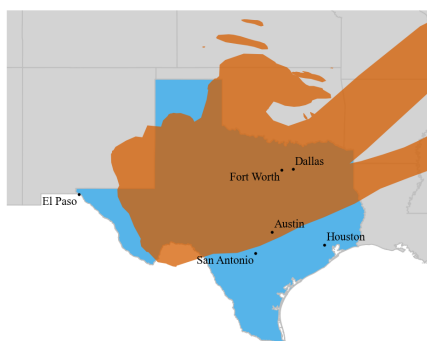
(a) Day -2



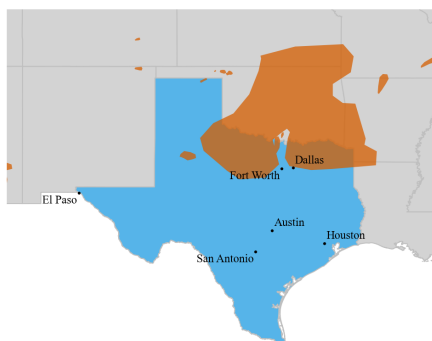
(b) Day -1



(c) Day 0



(d) Day 1



(e) Day 2



(f) Day 3

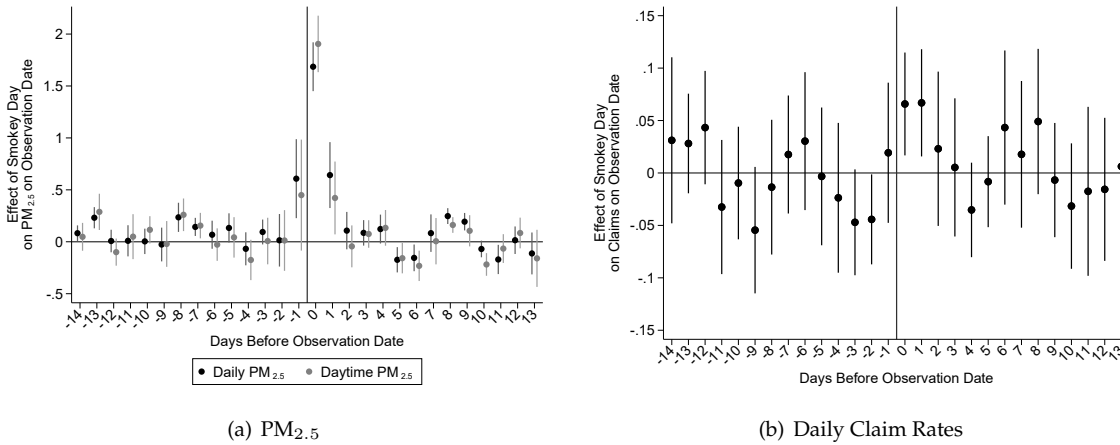
Notes: This figure displays smoke plume dynamics for smoke in the days surrounding the Starbuck Fire. The labels represent days relative to the start of the fire, with the day the fire broke out labeled as day 0 (March 6, 2017). In this figure, the location of the Starbuck fire is indicated with a star,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

Figure 3: Identifying Variation



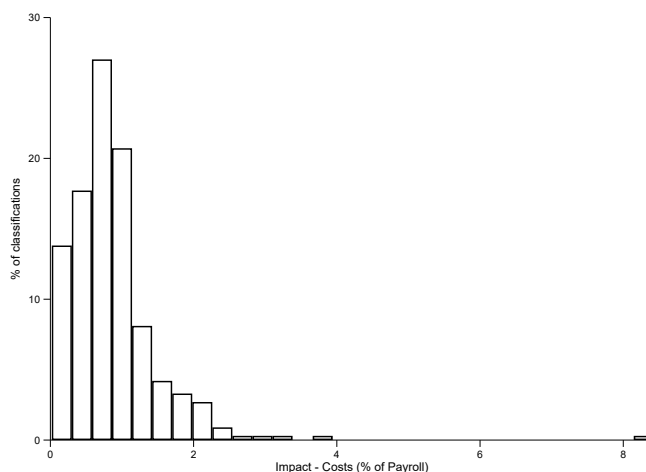
Notes: This figure shows means of the residual variation in smoke by year and by commuting zone. The residuals are calculated after first regressing the day's smoke on all of the controls in Equation (1), including the commuting-zone-by-quarter-by-year fixed effects, date fixed effects, indicator variables 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. The regression is weighted by commuting zones' mean employment during the sample period calculated from the Quarterly Census of Employment and Wages.

Figure 4: Distributed Lag Model: Impact of Smoke on Ambient Air Pollution and Injury Claims



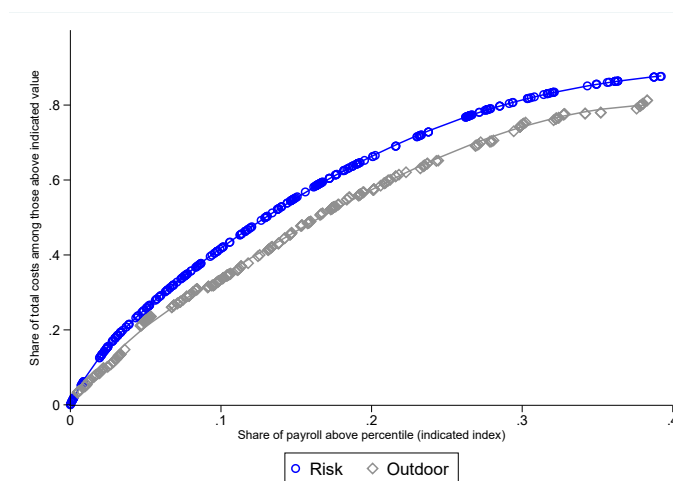
Notes: This figure displays estimates of the impact of smoke from estimating Equation (2) for the indicated dependent variable. The regression controls include commuting-zone-by-quarter-by-year fixed effects, date fixed effects, indicator variables for the quintile of the day's maximum temperature, indicator 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 5: Distribution of Impacts of $10 \mu\text{g}/\text{m}^3$ Increase in $\text{PM}_{2.5}$ by Industry-Occupation Classification



Notes: This figure displays a histogram of the distribution of the impact of a $10 \mu\text{g}/\text{m}^3$ increase in $\text{PM}_{2.5}$ 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 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 to have a mean of one across all covered payroll.

Figure 6: 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 Deviation
Panel A: Exposure		
Smoke event (%)	7%	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	1.9	1.6
Any claim (%)	97%	16%

Notes: This table describes the analytical dataset. The dataset includes all date and commuting zone pairings for the 4,868 dates from September 2005 through 2018 and the 62 commuting zones in Texas and has 301,816 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. There are approximately 10.7 million workers on average in Texas each year during our analysis period according to the Quarterly Census of Employment and Wages.

Table 2: Impact of Smoke on Ambient Air Pollution

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	PM _{2.5}	PM _{2.5}	PM ₁₀	O ₃	CO	NO ₂	SO ₂
		daytime					
Smoke	1.687 (0.122) [<0.001]	1.888 (0.139) [<0.001]	3.911 (0.619) [<0.001]	0.0023 (0.0002) [<0.001]	0.000 (0.002) [0.999]	-0.191 (0.074) [0.014]	0.031 (0.010) [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
Number of distinct commuting zones with obs	55	54	35	47	26	34	42
Number of distinct dates with obs	4,868	4,868	4,730	4,868	4,868	4,868	4,868

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. Note that the number of commuting zones multiplied by the number of dates does not equal the number of observations in each regression due to incomplete pollution reporting. 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 (0.048) [0.001]	0.143 (0.047) [0.004]	0.166 (0.043) [<0.001]	0.179 (0.053) [0.001]	0.221 (0.062) [0.001]	0.077 (0.024) [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 commuting zone by date 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 on 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 (0.048) [0.001]	0.065 (0.021) [0.003]	0.043 (0.021) [0.043]	0.008 (0.019) [0.668]	-0.015 (0.013) [0.251]	0.058 (0.024) [0.022]
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	1.6
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	2.7	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 commuting zone by date 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 (0.048) [0.001]	0.139 (0.050) [0.007]	0.026 (0.023) [0.262]	0.076 (0.038) [0.051]	0.090 (0.045) [0.049]	0.077 (0.024) [0.002]	0.088 (0.042) [0.041]	0.096 (0.049) [0.056]	0.069 (0.035) [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 commuting zone by date 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 (0.048) [0.001]	0.111 (0.039) [0.006]	0.044 (0.019) [0.021]	-0.023 (0.018) [0.209]	0.059 (0.020) [0.004]	0.046 (0.014) [0.002]	0.083 (0.026) [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 three-day claims for the indicated subgroup relative to overall population of workers. See Appendix Table A7 for analogous estimates adjusting the dependent variables so claim rates reflect group-specific denominators. Refer to the notes in Table 2 for a description of the baseline controls included in each regression. The sample includes commuting zone by date 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) All Claims	(2)	(3)	(4)	(5)	(6)	(7)	(8)
		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 (0.048) [0.001]	0.135 (0.046) [0.005]	0.042 (0.025) [0.099]	0.079 (0.021) [<0.001]	0.014 (0.027) [0.600]	0.072 (0.017) [<0.001]	0.022 (0.027) [0.406]	0.040 (0.019) [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 commuting zone by date 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: Impact of Smoke on 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, $\Sigma \beta_k$	0.026	0.035	0.049	0.058	0.049	0.073	0.086
	[0.002]	[<0.001]	[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 A9 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 commuting zone by date 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.

ONLINE APPENDIX

A Additional Details on 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 (Centers for Medicare & Medicaid Services 2019) 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 (Cabral, Cui, and Dworsky 2022).

We construct a measure of outdoor exposure based on O*NET data characterizing the frequency of work in particular settings. 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 (Cabral and Dillender 2026). We then measure the outdoor exposure of the industry-occupation as the inverse of the associated O*NET occupation’s frequency of work in indoor environmentally-controlled settings (O*NET 2023).¹ Appendix Table A15 shows the largest class codes by payroll in each tercile of the outdoor exposure distribution.

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.² After this imputation process, 78% of claims have industry-occupation classification exposure measures.

B Additional Background on Workplace Injuries

Appendix Figure A1 documents trends in three annual measures of workplace injuries: (1) workers’ compensation claims per 100 covered workers in Texas based on this study’s microdata, (2) workers’ compensation claims per 100 covered workers in Texas reported by the Texas Department of Insurance, and (3) BLS private industry injury and illness rates per 100 full-time workers in Texas.³ Several patterns are worth noting. First, the workers’ compensation claim rates for Texas calculated from the study’s microdata are nearly identical to the rates calculated using information reported by the Texas Department of Insurance, which is a reassuring validity check on our data. Second, workers’ compensation insurance claim rates in Texas are similar to the BLS injury rates. While the two measures differ in case definitions and coverage, the correspondence between them suggests that workers’ compensation claims track broader workplace injury patterns reasonably well. Third, all three measures of workplace injuries shown in Appendix Figure

¹Specifically, O*NET asks people how often their jobs involve working indoors in environmentally-controlled conditions, with the following possible responses: 1) Never, 2) Once a year or more but not every month, 3) Once a month or more but not every week, 4) Once a week or more but not every day, and 5) Every day. O*NET then takes a weighted average of people’s responses to this question to create a summary measure of each occupation’s time spent indoors in environmentally controlled conditions, where people who work in an environmentally controlled indoor setting every day receive a score of 5 and people who never work in an environmentally controlled indoor setting receive a score of 1. Our measure of exposure to the outdoors is the negative of O*NET’s summary measure.

²We 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 zipcodes and the insurer IDs.

³The reported claim information from the Texas Department of Insurance comes from Texas Department of Insurance (2018a) and Texas Department of Insurance (2023). The information on national workers’ compensation rates comes from Murphy and Wolf (2022). The information on BLS private industry injury rates comes from the Survey of Occupational Injuries and Illnesses and was accessed at National Institute for Occupational Safety and Health (2018).

A1 exhibit a slight downward trend over time. This decline matches national trends and reflects broader changes in workplace safety, as well as changes in industry composition away from higher-risk sectors. According to BLS state-level data from 2018, Texas's injury rate was below the national rate and similar to that of several other Southern states (U.S. Bureau of Labor Statistics 2019). Refer to Appendix Table A1 for comparisons between workers' compensation insurance claimants in Texas and the rest of the nation from the Current Population Survey Annual Social and Economic Supplement.

Workplace injuries are costly. In Section 5, we draw on an estimate of the average cost of a medically consulted workplace injury from the National Safety Council that aims to include different types of costs, including wage and productivity losses, medical expenses, and administrative costs. The National Safety Council estimates that a typical medically consulted workplace injury costs \$42,000. Several economics studies have focused specifically on understanding the earnings consequences of workplace injuries involving missed work and find large and persistent earnings losses on average (e.g., Boden and Galizzi 2003; Dworsky and Powell 2022; Reville and Schoeni 2001). For instance, Dworsky and Powell (2022) document that, on average, workplace injuries involving cash benefits in California led to about \$51,000 in earnings losses over a 14-year period in 2019 dollars.

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. 2025). 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, and the statistics are calculated using IPUMS weights.

Table A2: Impact of Smoke on Injury Claims, Distributed Lag Model with Interaction Terms

	(1)	(2)	(3)	(4)
Effect of Smoke X Days before Observation Date on Daily Claims on Observation Date				
0	0.073 (0.026) [0.007]	0.042 (0.039) [0.281]	0.069 (0.026) [0.010]	0.063 (0.043) [0.149]
1	0.070 (0.025) [0.007]	0.073 (0.030) [0.017]	0.068 (0.025) [0.010]	0.068 (0.030) [0.027]
2	0.017 (0.039) [0.661]	-0.008 (0.054) [0.886]	0.020 (0.037) [0.591]	-0.007 (0.054) [0.895]
3	-0.003 (0.032) [0.920]	-0.017 (0.036) [0.633]	0.001 (0.032) [0.969]	-0.020 (0.036) [0.590]
4			-0.037 (0.023) [0.105]	-0.017 (0.022) [0.451]
5			-0.012 (0.022) [0.586]	-0.024 (0.027) [0.381]
6			0.043 (0.037) [0.253]	0.076 (0.032) [0.019]
7			0.023 (0.037) [0.542]	0.025 (0.037) [0.495]
Continued on Next Page				

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Effect of Smoke on Observation Date Interacted with Smoke X Days before Observation Date

1	-0.017 (0.048) [0.725]	-0.003 (0.049) [0.949]
2	0.084 (0.084) [0.317]	0.099 (0.093) [0.287]
3	0.057 (0.050) [0.261]	0.092 (0.055) [0.099]
4		-0.096 (0.088) [0.281]
5		0.066 (0.072) [0.366]
6		-0.154 (0.090) [0.091]
7		-0.002 (0.069) [0.976]
Cumulative Effect of Smoke During Prior Window		
	0.124 [0.188]	0.002 [0.988]
Daily Claim Rate per 100,000 Workers		
Mean	5.8	5.8
Standard deviation	4.0	4.0
N	301,754	301,506

Notes: This table displays estimates of the impact of smoke on workers' compensation injury claims from estimating Equation (2) supplemented with interaction terms between smoke on the reference day and lagged values of smoke in the days directly before the reference day as indicated in the table. Each column displays estimates from a separate regression, where the dependent variable is the daily claim rate. Each regression includes the baseline controls as described in the notes in Table 2. The regressions in columns 1 and 2 include controls for temperature, precipitation, and smoke on the three days before and after the observation date. The regressions in columns 3 and 4 further include controls for temperature, precipitation, and smoke on the seven days before and after the observation date. The sample includes commuting zone by date 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 A3: Impact of Smoke on Weekly Hours Worked

	(1)	(2)	(3)	(4)	(5)	(6)
	OLS, First Stage		OLS, Reduced Form		IV	
	Mean	Mean	Weekly	Weekly	Weekly	Weekly
	Weekly	Weekly	Hours	Hours	Hours	Hours
	PM _{2.5}	PM _{2.5}	Worked	Worked	Worked	Worked
Smoke	0.807	0.847	0.020	0.003		
	(0.069)	(0.067)	(0.015)	(0.010)		
	[<0.001]	[<0.001]	[0.171]	[0.768]		
Mean Weekly PM _{2.5}					0.025	0.003
					(0.017)	(0.012)
					[0.156]	[0.804]
Controls						
Worker demographics	x		x		x	
Individual fixed effects		x		x		x
Mean of DV	9.4	9.4	38.5	38.5	38.5	38.5
N	3,175,230	3,175,230	3,180,184	3,180,184	3,175,230	3,175,230

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. For this analysis, we conduct the analysis at the county level and focus on counties identifiable in the Current Population Survey across the United States. 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 A4: Impact of Smoke on Injury Claims, Reporting Coefficients on Temperature Bins

	(1) Claims	(2) Claims	(3) Claims	(4) Claims	(5) Claims	(6) ED Claims
Smoke	0.165 (0.048) [0.001]	0.143 (0.047) [0.004]	0.166 (0.043) [<0.001]	0.179 (0.053) [0.001]	0.221 (0.062) [0.001]	0.077 (0.024) [0.002]
Temperature Bins (with bin 1 as reference bin)						
2	0.022 (0.051) [0.672]	-0.112 (0.053) [0.038]	0.083 (0.041) [0.047]	0.050 (0.057) [0.390]	-0.049 (0.075) [0.522]	0.017 (0.027) [0.520]
3	0.146 (0.063) [0.025]	-0.094 (0.053) [0.080]	0.186 (0.062) [0.004]	0.195 (0.066) [0.004]	0.095 (0.081) [0.245]	0.083 (0.034) [0.018]
4	0.311 (0.076) [<0.001]	-0.048 (0.067) [0.479]	0.275 (0.067) [<0.001]	0.385 (0.076) [<0.001]	0.230 (0.103) [0.029]	0.083 (0.039) [0.041]
5	0.326 (0.088) [<0.001]	-0.007 (0.106) [0.948]	0.279 (0.078) [0.001]	0.410 (0.088) [<0.001]	0.266 (0.116) [0.026]	0.091 (0.045) [0.047]
6		0.029 (0.101) [0.776]				
7		0.126 (0.111) [0.261]				
8		0.192 (0.104) [0.069]				
9		0.167 (0.101) [0.103]				
10		0.158 (0.124) [0.206]				
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 commuting zone by date 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 A5: 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 (0.028) [<0.001]	0.102 (0.028) [0.001]	0.110 (0.026) [<0.001]	0.120 (0.030) [<0.001]	0.153 (0.042) [0.001]	0.049 (0.015) [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 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	141	185	191
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 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 commuting zone by date 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 A6: Robustness: Two-Way Clustering of Standard Errors at Commuting Zone and Region by Quarter by Year

	(1) Claims	(2) Claims	(3) Claims	(4) Claims	(5) Claims	(6) ED Claims
Smoke	0.165 (0.044) [<0.001]	0.143 (0.043) [0.001]	0.166 (0.038) [<0.001]	0.179 (0.047) [<0.001]	0.221 (0.058) [<0.001]	0.077 (0.026) [0.005]
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 commuting zone by date 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 and the region by quarter by year level are reported in parentheses, and p-values are reported in brackets.

Table A7: 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 (0.048) [0.001]	0.207 (0.072) [0.006]	0.097 (0.040) [0.019]	-0.195 (0.123) [0.117]	0.269 (0.086) [0.003]	0.209 (0.059) [0.001]	0.275 (0.089) [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 QCEW employment measure used in the denominator has been scaled by the group's share of workers in Texas calculated using IPUMS American Community Survey five-year summary files (Schroeder et al. 2025) so that the injury claim rates reflect group-specific denominators. Refer to the notes in Table 2 for a description of the baseline controls included in each regression. The sample includes commuting zone by date 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: 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	Physical Requirements, Top Tercile	Physical Requirements, Middle Tercile	Physical Requirements, Bottom Tercile	Cognitive Requirements, Top Tercile	Cognitive Requirements, Middle Tercile	Cognitive Requirements, Bottom Tercile
Smoke	0.165 (0.048) [0.001]	0.135 (0.046) [0.005]	0.039 (0.019) [0.046]	0.065 (0.025) [0.013]	0.031 (0.026) [0.236]	0.051 (0.024) [0.038]	0.037 (0.018) [0.050]	0.048 (0.025) [0.058]
Daily Claim Rate per 100,000 Workers								
Mean	5.8	4.5	1.5	1.5	1.5	1.3	1.7	1.5
Standard deviation	4.0	3.5	1.5	1.4	1.5	1.4	1.6	1.4
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	2.6	4.3	2.1	3.8	2.2	3.1

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. We construct measures of job physical and cognitive demands using O*NET ability ratings. The physical measure is based on five abilities identified by O*NET as relevant for job performance: Dynamic Strength, Explosive Strength, Multilimb Coordination, Stamina, and Static Strength. The cognitive measure is based on seven abilities: Selective Attention, Inductive Reasoning, Deductive Reasoning, Memorization, Perceptual Speed, Speed of Closure, and Number Facility. For each occupation, we define the physical (cognitive) measure as the maximum score across the corresponding set of physical (cognitive) abilities. We then merge the physical and cognitive ability measures to the workers' compensation claims using industry–occupation classification information as described in the text. As with the outdoor and risk measures, we classify claims based on terciles within the distribution of the physical and cognitive measures. Refer to the notes in Table 2 for a description of the baseline controls included in each regression. The sample includes commuting zone by date 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 A9: Additional Robustness: Alternative Approach to Aggregate Impacts Over Time

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	1-day	2-day	3-day	5-day	7-day	10-day	14-day
Effect of Smoke (on Indicated Day before Observation Date) on Claims							
0	0.084 (0.026) [0.002]	0.076 (0.025) [0.004]	0.075 (0.026) [0.005]	0.071 (0.026) [0.008]	0.069 (0.026) [0.011]	0.068 (0.026) [0.011]	0.066 (0.025) [0.009]
1		0.072 (0.025) [0.006]	0.070 (0.024) [0.006]	0.070 (0.025) [0.007]	0.069 (0.025) [0.009]	0.068 (0.025) [0.009]	0.067 (0.026) [0.011]
2			0.016 (0.040) [0.700]	0.019 (0.037) [0.612]	0.021 (0.038) [0.583]	0.020 (0.037) [0.584]	0.023 (0.037) [0.533]
3				0.002 (0.032) [0.941]	0.000 (0.033) [0.990]	0.001 (0.033) [0.974]	0.005 (0.033) [0.873]
4				-0.033 (0.021) [0.131]	-0.036 (0.023) [0.110]	-0.036 (0.022) [0.114]	-0.035 (0.023) [0.123]
5					-0.010 (0.022) [0.641]	-0.011 (0.022) [0.628]	-0.008 (0.022) [0.704]
6					0.046 (0.035) [0.193]	0.040 (0.037) [0.286]	0.043 (0.037) [0.243]
7						0.015 (0.037) [0.675]	0.018 (0.035) [0.613]
8						0.043 (0.036) [0.240]	0.049 (0.035) [0.162]
9						-0.018 (0.026) [0.487]	-0.007 (0.027) [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 (0.026) [0.002]	0.148 (0.035) [<0.001]	0.160 (0.049) [0.002]	0.130 (0.058) [0.030]	0.158 (0.049) [0.002]	0.191 (0.073) [0.012]	0.162 (0.086) [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 (2). Each column displays estimates from a separate regression, where the dependent variable is the daily rate of claims. This table reports the key coefficients for smoke on the observation date and up to thirteen days before the observation date. The regressions also include indicators for smoke on the days after the observation date for the number of days indicated in the column. In addition, 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 leads and lags of these weather controls for the number of days indicated in the column. The sample includes commuting zone by date 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 A10: Robustness: Count Models

	(1) Claims	(2) Claims	(3) Claims	(4) Claims	(5) Claims	(6) ED Claims
Smoke	0.007 (0.002) [0.002]	0.006 (0.002) [0.006]	0.007 (0.002) [<0.001]	0.007 (0.003) [0.007]	0.009 (0.003) [0.001]	0.011 (0.004) [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	1.4	2.0	0.6
Implied % impact relative to mean daily claims	2.2	1.9	2.1	2.2	2.3	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 commuting zone by date 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 A11: Additional Robustness: Varying Definition of Smoke or Sample Restrictions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
					Robustness to Excluding 99th Percentile of PM _{2.5} (99th percentile = 23.9)		
	Claims	PM _{2.5}	Claims	Claims	Claims	PM _{2.5}	Claims
Smoke	0.165 (0.048) [0.001]			0.127 (0.056) [0.026]	0.184 (0.050) [0.001]	1.419 (0.074) [<0.001]	0.182 (0.061) [0.004]
Full Smoke Coverage Indicator		1.291 (0.161) [<0.001]	0.136 (0.052) [0.011]				
Method Used to Identify Commuting Zone	Baseline	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	n/a	5.8	5.9	5.8	n/a	5.8
Standard deviation	4.0	n/a	3.9	3.9	3.9	n/a	3.9
N	301,816	252,950	301,816	301,816	252,950	252,167	252,167
Implied % impact relative to mean daily claim rate	2.8	n/a	2.3	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, 3-5, and 7 and is PM_{2.5} levels in columns 2 and 6. The regression for column 1 includes the baseline controls as described in the notes in Table 2. In columns 2 and 3, the baseline smoke measure is replaced with an indicator variable for the commuting zone being fully covered by smoke. In column 4, 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 5 through 7 exclude observations with missing PM_{2.5} information, while columns 6 and 7 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 A12: Additional Robustness: Conducting Analysis at the County Level

	(1) PM _{2.5}	(2) Claims	(3) Claims	(4) Claims	(5) Claims	(6) Claims	(7) ED Claims
Smoke	1.446 (0.089) [<0.001]	0.144 (0.037) [<0.001]	0.131 (0.037) [<0.001]	0.139 (0.035) [<0.001]	0.158 (0.042) [<0.001]	0.203 (0.049) [<0.001]	0.062 (0.024) [0.010]
Controls							
Set of weather controls	Baseline	Baseline	Expanded	Baseline	Baseline	Baseline	Baseline
County X quarter X year f.e.	x	x	x	x	x	x	x
Exact date f.e.	x	x	x	x	x	x	x
County X month-of-the-year f.e.				x			
Sample Restrictions							
Excluding county obs within 200 km of wildfires					x		
Excluding weekends						x	
Daily Claims							
Mean daily claims	n/a	5.8	5.8	5.8	5.8	7.5	1.8
Standard deviation	n/a	5.8	5.8	5.8	5.8	5.9	3.3
N	1,086,000	1,236,000	1,236,000	1,236,000	1,148,000	882,838	1,236,000
Implied % impact relative to mean daily claims	n/a	2.5	2.3	2.4	2.7	2.7	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 PM_{2.5} levels in column 1, the three-day claim rate in columns 2 through 6, and the three-day claim rate of injuries originating in the ED for column 7. The regressions for columns 1 and 2 include the baseline controls as described in the notes in Table 2 except defined at the county level rather than at the commuting zone level. The regression for column 3 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 4 supplements the baseline controls with county-by-month-of-year fixed effects. The sample for the claims analysis includes observations from September 2005 through 2018 for all 254 counties in Texas. Column 5 excludes observations for counties with wildfires occurring within a day of the observation date, while column 6 excludes weekends. All regressions are weighted by counties' mean employment during the sample period calculated from the Quarterly Census of Employment and Wages. Standard errors clustered at the county level are reported in parentheses, and p-values are reported in brackets.

Table A13: Additional Robustness: Excluding Observations with Nearby Fires

	(1) Claims	(2) Claims	(3) Claims
Smoke	0.165 (0.048) [0.001]	0.179 (0.053) [0.001]	0.175 (0.067) [0.012]
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	3.0

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. Columns 2 and 3 exclude observations for commuting zones with wildfires occurring within a day of the observation date. Refer to the notes in Table 2 for a description of the baseline controls included in each regression. The sample includes commuting zone by date 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 A14: Aggregate Cost Associated with Other Health Impacts of Pollution Based on Prior Estimates

Paper	Reported findings	Additional information used	National impact of a 1 $\mu\text{g}/\text{m}^3$ increase in $\text{PM}_{2.5}$ (in 2021 dollars)
Aguilera et al. (2021b)	From Table 1: 1 $\mu\text{g}/\text{m}^3$ increase in $\text{PM}_{2.5}$ from smoke for one day increases pediatric respiratory ED visits by 3.0%	Number of respiratory ED visits ages 0-18: 9,606,700 (from McDermott, Stocks, and Freeman 2018) Cost of ED visit for children: \$290 (from Moore and Liang 2020)	Number of annual ED visits: 288,201 Annual cost: \$92 million
Alexander and Schwandt (2022)	From Table 6: An additional cheating diesel car (per 1000 cars): -increases $\text{PM}_{2.5}$ by 0.60 $\mu\text{g}/\text{m}^3$ -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 U.S. Census Quick Facts 2020) Cost of ED visit for children: \$290 (from Moore and Liang 2020)	Number of annual ED visits: 29,760 Annual cost: \$12 million
Deryugina et al. (2019)	From Table 3: Instrumental variables estimate: 1 $\mu\text{g}/\text{m}^3$ increase in $\text{PM}_{2.5}$ for one day leads to an extra \$19,339 in inpatient spending per 1 million fee-for-service Medicare beneficiaries	Number of Medicare beneficiaries: 44 million (from pg. 4203, footnote 36)	Number of annual inpatient admissions: 35,444 Annual cost: \$406 million
Deryugina et al. (2019)	From Table 4 column 6: 1 $\mu\text{g}/\text{m}^3$ increase in $\text{PM}_{2.5}$ 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: \$6.3 billion
Miller, Molitor, and Zou (2024)	From Table A.2: 1 $\mu\text{g}/\text{m}^3$ increase in $\text{PM}_{2.5}$ from smoke for one day increases 3-day mortality by 0.43 per 1 million Medicare beneficiaries	Number of life years lost from each death: 3.5 (from page 15) Value of each life year lost: \$136,000 (from page 15) Number of Medicare beneficiaries: 44 million (from Deryugina et al. 2019)	Annual cost of life years lost: \$3.7 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 (1) through (3) are adjusted to 2021 dollars using the CPI-U.

Table A15: Largest Classifications by Segment of Outdoor Exposure Distribution

Classification Number	Classification Name
<i>Panel A: Top Tercile of Outdoor Exposure</i>	
8391	AUTOMOBILE REPAIR SHOP & PARTS DEPARTMENT EMPLOYEES, DRIVERS
7219	TRUCKING: NOC - ALL EMPLOYEES & DRIVERS
5191	OFFICE MACHINE OR APPLIANCE INSTALLATION, INSPECTION, ADJUSTMENT OR REPAIR
5183	PLUMBING NOC & DRIVERS
5190	ELECTRICAL WIRING & DRIVERS
7423	AIRCRAFT OR HELICOPTER OPERATION: NOC: ALL OTHER EMPLOYEES & DRIVERS
6202	OIL OR GAS WELL & DRIVERS
7600	TELEPHONE OR TELEGRAPH CO.: ALL OTHER EMPLOYEES & DRIVERS
7720	POLICE OFFICERS & DRIVERS
3126	TOOL MFG - AGRICULTURAL, CONSTRUCTION, LOGGING, MINING, OIL OR ARTESIAN WELL
<i>Panel B: Middle Tercile of Outdoor Exposure</i>	
8017	STORE: RETAIL NOC & DRIVERS
5606	CONTRACTOR - EXECUTIVE SUPERVISOR OR CONSTRUCTION SUPERINTENDENT
3724	MACHINERY OR EQUIPMENT ERECTION OR REPAIR NOC & DRIVERS
4740	OIL REFINING - PETROLEUM - & DRIVERS
8748	AUTOMOBILE SALESPERSONS
7405	AIRCRAFT OR HELICOPTER OPERATION: AIR CARRIER - FLYING CREW
8008	STORE: CLOTHING OR WEARING APPAREL - RETAIL
3719	OIL STILL ERECTION OR REPAIR
8107	MACHINERY DEALER NOC - STORE OR YARD -& DRIVERS
7539	ELECTRIC LIGHT OR POWER CO NOC - ALL EMPLOYEES - & DRIVERS
<i>Panel C: Bottom Tercile of Outdoor Exposure</i>	
8810	CLERICAL OFFICE EMPLOYEES NOC
8742	SALESPERSONS, COLLECTORS OR MESSENGERS - OUTSIDE
8832	PHYSICIAN & CLERICAL
8868	COLLEGE: PROFESSIONAL EMPLOYEES & CLERICAL
8809	EXECUTIVE OFFICERS NOC - PERFORMING CLERICAL OR OUTSIDE SALESPERSONS DUTIES ONLY
8833	HOSPITAL: PROFESSIONAL EMPLOYEES
8601	ARCHITECT OR ENGINEER - CONSULTING
8820	ATTORNEY - ALL EMPLOYEES & CLERICAL, MESSENGERS, DRIVERS
8803	AUDITOR, ACCOUNTANT OR FACTORY COST OR OFFICE SYSTEMATIZER - TRAVELING
9079	RESTAURANT NOC

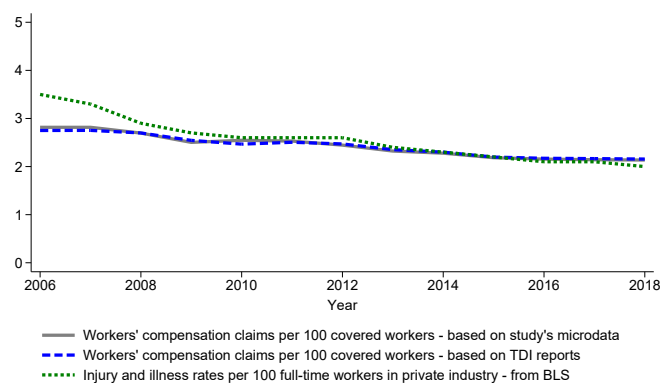
Notes: This table lists the top ten classifications in the indicated segment of the outdoor exposure distribution, where terciles are calculated with respect to the distribution of workers' compensation claims. The table displays the workers' compensation classification number and the classification name. The measure of outdoor exposure used for this classification comes from O*NET.

Table A16: 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 $\mu\text{g}/\text{m}^3$ increase in $\text{PM}_{2.5}$ costs (% relative to daily payroll)
<i>Panel A: Largest Among Top 5% of Relative Risk</i>				
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	FOUNDRIY - 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%
<i>Panel B: Largest Among Classifications Between Median and Top 5% of Relative Risk</i>				
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%
<i>Panel C: Largest Among Classifications Between Bottom 5% and Median of Relative Risk</i>				
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%
<i>Panel D: Largest Among Classifications in Bottom 5% of Relative Risk</i>				
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 SALES PERSONS 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%

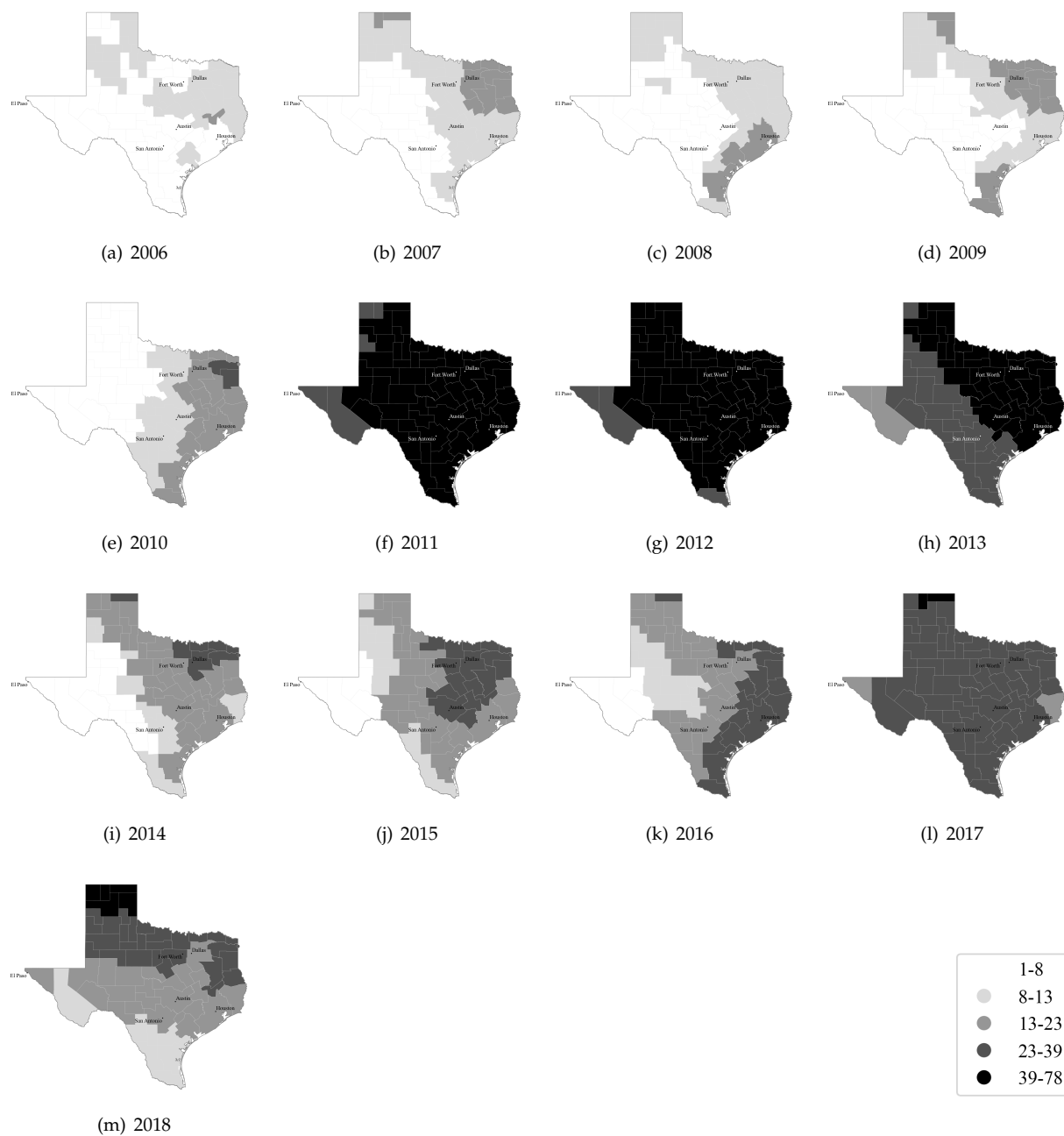
Notes: This table lists the top ten classifications in the indicated segment of the risk distribution, where percentiles are taken with respect to (unweighted) industry-occupation workers' compensation classification codes. The table displays the workers' compensation classification number, the classification 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).

Figure A1: Annual Injury Rates in Texas from 2006 to 2018



Notes: This figure displays injury rates across Texas.

Figure A2: Smoke Days in Texas by Year



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