Air Pollution, Workplace Safety, and Productivity: Evidence Beyond LATE

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Abstract

This paper studies the causal effect of air pollution on workplace safety in the United States using novel nationwide administrative data on severe workplace injuries. Moving beyond the standard method that exploits instrumental variable to address endogenous air pollution and identify the local average treatment effect (LATE) for *compliers*, this study applies partial identification approaches based on weaker assumptions to recover informative bounds on the average treatment effect (ATE). I find that PM2.5 pollution raises the incidence of severe workplace accidents. Counterfactual reductions in high-pollution days yield sizable economic benefits, equivalent to at least 9% of the EPA's annual air-pollution control expenditures.

Keywords: Air Pollution, Workplace Safety, Labor Productivity, Bounds, Imperfect IV

JEL Classification: Q53 , Q51 , J28 , J24

1 Introduction

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

There has been sustained interest among both the public and researchers in the impacts of air pollution. While the adverse effects of air pollution on mortality and public health are well established (Anderson, 2020; Carozzi & Roth, 2023; Deryugina, Heutel, Miller, Molitor, & Reif, 2019; Giaccherini, Kopinska, & Palma, 2021; Pestel & Wozny, 2021; Schlenker & Walker, 2016, among others), an expanding body of research has begun to examine impacts beyond direct health outcomes.[1] These "non-health" effects include reductions in labor supply (Hanna & Oliva, 2015) and workplace performance (Archsmith, Heyes, & Saberian, 2018; Chang, Graff Zivin, Gross, & Neidell, 2016, 2019; Fu, Viard, & Zhang, 2021; Graff Zivin & Neidell, 2012; J. He, Liu, & Salvo, 2019), impaired attention and cognitive ability (Bharadwaj, Gibson, Graff Zivin, & Neilson, 2017; Ebenstein, Lavy, & Roth, 2016; Heissel, Persico, & Simon, 2019; Künn, Palacios, & Pestel, 2023; Sager, 2019), and behavioral responses (Bondy, Roth, & Sager, 2020; Persico & Marcotte, 2022). Collectively, this literature indicates that the economic consequences of air pollution can extend beyond health, in part through its influence on workers' productivity.

In addition to standard measures of productivity, such as output, wages, on-the-job performance, and total factor productivity, workplace safety can also be an important determinant of labor productivity. Workplace injuries are costly and can lead to nonnegligible productivity losses. Severe injuries that involve hospitalization and amputation often result in work absences lasting from days to weeks. According to estimates by the National Safety Council (Weiss, Murphy, & Boden, 2020), productivity losses, along with workers' compensation payments and medical expenses incurred due to work-related deaths and injuries, cost the United States more than $234 billion in 2018.

Air pollution, especially fine particulate matter, can affect workplace safety via not only visibility but also biological channels. Fine particulate matter, known as PM2.5, is inhalable and can penetrate deep into human bodies. Recent studies have found links between PM2.5 and the decline of cognitive functions that play an important role in avoiding workplace accidents: e.g., memory, attention, and fluid reasoning (Bedi, Nakaguma, Restrepo, & Rieger, 2021; La Nauze & Severnini, 2021; Shehab & Pope, 2019).

Existing studies on the effects of air pollution typically rely on instrumental variables (IV) strategies to address the endogeneity of pollution. Among other requirements, a valid IV must satisfy the exclusion restriction, i.e., the instrument must be uncorrelated with workplace safety except through its effect on air pollution, and the monotonicity assumption, i.e., the instrument must affect air pollution in a monotonic way. In practice, however, valid instruments are difficult to obtain. Moreover, IV estimates capture effects for only a subset of observations whose exposure to air pollution is shifted by the instrument, i.e., the *compliers*. Consequently, the estimated effect pertains only to the margin of variation induced by the instrument and may differ from the average effect across the whole population. Because different instruments or contexts generate different margins of variation, estimates are often not directly comparable across settings or studies. This feature complicates interpretation and limits the external validity of the estimates for policy evaluation, where interest typically lies in broader population effects rather than responses tied to a specific source of variation.

[1] see Aguilar-Gomez, Dwyer, Graff Zivin, and Neidell (2022) for a comprehensive survey.

This paper studies the causal impact of fine particulate pollution on workplace safety, utilizing a novel nationwide panel dataset for the United States. The dataset combines administrative records on severe workplace injuries with high-resolution data on air pollution and meteorological variables. I adopt an alternative approach based on partial identification, which does not require the assumptions needed for point identification and instead derives informative bounds on the average treatment effect. Specifically, using a readily available, commonly observed, and easily processed climate variable—rainfall—as the instrument, I apply the method of Nevo and Rosen (2012) to estimate semiparametric bounds and the method of Ban and Kédagni (2022) to estimate more flexible nonparametric bounds in a large panel dataset, providing one of the first large-scale empirical implementations of these techniques in this context. By exploiting variation that may be insufficient for credible point identification but still informative about the direction and magnitude of the effect, this approach allows credible analysis in settings where standard IV strategies are difficult to justify.

Both semiparametric and nonparametric bounds suggest an adverse effect of PM2.5 pollution on workplace accidents involving severe injuries. The semiparametric bounds imply that experiencing PM2.5 pollution exceeding 25 micrograms per cubic meter increases the workplace accident rate by at least 0.4 percentage points (ppts) and up to 9.3 ppts, equivalent to a 2% to 44% increase relative to the sample mean rate. Imposing an additional assumption, the nonparametric bounds further tighten the bounds to 0.4 ppts (2%) to 5.5 ppts (26%).

Examining heterogeneous impacts across industries, I find that the effects are more pronounced in the manufacturing sector and in non-manufacturing sectors requiring (semi-)outdoor work, such as transportation and construction. The effects also appear larger in densely populated regions. Further analysis indicates that the relatively larger impacts are concentrated in populous areas, consistent with the preceding finding. These results speak to environmental justice: individuals are exposed to different levels of environmental hazards (in this case, air pollution) not only based on where they live but also on where they work.

To assess the economic costs of air pollution-induced workplace accidents, I use the estimated bounds to quantify the impact of PM2.5 pollution on workers' compensation expenditures. A back-of-the-envelope calculation indicates that one additional high-pollution day (PM2.5 concentrations above 25 micrograms per cubic meter) increases annual workers' compensation costs by approximately 0.3 to 12.8 million. Under a counterfactual scenario that eliminates all high-pollution days, the resulting reduction in severe workplace injuries would generate savings ranging from 19.8 million to 962 million dollars. These savings correspond to about 0.03% to 1.6% of total workers' compensation payments, a meaningful share given that they arise from a single injury category. Remarkably, the benefits from reducing PM2.5-induced severe workplace injuries alone would amount to at least 9% of the EPA's annual air pollution control budget in 2020.

This paper contributes to the literature in two primary ways. First, it complements the burgeoning literature on environmental hazards and workplace safety. Recent evidence comes from Saharan dust outbreaks reaching Spain that increase workplace accidents (Hattemer & Moreno-Martinez, 2025), construction-site nitrogen dioxide exposure raising accident risk in Israel (Lavy, Rachkovski, & Yoresh, 2022), air quality variation in Italy driven by winter heating and planetary boundary layer conditions elevating accident rates (Palma, Depalo, & Curci, 2024), and wildfire smoke–driven PM2.5 exposure affecting Texas workers' compensation injury claims (Cabral & Dillender, 2024). Alongside air pollution, a few studies document temperature effects on workplace injuries in California (Park, Pankratz, & Behrer, 2021) and Texas (Dillender, 2021). This paper provides novel nationwide evidence from the United States that exposure to PM2.5 pollution adversely affects workplace safety by increasing the rate of accidents involving severe injuries.

By linking air pollution to workplace safety, this paper shows that air pollution imposes non-negligible economic costs through workplace injuries and productivity losses, implying that improvements in air quality can benefit both employers and employees. Ignoring the workplace safety channel would therefore understate the gains from cleaner air. This consideration is particularly relevant given recent U.S. policy developments regarding the National Ambient Air Quality Standards (NAAQS) PM2.5 standards and regulatory evaluation, including debates over rolling back tighter standards and revisions to cost-benefit analysis that exclude monetized health benefits (Spring & Ajasa, 2026; Washington Post, 2025). Our results imply that the benefits of air-quality regulation may be larger than conventionally measured, as they encompass not only health improvements but also reductions in workplace injuries, which are economically non-negligible.

Moreover, workplace injuries are an important determinant of labor productivity. This study therefore identifies a mechanism through which air pollution affects productivity: by increasing severe workplace injuries. In this sense, it contributes to research that documents causal links between environmental conditions and labor productivity (Archsmith et al., 2018; Chang et al., 2016; Dillender, 2021; Fu et al., 2021; Graff Zivin & Neidell, 2012; J. He et al., 2019; Park et al., 2021; Yu & Shi, 2025, among others).

Second, the paper moves beyond the standard instrumental variables (IV) framework, which identifies a Local Average Treatment Effect (LATE) for *compliers*, units whose exposure to air pollution changes in response to the instrument. Instead, this study adopts a partial identification approach that estimates bounds on the Average Treatment Effect (ATE). This approach relies on a different and generally weaker set of assumptions than the conventional IV method, trading point identification for an identified set. Specifically, it exploits heavy rainfall as an instrument for pollution exposure. While rainfall may not satisfy the relatively stronger assumptions required for point identification under IV, as demonstrated by the IV test results reported in the paper, it arguably satisfies the assumptions needed for partial identification. Consequently, the method delivers informative and policy-relevant estimates that would be unattainable using traditional approaches with an imperfect IV. Taken together, our exercise suggests that partial identification can be a useful alternative when standard IV assumptions are difficult to defend and interest centers on effects for the broader population, which can be more relevant for welfare and policy analysis.

The rest of the paper is organized as follows. Section 2 provides background on PM2.5 and the biological mechanisms underlying its effects. Section 3 reviews conventional estimators and the instrumental variable used in this study. In Section 4, I introduce the partial identification methods and their empirical implementation for large panel datasets. Section 5 describes the data, and Section 6 presents the estimated bounds. Based on these results, Section 7 evaluates the impact of PM2.5 pollution on workers' compensation. Section 8 concludes.

2 Background

2.1 Particulate Matter

Particulate matter (PM) is a mixture of solid particles and liquid droplets found in ambient air, which varies greatly in size and composition. Fine PM (PM2.5) refers to those with a nominal mean aerodynamic diameter of up to 2.5 micrometers. Particles of different sizes differ in their atmospheric lifetimes, transport distances, and removal processes (EPA, 2009). Specifically, PM2.5 can transport from 10 km to 100 km and remain suspended in the air for days to weeks. The major processes for removing PM2.5 from the atmosphere are incorporation of particles into cloud droplets that fall as rain (rainout), collisions with falling rain (washout), and fallout (EPA, 2009). This motivates the choice of the rainfall IV for PM2.5 pollution.

Exposure to PM is not limited to outdoor activities. In indoor environments without indoor sources of pollution, pollutants from outdoors are the main cause of indoor air pollution (WHO, 2021). Outdoor air pollutants can affect the indoor air quality via the processes of ventilation and penetration through the building envelope. PM2.5 is found to have the highest ventilation rate and penetration rate (WHO, 2021). Indoor workers, especially those who work in poorly insulated and well-ventilated workplaces, are found to be affected by PM2.5 (Chang et al., 2016). Thus, presumably, PM2.5 exposure and its effect on workplace accidents should not be limited to industries with more outdoor jobs, though one may expect a stronger impact for these industries.

2.2 Biological Channels

PM2.5 is inhalable and found to have serious adverse health effects due to its ability to penetrate deep into the lungs, blood streams and brain, causing health problems including heart attacks, respiratory diseases, and premature death (for a comprehensive review on the adverse health effects of PM2.5, see EPA, 2009, 2019). In addition, exposure to PM2.5 also leads to more subtle effects, such as changes in blood pressure, irritation in the eyes, ear, nose, throat, and skin, and mild headaches (Auchincloss et al., 2008; Pope, 2000). These milder effects, which arise from exposure to lower levels of PM2.5, typically do not lead to health care encounters, but may be associated with inattention and distraction (Chang et al., 2016).

A number of studies have documented the impacts of PM2.5 on human cognitive ability. PM2.5 is found to impair human cognitive functions (Bedi et al., 2021; Guxens et al., 2018; La Nauze & Severnini, 2021; Peters et al., 2000) and affect mental well-being (de Prado Bert, Mercader, Pujol, Sunyer, & Mortamais, 2018; Weuve et al., 2012). Even short-term exposure to PM2.5 can result in the decline of adults' cognitive performance (Shehab & Pope, 2019). The cognitive functions affected by PM2.5 include memory, attention, and fluid reasoning. Especially, La Nauze and Severnini

(2021) found that exposure to PM2.5 impairs adults' cognitive performance, with the largest effect for those in prime working age and the strongest effect on memory.

Putting these together, PM2.5 pollution can affect workplace safety through its link with declines in human cognitive performance. Potential channels include inattention, memory change, and the decline of the fluid reasoning ability. While there is no direct evidence of the association between the lack of attention and work accident occurrence, inattention and distraction are found to be an important factor leading to road accidents (Rezaei & Klette, 2014; Talbot, Fagerlind, & Morris, 2013). Memory change is found to be correlated to the reduced ability to ignore irrelevant information and slowed processing speed (Harada, Love, & Triebel, 2013), which are potential factors increasing the incidence of workplace accidents. Lastly, fluid reasoning is the ability to think flexibly and solve problems in novel situations. It help human beings to deal with uncertainty and fast-changing situation. The decline of the fluid reasoning ability may reduce workers' ability to avoid accidents in the workplace or to reduce the extent of injuries caused by the accident.

3 Classical Estimators and Instrumental Variables

When assessing the causal effect of air pollution on workplace safety, the standard OLS estimate suffers from the endogeneity problem and is likely biased. Human and economic activities are highly correlated to both PM2.5 pollution and workplace accidents. Workers and employers can respond to air quality changes and adjust their exposure to PM2.5 pollution in multiple ways. For instance, workers may change their work schedule to reduce the time exposed to air pollutants. Changes in working hours affect both workers' exposure to PM2.5 pollution and workplace accidents.[2] Moreover, the OLS estimator may suffer from the selection bias, if the extent to which workers and firms respond to air quality differs across locations due to unobserved factors. For example, if workers and firms are more cautious in places with poorer air quality and thus more responsive to air quality deterioration, then this unobserved attribute will be associated with both workplace accidents and PM2.5 pollution, introducing selection bias.

A common way to deal with the endogeneity of air pollution exposure is to adopt the instrumental variable (IV) strategy and the two-stage least squares (2SLS) estimator. This approach identifies the local average treatment effect (LATE) for compliers, that is, units whose air pollution exposure is affected by the instrument, under the so-called relevance, exclusion restriction, and monotonicity assumptions. The relevance assumption states that the instrumental variable is correlated to the treatment variable. The exclusion restriction assumes that the instrument must be uncorrelated with the outcome variable except through its effect on the treatment. The monotonicity assumption states that the instrument must affect the treatment in a monotonic way. Violation of these restrictions will render the instrumental variable invalid, cause the

[2]By definition, workplace accidents are incidents occurred at workplaces. Given the probability of occurring a workplace accident per unit of time, the longer workers spend at the workplace, the higher the workplace accident rate. Another way to think of this relationship is that the longer the working hours, the more fatigued are workers (workers become less focused), and the more likely for workers to make mistakes, hence the higher risk of workplace accidents.

traditional IV estimator to be biased, and make it infeasible to point identify the causal effect of interest.

Empirically, a variety of instruments are proposed. Although the validity of these IVs is not formally tested in the study, their validity is typically argued on conceptual grounds. Prominent examples include wind direction and thermal inversion (see, for example, Anderson, 2020; Balietti, Datta, & Veljanoska, 2022; Deryugina et al., 2019; Heyes & Zhu, 2019).[3] In addition to the adopted IVs, another candidate is rainfall. Studies in environmental science have found that precipitation can "washout" PM pollutants in the air (see, Guo et al., 2016; Tai, Mickley, & Jacob, 2010). This "washout" effects are found to be most effective for heavy rain. Relative to commonly used instruments such as wind direction and thermal inversions, (heavy) rainfall offers several practical advantages: it is readily available, commonly observed, and naturally accumulates over the day, allowing reliable daily aggregation and reducing measurement error. High-resolution wind direction and thermal inversion data typically come from climate reanalysis products, which require substantial data processing prior to estimation. Moreover, wind direction is highly volatile within a day and usually requires aggregation choices (e.g., dominant direction, vector averaging, or threshold rules), while thermal inversions are often defined at specific times, such as early morning, which may not correspond to exposure windows relevant for the outcomes. Nevertheless, the validity of rainfall as an instrumental variable for workplace accident outcomes is not obvious. The rainfall IV may violate the exclusion restriction because the rainfall itself can cause workplace accidents independently of PM2.5 pollution. Additionally, workers may actively adjust their intertemporal labor supply on rainy days to avoid difficulties of commuting to work during the bad weather. The weather-related labor shortage could be correlated to the probability of workplace accidents. Besides, outdoor jobs are more likely to be rescheduled on days with rainy weather conditions and thus outdoor workers may be asked by employers to work shorter hours or even to not work on days with bad weather, which passively adjusts their labor supply. Such adjustments are more salient for workers who have flexible work schedule, who work outdoor, and in extreme weather days.

Indeed, following Mourifié and Wan (2017) and extending their method to a panel data setting with covariates, I provide statistical evidence that the joint validity of the point-identification restrictions is likely unfounded for the rainfall IV in our setting.[4]

This raises an immediate question of whether it is still possible to use a readily available but potentially invalid instrument to learn about the causal effect of interest, even if point identification is not attainable. Fortunately, the answer is yes. In the next section, I discuss two partial identification strategies that impose weaker assumptions than the conventional IV approach. Importantly, these methods go beyond identifying a local average treatment effect and instead establish bounds on the average treatment effect.

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[3] Other IVs are adopted in recent studies such as dust storms (Hattemer & Moreno-Martinez, 2025), winter heating regulations and planetary boundary layer (Palma et al., 2024), straw burning (G. He, Liu, & Zhou, 2020), and wildfire events (Cabral & Dillender, 2024).

[4] Appendix B illustrates the IV testing approach and corresponding results for the rainfall IV.

4 Partial Identification Strategies

The partial identification methods replace point identification assumptions with weaker assumptions and instead of obtaining a point estimate, it estimates bounds on the average treatment effect of interest. I start with the approach by Nevo and Rosen (2012), a method based on a linear parametric model assuming constant treatment effects. The constant treatment effect assumption is strong in this empirical setting. For this reason, I turn to a recent nonparametric strategy proposed by Ban and Kédagni (2022) which extends Nevo and Rosen (2012) to allow for heterogeneous treatment effects. In the following section, I illustrate the assumptions and bounds derived by these two methods.[5] This section is closed with a detailed discussion of the validity of these assumptions in the context of this paper.

4.1 Parametric Bounds: Nevo and Rosen (2012)

Nevo and Rosen (2012) identify the average treatment effect, ATE(d) $= E[Y_d] - E[Y_0]$ for $d \in \mathbb{D}$. The parameter d measures the binned daily PM2.5 pollution level and takes values in $\mathbb{D} = \{0, 1, 2, 3\}$ where

$$d = \begin{cases} 0 \text{ if } & PM2.5 \leq 10\ \mu g/m^3 \\ 1 \text{ if } & PM2.5 \in (10, 15]\ \mu g/m^3 \\ 2 \text{ if } & PM2.5 \in (15, 25]\ \mu g/m^3 \\ 3 \text{ if } & PM2.5 > 25\ \mu g/m^3 \end{cases}$$

The observed outcome variable, the prevalence rate of workplace accidents Y is written as $Y = \sum_{d=0}^{3} Y_d 1(D = d)$ under the potential outcome model with multivalued treatment, where Y_d are potential outcomes. In the circumstance of invalid IV, they establish sharp bounds on ATE under the following assumptions.

Assumption A1. *(SDC - Same Direction of Correlation):* $Cov(Y_d, D)Cov(Y_d, Z) \geq 0,\ \forall\ d \in \mathbb{D}$.

where d denotes the treatment status. Assumption SDC states that the direction of the correlation between the treatment D and the potential outcomes Y_d are the same as the correlation between the invalid IV Z and Y_d.[6]

Assumption A2. *(LEI - Less Endogenous Instrument):* $|\rho_{Y_d,D}| \geq |\rho_{Y_d,Z}|,\ \forall\ d \in \mathbb{D}$.

where ρ denotes the correlation. Assumption LEI asserts that the invalid IV is weakly less correlated with the potential outcomes than is the endogenous treatment. In other words, it argues that, although Z is invalid, it is less endogenous than the treatment.

Intuitively, Nevo and Rosen (2012) propose constructing a new variable (denoted as V) as a function of Z, D, and Y_d, such that it satisfies the moment condition $E[V \cdot Y_d] = 0$, i.e., V is uncorrelated to the potential outcome. Since V is empirically unobserved,

[5] For the formal derivation of bounds, please refer to Nevo and Rosen (2012) and Ban and Kédagni (2022).

[6] Ban and Kédagni (2022) show that Assumption SDC can be seen as a weaker version of the monotone IV (MIV) and monotone treatment selection (MTS) assumptions employed by Manski and Pepper (2000).

the IV estimator employing V as the IV cannot achieve point identification. However, they show that as long as V can be bounded by some finite values, it is feasible to partially identify the ATE. Specifically, consider:

$$\lambda^* \equiv \begin{cases} \rho_{Y_d,Z}/\rho_{Y_d,D} & \text{if} \quad \rho_{Y_d,D} \neq 0 \\ 0 & \text{if} \quad \rho_{Y_d,D} = \rho_{Y_d,Z} = 0 \end{cases}$$

Under Assumptions SDC and LEI, it can be shown that

$$E[(\sigma_D Z - \lambda^* \sigma_Z D)Y_d] = 0 \tag{1}$$

where σ_D and σ_Z are the standard deviation of D and Z, respectively. Equation (1) suggests that $\sigma_D Z - \lambda^* \sigma_Z D$, a weighted average of Z and D, satisfies the exclusion restriction. Define $V(\lambda) = \sigma_D Z - \lambda \sigma_Z D$. Since $E[V(\lambda^*) \cdot Y_d] = 0$ and $Cov(V(\lambda^*), D) \neq 0$, $V(\lambda^*)$ can serve as a valid IV. While λ^* is empirically unknown, Assumptions SDC and LEI imply that λ^* is bounded between 0 and 1: $\lambda^* \in [0, 1]$. Plugging the boundary values of λ ($\lambda = 0$ and $\lambda = 1$) into Equation (1) yields $V(0) = \sigma_D Z$ and $V(1) = \sigma_D Z - \sigma_Z D$. Nevo and Rosen (2012) show that the ATE is bounded by the two IV estimators that separately employ $V(0)$ and $V(1)$. I denote θ^Z_{IV}, $\theta^{V(0)}_{IV}$, and $\theta^{V(1)}_{IV}$ as the IV estimators employing Z, $V(0)$, and $V(1)$, respectively. It is intuitive to see that $\theta^{V(0)}_{IV} = \theta^Z_{IV}$. Proposition 1 summarizes the bounds derived by Nevo and Rosen (2012):

Proposition 1. *(Nevo and Rosen, 2012) Given assumptions SDC and LEI, if $Cov(D, Z) < 0$, then there exists a two-sided bound where $\theta^Z_{IV} \leq ATE \leq \theta^{V(1)}_{IV}$ if $Cov(Y_d, D), Cov(Y_d, Z) \geq 0$ or $\theta^{V(1)}_{IV} \leq ATE \leq \theta^Z_{IV}$ if $Cov(Y_d, D), Cov(Y_d, Z) \leq 0$. Instead, if $Cov(D, Z) > 0$, then there exists a one-sided bound where $ATE \leq \min\{\theta^Z_{IV}, \theta^{V(1)}_{IV}\}$ if $Cov(Y_d, D), Cov(Y_d, Z) \geq 0$ or $ATE \geq \max\{\theta^Z_{IV}, \theta^{V(1)}_{IV}\}$ if $Cov(Y_d, D), Cov(Y_d, Z) \leq 0$. These bounds are sharp.*

Proposition 1 states that when D is negatively correlated with the invalid IV, ATE can be bounded between θ^Z_{IV} and $\theta^{V(1)}_{IV}$, while when D and the invalid IV are positively correlated, only a one-sided bound is estimated. The direction of the one-sided bound is determined by the sign of $Cov(Y_d, D)$ and $Cov(Y_d, Z)$.

Empirically, the method of Nevo and Rosen (2012) is easy to implement and can be readily applied to the panel data, accommodating covariates and (high dimensional) fixed effects. However, these advantages are at the expense of imposing the constant treatment effect assumption and assuming a linear parametric specification.

4.2 Nonparametric Bounds: Ban and Kédagni (2022)

Ban and Kédagni (2022) extend the method of Nevo and Rosen (2012) to a nonparametric setting, allowing for heterogeneous treatment effects. In addition to assuming SDC and LEI, as in Nevo and Rosen (2012), Ban and Kédagni (2022) impose two additional assumptions:

Assumption A3. *(BOS - Bounded Support): $Supp(Y_d|D \neq d) = Supp(Y_d|D = d) = [\underline{y}_d, \bar{y}_d], \ \forall\ d \in \mathbb{D}$.*

The BOS assumption ensures the same support of the counterfactual outcome and the factual outcome. It is a standard assumption when estimating nonparametric bounds (Manski, 1990; Manski & Sims, 1994). By imposing the bounded support assumption, Ban and Kédagni (2022) relax the parametric linear assumption in Nevo and Rosen (2012) and obtain two-sided bounds regardless of the sign of $Cov(Z, D)$.[7] Moreover, they show that if Assumption BOS holds for the outcome variable, the SDC assumption has a testable implication: SDC is rejected if the nonparametric bounds defined under BOS and SDC are empty. In practice, the rejection of SDC suggests the data using for analysis is not compatible with the identification assumptions for the partial identification strategy in use.

Assumption A4. *(MTR - Monotone Treatment Response): $Y_d \geq Y_{d'}, \ \forall\ d > d'$.*

Assumption MTR claims that the potential outcome weakly increases with the level of the treatment (Manski, 1997). Adding the MTR assumption can effectively tighten the bounds.

Ban and Kédagni (2022) identify bounds on the potential outcome expectation $\theta_d = E[Y_d]$ for $d \in \mathbb{D}$, such that $LB_d \leq \theta_d \leq UB_d$. Bounds on the ATE(d) $= \theta_d - \theta_0$ are therefore defined as $LB_d - UB_0 \leq$ ATE(d) $\leq UB_d - LB_0$. The identification shares a similar intuition with Nevo and Rosen (2012), which involves bounding the weighted average of D and Z to obtain bounds on θ_d and, hence, ATE. For example, the derivation of nonparametric bounds under the BOS and SDC assumptions involves moment inequalities $E[\delta(\alpha, \beta)Y_d] \geq \theta_d$ where $\delta(\alpha, \beta) = 1+\alpha(\beta(D-E[D])+(1-\beta)(Z-E[Z])$. Like $V(\lambda)$ of the parametric method, $\delta(\alpha, \beta)$ is an nonparametric analogue of the weighted average of D and Z with parameters α and β.[8] Lastly, the construction of the confidence sets of bounds $[LB_d, UB_d]$ follows the intersection bounds framework of Chernozhukov, Lee, and Rosen (2013) and can be estimated by the existing inferential method (Chernozhukov, Kim, Lee, & Rosen, 2015).

4.3 Discussion of Assumptions

Next, I discuss whether assumptions of Nevo and Rosen (2012) and Ban and Kédagni (2022) apply to the context of this paper. I start with SDC and LEI assumptions for Nevo and Rosen (2012). Both assumptions impose restrictions on $Cov(Y_d, D)$ and $Cov(Y_d, Z)$. They likely hold for the rainfall IV used in the setting of this study.

First, it is likely that the correlation of PM2.5 pollution with the latent workplace accident rate is weakly positive and hence $Cov(Y_d, D) \geq 0$. Better air quality (less air pollution) is naturally linked with safer workplaces (fewer workplace accidents), because localities that value clean air and are willing to invest money in air quality

[7] Recall that Nevo and Rosen (2012) identify two-sided bounds when $Cov(D, Z) < 0$ and a one-sided bound when $Cov(D, Z) > 0$.

[8] Additional steps are needed to formally derive the upper bound estimator of θ_d, but the main idea is bounding the moment function of the weighted average $\delta(\alpha, \beta)$. See Ban and Kédagni (2022) for a formal derivation.

improvement (usually localities with higher income level) tend to also value work safety and are willing to invest money in creating safer workplaces. At the same time, localities with more intensive industrial activities are more likely to simultaneously experience a higher level of air pollution and a higher rate of workplace accidents, assuming the probability of workplace accidents is positively correlated to the intensity of production activities.

Moreover, existing literature has documented that workers reduce their intertemporal labor supply on air-polluted days (for example, Currie, Hanushek, Kahn, Neidell, & Rivkin, 2009; Hanna & Oliva, 2015; Hansen & Selte, 2000).[9] Although being absent from work reduces the probability of workplace accidents for the worker on leave, work absenteeism is likely positively correlated to the rate of accident at the grid-day level for two reasons: First, on the day(s) the worker being absent from work, the workload of coworkers increases. Second, on days after the absent-from-work day(s), the worker may be asked by the employer to work longer time in order to compensate the productivity loss on previous days. It may weakly increase the likelihood of accidents on the succeeding days. Given all these factors, it is likely $Cov(Y_d, D) \geq 0$.

Considering the correlation between the latent workplace accident rate and the instrumental variables, rainfall, heavy rainfall itself can increase the likelihood of workplace accidents. Moreover, workers' intertemporal labor supply likely changes with heavy rainfalls in a similar way with the change of air quality, i.e., workers reduce their labor supply on rainy days.[10] Therefore, the weather-driven work absenteeism would also be positively correlated to the grid-day level workplace accident rate for similar reasons. It implies that the correlation between the workplace accidents and the rainfall IV would share the same sign with the correlation between the workplace accidents and the PM2.5 pollution. In summary, the same direction of correlation (SDC) assumption likely holds for the rainfall IV.

As for the less endogenous instrument (LEI) assumption, although rainfall, especially heavy rainfall, may directly affect workplace accident by affecting, for example, the visual condition at the workplace, its link with workplace accidents is likely not as strong as the link between PM2.5 and workplace accidents. Because, first, the effect of rainfall on workplace accidents is likely limited to (semi-)outdoor workers who work on rainy days, whereas PM2.5 may have a broader effect for both outdoor and indoor workers, as PM2.5 can easily penetrate indoors. In addition, it is unlikely for the rainfall to affect workers' cognitive performance, a biological channel through which PM2.5 pollution affects workplace accidents. Moreover, air pollution is highly correlated to economic activities which simultaneously affect the incidence of workplace accidents, while the link between economic activities and rainfall is in general much weaker. Given all of these factors, it is arguably plausible to assume that the rainfall

[9] Several studies document a negative relationship between air pollution and labor supply. An increase in air pollution is found to be associated with an increase in work loss days (Hausman, Ostro, & Wise, 1984; Ostro, 1983), sick-leaves (Hansen & Selte, 2000), and sick-related absenteeism (Pönkä, 1990), while the decline in air pollution leads to an increase in working hours (Hanna & Oliva, 2015). Moreover, air pollution can be associated with school absences (Currie et al., 2009; Ransom & Pope III, 1992), implying that pollution may also have real effects on work hours if it induces absenteeism among workers who are responsible for child care (Hanna & Oliva, 2015).

[10] Appendix D provides empirical evidence that workers change their work schedule on rainy days. Workers are found to reduce working hours and are more likely to be absent from work on days with heavy rainfall.

is less correlated with the workplace accidents than is the PM2.5 pollution. Therefore, the less endogenous instrument (LEI) assumption likely holds.

For the two additional assumptions imposed by Ban and Kédagni (2022), BOS and MTR, the BOS assumption is satisfied because intrinsically the number of workplace accidents is zero or a positive integer and thus the outcomes are bounded in the left tail. Researchers can conservatively top-code the sample in the right tail to further ensure the outcome support is bounded. Assumption MTR states that the potential outcome weakly increases with the level of the treatment. In the context of this paper, because the analysis is at the grid-day level, MTR states that exposure to a PM2.5-polluted day does not *decrease* workplace accidents. It is plausible to assume MTR at the grid-day level because the adverse impact of PM2.5 on human cognitive functions provide a channel through which PM2.5 may increase workplace accidents. Even though workers can respond to air quality deterioration by calling in sick on the air polluted days, it has a spillover effect on coworkers. Coworkers may be subjected to a higher hazard of workplace accidents, as their workload may be increased, exposing them to additional stress and fatigue. The probability of accidents is the same or higher for workers who are fatigued, discomforted, or experience cognitive decline.[11] For these reasons, it is unlikely that PM2.5 pollution has an overall negative effect, making the MTR assumption plausible.

5 Data

To estimate the impact of air pollution on work safety, I create a novel panel data combining administrative data on severe workplace injuries with high-resolution data on daily PM2.5 and meteorological variables for the contiguous United States (48 states excluding Alaska, Hawaii, and the District of Columbia) from 2015 to 2018. The geographical unit of analysis is a grid raster at 0.5 degree scale (approximately 55 km). Appendix A provides a detailed discussion regarding data sources and the data construction process. The final data used in the analysis consists of 2770 grids spanning 1461 days (01/01/2015-12/31/2018), with total sample size of 4,046,970 (= 1461×2770).[12]

I quantify workplace safety using the prevalence rate of workplace accidents that involve severe injuries. Y_{ij} denotes the daily average accident rate per million population in grid i and day j.[13] To measure daily ambient PM2.5 pollution, I classify

[11]Studies on the risk factors of workplace injuries have found that fatigued workers are exposed to a higher risk of injuries at workplaces (Swaen, Van Amelsvoort, Bültmann, & Kant, 2003; Tucker, 2003).

[12]The geographical unit of analysis is a raster with 4426 grids at 0.5 degree scale (approximately 55 kilometers or 33 miles). As shown in Appendix Figure E1, each grid cell is of about 3025 square kilometers (1168 square miles), and equivalent to areas combined Houston and Phoenix. I exclude grids with population count of zero (hence missing population density values) and grids missing air quality and meteorological measures from the analysis sample. The excluded grids (1656 of them) are shown as gray shaded areas in Figure E1. Most of them are in remote areas in the West and Midwest. To visually illustrate the size of a grid, I plot two grids that cover the New York city in Figure E2.

[13]To remove outliers and to ensure the common support (BOS) assumption for the nonparametric bounds estimation (See Section 4.2), I top-code the accident rate at the 0.05th percentile in the right tail. All empirical analyses use the same top-coded outcome variable.

the daily PM2.5 level into four bins: $\leq 10\mu g/m^3$ (baseline), $(10\mu g/m^3, 15\mu g/m^3]$, $(15\mu g/m^3, 25\mu g/m^3]$, and $> 25\mu g/m^3$.[14]

The thresholds of PM2.5 treatment are set up according to the World Health Organization's air quality guideline value of 24-hour exposure to PM2.5 (WHO, 2006, 2021). In the 2005 guideline, the air quality guideline value of 24-hour exposure is $25\mu g/m^3$ (WHO, 2006). The new guideline released in 2021 updates the air quality guideline value to $15\mu g/m^3$ (WHO, 2021). Figure 1 plots the density of the average daily PM2.5 estimates by year over the sample period of 2015-2018. The vast majority of daily PM2.5 estimates range from 0 to 35 $\mu g/m^3$, with some outliers as large as 100-250 $\mu g/m^3$. In addition, as shown in Figure 2, even though the majority of PM2.5 observations range from 0 to 35 $\mu g/m^3$, there are sizable variations among PM2.5 above 25 $\mu g/m^3$.

Table 1 presents the summary statistics for the data. The sample average workplace accident rate per 1 million population is about 0.34. For an average grid with population size at the sample mean (112,291), an accident rate at 0.34 is equivalent to a rate of workplace accidents (with severe injuries) of about 0.04. The daily average PM2.5 level in the contiguous United States is about 7.28 micrograms per cubic meter.[15]

6 Bounds Estimation Results

The semiparametric method of Nevo and Rosen (2012) and the nonparametric approach of Ban and Kédagni (2022) are applied separately to the U.S. data.[16] I begin by presenting the bound estimation results based on Nevo and Rosen (2012). According to Proposition 1, the direction of the correlation between the treatment and the instrumental variable determines the type of bounds (e.g., one-sided versus two-sided). As shown in Table 2, the treatment variables, PM2.5 measures, are negatively correlated with the heavy rainfall instrument. For example, a one–standard deviation increase (0.29) in the probability of heavy rainfall is associated with a 0.3 percentage point reduction in the likelihood that daily PM2.5 exceeds 25 micrograms per cubic meter, which corresponds to a 32% reduction relative to the sample mean rate (approximately 0.01). Therefore, two-sided bounds can be obtained using the approach of Nevo and Rosen (2012).[17]

Table 3 summarizes the corresponding estimated semiparametric bounds. It shows evidence that PM2.5 pollution increases the accident rate associated with severe

[14] The unit of PM2.5 measure is $\mu g/m^3$. For the convenience of exposition, both the unit of measure and the subscript are omitted in the rest of discussion, unless it is needed.

[15] Appendix Table F1 further presents the summary statistics of the outcome variables by industry, year, month, and day of week. The workplace accident rate is similar across years, with a higher rate observed in 2017 and 2018. Workplace accidents mostly occurred on weekdays, with a slightly higher rate during the summer months: June, July, and August, and a smaller rate in the holiday season in November and December. Natural Resources and Mining, Manufacturing, Construction, and Trade/Transportation/Utilities are industries observed a higher rate of workplace accidents.

[16] A detailed illustration of the implementation of these two methods is available in Appendix C.

[17] It is worth noting that other instrumental variables proposed in the existing literature, such as wind direction, thermal inversion, straw burning and wildfires, and winter heating, are typically positively correlated with air pollution. Under our partial identification framework, namely Nevo and Rosen (2012), using these IVs is therefore unable to produce two-sided bounds. This suggests an additional advantage of adopting rainfall as an instrumental variable in this setting.

injuries. Under the preferred specification with the most granular fixed effects (Column 3), daily exposure to PM2.5 levels exceeding 25 micrograms per cubic meter increases the accident rate by at least 0.4 ppts and at most 9.3 ppts. The corresponding effect is likely smaller for moderate pollution levels: for daily PM2.5 levels between 10 and 15 micrograms per cubic meter, the effect is bounded between 0.1 ppts and 0.5 ppts, while for levels between 15 and 25 micrograms per cubic meter, the effect is bounded between 0.2 ppts and 1.3 ppts. Both the estimated bounds and their 95% confidence intervals exclude zero. Comparing the bounds on the effects of PM2.5 pollution at lower versus higher concentration levels, the bounds shift disproportionately upward, implying that the effect exhibits some degree of nonlinearity.[18]

The method of Nevo and Rosen (2012) imposes a strong assumption of constant treatment effect, which is likely violated in the empirical setting of this paper. Since workers' exposure to air pollution can be affected by various factors, such as the work environment, workplace location, and job context, the effect of air pollution on workplace accidents may vary across regions and industries. Next, I present the nonparametric bounds results estimated using Ban and Kédagni (2022), a more flexible method which relaxes the constant treatment effect assumption. These results are reported in Table 4. The bounds are estimated separately for two sets of assumptions: a) BOS, SDC and LEI (shown in Column 1), and b) BOS, SDC, LEI, and MTR (shown in Column 2).

Assuming BOS, SDC, and LEI, the estimated bounds include zero. Nevertheless, the estimated bounds still provide information about the interval in which the average treatment effect of interest falls. For example, the estimated bounds for PM2.5 levels exceeding 25 micrograms per cubic meter rule out negative effects smaller than -0.19 and positive effects greater than 0.89. Imposing the MTR assumption significantly tightens the nonparametric bounds. Column (2) shows that the effect of PM2.5 pollution is estimated to be at least 0.4 ppts and at most 5.5 ppts for daily PM2.5 concentrations exceeding 25 micrograms per cubic meter. The bounds range from 0.3 ppts to 5.5 ppts for PM2.5 concentrations between 15 and 25 micrograms per cubic meter, and from 0.4 ppts to 7 ppts for concentrations between 10 and 15 micrograms per cubic meter. Both the point estimates of nonparametric bounds and their 95% confidence intervals exclude zero, although the confidence interval for the lower bound lies extremely close to zero and rounds to 0 in reported values. Also, the nonparametric bounds are less nonlinear than the semiparametric bounds reported in Table 3. The estimated bounds overlap across the three PM2.5 bins and are similar in magnitude, with their width shrinking slightly as PM2.5 increases (0.066 for 10–15 $\mu g/m^3$, 0.0517 for 15–25$\mu g/m^3$, and 0.0514 for above-25$\mu g/m^3$).

Table 5 reports the OLS estimates and 2SLS estimates using the heavy rainfall instrument. In general, the semiparametric bounds contain the OLS estimates, whereas the nonparametric bounds exclude them. One exception is for PM2.5 concentrations above 25 micrograms per cubic meter: the OLS estimate suggests an effect of approximately 0.0017, which is excluded from the semiparametric bounds. For the 2SLS estimates, note that, by definition (see Proposition 1), the upper bound of the

[18] However, this interpretation should be made with caution, as comparing bound estimates across groups is inherently more difficult than comparing point estimates.

semiparametric bounds essentially coincides with the 2SLS estimate that uses heavy rainfall as an IV. For the nonparametric bounds, under the MTR assumption, they exclude the 2SLS estimates that adopt a potentially invalid IV for the indicator of PM2.5 above 25 micrograms per cubic meter. In contrast, for the treatment variable when PM2.5 lies between 10 and 15 micrograms per cubic meter and between 15 and 25 micrograms per cubic meter, the 2SLS estimates are encompassed by the nonparametric bounds.

To gauge the magnitude of our estimates, we compare our bounds with point estimates reported in prior studies. Table F3 summarizes the main findings of the related literature. For example, Hattemer and Moreno-Martinez (2025) shows that in Spain, a dust-exposure day, which on average raises PM10 concentrations by about 12 $\mu g/m^3$, increases workplace accidents by roughly 1.2%. In Israel, a 10-ppb increase in NO_2 raises accident risk at construction sites by up to 25%, with substantially larger effects at very high pollution levels (Lavy et al., 2022). Using quasi-experimental variation in Italy, Palma et al. (2024) finds that a one-unit increase in PM10 causes 0.0065 additional accidents (about a 0.08% increase relative to the sample mean), with no effect on disabilities. In the United States, Cabral and Dillender (2024) documents that an additional day of wildfire smoke, which on average raises PM2.5 levels by 1.7 $\mu g/m^3$, increases workers' compensation injury claims in Texas by approximately 2.8%. Related work on temperature finds similarly meaningful effects: days above 100°F raise injury claims by about 3.5–3.7% relative to 59–61°F in Texas (Dillender, 2021) and by 10–15% relative to temperatures in the 60's in California (Park et al., 2021).

As noted above, our estimates suggest that, relative to a day with PM2.5 below 10 $\mu g/m^3$, a day with PM2.5 above 25 $\mu g/m^3$, approximately a 15-unit increase, raises the accident rate by at least 0.4 percentage points (about 2% relative to the sample mean) and up to 5.5 percentage points (26%). Since estimates across pollutants and environmental factors are not directly comparable, the most comparable evidence comes from Cabral and Dillender (2024), which studies wildfire smoke–related PM2.5 exposure. Translating their estimate, a 2.8% increase in injury claims associated with a 1.7 $\mu g/m^3$ rise in PM2.5 implies roughly a 25% increase for a 15 $\mu g/m^3$ change, a magnitude close to our estimated upper bound.

Heterogeneous Effects

The following analyses assess the heterogeneous effects of air pollution on the workplace accident rate.[19] I start by exploring how the effects vary across industry groups. I classify accidents into 11 industry sectors by 2-digit NAICS codes following the BLS's classification. The bounds estimation is then conducted separately for each industry category. Because the frequency of accidents in certain industries, such as financial

[19] As in prior work, it would be useful to examine whether the estimated effects differ across various dimensions, including worker characteristics (e.g., age and gender) and injury characteristics (e.g., causes and injury types). However, due to data limitations, we are unable to conduct such heterogeneity analyses in this study. Unlike workers' compensation claim records, the severe injury dataset used here does not contain information on worker demographics or detailed injury attributes. Instead, we focus on differential effects across industries, space, and population density. The high-resolution accident location data allow us to analyze heterogeneity at a much finer spatial scale.

activities, education and health, and leisure and hospitality, is very low in the sample (≤ 0.0004), it is infeasible to estimate nonparametric bounds separately for these industries. Since most of jobs in those industries are conducted indoor, I aggregate them into one category denoted as "Aggregated Indoor". Moreover, I combine the other service and public administration industries into one group, denoted as "Other Services & Public Administration".

The corresponding results are summarized in Figure 3. There is suggestive evidence that the effects could be larger for industries where workers work in outdoor or semi-outdoor environment given that their estimated bounds are shifted towards the right. For example, the estimated upper bounds suggest the effect is estimated between 0.09 ppts and 0.87 ppts for construction, 0.36 ppts and 0.67 ppts for transportation. In contrast, the suggested effect is between 0.020 ppts and 0.021 ppts for other services and public administration, 0.06 ppts and 0.12 ppts for aggregated indoor industries, and between 0.03 ppts and 0.39 ppts for professional and business services. We also estimate a small effect for the natural resources and mining sector, ranging between 0.03 ppts and 0.07 ppts. Notably, for manufacturing sector, the effect is estimated to be at least 0.48 ppts and up to 1.28 ppts. Both the bounds and their 95% confidence sets exclude zero. While workers typically work indoors in the manufacturing sector, manufacturing plants are typically located in areas with high levels of air pollution. This suggestive larger effect found for the manufacturing sector are consistent with recent studies that provide evidence of PM2.5-driven worker productivity loss from indoor factories (Chang et al., 2016; J. He et al., 2019).

It is important to keep in mind that the true effect can be at any point within the estimated bounds. Therefore, it is difficult to directly compare the effects across different industries — a common feature when employing bounds, as the estimated intervals for each group often overlap substantially. Nonetheless, as shown in Figure 3, the bounds for the manufacturing and transportation sectors appear to lie entirely to the right of those for the aggregated indoor and public administration sectors, and marginally to the right of those for the professional and business services sector, while the bounds for the construction industry lie strictly to the right of those for public administration.

Next, to examine whether the PM2.5 effect differs across regions, I split the sample into four sub-samples by population density: a) bottom 25% grids where population density is smaller than 2 people per square kilometer (pp/km^2); b) 25%-50% grids where the density is between 2 pp/km^2 and 11 pp/km^2; c) 50%-75% grids where the density is greater than or equal to 11 pp/km^2 but below 34 pp/km^2; and d) top 25% grids where population density is above or equal to 34 pp/km^2. The bounds estimation is then conducted separately for each sub-sample. Figure 4 summarizes the estimated bounds and their 95% confidence intervals by population density. This implies a relatively larger effect in more densely populated regions. The estimated bounds are of similar magnitude across the bottom 75% of population density groups, while both the lower and upper bounds are larger for densely populated areas. For instance, the estimated effect ranges from approximately 0.06 to 0.93 ppts for the bottom 75% population density groups, compared with a range of approximately 0.15 to 3 ppts for the top 25% population density group. To further examine the geographic distribution of the PM2.5 effect, I plot the estimated bounds on the effect of PM2.5 above 25 micrograms per cubic meter by grid in Figure 5. I flag in blue the top 300 Core Based Statistical Areas (CBSAs) in terms of the total population in the Census 2010 in the map. As shown in the figure, the estimated effects tend to be larger, indicated by upward shifts in both the lower and upper bounds, in hotspot areas with darker colors across Rust Belt regions extending from southeastern Pennsylvania through the Detroit area, the Ohio corridor, and the Chicago metropolitan area, as well as in California (particularly Southern California) and Texas. These areas largely coincide with more populous regions (shown as blue polygons), which is consistent with the previous findings in Figure 4.

7 The Impact on Workers' Compensation

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

Based on the estimated bounds of PM2.5 effects on severe workplace accidents, I offer a back-of-the-envelope estimate of its impact on workers' compensation costs. The changes in the annual workers' compensation costs associated with one additional day of PM2.5 exposure across the country can be estimated using the following formula:

$$C(t) = \hat{\beta}(d) \times \frac{\text{Population}}{1,000,000} \times \Delta\text{PM2.5 Pollution Days} \times c \tag{2}$$

where population represents the total population of the United States and c denotes the estimated workers' compensation cost per worker. $\hat{\beta}(t)$ denotes the impact of PM2.5 exposure on the workplace accident rate at exposure level d. ΔPM2.5 Pollution Days represents the pre-specified change in the number of PM2.5 pollution days per year. I assume that each accident causes one injury. The total population statistics are retrieved from the 2020 U.S. Census. NSC estimates the average cost of workers' compensation claims was about $\$114,000$ per claim in 2018-2019 for severe injuries such as amputation.[20] Hence, c is set at \$114,000. $\hat{\beta}(d)$ comes from the estimated bounds of the PM2.5 effect in Table 4 under the MTR assumption.

[20]Source: NSC Injury Facts https://injuryfacts.nsc.org/work/costs/workers-compensation-costs/.

I summarize the back-of-the-envelope calculation in Table 6. It implies that exposure to one extra day of PM2.5 above 25 micrograms per cubic meter is associated with an increase in the annual cost of workers' compensation of at least 0.26 million US dollars and at most 12.8 million U.S. dollars. Based on EPA's 2019 monitoring data, there were on average approximately 75 days across the United States with daily mean PM2.5 concentrations above 25 micrograms per cubic meter. Therefore, under a counterfactual scenario in which all such pollution days are eliminated, the resulting reduction in severe workplace injuries would lead to workers' compensation savings of at least 19.8 millions US dollars and at most 962 millions US dollars. Weiss et al. (2020) reports aggregate workers' compensation payments of approximately 62.9 billion dollars in 2018. The estimated savings thus represent approximately 0.03%–1.6% of total payments, a meaningful share given that they arise from a single category of injuries.

The above analysis implies a sizable monetary cost of PM2.5-driven work-related accidents and potential benefits of environmental policies to improve the air quality in workplaces. To benchmark the magnitude of these monetary benefits, it is useful to consider the scale of resources devoted to improving and maintaining air quality in the United States. According to the EPA's fiscal year 2020 budget, approximately $228 million was allocated to support State, Local, and Tribal Air Quality Management programs (United States Environmental Protection Agency, 2019). These funds are administered by multi-state, state, and local air pollution control agencies to support the development and implementation of air pollution prevention and control programs, as well as the enforcement of the National Ambient Air Quality Standards (NAAQS) designed to protect public health and the environment. Based on this figure, and focusing on a single benefit category—reductions in severe workplace injuries—a one-day reduction in high-pollution days would generate cost savings equivalent to at least 0.1% and up to 6% of the EPA's annual air pollution control budget. Moreover, the benefits associated with eliminating all days with PM2.5 concentrations above 25 micrograms per cubic meter would be substantially larger, amounting to at least 9% of the EPA's annual air quality budget.

8 Conclusion

This paper investigates whether air pollution impairs workplace safety using novel data on workplace severe injuries in the United States. I focus on fine particulate matter (known as PM2.5), a major air pollutant found to have adverse impacts on human cognitive functions and thus potentially affecting workplace accidents via biological channels.

Credibly pinning down the causal effect of air pollution on workplace accidents is challenging because air pollution is endogenous. The conventional approach exploiting exogenous variation from instrumental variables point-identifies the local average treatment effect (LATE) for *compliers* and requires a valid instrument satisfying both the exclusion restriction and the monotonicity assumption. This paper employs partial identification strategies to estimate bounds on the average treatment effect (ATE) under assumptions compatible with imperfect IVs, providing evidence beyond 2SLS estimates of LATE.

Using heavy rainfall, a readily available factor, as an imperfect instrumental variable, both semiparametric and nonparametric bounds indicate an adverse effect of PM2.5 pollution on workplace accidents involving severe injuries. The estimated effects appear to be more prominent for the manufacturing sector and non-manufacturing sectors that require (semi-)outdoor work, such as transportation and construction, and for densely populated regions. Using the estimated bounds to evaluate the impact of air pollution on workers' compensation, a back-of-the-envelope calculation indicates that eliminating all high-pollution days would generate significant cost savings equivalent to at least 9% of the EPA's annual air pollution control budget in 2020.

Our findings suggest that improving air quality can potentially benefit both employers and employees. It likely reduces labor productivity loss and both the direct and indirect costs of work-related accidents. These findings call for caution in the benefit and cost evaluation of environmental policies. Without considering the likely gains from improving work safety, the benefits of environmental policies that intend to improve air quality, whether outdoor or indoor, are likely to be underestimated.

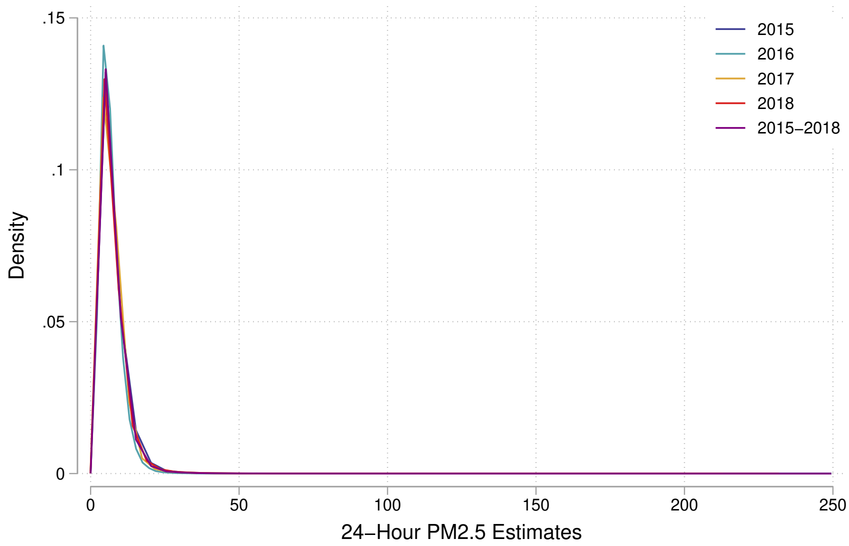

Fig. 1 The Density of Daily PM2.5 Estimates.

Notes: This figure presents the density of the average 24-Hour PM2.5 estimates by year and for the sample period 2015-2018 for the whole sample.

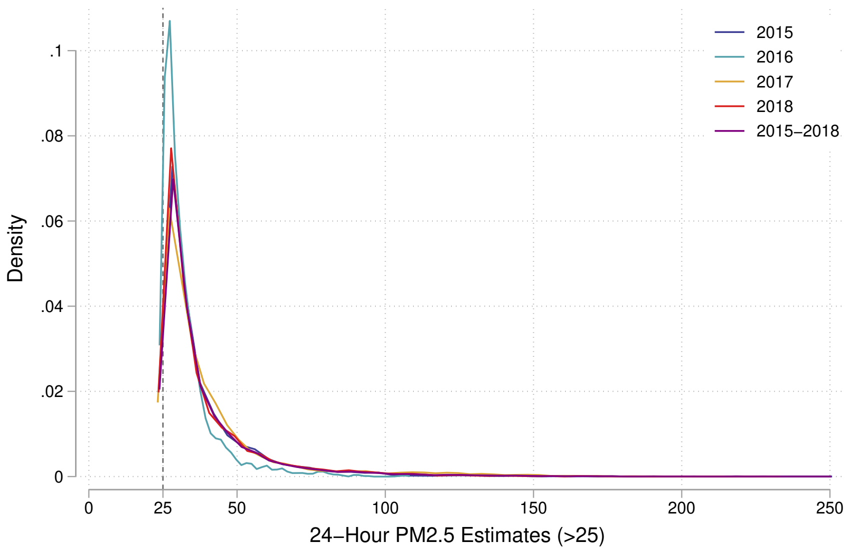

Fig. 2 The Density of Daily PM2.5 Estimates.

Notes: This figure presents the density of the average 24-Hour PM2.5 estimates by year and for the sample period 2015-2018, zooming in to the area where PM2.5 is greater than 25 $\mu g/m^3$.

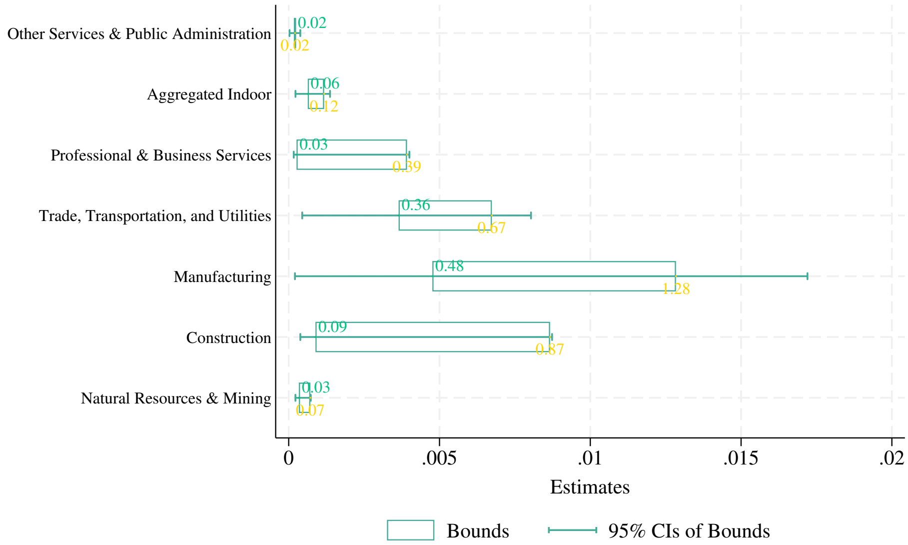

Fig. 3 Point Estimates and the 95% Confidence Intervals of Bounds by Industry

Notes: Figure 3 summarizes the estimated nonparametric bounds on the effect of PM2.5 pollution by industry, employing the heavy rainfall IV. Numbers aside the boxes presents the estimated lower (in green) and upper (in yellow) bounds in percentage points.

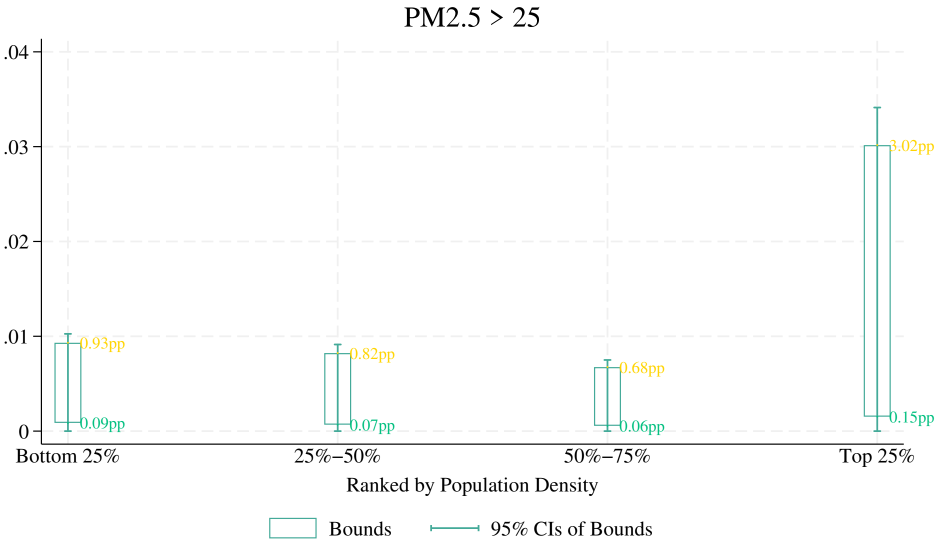

Fig. 4 Point Estimates and 95% Confidence Intervals of Bounds by Population Density

Notes: This figure presents the estimated nonparametric bounds on the effect of PM2.5 pollution by population density, employing the heavy rainfall IV. Numbers aside the boxes presents the estimated lower (in green) and upper (in yellow) bounds in percentage points.

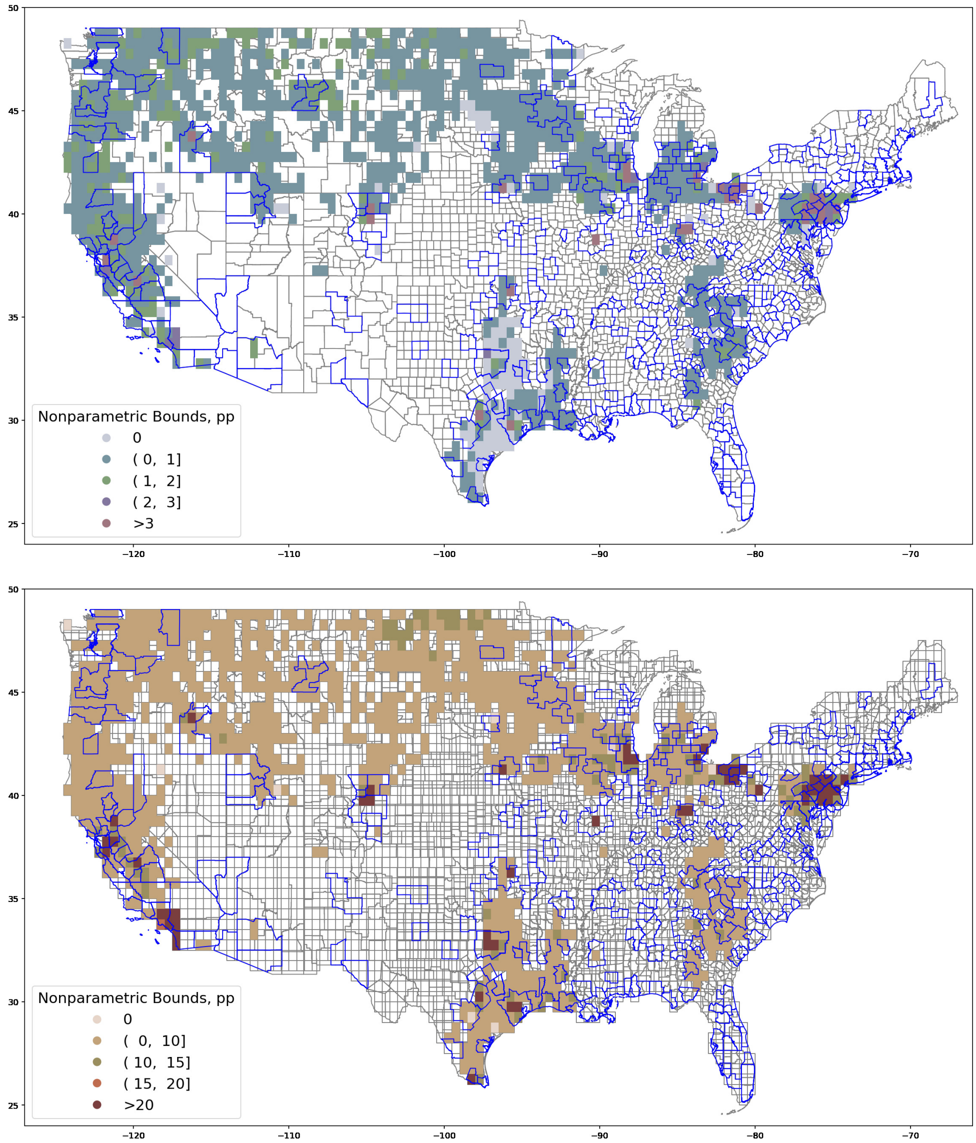

Fig. 5 Nonparametric Bounds for PM2.5 $> 25\mu g/m^3$ Under MTR Assumptions

Notes: This figure presents the estimated nonparametric bounds (in percentage points) on the effect of PM2.5$> 25\mu g/m^3$ by grid under the BOS, SDC, LEI, and MTR assumptions, employing the heavy rainfall IV. The upper panel plots the lower bound, while the bottom panel plots the upper bounds. Blue polygons flag the top 300 Core Based Statistical Areas (CBSAs) in terms of the total population in the Census 2010.

Table 1 Summary Statistics

Variable Name	Mean	Std.	Min	Max
Outcome Variable				
All Industries				
Accident Rate per 1 million population	0.34	38.22	0	30188.30
Y (Top Coded Accident Rate)	0.21	7.20	0	721.52
Treatment Variable				
PM2.5 Level ($\mu g/m^3$)	7.28	4.74	0.16	249.28
$D =$ PM2.5				
≤ 10	0.81	0.39	(N=3,287,373)	
$\in (10, 15]$	0.14	0.35	(N=577,413)	
$\in (15, 25]$	0.04	0.19	(N=155,834)	
> 25	0.01	0.08	(N=26,350)	
Instrumental Variable				
$Z : 1(Prcp \geq 7.6)$	0.09	0.29	0	1
Covariate				
Precipitation (Prcp, mm/day)	2.35	6.34	0	257.57
Wind Speed (m/s)	3.50	1.86	0	20.47
Temperature (°C)	13.15	11.15	-31.42	40.67
$1(Temperature \geq 30C)$	0.03	0.16	0	1
Visibility (Bad to Good: 1-4)	3.91	0.36	1	4
Population Count	112,291	350,461	1	9,205,318
Population Density (population/km^2)	51.89	192.72	0	6167.98
				N = 4,046,970

Notes: This table lists the sample mean, standard deviation, maximum, and minimum of the outcome variable, treatment variable, instrumental variable and covariates. Outcome variable is defined as the prevalence rate of workplace accidents that involve severe injuries and fatalities. To eliminate outliers, I define a top-coded accident rate at the 0.05th percentile in the right tail, denoted as Y. Treatment variable D is a categorical variable classifying the daily PM2.5 level into four groups. Covariates include precipitation, temperature, wind speed, visibility, population count, and population density.

Table 2 The Correlation Between Heavy Rainfall and PM2.5

	(1)	(2)	(3)
	$1(PM2.5 \in (10, 15])$		
$1(\text{Prcp} \geq 7.6)$	-0.152***	-0.152***	-0.150***
	(0.0017)	(0.0016)	(0.0016)
First Stage F Statistics	8547	8576	9077
	$1(PM2.5 \in (15, 25])$		
$1(\text{Prcp} \geq 7.6)$	-0.0553***	-0.0552***	-0.0551***
	(0.0008)	(0.0008)	(0.0008)
First Stage F Statistics	4708	4709	4727
	$1(PM2.5 > 25)$		
$1(\text{Prcp} \geq 7.6)$	-0.0067***	-0.0068***	-0.007***
	(0.0002)	(0.0002)	(0.0002)
First Stage F Statistics	929	929	939
Baseline Model	✓		
Baseline + Grid × DoW		✓	
Baseline + Grid × DoW + DoM × Month			✓

Notes: Standard errors are presented in parentheses. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$. Standard errors clustered at the grid level. All specifications include time-varying weather controls, and grid, month by year, and day of week fixed effects. All models are weighted by grid-level total population in 2015.

Table 3 Estimated Bounds from Nevo and Rosen (2012)

	(1)	(2)	(3)
	Outcome: Accident Rate (per million population)		
$PM2.5 \in (10, 15]$			
Point Estimates	(0.001, 0.005)	(0.001, 0.005)	(0.001, 0.005)
95% CI of Identified Set	[0.0005, 0.0078]	[0.0005, 0.0076]	[0.0006, 0.0077]
$PM2.5 \in (15, 25]$			
Point Estimates	(0.001, 0.012)	(0.002, 0.012)	(0.002, 0.013)
95% CI of Identified Set	[0.0006, 0.020]	[0.0007, 0.020]	[0.0008, 0.021]
$PM2.5 > 25$			
Point Estimates	(0.003, 0.089)	(0.003, 0.090)	(0.004, 0.093)
95% CI of Identified Set	[0.0009, 0.1549]	[0.0013, 0.1553]	[0.0018, 0.1569]
Baseline Model	✓		
Baseline + Grid × DoW		✓	
Baseline + Grid × DoW + DoM × Month			✓

Notes: This table summarizes the semiparametric bounds using the method of Nevo and Rosen (2012). Standard errors are presented in parentheses. For each treatment variable, the reference group is $PM2.5 < 10\mu g/m^3$. All specifications include time-varying weather controls, and grid, month by year, and day of week fixed effects. All models are weighted by grid-level total population in 2015.

Table 4 Estimated Bounds from Ban and Kédagni (2022)

	(1)	(2)
	Outcome: Accident Rate (per million population)	
	BOS, SDC, & LEI	*BOS, SDC, LEI & MTR*
$PM2.5 \in (10, 15]$		
Point Estimates	(-0.136, 0.215)	(0.004, 0.07)
95% CI of Identified Set	[-0.148, 0.229]	[0.000, 0.010]
$PM2.5 \in (15, 25]$		
Point Estimates	(-0.162, 0.480)	(0.003, 0.055)
95% CI of Identified Set	[-0.209, 0.532]	[0.000, 0.096]
$PM2.5 > 25$		
Point Estimates	(-0.186, 0.885)	(0.004, 0.055)
95% CI of Identified Set	[-0.264, 0.976]	[0.000, 0.061]

Note: This table shows nonparametric bounds estimated by Ban and Kédagni (2022) under the BOS, SDC and LEI assumptions, and the BOS, SDC, LEI, and MTR assumptions. For each treatment variable, the reference group is $PM2.5 < 10\mu g/m^3$.

Table 5 OLS and 2SLS Results

	(1)	(2)
	Outcome: Accident Rate (per million population)	
	OLS	2SLS
$PM2.5 \in (10, 15]$	0.0006***	0.005***
	(0.0002)	0.0015)
$PM2.5 \in (15, 25]$	0.0008**	0.013***
	(0.0003)	(0.0042)
$PM2.5 > 25$	0.0017**	0.093***
	(0.0007)	(0.0327)

Note: Standard errors are presented in parentheses. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$. Standard errors clustered at the grid level. The estimation uses the preferred model including time-varying weather controls, and grid, month by year, day of week, grid by day of week and day of month by month fixed effects. All models are weighted by grid-level total population in 2015.

Table 6 Estimation of Impacts on Workers' Compensation Costs

	(1)	(2)	(3)
t	$PM2.5 \in (10, 15]$	$PM2.5 \in (15, 25]$	$PM2.5 > 25$
$\hat{\beta}(t)$	(0.015, 0.382)	(0.012, 0.326)	(0.007, 0.34)
$C(t)$	(\$566,010, \$14,414,388)	(\$452,808 , \$12,301,284)	(\$264,138, \$12,829,560)

Note: $C(t)$ represents the change in annual workers' compensation costs associated with PM2.5 pollution in the contiguous United States. The estimated workers compensation costs per worker is set at \$114,000. $\hat{\beta}(t)$ denotes the estimated bounds on the effect of PM2.5 pollution as shown in Table 4 for a given t. The total U.S. population is based on the 2020 Census.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the author used ChatGPT in order to proofread and improve the language. After using this tool/service, the author reviewed and edited the content as needed and takes full responsibility for the content of the published article.

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Appendix A Data Appendix

Here, I discuss data sources and the data construction process in more detail. Workplace safety is measured by the prevalence rate of workplace accident involving severe injuries per 10,000 population. Data on the daily count of workplace accidents with severe injuries comes from two OSHA datasets: the Severe Injury Reports and Integrated Management Information System (IMIS) Enforcement Data.[21] Starting from January 1st, 2015, the Occupational Safety and Health Administration (OSHA) requires employers to report all severe work-related injuries, defined as an amputation, in-patient hospitalization, or loss of an eye. The reported severe injury records are compiled into a public-available dataset named the Severe Injury Reports by OSHA. The Severe Injury Reports (SIR) Data lists all employer-reported injuries with information on the date, address, and geographic coordinates of the accident. The IMIS Enforcement Data consists of closed OSHA inspection cases dated back to 1970s. Linking the inspection table, accident table, and injury table from the IMIS Enforcement Data allows researchers to observe work-related injuries. Like the Severe Injury Reports, the IMIS Enforcement Data contains the exact date and address of the accident and information about the injury associated with the accident.

To construct the grid-level measure of workplace accidents, I map accidents into the 0.5 degree scale raster using their geographic coordinates.[22] To obtain the workplace accident measure by industry, I classify accidents into 11 industry sectors by 2-digit NAICS codes. The classification of industries follows BLS which groups the 21 NAICS industry categories into two broad categories: goods-producing industries and service-providing industries, and several sub-groups within the two groups.[23] Appendix Table F2 lists a crosswalk of industry categories according to the 2-digit NAICS codes and the classification by BLS.

It is worth noting that unlike the self-report Workers' Compensation claims which are commonly used in studies on work safety, the administrative data used in this paper contains only workplace injuries associated with physical illness (compared to psychiatric or mental illness) that are severe, involving hospitalization and surgery.

As a measure of air pollution, daily PM2.5 data is retrieved from EPA's Fused Air Quality Surface Using Downscaling (FAQSD) dataset.[24] FAQSD is based on a scientific model (Bayesian space-time downscaler model) that projects the station-based atmosphere variables (e.g., PM2.5 and Ozone) to outputs at a finer scale.[25] Specifically, data from FAQSD provide a daily measure of ambient PM2.5 level at the 12 km scale. To merge the PM2.5 data with the workplace accidents data, I aggregate the daily PM2.5 data to the 55 km gridded raster by taking the average over all points within each 55 km grid cell.

[21] The Severe Injury Reports data used in this paper was downloaded on February 3rd, 2021 and IMIS Enforcement Data was downloaded on January 2nd, 2021.

[22] Since the IMIS data only provides addresses of accidents and does not contain information of geographic coordinates, I use the Google Maps API to search and acquire the longitude and latitude of each accident's address.

[23] BLS's classification can be found here: https://www.bls.gov/iag/tgs/iag_index_naics.htm.

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

[25] The model uses both the daily fine particulate air monitoring data from the national, state, and local air monitoring stations, and emission and meteorological data from the Community Multiscale Air Quality (CMAQ) model.

To create the instrumental variable, daily (24 hours) accumulation precipitation data are collected from the North American Regional Reanalysis (NARR, Mesinger et al., 2006), which is a long-term, consistent, high-resolution climate dataset for North America.[26] The raw data is at about 32 km scale. Like the PM2.5 data, the precipitation data is integrated into the 55 km $\times$ 55 km grid cells. Moreover, considering that the propensity of workplace incident may be affected by local weather conditions. to further control for time-varying near-surface meteorological conditions, I collect weather parameters such as daily average air temperature (in degrees Celsius), wind speed (m/s), and visibility from NARR.

Additionally, I collect demographic data from the Gridded Population of World (GPW).[27] GPW provides estimation of population density (number of persons per square kilometer) and population count based on counts consistent with national censuses and population registers. GPW data is available at various resolutions including the 0.5 degree scale, which allows me to merge it to the gridded raster data at hand. I am using the population count and population density for year 2015 which is the starting year of the sample. Acquiring the grid-level population density and count data helps me to explore the heterogeneity in the treatment effect across areas with high/low population density. One concern of the PM2.5 data is that PM2.5 in sparsely populated areas are poorly estimated due to the relatively smaller amount of monitors. In the empirical analysis, I present results restricted to areas with denser population.

Appendix B The IV Validity Test

Formally, consider the potential outcome model (Rubin, 1974) where $Y = Y_1 \cdot T + Y_0 \cdot (1 - T) \in \Upsilon \subset \mathbb{R}$. Y_1 and Y_0 are potential outcomes indicating the outcome with or without treatment. Here, Y denotes the workplace accident rate. Let T denote the binary treatment variable measuring the PM2.5 pollution.[28] Z denote the rainfall IV. Let T_z be the potential treatment if the IV had been exogenously set to $z = 0, 1$. Imbens and Angrist (1994) show that the IV method identifies the local average treatment effect under the following two assumptions.

Assumption LI. *(LATE Independence): (a) the quadruple* (Y_0, Y_1, T_0, T_1) *is jointly independent of* Z *and (b)* $P[T = 1|Z = 0] \neq P[T = 1|Z = 1]$.

Assumption LI states that the IV is correlated to the treatment variable but independent of the potential outcomes and the potential treatments. It implies that Z can only affect Y through its effect on T, i.e., the exclusion restriction. Empirically, one can verify the correlation between T and Z via a first-stage regression.

[26] NARR data used in this study is downloaded from the NOAA Physical Sciences Laboratory (PSL). For more information, see https://psl.noaa.gov.

[27] Center for International Earth Science Information Network - CIESIN - Columbia University (2018). For more information about the data, check its website https://sedac.ciesin.columbia.edu/data/set/gpw-v4-population-density-rev11.

[28] Since Mourifié and Wan (2017) applies only to a binary treatment variable, to facilitate the testing procedure, I transform the binned treatment variable D into three binary outcomes $D1$, $D2$, and $D3$, where $Dd = 1$ if $D = d$ and 0 if $D = 0$, for all $d \in 1, 2, 3$. In essence, this procedure mimics the inclusion of binary dummies for a categorical variable, with $D = 0$ serving as the reference group in linear regressions. The test is then conducted separately for each Dd, i.e., $T = Dd, \forall d = 1, 2, 3$.

Assumption LM. *(LATE Monotonicity): Either $T_0 \leq T_1$ almost surely or $T_0 \geq T_1$ almost surely.*

Assumption LM implies the absence of defiers. It asserts that exposing to heavy rainfall ($Z = 1$) should lead to lower PM2.5 level ($T = 0$) and vice versa for each grid-day cell.

To test the joint validity of assumptions LI and LM, Mourifié and Wan (2017) show that, under $T_0 \leq T_1$:

$$\theta(y, 1) = E[c_1 T(1 - Z) - c_0 TZ | Y = y] \leq 0 \tag{B1}$$

$$\theta(y, 0) = E[c_0(1 - T)Z - c_1(1 - T)(1 - Z) | Y = y] \leq 0 \tag{B2}$$

where $c_k = P(Z = k)$, $k = 0, 1$. Equations (B1) and (B2) are the testable sharp characterization of LI and LM assumptions. In other words, it can be shown that if LI and LM jointly hold, equations (B1) and (B2) hold. Hence, the null hypothesis for the valid IV test can be formulated as:

$$H_0 : \theta_0 = \sup_{v \in \nu} \theta(v) \leq 0, \quad H_1 : \theta_0 > 0 \tag{B3}$$

where $v \in \Upsilon \times \{0, 1\}$. θ_0 denotes the test statistic and one can test H_0 by testing whether θ_0 is less than or equal to zero. Mourifié and Wan (2017) implement this test by adopting the intersection bounds framework of Chernozhukov et al. (2013) to estimate nonparametric bounds on θ_0 and performing an intersection bounds test. The null hypothesis is rejected if a collection of lower intersection bounds of θ_0 is greater than zero.

I extend Mourifié and Wan (2017) to the panel data setting, incorporating covariates. Several practical problems emerge when applying the test in the context of this paper. First, this study uses a large panel dataset. Computing nonparametric bounds for a large sample requires a significant amount of computing power, rendering it empirically infeasible to perform the test using the entire sample. A practical solution to deal with this issue, as suggested by the applications in Mourifié and Wan (2017), is splitting the sample and separately conducting the test on each sub-sample. Second, it is more plausible to assume that the IV is independent of the potential outcomes and potential treatments conditional on covariates, due to the existence of confounders (either time-specific or grid-specific). That is, for covariates X with support χ, $(Y_0, Y_1, T_0, T_1) \perp Z | X = x$ and $P[T = 1 | Z = 0, X = x] \neq P[T = 1 | Z = 1, X = x], \forall x \in \chi$. As shown in Mourifié and Wan (2017), under conditional independence, for all $(x, y) \in \chi \times \Upsilon$, inequalities (B1) and (B2) become:

$$\tilde{\theta}(x, y, 1) = E[c_1(x)T(1 - Z) - c_0(x)TZ | Y = y, X = x] \leq 0 \tag{B4}$$

$$\tilde{\theta}(x, y, 0) = E[c_0(x)(1 - T)Z - c_1(x)(1 - T)(1 - Z) | Y = y, X = x] \leq 0 \tag{B5}$$

where $c_k(x) = P(Z = k | X = x)$. Covariates X can consist of multiple variables. For continuous X, they can be incorporated as additional conditioning variables. To accommodate discrete or categorical covariates, it involves dividing the sample according to the value of covariates and evaluating inequalities (B4) and (B5) on each sub-sample. For this paper, the desired covariates X should at least include time-varying weather conditions and month by year fixed effects to control for the seasonality pattern or time-specific confounders. However, it is empirically infeasible to simultaneously consider the weather controls and the grid- and time-specific confounders. Because to do this, the sample needs to be divided by grid, time, and covariates dummies, and the size of the sub-sample may become so small that the distribution of Z or the conditioning variable Y degenerates to a masspoint, making the sub-sample untestable. Since the null hypothesis for the entire sample, H_0, is defined as the intersection of null hypotheses for the sub-samples H_0^s, one would fail to test H_0 if the vast majority of sub-samples is untestable.

To handle these issues, I propose a pre-testing estimation procedure and implement the test separately for each grid. Specifically, I divide the sample into $S = 2770$ sub-samples by grid. In other words, the panel data is reduced to a set of time-series data for each grid. The null hypothesis H_0 then can be defined as $H_0 = H_0^{(1)} \cap H_0^{(2)} \cap \cdots \cap H_0^{(S)}$, where $H_0^{(s)}$ assumes that the IV is valid for sub-sample s. Rejection of any $H_0^{(s)}$ implies the rejection of H_0. In addition, to incorporate multiple categorical covariates, I propose a two-stage estimation procedure. In the first stage, I run a fixed-effects regression of the accident rate Y with granular grid and time fixed effects, and obtain the residuals $\hat{u}$:

$$Y_{ij} = \gamma_i + X_{ij} + \tau_{my} + \delta_{dow} + u_{ij}$$

where Y_{ij} denotes the accident rate and γ_i, τ_{my}, δ_{dow} represent the grid, month by year, and day of week fixed effects, respectively. X_{ij} are a vector of weather controls including daily average temperature, wind speed, etc.

Residuals $\hat{u}$ can be viewed as the adjusted accident rate where grid-specific and time-specific factors are partialled out. In addition, I demean the estimated residuals by subtracting their sample mean. Instead of conditioning on Y and multiple covariates X, I use $\hat{u}$ as the conditioning variable and compute the intersection bounds. Conditioning on a single variable $\hat{u}$ accelerates the testing process and provides a flexible way to accommodate the categorical covariates in testing.

Together, the implementation of the testing procedures can be summarized as follows:

1. Divide the sample into $S = 2770$ sub-samples. For each sub-sample, denote each observation as $i = 1, ..., n$ and the total number of observations as n.
2. For each sub-sample, conduct the test as follows:
   (a) Estimate c_1 and c_0 by $\hat{c}_1 = \frac{1}{n}\sum_{i=1}^{n} Z_i$ and $\hat{c}_0 = 1 - \hat{c}_1$, respectively.
   (b) Define $\hat{L}_i^1 = \hat{c}_1 T_i(1 - Z_i) - \hat{c}_0 T_i Z_i$ and $\hat{L}_i^0 = \hat{c}_0(1 - T_i)Z_i - \hat{c}_1(1 - T_i)(1 - Z_i)$.
   (c) Run the *clrtest* command (Chernozhukov et al., 2015) using the two moment inequalities. Specify $\hat{L}_i^1$ and $\hat{L}_i^0$ as the dependent variables for each conditional inequality, respectively. For the conditional independence assumption, specify $\hat{u}_i$ as the conditioning variable for both inequalities.
3. Define the null hypothesis as $H_0 = H_0^{(1)} \cap H_0^{(2)} \cap \cdots \cap H_0^{(S)}$, where $H_0^{(s)}$ suggests that the moment inequalities hold for sub-sample s. Rejection of a significant amount of $H_0^{(s)}$ implies the rejection of H_0.

The intersection bound test is based on local linear estimation. The choice of bandwidth and kernel functions is the same as in Mourifié and Wan (2017) and is recommended by Chernozhukov et al. (2015, 2013). Because the test is conducted for a large number of sub-samples, it is necessary to control the family-wise error rate (FWER) at targeted levels. I follow Mourifié and Wan (2017) and Holm (1979) and adapt a multiple testing procedure. For each test on the sub-sample, I subsequently check whether $H_0^{(s)}$ is rejected at the significance level 10%, 5%, 1%, 0.5%, 0.003%, and 0.0018% to find the marginal level of rejection. Any rejection of $H_0^{(s)}$ at the significance level 0.003% implies that H_0 is rejected with the FWER controlled by no greater than $0.003\% \times 2770 = 8.3\%$.[29]

Figures E3 presents results of the IV validity test for the rainfall IV. The marginal significance level is set at 0.003%, which gives the FWER at 8.3%.[30] Green flags grids where the null hypothesis is not rejected, while gray flags grids where the null hypothesis is rejected. Hatched red grid indicates no test is conducted, either because the outcome distribution reduces to a masspoint of zero or because the distribution of the IV indicator is degenerated to zero. Grids that are not in the sample are marked as white. The figure clearly shows that $H_0^{(s)}$ is rejected in most grids. Thus, H_0 for the entire sample is rejected at the conventional level, rendering the rainfall IV invalid.

Appendix C Implementation of Bounds Estimation

To estimate bounds derived by Nevo and Rosen (2012), first notice that according to the first-stage results, PM2.5 pollution is found to be negatively associated with the heavy rainfall IV, which implies $Cov(D, Z) < 0$. Therefore, Proposition 1 implies two-sided bounds. Because $Cov(Y_d, D), Cov(Y_d, Z) > 0$, the ATE is bounded between β_{IV}^{Z} (the lower bound) and $\beta_{IV}^{V(1)}$ (the upper bound), where $V(1)$ denotes the constructed weighted average of the invalid instruments, as defined in section 4.1. $\beta_{IV}^{Z} and \beta_{IV}^{V(1)}$ can be estimated using the standard 2SLS regression.

To implement Ban and Kédagni (2022) on a panel dataset, I adopt the following steps:

1. First, run a panel regression and obtain the residuals partialling out the fixed effects and covariates and demean the estimated residuals by subtracting their sample mean.
2. Second, to facilitate computation, divide the panel data by grid and obtain 2770 sub-samples.
3. For each grid j, following Ban and Kédagni (2022) to use the Stata command *clr3bound* (Chernozhukov et al., 2015) to estimate the nonparametric bounds and their 95% two-sided confidence set on the demeaned residual. Let's denote the estimated bounds under different assumptions as $LB_j^s(t) \le Y(t) \le UB_j^s(t)$, for each treatment $t \in \{0, 1\}$, sub-sample j,

[29] Any number below $10\%/2770 = 0.0036\%$ should work as a marginal significance level. For the main analysis, I pick the marginal significance level 0.003% to control the FWER at around 10%.

[30] It is an *ad hoc* choice to set the significance level at 0.003%. I choose 0.003% for the 2770 sub-samples to have a FWER around a conventional 10% level. Supplementary exercises that control the FWER at around 5% does not change the conclusion. The corresponding results are available upon request.

and assumption set $s \in \{\text{LEI, MTR}\}$.[31] Then the bounds on the average treatment effect of the sub-sample can be obtained as $LB^s_j(1) - UB^s_j(0) \leq \text{ATE}^s_j \leq UB^s_j(1) - LB^s_j(0)$.

4. ATE_j gives the heterogeneous effect of PM2.5 on the accident rate for each grid. One can obtain bounds on the average treatment effect for the entire sample by taking the average of the estimated bounds over all grids.

Moreover, the nonparametric bounds in Ban and Kédagni (2022) involve maximum and minimum operators. The regular inference procedure to estimate the confidence regions for bounds containing maximum and minimum operators suffers from bias in finite samples. Because the concavity (convexity) of the minimum (maximum) operator causes the sample estimates of bounds narrower relative to the corresponding true bounds. To obtain the correct confidence regions, I follow Ban and Kédagni (2022) and implement the valid-inference procedure proposed by Chernozhukov et al. (2013). The bounds estimators in Chernozhukov et al. (2013) are half-median unbiased in a sense that the estimated lower (upper) bound falls below (above) the true lower (upper) bound with a probability of at least one-half asymptotically. The resulting confidence intervals are valid for the true parameter of interest.

Appendix D Rainfall and Workers' Intertemporal Labor Supply

D.1 Data and Empirical Strategy

The data used for this complementary analysis combines two data sources: the American Time Use Survey (ATUS) data and the Daymet (Thornton et al., 2020). I extract workers' intertemporal labor supply (hours worked and work absence status) and their demographical, educational, and employment characteristics from the ATUS. I link the ATUS data to daily weather data utilizing the date of the diary day and the respondent's geographic location. The weather data comes from Daymet (Thornton et al., 2020), which provides weather parameters of daily surfaces of minimum and maximum temperature, precipitation, vapor pressure, radiation, snow water equivalent, and day length on a 1 km $\times$ 1 km gridded surface. I aggregate the Daymet data at the county level by taking the average of the Daymet observations that falls into the boundary of each county and merge the 2005-2019 ATUS data with the Daymet data using county FIPS codes. Table F4 reports the summary statistics.

To examine whether and to what extent employed workers change their work schedule with rainfall. I consider two outcomes: (a) working hours that measures time spend on work and work-related activities; (b) absenteeism measured by a binary indicator which equals one if the respondent were absent from work during the past seven days.[32] For the treatment variable, I consider the heavy rain defined as the daily accumulated precipitation exceeding 7.6 mm.

[31] For brevity, I use LEI and MTR to denote the assumption set of BOS + SDC + LEI and BOS + SDC + LEI + MTR.

[32] The ATUS only has a question about whether the respondent were absent from work in the past week. Work and work-related activities include time spend on activities in Categories 0501 and 0502. See American Time Use Survey Activity Lexicon 2003-2019 for the definition.

Formally, I use i, t, c to denote a respondent, a diary day, and the geographic unit the respondent resides, respectively. I estimate the following model:[33]

$$Y_i = \beta_0 + \beta_1 1(Prcp_{ct} > 7.6) + \gamma X_i + \sigma Z_{ct} + f(month, year, dow, c) + \varepsilon_i \tag{D6}$$

where Y_i measures the hours-worked (in minutes) for individual i on a diary day and $\mathbb{1}(Prcp_{ct} > 7.6)$ is the heavy rain indicator for location c on day t. Z_{ct} controls for other time-varying weather attributes that are potentially correlated with working hours, such as daylight and daily maximum and minimum temperature. X_i denotes a vector of individual-level covariates as listed in Table F4. $f(month, year, dow, c)$ includes day of week dummy variables to account for differences in schedules throughout the week and year and month dummy variables to control for seasonal and annual time trends in the intertemporal labor supply. It also includes location fixed effects that capture all time-invariant observable and unobservable attributes that affect labor supply decisions. The parameter of interests is β_1, which captures the changes in the hours-worked in days with heavy rainfalls.

To examine the effect of rainfalls on work absenteeism, I estimate the following model:

$$1(Absence) = \alpha_0 + \alpha_1 1(Prcp_{cw} > 30) + \gamma X_i + \sigma W_{cw} + f(month, year, c) + \varepsilon_i \tag{D7}$$

w denotes the week before the diary day t. Since the absent-from-work indicator is measured in the past week, I define a weekly level treatment variable as a binary dummy indicating that the accumulated precipitation in the past week is greater than 30 mm.[34] Z_{cw} denotes weekly weather attributes, including weekly mean daylight, the number of days when daily maximum temperature is greater than 35 degrees Celsius. Similar to β_1, α_1 captures the changes of the probability of work absenteeism with heavy rainfalls. Lastly, all models are conditional on employment, i.e., applying to employed individuals, and all estimates are weighted by the ATUS final weight.

D.2 Main Findings

I summarize the estimation results in Table F5. The first three columns present results for the hours-worked outcome, while the last two columns show results for the absent from work indicator.

Column (1) shows the result estimated by the employed individual sample. I do not find statistically significant effect of heavy rainfalls. Restricting to respondents who work in "outdoor" industries that usually requires workers to perform tasks in outdoor or semi-outdoor environments, Column (2) reports that workers work about 20 minutes fewer on days with heavy rainfalls.[35] Column (3) further restricts the sample to male workers and suggests that heavy rain is associated with a reduction in hours-worked of about 16 minutes. In addition, Column (4) suggests that having

[33] This is a similar model specification as in Connolly (2008); Graff Zivin and Neidell (2014).

[34] The daily accumulated precipitation at 7.6 mm is equivalent to having a heavy rain for about an hour.

[35] The outdoor industries are defined as Agriculture, forestry, fishing, and hunting, Mining, Construction, and Transportation and utilities. I classify respondents' working industry using the major industry code for the main job provided by the ATUS.

heavy rainfalls in the past week is associated with a statistically significant increase in the probability of work absence of about 0.3 ppts for employed respondents. For outdoor workers, the effect is larger at about 0.9 ppts and is statistically significant at the 10% level.

Results in Table F5 differ from the findings in Connolly (2008), who uses 2003 and 2004 ATUS data and finds no evidence that female workers adjust their intertemporal labor supply on rainy days, while on average male workers work about 30 minutes more on rainy days. However, these findings are not directly comparable to those in Connolly (2008), as i) although both studies use the ATUS data, we consider different sample periods: 2005-2019 in this paper and 2003-2004 in Connolly (2008); ii) we consider different treatments: Connolly (2008) define the treatment as having rainfalls of at least 0.1 inches over 24 hours, while I consider the treatment as heavy rainfalls with daily precipitation over 7.6 mm.

Appendix E Appendix Figures

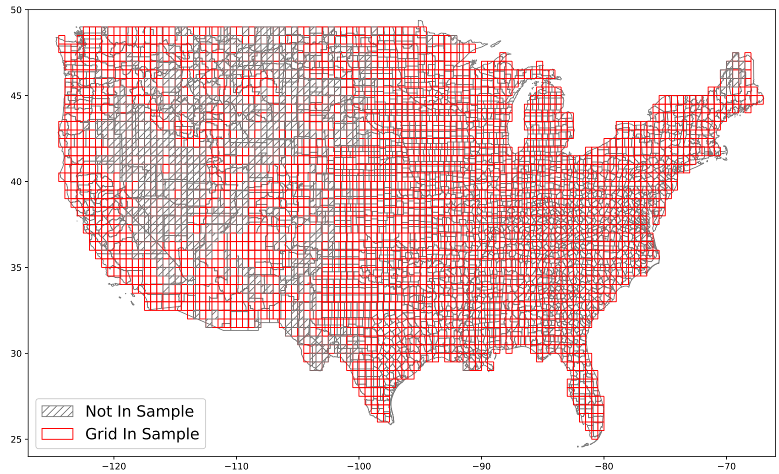

Fig. E1 Geographical Unit of Analysis

Notes: This figure presents the geographical unit of analysis. The contiguous US (excluding Alaska and Hawaii) is transformed into a raster with 4426 grids at 0.5 degree scale. Each cell is a square with width of about 55 kilometers, of about 3025 square kilometers (1168 square miles), and equivalent to areas combined Houston and Phoenix.

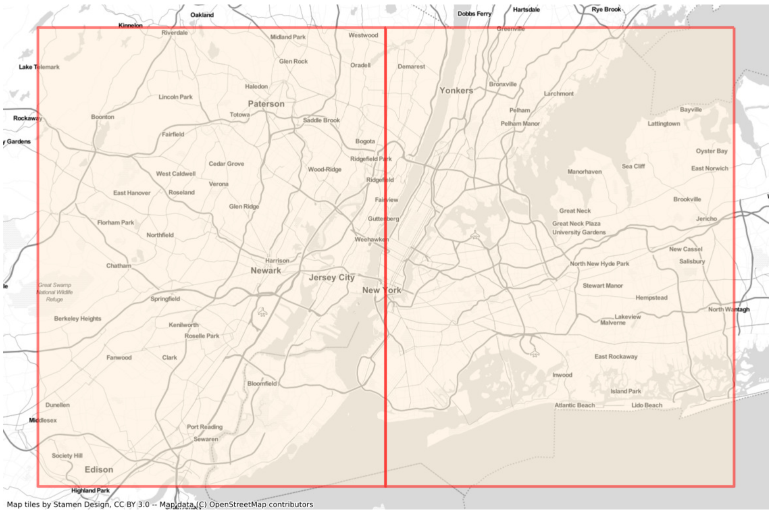

Fig. E2 An Example of the Geographical Unit of Analysis

Notes: This figure shows an example of two grids covering the New York city. In the analysis, I further remove grids whose population count is zero (and thus missing population density values) and grids whose weather condition measures are missing. The gray shaded areas are grids that are excluded from the analysis sample.

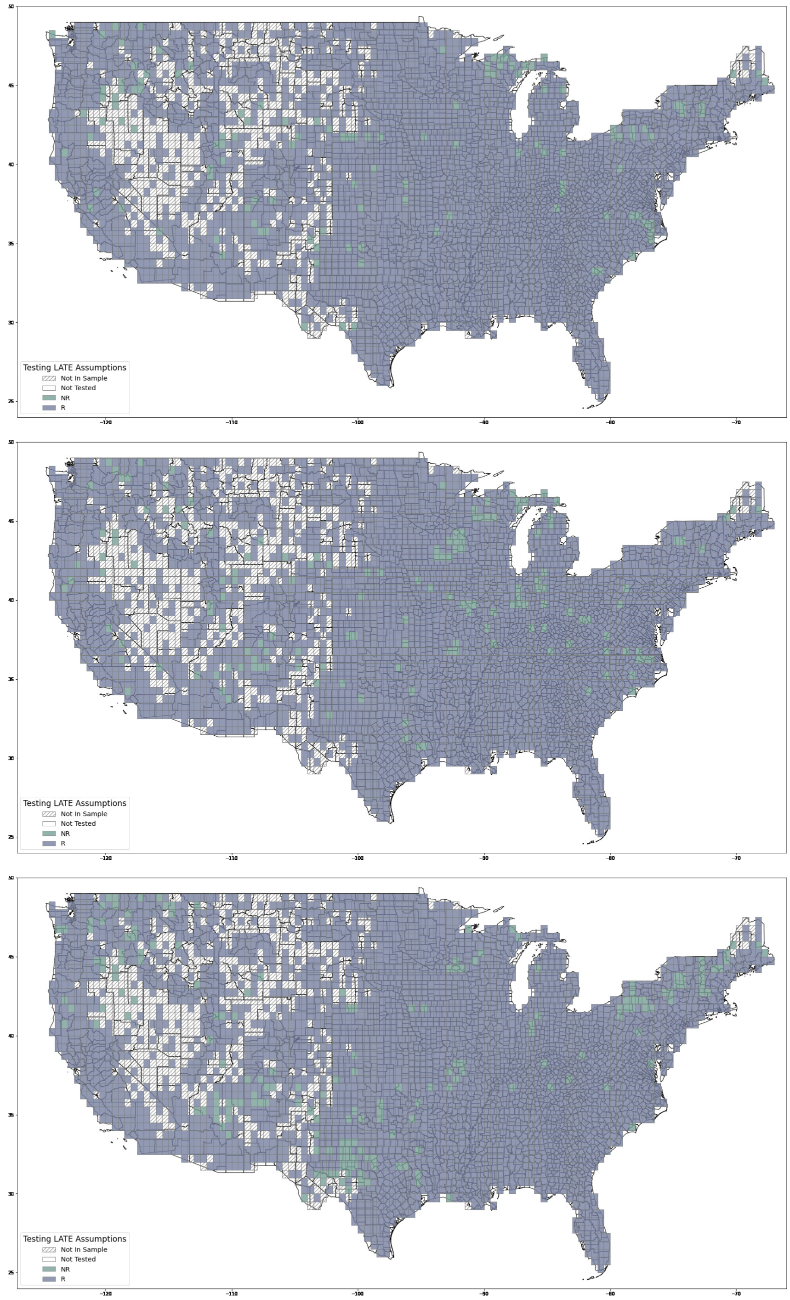

Fig. E3 Results of the IV Validity Test, Rainfall

Notes: This figure presents results of the IV validity test for the rainfall IV for the treatment D1, D2, and D3, respectively. The marginal significance level is set at 0.003%. Green implies that $H_0^{(s)}$ is not rejected, while gray suggests that $H_0^{(s)}$ is rejected. Hatched red grid indicates no test is conducted, either because the outcome distribution reduces to a masspoint of zero or because the distribution of the IV indicator is degenerated to zero. Grids that are not in the sample are marked as white.

Appendix F Appendix Tables

Table F1 Summary Statistics

Variable Name	N	Mean	Std.	Min	Max
By Industry					
Natural Resources & Mining		0.1395	27.31	0	26756.87
Construction		0.0485	12.42	0	14837.41
Manufacturing		0.0528	3.90	0	3732.02
Trade/Transportation/Utilities		0.0414	10.33	0	13530.29
Information		0.0012	0.36	0	405.60
Financial Activities		0.0028	3.38	0	6765.15
Professional and Business Services		0.0134	4.59	0	7683.68
Education & Health		0.0054	1.71	0	2523.38
Leisure & Hospitality		0.0135	10.28	0	14847.23
Other Service		0.0047	3.64	0	6765.15
Public Administration		0.0136	15.18	0	30188.30
By Year					
2015	10,11,050	0.2513	25.54	0	14847.23
2016	1,013,820	0.2418	32.24	0	26756.87
2017	1,011,050	0.4104	38.99	0	14837.41
2018	1,011,050	0.4433	51.30	0	30188.30
By Month					
January	343480	0.4215	38.22	0	7651.08
February	313010	0.2178	14.42	0	6765.15
March	343,480	0.3437	39.62	0	13530.29
April	332,400	0.3750	41.30	0	15143.70
May	343,480	0.3083	32.08	0	13530.29
June	332,400	0.3965	60.51	0	30188.30
July	343,480	0.3351	25.34	0	6765.15
August	343,480	0.3958	41.78	0	14837.41
September	332,400	0.3133	27.66	0	6765.15
October	343,480	0.3607	53.62	0	26756.87
November	332,400	0.3155	34.65	0	15367.35
December	343,480	0.2482	24.53	0	6765.15
By Day of Week					
Sunday	578,930	0.1611	27.24	0	13530.29
Monday	578,930	0.4255	53.34	0	30188.30
Tuesday	576,160	0.4447	43.24	0	14847.23
Wednesday	576,160	0.3396	25.33	0	6765.15
Thursday	578,930	0.3403	23.13	0	7651.08
Friday	578,930	0.3169	23.84	0	7683.68
Saturday	578,930	0.3292	54.95	0	26756.87

Notes: This table presents the mean, standard deviation, maximum, and minimum of the accident outcome variables by industry, year, month, and day of week.

Table F2 Industry Category Crosswalk

NAICS Code	Industry Title	Industry Name in Paper
Goods-Producing Industries:		
11	Agriculture, Forestry, Fishing and Hunting	Natural Resources & Mining
21	Mining	
23	Construction	Construction
31-33	Manufacturing	Manufacturing
Service-Providing Industries:		
42	Wholesale Trade	Trade, Transportation, and Utilities
44-45	Retail Trade	
48-49	Transportation and Warehousing	
22	Utilities	
51	Information	Information
52	Finance and Insurance	Financial Activities
53	Real Estate Rental and Leasing	
55	Management of Companies and Enterprises	Professional & Business Services
56	Administrative and Support and Waste Management and Remediation Services	
54	Professional, Scientific, and Technical Services	
61	Educational Services	Education & Health
62	Health Care and Social Assistance	
71	Arts, Entertainment, and Recreation	Leisure & Hospitality
72	Accommodation and Food Services	
81	Other Services (except Public Administration)	Other Services
92	Public Administration	Public Administration

Note: This table lists the crosswalk mapping the 21 industries classified by 2-digit NAICS to the 11 industry sectors defined by BLS. See BLS's website (https://www.bls.gov/iag/tgs/iag_index_naics.htm) for more details. The industry category used in this paper is the same as BLS's classification.

Table F3 Summary of Related Literature

Study	Country	Context	Pollutant	Outcome Measure	Key Findings
Hattemer and Moreno-Martinez (2025)	Spain	Saharan dust exposure and workplace accidents	PM10	Accident claims at the municipality-day level, 2015–2019	Experiencing one day of Saharan dust increases workplace accidents by 1.2%. A dust event raises PM10 concentrations by about 12 $\mu g/m^3$ on average.
Lavy et al. (2022)	Israel	Nitrogen dioxide exposure at construction sites	NO_2	Accidents at the site-day level, 2017–2019	A 10-ppb increase in NO_2 raises the likelihood of an accident by up to 25%. The effect is non-linear: accident probability nearly quadruples when NO_2 exceeds "unhealthy" levels (above the 99th percentile) relative to "clean" levels (below the 95th percentile).
Palma et al. (2024)	Italy	Air quality variation driven by winter heating and atmospheric dispersion	PM10 and AQI	Work-related accidents and disabilities at the municipality-day level, 2014–2018	A one-unit increase in PM10 causes 0.0065 additional accidents (equivalent to a 0.08% change relative to the sample mean), with no effect on disabilities.
Cabral and Dillender (2024)	Texas, United States	Wildfire smoke exposure and occupational injuries	PM2.5	Texas workers' compensation injury claims at the commuting-zone-day level, 2005–2018	An additional day of smoke exposure increases workplace injury claims by 2.8%. Similar percentage increases occur across injury types and worker groups.
Dillender (2021)	Texas, United States	Temperature and occupational injuries	—	Texas workers' compensation claims at the MSA-day level, 2006–2014	Both high and low temperatures increase injury risk. Days at 86–88°F raise three-day claim rates by 2.1–2.8% relative to 59–61 °F, temperatures above 100°F raise rates by 3.5–3.7%, and temperatures below 35°F raise rates by 3.4–5.8%.
Park et al. (2021)	California, United States	Temperature and occupational injuries	—	California workers' compensation claims at the ZIP-code-day level, 2001–2018	A day with high temperatures between 85 and 90 °F leads to a 5 to 7 percent increase in same-day injury risk, relative to a day in the 60's. A day above 100°F leads to a 10 to 15 percent increase.

Table F4 Summary Statistics: Rainfall and Intertemporal Labor Supply

	N	Mean	Std.	Min	Max
Intertemporal Labor Supply:					
Working Time (in Minutes)	175893	155.27	239.73	0	1380
1(Absence)	175893	0.03	0.16	0	1
Weather:					
1($Prcp > 7.6$)	175893	0.31	0.46	0	1
Minimum Temperature (C)	140059	7.56	10.05	-38	33
Maximum Temperature (C)	140059	20.31	10.67	-22	49
Accumulated Precipitation (mm/day)	140059	3.05	7.91	0	185
Day Length (s/day)	140059	43077.26	6685.32	28921	57432
1($Prcp$Last Week > 30)	175893	0.40	0.49	0	1
# Days Max Temp > 35 Last Week	140059	0.32	1.23	0	7
Avg Prcp Last Week	140059	21.11	27.69	0	899
Avg Day Length Last Week	140059	43051.70	6688.40	29053	57468
Covariates:					
Diary day a holiday	175893	0.02	0.13	0	1
Male	175893	0.44	0.50	0	1
Married	175893	0.50	0.50	0	1
Has Child < 18	175893	0.45	0.50	0	1
Age	175893	47.84	17.90	15	85
% Age > 65	175893	0.19	0.39	0	1
Employed Part-Time	175893	0.13	0.34	0	1
Paid Hourly	175893	0.30	0.46	0	1
% Reside in Urban Area	175893	0.83	0.38	0	1
% Hispanic	175893	0.14	0.35	0	1
% Black	175893	0.14	0.35	0	1
% Asian	175893	0.04	0.19	0	1
% < High School	173876	0.14	0.34	0	1
% High School Graduate	173876	0.26	0.44	0	1
% Some College	173876	0.48	0.50	0	1

Table F5 The Effect of Rainfalls on Workers' Intertemporal Labor Supply

	(1)	(2)	(3)	(4)	(5)
	Working Time			1(*Absence*)	
	Employed	Outdoor	Outdoor & Male	Employed	Outdoor
1($Prcp_{ct} > 7.6$)	0.0628	-19.70***	-16.17**		
	(2.229)	(7.057)	(7.980)		
1($Prcp_{cw} > 30$)				0.00333**	0.00913*
				(0.00161)	(0.00493)
N	86690	9929	7936	86690	9929

Notes: Standard errors in parentheses. * p<0.10 ** p<0.05 *** p<0.01. Variable "Working Time" is measured in minutes.