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Air pollution and workplace accidents: Evidence and implications

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HIGHLIGHTS

- We study how air pollution affects workplace accidents in Italy (2014–2018).
- A 10-unit increase in PM_{10} causes 0.073 additional accidents (elasticity of 0.12).
- Effects are driven by less severe accidents, with no impact on permanent disabilities.
- About 60 % of compensation claim costs for air pollution-induced accidents are borne by employers.
- Very young workers (ages 15–25) exhibit strong effects from air pollution.

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ABSTRACT

We estimate the impact of air pollution on workplace accidents and permanent disabilities in Italy, a setting characterized by stringent air pollution and work safety regulations. Using daily administrative data between 2014 and 2018, we leverage winter heating regulations and atmospheric dynamics to address the endogeneity of air pollution generation and exposure. We find an elasticity of accidents with respect to particulate matter (PM_{10}) of 0.12 and estimate no effect of pollution on disabilities. Using age groups as a proxy for work experience, we find larger impacts for less experienced workers. Increasing PM_{10} by 10 μg/m^3 would raise the average cost of an accident by 78 euros (7.3 %); employers bear 60 % of this cost, and public insurers bear 40 %.

1. Introduction

According to the International Labor Organization (ILO), workplace accidents (WPA, hereafter) cause approximately 320 million non-fatal injuries and two million deaths worldwide each year. WPA impose substantial social costs and lead to severe losses of human capital and job-specific skills, hindering both economic and social development (Pouliakas and Theodossiou, 2013).[1]

Although workplace accidents linked to production processes are well studied (e.g. Galizzi, 2013), environmental factors remain under-examined despite their growing impact on workplace safety. Understanding these factors is crucial for policymakers and employers to improve safety and assess the true costs of environmental externalities. In particular, the causal effect of extreme temperatures on workplace injuries has been investigated across various contexts (Behrer et al., 2021; Dillender, 2021; Drescher and Janzen, 2025; Filomena and Picchio,

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[1] Recent ILO estimates indicate that workplace accidents and illnesses result in the loss of 3.9 % of total work-years globally, corresponding to an economic cost of about USD 2.68 trillion.

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2024), whereas evidence on the effects of air quality is only beginning to emerge (Lavy et al., 2022; Cabral and Dillender, 2024). This paper is among the first to provide quasi-experimental, nationwide evidence on the impact of air pollution on WPA, its associated costs, and implications for employers' optimal cost-minimization strategies in a context of stringent air quality and workplace safety regulations.

We match Italian administrative data on the universe of workplace accidents in eight regions (2014–2018) at the municipal level with air pollution measures from monitoring stations. Using an original instrumental variable (IV) framework that leverages variation in winter heating periods and the height of the Planetary Boundary Layer (PBL), we find that a 10-unit increase in PM_{10} leads to 0.073 additional accidents (elasticity of 0.12), with no significant effect on permanent disabilities. This result is robust to various model specifications that account for overall air quality measured by the Air Quality Index (AQI), extreme weather events, the skewed distribution of accidents, the exclusion of most risky sectors, and the inclusion of controls for labor force composition or injured workers' characteristics. We also provide a rich heterogeneity analysis by age group, gender and sector of the economy. On the first margin, we find that young workers (aged 15–25), who are likely to have weaker labor market attachment and less job experience, are as adversely affected by pollution-related WPA as older workers. By gender, the effects for men are only slightly larger than those for women. As for the sectoral dimension, the effects are stronger in traditionally higher-risk sectors such as manufacturing and construction. Importantly, we find that air pollution also affects less risky sectors such as services, which implies that risk mitigation regulations related to air quality in the workplace should also be adopted in sectors often considered 'safe'.

In addition, we find that approximately 63 % of air pollution–related accidents are non-severe, involving absences from work of fewer than four days. Based on these estimates and official statistics from the European Agency for Safety & Health at Work (EU-OSHA), we present a back-of-the-envelope calculation of the costs associated with pollution-induced WPA, distinguishing between the share borne by employers and the share covered by the public insurer in a setting with mandatory workplace insurance and a mixed compensation scheme. We calculate that a 10-unit increase in PM_{10} is associated with an increase of approximately 78 euros per employed person/year, corresponding to about 7.3 % of the total cost of an accident. Of this amount, about 60 % is borne by employers, while the remaining share is covered by the public insurer.

Our paper provides three main contributions. First, it adds to the literature examining the less visible effects of air pollution on the labor market, which so far has mainly focused on productivity losses and sickness-related absences. We extend the documented effects of air pollution to workplace safety—a key labor market outcome—by estimating its impact on workplace accidents and permanent disabilities. A growing body of economic studies shows that, besides the health effects (Carozzi and Roth, 2023; Deryugina et al., 2019; Giaccherini et al., 2021; Pestel and Wozny, 2021; Schlenker and Walker, 2015; Simeonova et al., 2018), air pollution can exert significant, less visible, 'non-health' impacts (Aguilar-Gomez et al., 2022). These include reductions in labor supply (Hanna and Oliva, 2015) and on-the-job performance (Archsmith et al., 2018; Chang et al., 2016; Fu et al., 2021; Graff Zivin and Neidell, 2012; Huang et al., 2020; He et al., 2019), attention deficits and lower cognitive ability (Ebenstein et al., 2016; Künn et al., 2023; Heissel et al., 2020; Sager, 2019; Zhang et al., 2018), and altered behavior (Bondy et al., 2020; Persico and Marcotte, 2022), to mention a few. These subtle impacts affect a large fraction of the population and result in sizable losses for economic growth and excess health expenditures.

Two main health mechanisms underlie these findings. Particle pollution (PM_{10} and $PM_{2.5}$) is associated with inflammation and oxidative stress processes occurring in the brain and also affecting the central nervous system (Kleinman and Campbell, 2014; Genc et al., 2012). In addition, pollution particles can directly move to the circulatory system, impairing respiratory function as well as blood flow and circulation (Mills et al., 2009; Dockery and Pope, 1994; Seaton et al., 1995). Due to intensive aerobic metabolic processes, brain requires a disproportionate amount of energy compared to its body mass (Özugur et al., 2020). Therefore, brain reacts very sensitively to oxygen deficiency, affecting mental acuity and cognitive performance (Clarke, 1999; Calderón-Garcidueñas et al., 2008).[2] In this paper, we hypothesize that when individuals perform job tasks, these physio-pathological mechanisms can cause fatigue, impaired memory, reduced concentration and judgment, and attention deficits, thereby increasing the risk of workplace accidents.

Two contemporaneous studies tackle a similar question in different contexts or specific economic sectors. Lavy et al. (2022) find that high concentrations of nitrogen dioxide (NO_2) – a gas produced during the combustion of fossil fuels at high temperatures – increase the number of accidents at construction sites in Israel. Cabral and Dillender (2024) estimate that an additional day of wildfire smoke exposure – which raises $PM_{2.5}$ concentrations by nearly 20 % – leads to a 2.8 % increase in workplace injury claims in Texas, with a 10-unit increase in $PM_{2.5}$ resulting in aggregate costs of up to two billion USD. Our paper complements these studies by assessing the impact of air pollution introducing an original identification strategy based on instrumental variables that exploit exogenous variation in both pollution generation and its concentration in the air.

While the dispersion of air pollution largely depends on uncontrollable factors such as atmospheric dynamics, its generation is mainly anthropogenic and driven by specific sources.[3] This represents an empirical challenge because fluctuations in pollution concentrations co-vary with the economic activity. An increase in the economic activity may induce workers to produce more, increasing the probability of WPA. At the same time, if workers produce more, they also pollute more. To break this simultaneity bias, several studies employ a single instrument that targets either the pollution generation-related bias (Almond et al., 2009; Fan et al., 2020) or the dispersion-related bias using, for instance, exogenous variation in wind direction and speed or thermal inversions (Deryugina et al., 2019; Sager, 2019).

Our IV approach combines winter heating regulations to capture variation in pollution generation, and atmospheric dynamics to model dispersion. The first IV leverages the institutional setting in Italy, where winter heating largely relies on the combustion of fossil fuels and is strictly regulated by law at the municipal level. The second IV is the height of the planetary boundary layer (PBL), the lowest part of the Earth's atmosphere, which plays a crucial role in determining the concentration of pollutants in the atmosphere. A higher PBL provides more space for the vertical dispersion of pollutants, while a lower PBL leads to the accumulation of pollutants near the surface.[4] This approach is potentially replicable in other contexts, as winter heating regulations are common in several countries (including areas of the US, Canada, and China), and PBL dynamics is a continuous atmospheric phenomenon that occurs globally and can be universally utilized in empirical analysis.

As a second contribution, we analyze the theoretical and empirical implications of increased WPA risk due to air pollution in relation to employers' optimal investment decisions, which can mitigate the costs associated with workplace accidents. This dimension has been largely overlooked, despite its relevance: employers may be, at least partially, liable for compensating injured workers. Understanding whether, and to what extent, these costs are borne by employers or shifted to third parties

[2] Studies using neuroimages to analyze *in vivo* effects document that air pollution affects the functioning of cerebral white matter, cortical gray matter, and basal ganglia, causing cognitive changes (de Prado Bert et al., 2018).

[3] For instance, other studies exploit road transport (Bauernschuster et al., 2017; Giaccherini et al., 2021), air transport (Schlenker and Walker, 2015) or boat traffic (Moretti and Neidell, 2011).

[4] Although we are not the first to use the PBL height as an instrument for air quality (Godzinski and Castillo, 2021), its combined use with pollution generation instruments has never been adopted.

(e.g. the public insurer) is crucial for optimizing cost-minimization strategies and guiding investment in workplace safety. Employers internalize accident-related costs by investing in safety until the marginal cost equals the expected marginal benefit from reduced accidents. Air pollution, however, introduces an external risk about which employers may not be fully informed. While they remain responsible for ensuring safe working conditions and providing accident insurance, the allocation of compensation costs varies across institutional contexts and insurance schemes.[5]

If employers bear all or part of these costs, they may have an incentive to respond to environmental risks deriving from a 'public bad', by investing in workplace safety measures that limit their own exposure to pollution as part of a strategy to minimize private costs.[6] Since no clear empirical evidence currently exists on who bears the costs of pollution-induced accidents, the employer's optimal investment strategy remains uncertain. To address this issue, we present a theoretical framework to characterize the employer's optimal investment strategy, using a cost function that accounts for the number and cost of pollution-induced WPA. This allows us to derive a cost-minimization strategy under air pollution risk, along with an insurance scheme that defines the employer's share of these costs.

Following this theoretical framework, the empirical analysis estimates the number of accidents attributable to WPA, the associated compensation costs, and the share of those costs borne by employers. We do this by leveraging the institutional setting in Italy, where employers are directly responsible for compensating less severe accidents, i.e. those resulting in fewer than four days of absence, while more severe accidents are covered by the public insurer. Our estimates show that approximately 63 % of total pollution-induced WPA are mild and result in costs borne directly by employers. This implies that when employers are responsible for covering accident costs, they may have strong economic incentives to internalize these costs through preventive safety investments, such as masks or air filtration systems.

The third contribution is a comprehensive heterogeneity analysis based on universal data on workplace accidents covering the entire Italian workforce. This enables us to expand existing evidence on how air pollution affects workplace safety across different population groups. In doing so, the paper also contributes to the literature on environmental inequality and the distributional impacts of pollution exposure, commonly framed within the environmental justice perspective (Banzhaf et al., 2019b,a; Drupp et al., 2025; Hausman and Stolper, 2021; Shapiro and Walker, 2021). Most existing studies have focused on how pollution burdens are unevenly distributed across communities or demographic groups. We extend this perspective to the workplace dimension by documenting systematic heterogeneity in the effect of air pollution on workplace accidents across age, gender, and sectors. Overall, our effects heterogeneity analysis suggests a pervasive impact of air pollution and extends the finding of a "near universal" effect in Cabral and Dillender (2024), who examine risk distribution across occupations and injury types. At the same time, the significant and sizable effects found for some more vulnerable categories, such as younger workers, echo the concern that environmental and occupational risks may interact to amplify inequality in the labor market.

The remainder of the paper is organized as follows. Section 2 outlines the theoretical framework. Section 3 describes the data. Section 4 presents the econometric strategy, and Section 5 discusses the main results. Section 6 estimates the costs of pollution-induced accidents. In Section 7, we conduct a series of robustness checks and explore alternative model specifications to validate our findings. Section 8 concludes with the policy implications.

2. Air pollution, workplace accidents and employer's incentives

In this section, we present a simple theoretical framework illustrating how air pollution—an external and often invisible risk factor—can account for a share of observed workplace accidents and influence employers' safety investments. Because exposure and its effects on accident probability are not directly observable within the firm, information asymmetry may lead employers to underestimate pollution-related risks and adopt suboptimal prevention levels. As noted by Hausman and Stolper (2021), incomplete or distorted information about air quality can systematically bias agents' behavior, a mechanism that may similarly apply to firms facing latent pollution risks in the workplace.

The framework informs the empirical analysis in two ways. First, it yields a testable implication: if employers determine their safety investments based on observed workplace accidents without recognizing that part of these accidents stems from unobserved pollution exposure, then accident rates should systematically increase with air pollution. This allows us to identify whether pollution acts as a hidden component of workplace risk. Second, conditional on this effect, the framework clarifies the interpretation of the cost implications—specifically, how the burden of pollution-induced accidents is distributed between employers and the public insurer under a mixed compensation scheme.

We start by defining a cost function that incorporates the costs of accidents deriving from two risk components: employer's activities and air quality. In addition, we separate the cost shares under a mixed compensation scheme.[7] Let CA denote the compensation cost of workplace accidents.[8] While in most countries employers are required to insure their workers against WPA, the responsibility for covering compensation costs may fall on the employer, the public insurer (i.e., the state through a national insurance plan), or both, depending on the institutional setting. In a mixed compensation scheme, a share $\alpha \in [0,1]$ of CA is borne by the employer (CA_E), while a share $(1-\alpha)$ is borne by the public insurer (CA_P):

$$CA = \alpha\, CA_E + (1-\alpha)\, CA_P. \tag{1}$$

In our setting, α is exogenous (set by the law) and it is equal to 1 if the injury is classified as minor, i.e. the sick leave is less than four working days. The employer's optimization problem is to choose the optimal workplace safety level s^* that minimizes the cost function:

$$\min_s CA_E[\gamma(s), \phi(s)] + CS(s) \tag{2}$$

where $s \in (0, \infty)$ is the level of safety at the workplace, with $\underline{s} > 0$ being the minimum level set by current regulations and $\bar{s}$ the maximum safety level achievable by current technology such that $\underline{s} < \bar{s}$. γ is a function representing all risk factors internal to the employer, with $\gamma(\cdot) > 0$ and

[5] For instance, in the US, workers' compensation insurance is regulated at the state level. Employers are generally required to purchase private insurance policies or participate in state-run funds. In some cases, they may opt for self-insurance, taking on direct responsibility for compensation costs. In Canada, costs are covered by the Workers' Compensation Board, but employers may face higher premiums based on their accident history. In France, employers pay the worker's salary only on the day of the accident, but they may be required to contribute further in cases of negligence or direct liability.

[6] While employer-level responses may offer some protection, uncoordinated and decentralized action is generally less effective than centralized regulation. For instance, smaller employers may lack access to reliable information on air pollution risks or face higher relative costs in implementing safety investments, leading to uneven levels of protection and a higher disparity across employers.

[7] Although we focus on air pollution, this theoretical framework can be extended to other types of environmental risks that are not always directly caused by individual firms, such as extreme temperatures.

[8] The compensation cost of accidents CA is equal to the sum of the cost of each single accident c_i experienced by the employees within a year, with $i = 1, \ldots, N$:

$$CA = \sum_{i=1}^{N} c_i$$

$\gamma'(\cdot) < 0$. ϕ is a function that incorporates the environmental risk of accidents deriving from exposure to poor air quality. The employer might fail to account for this additional risk factor due to a lack of information. Nonetheless, this risk can be reduced by increasing the level of defensive investments s. Similarly to the other risk factors, ϕ is assumed to be continuously differentiable and non-decreasing in s, with $\phi(\cdot) > 0$ and $\phi'(\cdot) < 0$. CA_E is the function representing the compensation cost of accidents borne by the employer, assumed to be continuous, differentiable and non-decreasing in γ and in ϕ. Finally, CS is the cost of defensive investments aimed at increasing safety for risks unrelated to environmental factors, which is continuous and differentiable in s, with $CS(\cdot)' > 0$.

The optimal safety level s^* is achieved by balancing the marginal cost (MC) of defensive investments and the related marginal benefit (MB) in terms of expected reduction of WPA, by satisfying the following first-order condition (FOC):

$$\frac{\partial CA_E}{\partial \gamma}\frac{\partial \gamma}{\partial s} + \frac{\partial CA_E}{\partial \phi}\frac{\partial \phi}{\partial s} = -\frac{\partial CS}{\partial s}. \tag{3}$$

The left-hand side of Eq. (3) represents the MB stemming from the expected marginal reduction in accident costs owing to a marginal increase in the level of safety, while the right-hand side represents the MC of additional safety.[9] In the model, an employer that does not consider air pollution-related risk factors, fails to account for the component $\frac{\partial CA_E}{\partial \phi}$ when determining s^*, thereby reducing the associated MB. This behavior is justified if air pollution has no effect on WPA, i.e. $\frac{\partial CA_E}{\partial \phi} = 0$, otherwise it results in a suboptimal level of defensive investment. If $\frac{\partial CA_E}{\partial \phi} > 0$, an informed employer should optimally increase s if specific technologies are available to mitigate exposure to poor air quality in the workplace, as this additional investment would reduce the expected cost of accidents borne by the employer.[10]

In our cost analysis, we approximate the derivative $\frac{\partial CA_E}{\partial \phi}$ by estimating the number of WPA attributable to a marginal increase in air pollution, measured in terms of PM_{10} concentration levels at the workplace. More precisely, our dataset provides the observed number of accidents, N. Defining the average cost of an accident as $\bar{C}$, we can rewrite Eq. (1) as:

$$CA = N\bar{C} = \alpha N_E \bar{C} + (1-\alpha) N_P \bar{C} \tag{4}$$

where N_E are the accidents causing a sick leave of fewer than four working days and compensated by the employer, and N_P represents all other accidents compensated by the public insurer.

Whether, and to what extent, air pollution generates costs due to WPA, and who bears the costs of these accidents, represent two important empirical issues. In Section 5 we address the first question showing that air pollution significantly affects the number of WPA by providing an explicit estimate of the change in N caused by a marginal change in ϕ, i.e. $\frac{\Delta N}{\Delta \phi}$. In Section 6 we disentangle the effect of a marginal change in pollution exposure on N_E and N_P, i.e. $\frac{\Delta N_E}{\Delta \phi}$ and $\frac{\Delta N_P}{\Delta \phi}$, finding that $\frac{\Delta N_E}{\Delta \phi} > \frac{\Delta N_P}{\Delta \phi}$.

In our setting characterized by a mixed compensation scheme, this implies that employers are more affected by mild pollution-induced WPA, as these accidents disproportionately increase with pollution exposure and their compensation costs are typically borne by the employers rather than the public insurer. To the best of our knowledge, this is the first study to precisely disentangle these two components. This distinction is crucial for understanding employers' incentives to (under)invest in safety equipment that can prevent pollution-induced WPA.

[9] We assume that all functions are such that second-order conditions are satisfied.

[10] The level of investment s set by the employer is equal to s^* only if $s^* > \underline{s}$, i.e. the minimum level of safety set by the law, and it is equal to $\underline{s}$ otherwise.

3. Data

3.1. Work related accidents

We use administrative data on the universe of accidents occurring in Italy provided by the Italian National Institute for Insurance against Accidents at Work (INAIL). The same data were employed in Alacevich and Nicodemo (2023) and Filomena and Picchio (2024). WPA are defined as external traumatic events on the job that cause an injury (Italian Legislative Decree 38/2000). An injury can lead to temporary work disability, permanent work disability (complete or partial), or death. Throughout the analysis, we refer to permanent impairment simply as 'disability', following the official classification established by INAIL.

With very few exceptions (e.g. policemen), by law all workers must be insured against WPA through INAIL. The mandatory enrollment and the fact that INAIL registers an accident no matter how the information is collected, e.g. through newspapers, strongly limit the possibility of losing information for undeclared workers.[11] INAIL provides us with information on municipalities (instead of provinces, as readily available from the public website) for eight Italian regions (5,201 municipalities): Lombardia, Veneto, and Piemonte (North), Toscana and Lazio (Center), Campania, Puglia, and Sicilia (South). The municipality-level data makes our analysis highly granular, as the regions in our sample include nearly 5,100 municipalities–out of approximately 8,000 nationwide–with an average area of less than 33 square km. The study covers the period from 2014 to 2018. Each observation corresponds to a worker involved in an accident. The initial sample consists of more than 2.1 million observations (about 421,000 each year), which cover approximately 65 % of the total number of injured workers in Italy during that period.

We have information on: worker's characteristics (anonymized worker identifier, age, gender, nationality and birth municipality); employer's characteristics (employer's identifier, type of insurance, economic sector); accident's characteristics (date and municipality of event, severity of accident including death, accident on the job or *in itinere*, i.e. accident with or without transport means, degree of disability, no. of compensated days). Unfortunately, the available data do not allow us to identify the causes of the accident and the characteristics of the injury.[12]

We restrict our sample to accidents occurring to individuals in the working age, which we conventionally define as 16–67 years. We exclude *in itinere* events because these mainly constitute traffic-related accidents, which might represent a confounding factor in our setting, and because we do not know their exact location. After these restrictions, we obtain about 1.5 million observations. Since we observe the finest worker's location at municipality level, we collapse the data by workplace municipality and day of the event. Then we expand our dataset to make it balanced over time and assign a zero to cells where accidents do not occur. We also restrict our data to municipalities whose centroids are within a radius of up to 20 km from air pollution monitoring stations: this procedure leads to a total of 5,616,141 municipality-by-day-of-event cells, in 3611 municipalities. We primarily focus on municipalities with centroids located within 5 km of monitoring stations, resulting in 896,791 observations across 594 municipalities. From Table 1, we

[11] According to Eurostat "the data available from INAIL is very rich and suitable to analyze accidents at work, both in terms of variables investigated and number of recorded observations."

[12] According to an official report analyzing the causes of accidents in 2012 in Italy, in 46 % of cases the cause is related to the activity of the injured person (inadequate operating procedures), followed by problems concerning the work environment (22 %) and tools, machinery, or equipment (18 %). When the injured person's activity was identified as a risk factor, in more than 80 % of the cases the safety issue was due to a procedural error, and in 14 % to improper or incorrect use of equipment. Source: https://www.inail.it/portale/it/inail-comunica/pubblicazioni/catalogo-generale/catalogo-generale-dettaglio.2020.11.infor-mo-approfondimento-delle-dinamiche-dei-fattori-di-rischio-e-delle-cause.html.

Table 1
Summary statistics.

Variable	Mean	s.d.
Outcomes:		
Accidents	0.803	3.757
Disability	0.090	0.525
Characteristics of injured workers:		
Female	0.347	0.390
Age 15–25	0.143	0.288
Age 26–35	0.174	0.312
Age 36–45	0.254	0.359
Age 46–55	0.280	0.368
Age 56–67	0.149	0.291
No manufacturing	0.834	0.330
No construction	0.939	0.200
Manufacturing	0.187	0.342
Air pollution and weather:		
PM_{10} (μg/m^3)	14.692	15.317
AQI	28.033	26.865
Max. Temperature (°C)	19.228	8.330
Min. Temperature (°C)	9.820	7.314
Wind speed (m/s)	2.254	1.174
Total rainfall (mm)	2.421	7.487
Solar radiation (KJ/m^2/day)	2.358	6.215
Humidity (%)	71.439	12.812
Extreme rain events	0	0.013
Extreme hail events	0	0.009
Extreme wind events	0	0.013
Instrumental Variables:		
Winter heating	0.341	0.474
Planetary Boundary Layer (PBL) height (m)	363.039	217.095

Notes: Statistics obtained for data collapsed at municipality × day cells averaged over the period 2014–2018. The table is based on the sample of municipalities whose centroids are located within 5 km of an air pollution monitoring station, comprising 896,791 observations.

observe that, on average, in each municipality × day cell about 0.8 accidents and 0.090 disabilities occur.

Fig. 1 presents the distribution of accidents and disabilities across economic sectors and individual characteristics of injured workers such as age class and gender. Panel (a) shows that WPA incidents occur not only in traditionally high-risk sectors such as manufacturing, but also in lower-risk sectors, highlighting the importance of using universal administrative data. Nevertheless, traditional risky sectors show a higher number of disabilities. Panel (b) shows how accidents and disabilities are distributed across different age classes: although the number of permanent disabilities is very small, very young workers (aged 15 to 25) exhibit a relatively high number of accidents. Finally, panel (c) shows that men are more likely to incur in accidents and disabilities than women.[13]

3.2. Air quality

We collect air pollution data from the European Air Quality Database (Airbase), which contains validated information on hourly concentrations registered by monitoring stations.[14] We collect concentration data for four pollutants: PM_{10}, CO, NO_2 and SO_2.[15] Depending on the pollutant, the number of monitoring stations can vary across space and time, as some municipalities installed stations after the introduction of more stringent regulations on air quality. Furthermore, monitoring stations could not operate continuously. We mainly focus on PM_{10}, whose stations have a larger coverage than other pollutants.[16]

Following the same procedure for WPA, we collapse air pollution data to municipality-by-day cells. For municipalities with more than one monitoring station, we assign the median pollutant concentration registered across all the monitoring stations belonging to that municipality.[17]

As an indicator alternative to PM_{10} for air pollution, we calculate the Air Quality Index (AQI). The AQI is a well-known indicator used to measure air quality in a multi-pollutant setting (Dominici et al., 2010; Cheng et al., 2007; Chang et al., 2018) because it allows for the independent effect of each single pollutant included in the index to be accounted for. We build the indicator following the strategy suggested by the European Environment Agency (EEA) and the US Environmental Protection Agency (EPA). Details are in Appendix B.

After matching WPA and pollution data, our initial sample includes 205 ‘core’ municipalities, where air pollution monitoring stations are located. Following a standard procedure (Schlenker and Walker, 2015; Moretti and Neidell, 2011; Chay and Greenstone, 2003), we extend the sample to neighboring municipalities up to a 20-km radius from each monitor’s centroids by weighting the pollutants’ concentrations with the inverse distance. With this procedure, our final sample covers from about 40 % (0-km radius) to 78 % (20-km radius) of total accidents occurring in the eight regions available. Fig. 2 displays the geographical distribution of municipalities with monitoring stations and those within a 20 km radius. We mainly focus on municipalities with centroids at 5 km from monitoring stations, using the others for robustness checks.

From the descriptive statistics in Table 1, the average concentration level of PM_{10} is 14.7 μg/m^3, and the average level of AQI is 28. These are relatively low values that indicate a good air quality in our sample of municipalities. However, the standard deviation (s.d.) is substantial, signaling that some municipalities experience very poor air quality. Considering the PM_{10} concentration limit of 50 μg/m^3 set by the European Union, this threshold was exceeded for approximately 30 days per year on average in our regions during the period 2014–2018, with an average exceedance of 20 μg/m^3.

3.3. Weather and extreme events

Weather factors can independently affect both workers’ productivity and the likelihood of work accidents (Behrer et al., 2021; Deschênes et al., 2009). Therefore, we include a full set of weather variables available from the Gridded Agro-Meteorological Database (GAMD). GAMD covers a regular grid of approximately 25 × 25 km in all the municipalities for which accident data are available. We consider daily minimum and maximum temperatures (degrees Celsius, °C), wind speed (m/s), total precipitation (mm of rain), and solar radiation (KJ/m^2/day). Since GAMD data do not include humidity information, we also collect humidity data (in percentage) from the E-OBS dataset administered by Copernicus, which is part of the European Union’s Space program; the

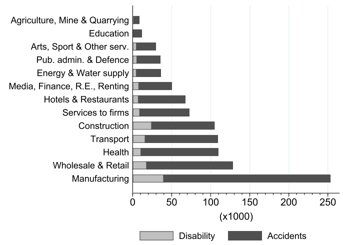
[13] These conclusions remain valid if we consider the same indicators normalized by the number of workers along the relevant dimensions considered in our analysis (e.g., the number of individuals aged 15 to 25, when we consider that age group). Normalized graphs are shown in Appendix Fig. A1.

[14] The Airbase database is maintained by the European Environmental Agency (EEA) through the European Topic Center on Air Pollution and Climate Change Mitigation. It contains air quality data delivered annually under the 97/101/EC Council Decision, establishing a reciprocal exchange of information and data from networks and individual stations measuring ambient air pollution within the member states.

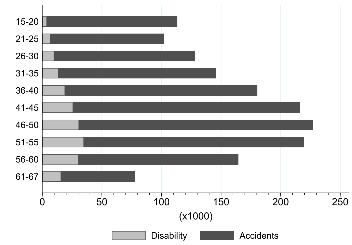
[15] We exclude $PM_{2.5}$ and O_3. The former is monitored only by a few stations, which would therefore strongly reduce the sample of municipalities. However, $PM_{2.5}$ is highly correlated with PM_{10} (Stafoggia et al., 2019). As for O_3, it is a highly seasonal pollutant whose formation process in the atmosphere strongly depends on chemical reactions between PM, NO_2, other compounds and sunlight.

[16] In our analysis, at least 95 % of readings are balanced, which limits concerns about the endogeneity of monitor ‘births’ and ‘deaths’ to strategically alter pollution concentration measures (Bharadwaj et al., 2017; Auffhammer and Kellogg, 2011).

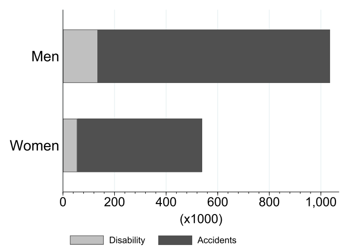
[17] We also consider the mean in assigning monitors to municipality areas, with results that are virtually identical. These results are available upon request.



(a) Across economic sectors



(b) Across age classes



(c) Across gender

Fig. 1. Number of accidents and disabilities by economic sector, age class and gender. Notes: The figure shows the total number of workplace accidents in each reference category. Panel (a) reports accidents by industry sector, panel (b) by age group, and panel (c) by gender. Source: own elaboration based on administrative accident data from INAIL.

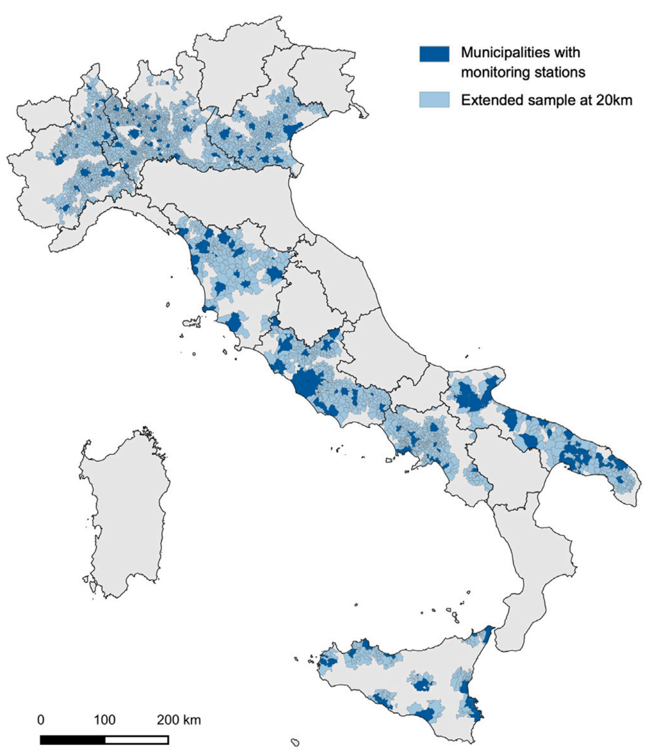


Fig. 2. Geographical Distribution of Municipalities Included in the Sample. Notes: The figure displays Italian municipalities with monitoring stations in the eight regions under analysis (dark blue areas), as well as municipalities located within a 20 km radius of core monitoring stations (light blue areas). Source: own elaboration. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

granularity of this data is about 12 × 12 km. For consistency with pollution data, we assign values of the GAMD grid to municipalities using median and weighting. For each weather variable, we construct 10-bin dummies at the municipality-by-day level to non-linearly control for ground weather conditions.

A distinctive advantage of our empirical analysis is the inclusion of extreme weather event data, sourced from the European Severe Weather Database (ESWD) and maintained by the European Severe Storms Laboratory. These data include information on specific events, i.e. severe wind, large hail and heavy rain. These events can significantly alter the risk of work accidents and affect pollution concentration at the same time, beyond standard weather conditions. For each of these events, we know the exact geographical location and time.[18] We use this information to compute event-specific dummy variables.

Lastly, we collect data on the height of the planetary atmospheric boundary layer (PBL) from the European Centre for Medium-Range Weather Forecasts (ECMWF) reanalysis for the global weather version 5 (ERA5). This data is freely available from the European Copernicus Climate Change Service on an hourly basis with a horizontal resolution of approximately 27 × 27 km. We assign PBL height values, expressed in meters, at the municipality level using bilinear interpolation and calculate daily medians as for weather data.[19]

3.4. Other data

We obtain administrative employer-employee monthly data from the National Institute for Social Security (INPS). For each private-sector employee, we observe demographic information (age, gender, working municipality), contract duration, type of contract

[18] Data also include an indicator of report status regarding the credibility of the recorded event. Report status is a measure of event reliability and assumes four values: GC0 (as received), QC0+ (plausibility check passed), QC1 (report confirmed by reliable source) and QC2 (scientific case study). We consider only events classified as QC0+ and above. However, GC0 events represent less than 1 % of total events.

[19] Bilinear interpolation is commonly used in meteorology to estimate values within a two-dimensional grid of known data points. This estimation is done by considering the values at the surrounding grid points and calculating a weighted average based on their distances from the target location. It assumes a linear relationship between the data points.

(full-time, part-time, fixed-term, open-end), qualification (blue-collar, white-collar, managers, apprentices) and economic sector (NACE codes - Nomenclature statistique des activités économiques dans la Communauté européenne). Controlling for workforce composition might be important in our setting to rule out potential bias due to labor market composition that may affect differential responses to air pollution fluctuations (Hanna and Oliva, 2015; Graff Zivin and Neidell, 2012; Lavy et al., 2022, among others). Although we do not have data at a daily frequency, INPS data enable us to account for labor supply. In particular, since production plans are decided well in advance, monthly data still allow us to capture a large fraction of firm-driven behavior.

Lastly, we collect data on single-day national general and transportation strikes from the Italian Strike Commission and the Ministry of Infrastructures and Transport, and data on the level of urbanization for each municipality from the Italian National Institute for Statistics (ISTAT).

4. Econometric framework

4.1. Baseline model

We begin our econometric analysis by estimating the following model:

$$Y_{clt} = \alpha + \beta PM10_{ct} + \mathbf{W}'_{ct}\gamma + \mu_c + \mathbf{T}_\tau + \phi_{lm} + \varepsilon_{clt} \tag{5}$$

where the outcome Y_{clt} represents a dummy equal to one when an accident or permanent disability occurs (extensive margin) in the municipality c of local labor market l on calendar day t, or the number of accidents and disabilities (intensive margin). $PM10$ is the concentration level of PM_{10} in µg/m^3 and $\mathbf{W}_{ct}$ contains a set of controls at the municipality-by-day level, namely weather conditions (10 bins of minimum and maximum temperatures, solar radiation, humidity, precipitation, and wind speed), national holidays, and general strikes.

Our baseline model employs a rich set of fixed effects. In addition to municipality (μ_c) and day-of-week ($\mathbf{T}_\tau$), we include local labor market-by-month-by-year fixed effects (ϕ_{lm}) to account for area-specific and time-varying unobserved changes in the labor markets. ε_{clt} represents a zero-mean idiosyncratic error term. The coefficient β, the parameter of interest, represents the effect of a 10-units change in PM_{10} concentration on the outcome of interest.

Although the β identified from the OLS-fixed effect model purges from a relevant portion of confounding factors, our estimates may still be biased. More intense economic activity in certain geographical areas and days may co-vary with more intense release of polluting emissions, generating endogeneity due to simultaneity. Similarly, our baseline fixed effects estimates may be biased if workers strategically avoid workplaces or periods with high pollution. Also, the assignment of pollution exposure of workers may become less accurate as we move away from monitors: in this case the parameter of interest would be biased from measurement error. To address these possible sources of bias, we exploit an instrumental variable (IV) method.

4.2. Quasi-experimental setting

We employ two instruments to make air pollution exposure plausibly exogenous. Our first instrument leverages winter heating regulations, similar to Almond et al. (2009) and Fan et al. (2020). In Italy, winter heating is regulated at the municipal level by specific laws to reduce harmful emissions released from heating devices, especially from traditional ones, such as gas boilers, wood-burning and pellet stoves.[20]

[20] Winter heating is regulated by the Presidential Decree Law no. 412/1993. Exceptions on this law are allowed only in cases of exceptional climate conditions, by a specific municipal law, and for a daily duration that must be lower than half of that normally allowed.

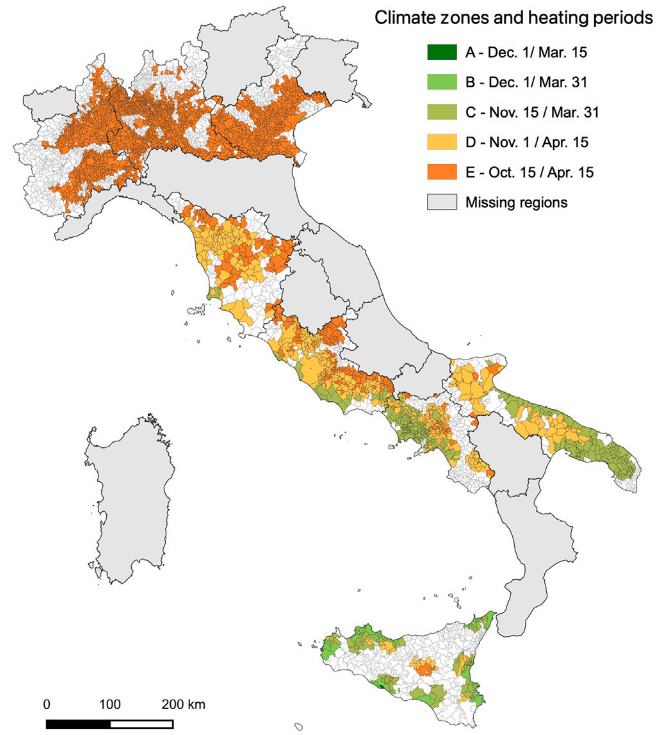


Fig. 3. Municipalities by climate zone and heating periods. Notes: The figure shows the municipalities (sample at 20 km) classified by five climate zones (from A to E). Each climate zone is characterized by a different period in which winter heating is allowed. Source: own elaboration.

Despite Italy benefits from advanced heating technologies, fossil fuels still play the lion's share in the mix of energy sources for winter heating. Natural gas, wood, and biomass represent approximately 85 % of the total fuel, while cleaner sources, like electricity, cover only 5 % of the energy mix (ENEA, 2017). When winter heating is permitted, it leads to a significant discharge of various harmful pollutants, primarily PM_{10} and CO. According to an official report of the Italian Institute for the Environmental Protection and Research (ISPRA), building heating is the primary source of particle pollution in Italy, particularly in major metropolitan cities, where the contribution of heating to total emissions is larger than 50 % (ISPRA, 2018).

Winter heating scheme consists of a classification of municipalities into six climate areas from 'A' to 'F', each one characterized by specific periods during which heating is allowed. Municipalities classified in the climate area 'A' are characterized by warmer temperature in winter and therefore are allowed to start heating only from December 1^{st} to March 31^{st}; municipalities classified as 'E' are allowed to start heating from October 15^{th} to April 15^{th} due to their severe and longer winter conditions.[21] Fig. 3 shows the map of in-sample municipalities classified according to the six climate zones, while Table A1 reports the share of municipalities across climate zones included in our estimation sample. Thanks to this regulation, winter heating generates differential shocks in air pollution concentrations in specific municipality-period groups that are beyond the control of employers and workers.

[21] We exclude from the sample municipalities belonging to climate zone 'F', which are allowed to use heating in any day of the year, because there is no variation in treatment exposure. These few municipalities are mainly situated in mountain areas of Northern Italy.

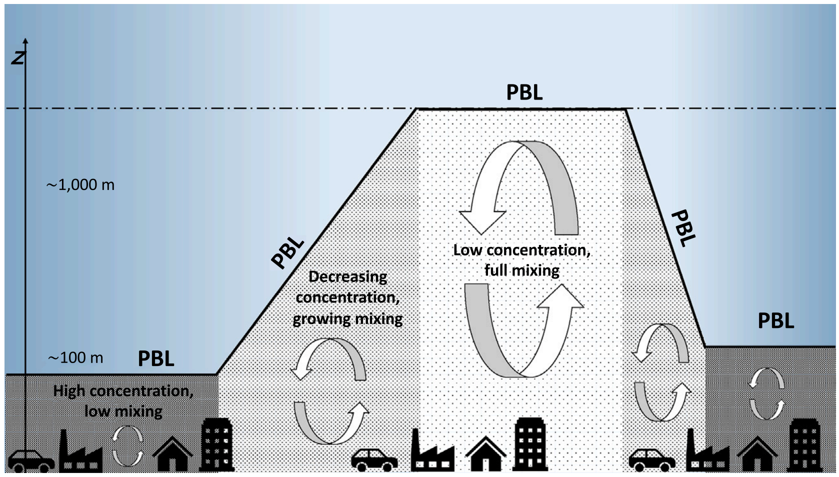


Fig. 4. Relationship Between Planetary Boundary Layer (PBL) height and air pollutants' concentration. Notes: The figure illustrates the mechanism between the PBL and pollutant concentration. When PBL is lower, the air moves in a smaller space, thereby increasing pollutant concentration. Source: own elaboration.

One potential threat to the validity of this instrument is that it captures both central heating systems (serving multiple homes) and independent heating systems (serving only one home). While manipulation of winter heating dates is negligible in central heating systems, independent heating may be activated early during severe cold spells, potentially violating heating regulations. If such cases constituted defiers in the sense of Angrist et al. (1996), our IV estimates could be biased. However, we argue this is unlikely, primarily due to precise controls for weather conditions. Heating costs are substantial, and colder outdoor temperatures are the primary factors influencing winter heating decisions against the law. The identifying assumption of this instrument rests on the premise that winter heating is unrelated to WPA except through its influence on air quality, after controlling for fixed effects and weather conditions. In addition, if temperatures are mild during periods in which winter heating is allowed, individuals might prefer not to activate their independent heating systems, to save money. Therefore, if anything, the sole consequence of non-compliance with the instrument would be a reduction in its relevance.

Our second instrument is the height of the planetary boundary layer (PBL), which leverages the complex dynamics of the atmosphere closest to the Earth's surface, i.e. the troposphere (Stull, 2015). The main mechanism of PBL and pollution concentration is shown in Fig. 4. Intuitively, the relationship between the PBL and pollutant concentration can be summarized as a cylinder that fluctuates in height. As it compresses and expands, it affects the air concentration inside it, which contains pollutant molecules. When the cylinder is more compressed, the air moves in a smaller space, thereby increasing pollutant concentration. Due to this dynamic, PBL height is a key factor in predicting daily near-surface pollutant levels (Akimoto, 2003; Zheng et al., 2017; Jacob, 1999).[22] We exploit exogenous variation in PBL height as an instrument for endogenous air pollution dispersion. The exclusion restriction is satisfied if PBL height affects WPA solely through its impact on pollution concentration. This assumption is plausible, as PBL thickness is orthogonal to economic activity, unobservable to workers, and varies quasi-randomly at a daily frequency. These features reduce concerns about omitted variable bias or strategic behavioral responses to PBL fluctuations.

An alternative instrument that is partially related to PBL height and widely used in the literature is thermal inversion.[23] In their comparison of potential instruments leveraging atmospheric variables, Godzinski and Castillo (2021) show that the planetary boundary layer (PBL) has stronger predictive power than alternative instruments such as wind speed, wind direction, and thermal inversions (Bondy et al., 2020; Deryugina et al., 2019; Sager, 2019; Hicks et al., 2016; Schlenker and Walker, 2015). It is also worth highlighting additional advantages of using PBL in a high-frequency (daily) setting like ours. Unlike thermal inversions, which are intermittent phenomena and typically occur at night, PBL is a continuous phenomenon and therefore more consistently predictive of next-day air quality conditions. While these conditions may improve due to thermal inversion, they can still worsen throughout the day due to factors like low ventilation and significant cloud cover. In addition, calculating the thermal inversion requires the knowledge of the PBL height itself and the atmospheric temperature at that height. The thermal inversion intensity is equal to the difference between the temperatures at the PBL height and near the surface (Stull, 2012). Using a fixed upper level to calculate thermal inversion strength within the PBL may lead to inaccurate results.[24] Regarding the use of PBL compared to wind direction and speed, it is worth noting that wind data are available at the same resolution as PBL data. However, calculating wind-related variables (vector-based for direction and scalar for speed) can be relatively complex, as it requires accounting for all wind parameters across multiple atmospheric layers (altitudes). In contrast, using PBL not only offers larger explanatory power for variations in air pollution but also substantially reduces the computational burden, as it relies on a single parameter rather than multi-layer atmospheric data. Moreover, the vertical wind profile in the atmospheric boundary layer depends itself on the PBL height and conditions, thus it would introduce redundant and

[22] More in detail, the height of the PBL is influenced by a range of atmospheric and environmental factors. One of the primary drivers is the exchange of heat between the Earth's surface and the Sun, which induces a characteristic diurnal cycle: as solar radiation increases during the day, convective processes cause the PBL to rise, while at night, reduced surface heating leads to its contraction. Beyond this hourly pattern, the PBL height also exhibits seasonal variations driven by changes in surface meteorological conditions, such as temperature, humidity, and wind patterns. In addition, it can be affected by large-scale atmospheric dynamics that are even more difficult to predict.

[23] Thermal inversion consists of a reversal of the usual temperature gradient. Typically, air temperature decreases with altitude, but at the top of the PBL, a sharp temperature increase can occur, preventing vertical air mixing and effectively trapping pollutants below. As a result, pollutants and other airborne particles accumulate near the surface, leading to increased concentrations and worsened air quality.

[24] For instance, Sager (2019) computes measures of thermal inversion by considering a fixed height of PBL (set to 925hPa) and not the varying PBL cap. While this simplified procedure limits the data collection and computation procedures, it may result into inaccurate measures of thermal inversion.

more indirect information on the effect of PBL dynamics on atmospheric concentrations (Stull, 1988).

To sum up, our IV strategy employs a vector of binary variables indicating whether winter heating is allowed in each municipality-period group according to the six climate zones outlined in Table A1, and an additional continuous variable that measures PBL height. Formally, we estimate the following 2SLS model:

$$PM10_{cltm} = \alpha + \lambda_1 D(Heat)_{ct} + \lambda_2 D(PBL)_{ct} + \mathbf{W}'_{ct}\gamma + \mu_c + \mathbf{T}_\tau + \phi_{lm} + \eta_{cltm} \tag{6}$$

$$Y_{cltm} = \alpha + \beta \widehat{PM10}_{ct} + + \mathbf{W}'_{ct}\gamma + \mu_c + \mathbf{T}_\tau + \phi_{lm} + \epsilon_{cltm} \tag{7}$$

where $D(Heat)$ and $D(PBL)$ are two instrumental variables and $\widehat{PM10}$ is the first stage predicted value of $PM10$.

5. Results

We begin by presenting the empirical results from our preferred specification, which focuses on a 5 km radius surrounding the centroid of each core municipality, where the monitoring stations are located. We first document the impact of winter heating and PBL on air quality. Table 2 shows that our instruments produce a strong first stage effect. On average, winter heating increases the level of PM_{10} concentration and AQI: the estimated effects correspond to nearly 25 % of the PM_{10} mean and 13 % of the AQI mean. PBL shows a negative and highly significant correlation with air quality: for every meter increase in PBL height, PM_{10} decreases by 0.008 $\mu g/m^3$ and AQI by approximately 0.006 units. The F-statistic, reported in Tables 3 and 4, is 388.11, well above the threshold from the most recent research on valid IV inference (Lee et al., 2022).

To assess the validity of our two instruments, we follow Carneiro et al. (2011) and Mogstad et al. (2021) and use one variable as a single instrument while controlling for the other.[25] Similar considerations remain valid for the AQI. We discuss these results in Section 7 where we present additional robustness checks. Overall, these figures provide reassurance that our 2SLS model is not subject to weak identification and confirm the validity of the instruments.

Following Giaccherini et al. (2021) and Klauber et al. (2021), we present an event study analysis to further support the validity and relevance of our first-stage effect using winter heating rules. We consider a bandwidth of ±6 days around the date when heating is allowed, controlling for all weather factors, seasonal, and municipality fixed effects. Fig. 5 shows that air quality remains stable before the start of winter heating, but deteriorates once heating is allowed, with PM_{10} levels steadily increasing by up to nine units after six days.[26]

We now turn to the effect of pollution on WPA. We start from the extensive margin, i.e. the probability of observing accidents and disabilities. OLS coefficients, reported in columns 1 and 3 of Table 3, point to a probability increase for both accidents and disabilities (significant at 1 % level). However, OLS estimates may be biased. 2SLS estimates presented in Column 2 and Column 4 show that for a 10-unit increase in PM_{10} level, the probability of an accident increases by 0.015, corresponding to 6.7 % of the sample average, while the effects on disabilities is not significant.

Compared with 2SLS estimates, the magnitude of OLS coefficients is nearly five times smaller for accidents and not statistically different from zero for disabilities. For accidents, the OLS estimate suffers from attenuation bias (Section 4). This is confirmed in most of the literature analyzing the effect of air pollution in similar settings (Deryugina et al., 2019; Sager, 2019).

In Table 4 we present intensive margin estimates, i.e. the effect of PM_{10} on the number of accidents and disabilities. For the former outcome, the OLS estimate (column 1) signals once again that, even in settings with high-frequency data, non-experimental studies can severely underestimate the effects of pollution exposure. The 2SLS coefficient (column 2) shows that a 10-unit increase in PM_{10} causes 0.073 additional accidents (elasticity of 0.12). When we use 2SLS, PM_{10} has no significant effects on the number of disabilities.

These results allow us to conclude that air pollution significantly increases the overall number of accidents, although it does not cause a workers' permanent disabilities. Following the theoretical framework

Table 2
First stage estimates of the effect of winter heating and PBL on air quality.

	10 units	
	PM_{10} (1)	AQI (2)
Winter heating	3.71312*** (0.41356)	3.74981*** (0.43115)
Planetary Boundary Layer (height)	−0.00809*** (0.00031)	−0.00557*** (0.00028)
Day-of-week	✓	✓
Municipality	✓	✓
Local Labor Market × Year-month	✓	✓
N	896,791	896,791

Notes: OLS (first stage) estimates of the effects of winter heating and the Planetary Boundary Layer (PBL) height (in meters) on PM_{10} concentration (column 1) measured in $\mu g/m^3$ and Air Quality Index (column 2). The reference sample includes municipalities whose centroids are located within 5 km of an air pollution monitoring station, comprising 896,791 observations. Regressions include municipality, day-of-week and local labor market-by-calendar month fixed effects. We also control for non-linear weather (10 bins of minimum and maximum temperatures, solar radiation, humidity, precipitations and wind speed), dummies for national holidays and general strikes. Standard errors, in parentheses, are clustered on municipalities. Statistical significance: * 10 %; ** 5 %; *** 1 %.

Table 3
Effect of PM_{10} on the probability of accidents and disabilities.

	P(Accident)		*P*(Disability)	
	OLS (1)	2SLS (2)	OLS (3)	2SLS (4)
PM_{10}	0.00344*** (0.00046)	0.01546*** (0.00249)	0.00182*** (0.00036)	0.00174 (0.00160)
Day-of-week	✓	✓	✓	✓
Municipality	✓	✓	✓	✓
Local Labor Market × Year-Month	✓	✓	✓	✓
N	896,791	896,791	896,791	896,791
Elasticity	0.02	0.04	0.04	0.02
F-stat.		388.11		388.11
Outcome Mean	0.23	0.23	0.06	0.06
Outcome S.D.	0.42	0.42	0.23	0.23

Notes: Estimates of the effect of 10 $\mu g/m^3$ PM_{10} increase on the predicted probability of workplace accidents and permanent disabilities. OLS estimates are in columns 1 and 3, 2SLS estimates are in columns 2 and 4. The reference sample includes municipalities whose centroids are located within 5 km of an air pollution monitoring station, comprising 896,791 observations. Estimates include municipality, day-of-week and local labor market-by-calendar month fixed effects. We also control for non-linear weather (10 bins of minimum and maximum temperatures, solar radiation, humidity, precipitations and wind speed), as well as dummies for national holidays and general strikes. Standard errors, in parentheses, are clustered on municipalities. Statistical significance: * 10 %; ** 5 %; *** 1 %.

[25] Mogstad et al. (2021) show that this approach is consistent with the most flexible setting, as it remains valid even under heterogeneous effects and a weak form of monotonicity that they define as partial monotonicity.

[26] The observed delay of approximately two days before PM_{10} levels begin to rise significantly, is likely due to the fact that not all individuals or buildings activate their heating systems on day 0, and the proportion of compliers increases over time.

Table 4
Effect of PM_{10} on the number of accidents and disabilities.

	Accidents		Disabilities	
	OLS (1)	2SLS (2)	OLS (3)	2SLS (4)
PM_{10}	0.02605***	0.07255***	0.00347***	0.00190
	(0.00697)	(0.01481)	(0.00085)	(0.00246)
Day-of-week	✓	✓	✓	✓
Municipality	✓	✓	✓	✓
Local Labor Market × Year-month	✓	✓	✓	✓
N	896,791	896,791	896,791	896,791
Elasticity	0.04	0.12	0.05	0.02
F-stat.		388.11		388.11
Outcome Mean	0.80	0.80	0.09	0.09
Outcome S.D.	3.76	3.76	0.52	0.52

Notes: Estimates of the effect of 10 μg/m³ PM_{10} increase on the number of workplace accidents and permanent disabilities. OLS estimates are in columns 1 and 3, 2SLS estimates are in columns 2 and 4. The reference sample includes municipalities whose centroids are located within 5 km of an air pollution monitoring station, comprising 896,791 observations. Estimates include municipality, day-of-week and local labor market-by-calendar month fixed effects. We also control for non-linear weather (10 bins of minimum and maximum temperatures, solar radiation, humidity, precipitations and wind speed), dummies for national holidays and general strikes. The full set of coefficients is in Table A2. Standard errors, in parentheses, are clustered on municipalities. Statistical significance: * 10 %; ** 5 %; *** 1 %.

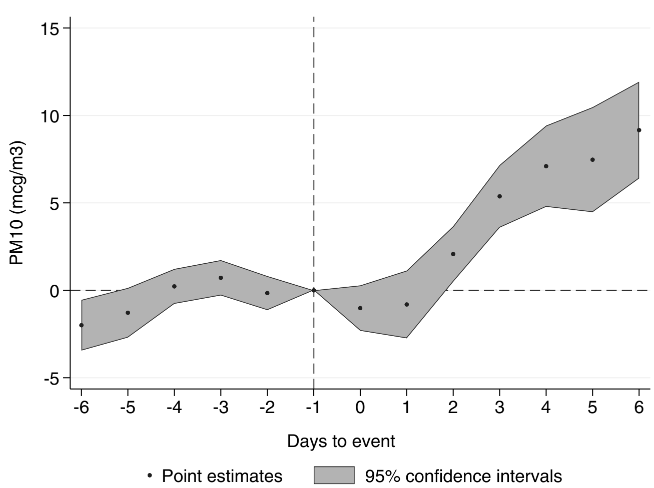


Fig. 5. Event study analysis of the effect of winter heating on PM_{10} in a 12-Day Window. Notes: The figure displays the effect on winter heating on the level of PM_{10} concentration measured in μg/m³ in a 12-day event study window. The omitted category is the day before winter heating is allowed. Estimates include municipality, day-of-week and local labor market-by-calendar month fixed effects. We also control for non-linear weather (10 bins of minimum and maximum temperatures, solar radiation, humidity, precipitations and wind speed), dummies for national holidays and general strikes. Standard errors are clustered on municipalities and confidence intervals (grey area) are at 95 %.

presented in Section 2, these findings imply that $\frac{\Delta N}{\Delta \phi} > 0$ and that the employer's cost function should include the component $\frac{\partial CA_E}{\partial \phi}$. Therefore, an employer ignoring the impact of air pollution on WPA would choose a suboptimal level of defensive investment. In Section 6, we derive the optimal investment level.

The benchmarking of our results relies on the very few papers related to ours. To the best of our knowledge, these include Lavy et al. (2022) and Cabral and Dillender (2024). Lavy et al. (2022) focuses on accidents occurring at construction sites, using NO_2 concentrations and the AQI as a measure of overall air quality; they find that a one-unit increase in the AQI increases the probability of accident by 0.0042 percentage points (p.p.). We find that an increase of a one unit in PM_{10} concentration leads to a 0.0015 increase in the probability of accidents in all sectors of the economy (0.0020 p.p. when we use AQI; Table A3). Therefore, our point estimates appear slightly smaller, yet in line with this study, which focuses only on a high-risk sector.

A comparison of our results appears more appropriate when considering the recent study by Cabral and Dillender (2024), which examines all economic sectors and air pollution from ultrafine particulate matter ($PM_{2.5}$). They estimate an increase of one accident per 100,000 workers with a 10 μg/m³ increase in $PM_{2.5}$. We find an effect of 0.073 additional incidents per 10-μg/m³ increase in PM_{10} on average per municipality. If we rescale our results using the median population per municipality in our sample (approximately 6,500 inhabitants) and the employment rate in the relevant age range (almost 65 %), we obtain about 1.5 additional WPA, which is very close to the effect found by Cabral and Dillender in the US.

On the other hand, our findings may seem at odds with the relatively few studies showing that air pollution heightens risk aversion (Chew et al., 2021; Liu et al., 2024) and reduces risky driving behaviors (Shr et al., 2023). These laboratory and quasi-experimental studies suggest that air pollution makes individuals more cautious when they can adjust their behavior. However, employees at the workplace typically have limited control over their tasks or the risks they face, reducing the likelihood that increased risk aversion leads them to adopt safer behavior. For instance, Galizzi and Tempesti (2015) find no evidence of a clear relationship between risk aversion and WPA in the US. Similarly, while drivers may engage in avoidance behavior – such as slowing down or altering their routes in response to visible pollution – other workers, particularly those in fixed outdoor occupations, typically have limited ability to modify their tasks, leaving them more exposed to environmental risks.

Additionally, the observed reduction in risky driving found by Shr et al. (2023) appears to stem primarily from a visual cue-hazy skies signaling poor air quality, rather than a physiological effect. This mechanism appears to be relevant in environments with extreme and highly visible pollution, but such conditions are relatively rare in our setting and in other economies subject to strict environmental regulations. In addition, Sager (2019) finds that air pollution in the UK increases traffic accidents, likely due to impaired cognitive function rather than changes in risk preferences. Similarly, we argue that in workplace settings, where individuals have less autonomy over their exposure to risk, pollution-induced declines in attention, information processing, and reaction time are more likely to lead to accidents rather than a reduction in risk-taking.

5.1. Heterogeneous effects

There is substantial evidence that air pollution exposure has a greater impact on individuals with lower socio-economic status (Neidell, 2004; Jbaily et al., 2022; Bell et al., 2013; Banzhaf et al., 2019b). Socio-economic status generally improves over a worker's career, which is closely—but not perfectly—related to age.[27] To explore this dimension, we split the sample into five age groups: very young workers with limited experience (15-25 years old), low-experienced workers (26-35 years old), mid-experienced workers (36-45 years old), high-experienced workers (46-55 years old), and senior workers close to retirement age (56-67 years old).

Fig. 6 graphically presents 2SLS estimates for both accidents (top panel) and disabilities (bottom panel). For workplace accidents, the impact of air quality is particularly pronounced among younger workers, as found by La Nauze and Severnini (2025) for the US. Those aged 15–25 are the most affected, with a coefficient of approximately 0.02 additional accidents for a 10-μg/m³ increase in PM_{10}. Middle-experience workers aged 26–35 and 36–45 experience a similar, though slightly

[27] While general work experience naturally increases with age, job-specific experience may follow a different trajectory, depending on job tenure, career transitions, and sectoral mobility.

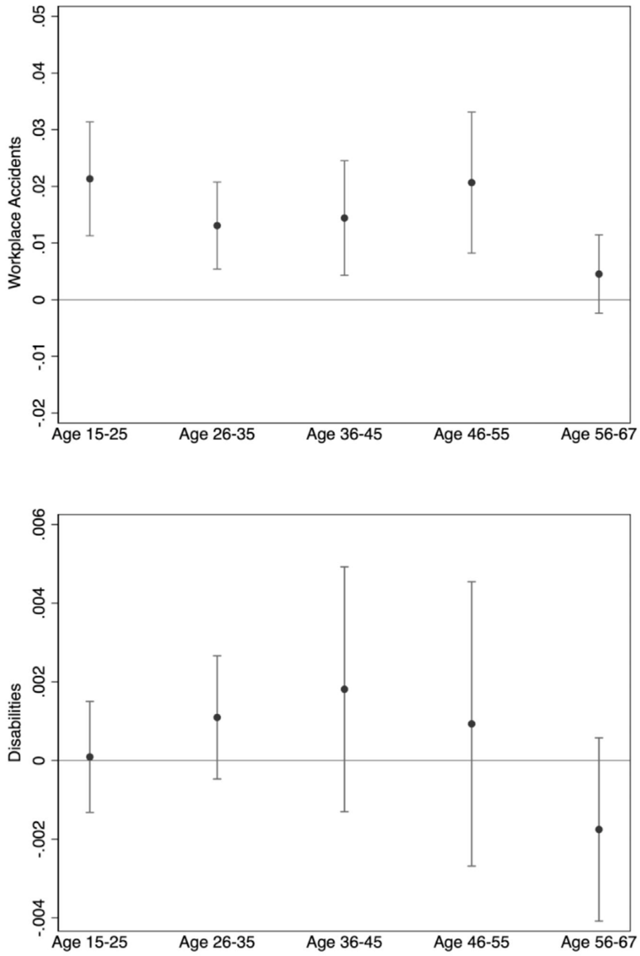


Fig. 6. Effect of PM_{10} on accidents and disabilities by age group. Notes: The figure shows 2SLS estimates of the effect of 10 μg/m^3 PM_{10} increase on workplace accidents (top) and disabilities (bottom) by age group. Estimated elasticities are as follows: Age 15–25: 0.22, Age 26–35: 0.13, Age 36–45: 0.09, Age 46–55: 0.11, Age 56–67: 0.04. Estimates include municipality, day-of-week and local labor market-by-calendar month fixed effects. We also control for non-linear weather (10 bins of minimum and maximum temperatures, solar radiation, humidity, precipitations and wind speed), dummies for national holidays and general strikes. First-stage F-statistics: age 15–25: 280.28, age 26–35: 287.23, age 36–45: 291.06, age 46–55: 291.43, age 56–67: 287.83. The reference sample includes municipalities whose centroids are located within 5 km of an air pollution monitoring station, comprising 896,791 observations. Standard errors are clustered on municipalities. Confidence intervals are at 95 %.

smaller, impact, with approximately 0.013 additional accidents. The effect returns to the level observed for very young workers among those aged 46–55. For the oldest age group, the impact is much weaker, though still statistically significant at the 10 % level, with an increase of about 0.005 accidents.

This set of results could be explained by the fact that young workers are among the most vulnerable groups in the labor market (Barnes and Wagner, 2009). The International Labor Organization provides several characteristics that make them more at risk than others (ILO, 2018). Firstly, they lack the skills and experience needed not only to perform their job but also to be aware of the risks associated with their tasks. Secondly, they have a weaker labor market attachment as very young workers are more likely to be employed informally or with unstable contracts, which are associated with lower salaries and fewer opportunities. Finally, their precarious economic conditions make them more susceptible to social pressure due to their desire to fit in and respond employer's expectations. Therefore, they are more likely to face harsher working conditions. All these socio-economic characteristics exacerbate the effects of air pollution exposure (Currie et al., 2023; Deryugina et al., 2021; Persico and Marcotte, 2022).

On the contrary, for older age groups, which include workers close to retirement (56-67 years old), we can hypothesize two channels for the less pronounced effects that we find. This group, despite being more vulnerable to the effects of air pollution, typically performs tasks that are less 'on the frontline' of danger and, at the same time, benefits from extensive experience in risk avoidance and management. Additionally, their pace of work, both for reasons opposite to those explained for young workers regarding psychological career pressure and due to reasons related to reduced physical performance, is necessarily slower.

However, other factors, such as sector composition or time use patterns, could explain these findings. To test the relevance of the former confounding mechanism, we estimate the sectoral composition by age (Appendix Table A4). Consistent with official statistics from the Italian National Statistical Institute (Istat), individuals younger than 35 years are more represented in service sectors than in construction and manufacturing sectors; the opposite holds true since age 36.[28]

As for time use patterns, we do not have direct information on this aspect. However, according to time-use data from Istat, young people tend to sleep more than older individuals. Since longer sleep is commonly associated with better physical and mental recovery, and ultimately with a lower likelihood of accidents, this habit would actually bias our estimates in the opposite direction.[29] To further support our results, we conduct two robustness checks. First, we use accident and disability rates per 100,000 workers as outcome variables and weight the estimates by the relevant group, following Cabral and Dillender (2024). Second, we include the number of workers in each age category as a control variable. These results are shown in Appendix Figs. A2 and A3, and confirm a fully significant and predominant effect for the youngest group of workers. Based on these considerations, we conclude that our results do not depend on these confounding factors. As for disabilities, we do not observe any statistically significant effect at the 5 % level, confirming also in this case the results of the main estimates.

We next examine whether work experience moderates the impact of pollution on workplace injuries. The rationale is that on-the-job experience enhances workers' ability to anticipate and avoid risks, while biological aging increases vulnerability. Consistent with this interpretation, we find that experience partly offsets the effect of air pollution, especially among older workers, whereas the protective role of experience appears limited for younger ones. Appendix Fig. A4 reports the resulting estimates for each experience categories across the five age groups. For accidents (top panel), these results indicate that experience mitigates pollution-related risks, particularly among older workers, for whom the effect of poor air quality on accident rates becomes markedly smaller. While these findings are consistent with a human-capital interpretation, they rely on aggregated experience data and should be viewed as suggestive. As for disabilities (bottom panel), we do not observe an interesting moderating role of work experience.[30]

In Table 5, we explore heterogeneous effects on two additional important labor market margins: gender and economic sector. The table

[28] This pattern reflects a shift toward service-oriented activities. For the Italian case, Depalo and Lattanzio (2025) document this structural transformation. In the decades preceding our analysis period, younger workers were in fact disproportionately employed in construction and manufacturing, whereas in more recent years their presence has declined in favor of service sectors.

[29] See Depalo (2023) for further evidence on sleeping mechanisms and WPA in Italy.

[30] To assess this mechanism, we estimate interacted 2SLS models by age and experience classes, using INPS administrative data described in Section 3.4 to construct three experience categories at the municipality–month level: low (<2 years), intermediate (2-7 years), high (>7 years).

Table 5
Effect of PM_{10} on workplace accidents by economic sector.

	Gender		Sectors				
	Males (1)	Females (2)	No manufacturing (3)	No construction (4)	Services (5)	Manufacturing (6)	Construction (7)
PM_{10}	0.04602***	0.02683***	0.05537***	0.06485***	0.01210**	0.01346***	0.01168***
	(0.00999)	(0.00727)	(0.01219)	(0.01341)	(0.00488)	(0.00406)	(0.00408)
N	895,054	880,678	896,791	895,054	856,221	858,702	886,470
Elasticity	0.12	0.11	0.11	0.11	0.11	0.12	0.13
F-statistic	305.06	302.18	416.12	415.48	379.15	404.34	293.04

Notes: 2SLS estimates of the effect of a 10 μg/m^3 increase in PM_{10} on the number of workplace accidents. The reference sample includes municipalities whose centroids are located within 5 km of an air pollution monitoring station, comprising 896,791 observations. Estimates include municipality, day-of-week, and local labor market-by-calendar month fixed effects. Controls include non-linear weather (10 bins of minimum and maximum temperatures, solar radiation, humidity, precipitation, and wind speed), as well as dummies for national holidays and general strikes. Standard errors, in parentheses, are clustered at the municipality level. Statistical significance: * 10 %; ** 5 %; *** 1 %.

reports the estimated impact of a 10-unit increase in PM_{10} on the number of WPA occurring among males (column 1) and females (column 2). Although the point estimates differ considerably in magnitude (0.046 for males vs. 0.027 for females), the corresponding elasticities are well aligned with those from the full sample, suggesting only a slightly larger effect for males.

Regarding economic sectors, we begin by assessing whether the effect of air pollution is driven by typically high-risk sectors, such as manufacturing and construction. We re-estimate the model after removing each sector in turn. The estimated effects are 0.055 when the manufacturing sector is excluded (column 3) and 0.065 when the construction sector is excluded (column 4). Both correspond to elasticities of 0.11, very close to the full-sample estimate of 0.12 reported in Table 4. Consistent with these results, we find elasticities of similar magnitude in the services sector (column 5) and slightly higher values in manufacturing (0.12, column 6) and construction (0.13, column 7).

As for disability, we do not observe any significant impacts except in the industrial sector, where we estimate 0.0018 additional disabilities per 10-unit increase in PM_{10}, corresponding to an elasticity of 0.11. The full set of results on disability is reported in Appendix Table A5. Overall, this set of results shows that the effects of air pollution are more pronounced in high-risk sectors, but they also impact the lower-risk sectors.

6. Who bears the costs of pollution-induced WPA?

The evidence that air pollution increases WPA carries substantial economic implications, which we examine through the lens of the theoretical model presented in Section 2. To this end, we quantify the cost of pollution-induced WPA and examine how these costs are distributed between employers and the public insurer.

In Italy, the responsibility for covering compensation costs is determined by national legislation. Employers are fully liable for less severe accidents, defined as those resulting in fewer than four days of sick leave, while more severe cases are covered by the public insurer. How pollution-specific WPA and their costs are distributed between employers and the public insurer remains an empirical issue that we address by conditioning on sick leave days. Following our theoretical framework presented in Section 2, these correspond to the components $\frac{\Delta N_E}{\Delta \phi}$ and $\frac{\Delta N_P}{\Delta \phi}$.

Column 1 of Table 6 shows the results for less severe accidents, whose costs are paid by employers. For this component, we estimate 0.045 additional WPA for a 10-unit increase in PM_{10}, representing about 62.6 % of the total pollution effect (0.045 vis-à-vis 0.073). Column 1 shows that the remaining 37.4 % of the effect of PM_{10}, corresponding to a coefficient of 0.027, can be attributed to more severe accidents that result in longer sick leaves paid by the public insurer. This decomposition reveals that most of the WPA caused by air pollution are not severe,

Table 6
Effect of PM_{10} on mild and severe accidents.

	Accidents	
	With sick leaves <4 days	With sick leaves ≥4 days
	(1)	(2)
PM_{10}	0.04542***	0.02728***
	(0.00996)	(0.00835)
Municipality	✓	✓
Year	✓	✓
day-of-week	✓	✓
Local Labor Market × Year-month	✓	✓
N	891,661	896,791
Elasticity	0.140	0.091
F-stat.	386.93	388.107

Notes: 2SLS estimates of the effect of 10-μg/m^3 PM_{10} increase on the number of mild accidents (column 1) and severe accidents (column 2). The reference sample includes municipalities whose centroids are located within 5 km of an air pollution monitoring station, comprising 896,791 observations. Estimates include municipality, day-of-week and local labor market-by-calendar month fixed effects. We also control for non-linear weather (10 bins of minimum and maximum temperatures, solar radiation, humidity, precipitations and wind speed), dummies for national holidays and general strikes. Standard errors, in parentheses, are clustered on municipalities. Statistical significance: * 10 %; ** 5 %; *** 1 %.

implying that $\frac{\Delta N_E}{\Delta \phi} > \frac{\Delta N_P}{\Delta \phi}$ and that the costs of compensation claims are disproportionately borne by employers. Therefore, employers have an economic incentive to invest in workplace safety measures aimed at reducing the risk of WPA caused by poor air quality, although such actions often represent an internalization of external costs.

To assess the magnitude of these costs, we provide a back-of-the-envelope calculation based on our estimates. EU-OSHA (2019) estimates that the total economic burden for work-related injuries in Italy is approximately 20,000 euros, corresponding to 1069 euros per employed person, on average (Table 7, col. 1; 2015 real term euros).[31]

[31] This amount includes all the cost components, both direct and indirect. EU-OSHA (2019); Tompa et al. (2021) employ this definition for Italy and other EU countries (Finland, Germany, Netherlands, Poland). Direct costs include formal healthcare costs paid for by the public sector or the insurer, the associated administration costs, the informal caregiving time from family members and the community as well as the worker out-of-pocket costs for healthcare products and services. Indirect costs include the loss in terms of market output, the related output/earning loss, payroll and fringe benefits to adjust for full wages, and the associated administration costs and home production loss costs. Intangible costs include the loss in terms of quality adjusted years of life (QALY). These costs assume a retirement age of 65 years old. All monetary amounts are in 2015 levels.

Table 7
Per-worker costs for total and pollution-induced accidents.

	Total marginal cost (1)	Marginal cost caused by air pollution (2)
By stakeholder:		
Employer	648	47.0
Public insurer	421	30.5
Total	1,069	77.6

Notes: Costs are in euros. Column 1 shows the marginal WPA cost per worker by stakeholder (employer and the public insurer), based on the European Agency for Safety and Health at Work (EU-OSHA, 2019). Column 2 shows the marginal cost of pollution-induced WPA derived from a ten unit increase in PM_{10}.

Next, we quantify the fraction of economic cost of air quality deterioration sustained by the employer and the public insurer.[32] According to our estimates, a 10-unit increase in PM_{10} concentration causes a total additional cost of approximately 78 euros (7.3 % of 1069) per employed person per year. Of these, 47 euros rest on the employer and 30.5 on the public insurer and (column 2 of Table 7). According to our theoretical prediction in Section 2, these figures can be interpreted as the maximum amount an employer is willing to spend on defensive expenditures to reduce the exposure to air pollution by ten units of PM_{10}. The cost of pollution-related WPA is substantial for all involved parties, which helps limit potential moral hazard by ensuring that no agent is fully insulated from the consequences. This cost closely aligns with the estimate by Cabral and Dillender (2024) in the US, who report a cost per worker of approximately 135 euros, after adjusting for differences in healthcare sector price levels between the two countries (OECD, 2023).

To better contextualize the policy implications of our estimates, we calculate the annual cost of pollution-induced WPA in Italy associated with non-compliance with the EU threshold defining good air quality for PM_{10} (50 μg/m^3). To this end, we use PM_{10} data collected from all official monitoring stations across the country. Using nation-level data, from 2014 to 2018, each monitored municipality exceeded the limit 26 days on average, with an average PM_{10} concentration of 69.6 μg/m^3, or 19.6 units higher than the threshold. According to these numbers, the average yearly cost of pollution-induced WPA is approximately 32 million euro ($= 7.8 \times 19.6 \times 26 \times 7,998$, namely the cost associated to a one-unit increase in PM_{10} $\times$ excess of air pollution with respect to the legal limit $\times$ number of days per year when excess is recorded $\times$ number of Italian municipalities).

7. Robustness checks

Alternative specifications – In Table 8 we present a set of additional estimates to validate our baseline results on WPA. First, in column 1 we account for the differential effect of single pollutants by using the AQI. The estimated coefficient is 0.0009 (significant at 1 % level), which confirms the main result and indicates that PM_{10} level is a reliable proxy for overall air quality. For comparability purposes, additional estimates of the effect of air quality using the AQI on the probability of accidents and disabilities are reported in Appendix Table A3.

Next, column 2 reports estimates of the effect of PM_{10} including a set of control dummies that account for extreme weather events (hailstorms, windstorms and rainstorms), with results that are identical to our baseline estimates.

In column 3, we account for the discrete nature of the accident distribution by estimating an IV Poisson model, obtaining similar results.[33]

In column 4, we control for labor supply composition (type of contract, qualification, full time or part-time employment and job experience), using administrative social security data (Section 3.4). Notice, however, that this control could be endogenous if air pollution affects the labor supply (Hanna and Oliva, 2015; Graff Zivin and Neidell, 2012). We find that our estimates are virtually identical (0.07385 vis-à-vis 0.07255). This finding may be interpreted as an indirect evidence that temporal avoidance is controlled for by our IV strategy and the rich set of covariates.

Finally, in column 5 we account for predetermined characteristics of injured workers by including controls for age, gender and nationality. These additional variables are available only when the events occurred, and not for the cells that we filled with the zeros (Section 3.1). Therefore, the available sample is smaller and likely suffers from sample selection bias. Not surprisingly, the estimated effect is larger than our baseline specification (0.151 *vis-á-vis* 0.072), albeit the two lead to the same conclusion of a detrimental effect of PM_{10} on WPA.

Sensitivity to different distances – Winter heating rules find maximum compliance in buildings with central heating systems, which are more concentrated in highly urbanized areas. While individuals living in independent houses with autonomous heating devices may anticipate or postpone heating, in buildings with centralized systems the heating rules cannot be manipulated. Our IV estimates can be sensitive to this issue, because when we extend the sample we also capture more rural areas with a prevalence of independent houses. This characteristic could make our instrument based on winter heating rules less relevant as we move farther from densely populated areas. Therefore, we estimate the model with different samples.

We consider three additional samples, with distance from core municipalities' centroids of 10 km, 15 km and 20 km. The results, presented in Table 9, indicate a negligible attenuation of relevant coefficients, with the effects ranging from 0.073 to 0.060 as we expand the sample of municipalities from 5 km to 20 km. The elasticity remains about 0.1 for accidents (panel A) and 0.03 for disability (panel B). This test also confirms that the effects on disabilities are not statistically significant, thereby hindering the inference of a causal role of air quality in permanent health effects resulting from workplace accidents.

Instrumental variables – We leverage over-identification restrictions to support the validity of our instruments. In Table 10, in addition to the baseline specification (column 1), we estimate four alternative models. Columns 2 and 3 use one variable as an instrument and the other as a control, respectively. Following Mogstad et al. (2021), the intuition behind these models is that a valid instrument has no effect on the outcome other than through the first-stage channel, conditionally on the control variables. Hence, controlling for the other instrument, we purge from its potential effect. Columns 4 and 5 employ a single instrument, either the winter heating rule or PBL, following standard practice in the existing literature. The estimated coefficients are remarkably stable across all specifications, and the implied elasticities remain close to those from the baseline model. We interpret this consistency as evidence supporting the exogeneity of the instruments and the robustness of our identification strategy.

To further support the validity of our instruments' exclusion restrictions with respect to ground weather controls, Appendix Table A6 also presents six additional reduced-form estimates of the number of WPAs, using both instruments jointly and individually, with and without weather controls. The results consistently point to an increase in the number of accidents, and the point estimates controlling for weather are only slightly lower and remain always statistically significant at the 1 % level. This provides additional support for the exogeneity of our instruments also when not conditioned on ground weather factors.

8. Conclusions

Drawing upon recent contributions that establish a causal link between air pollution and diminished cognitive ability and attention,

[32] The total cost should also include the component for employees, which we omit in order to remain aligned with our theoretical framework. Including the employee share, the total cost rises to 3,239 euros.
[33] Standard errors are bootstrapped with 500 replications.

Table 8
Alternative specifications.

	Overall Air Quality (AQI) (1)	Extreme events (2)	Poisson (3)	Including labor force composition (4)	Including composition of the injured workers (5)
PM_{10}		0.07296***	0.07399***	0.07385***	0.15119***
		(0.01515)	(0.00796)	(0.01531)	(0.04330)
AQI	0.00919***				
	(0.00182)				
N	896,791	896,791	880,034	845,230	205,843
F-stat.	256.89	388.16	388.11	364.92	251.01

Notes: All estimates refer to the sample at 5 km. Columns (1)-(2) and (4)-(6) are obtained using the 2SLS estimator, with winter heating rules and the height of the PBL as instruments for PM_{10} or AQI. Column 3 is estimated using a control function approach and bootstrapped standard errors with 500 replications. In column 6 the number of observations does not include zeros. Estimates include municipality, day-of-week and local labor market-by-calendar month fixed effects. We also control for non-linear weather (10 bins of minimum and maximum temperatures, solar radiation, humidity, precipitations and wind speed), dummies for national holidays and general strikes. The reference sample includes municipalities whose centroids are located within 5 km of an air pollution monitoring station, comprising 896,791 observations. Standard errors, in parentheses, are clustered on municipalities. Statistical significance: * 10 %; ** 5 %; *** 1 %. S.e. in column (3) are bootstrapped with 500 replications.

Table 9
Effect of PM_{10} at different distances.

	Distance (Km)			
	5	10	15	20
Panel A: Accidents	0.07255***	0.06110***	0.05919***	0.06024***
PM_{10}	(0.01481)	(0.01172)	(0.01147)	(0.01156)
Elasticity	0.118	0.105	0.098	0.094
N	896,791	2,895,589	4,578,874	5,616,141
Panel B: Disabilities	0.00190	0.00302	0.00253	0.00197
PM_{10}	(0.00246)	(0.00198)	(0.00200)	(0.00209)
Elasticity	0.025	0.042	0.033	0.024
N	896,791	2,895,589	4,578,874	5,616,141

Notes: 2SLS estimates of the effect of 10 μg/m^3 PM_{10} increase on the number accidents (Panel A) and disabilities (Panel B) at different distance samples. The distance is calculated from the centroid of the municipality where a monitoring station is installed to the centroids of the municipalities located within a variable radius of 5, 10, 15, or 20 km. Estimates include municipality, day-of-week and local labor market-by-calendar month fixed effects. We also control for non-linear weather (10 bins of minimum and maximum temperatures, solar radiation, humidity, precipitations and wind speed), dummies for national holidays and general strikes. Standard errors, in parentheses, are clustered on municipalities. Statistical significance: * 10 %; ** 5 %; *** 1 %.

Table 10
Effect of PM_{10} – alternative IVs.

Instrument:	Baseline	Multiple instruments		Single instruments	
	Winter Heating & PBL (1)	Winter Heating (2)	PBL (3)	Winter Heating (4)	PBL (5)
PM_{10}	0.0726***	0.0813***	0.0692***	0.0798***	0.0698***
	(0.0148)	(0.0180)	(0.0183)	(0.0162)	(0.0175)
N	896,791	896,791	896,791	896,791	896,791
Elasticity	0.118	0.132	0.112	0.130	0.113
Controlling for:	–	PBL	Winter Heating	–	–

Notes: 2SLS estimates of the effect of 10 μg/m^3 PM_{10} increase on the number accidents using different instrumental variables. Columns differ in the definition of instruments. Column 1 is the baseline approach which exploits winter heating rule and PBL as instruments. Column 2 uses winter heating rule as instrument and PBL as control. Column 3 uses PBL as instrument and winter heating rule as control. Column 4 uses only winter heating rules as instrument. Column 5 uses only PBL as instrument. Estimates in columns 2–3 follow the approach suggested by Mogstad et al. (2021), while columns 4–5 are consistent with the existing literature using just-identified models. The row heading 'Instrument' refers to the instrument(s) used. The row heading 'Controlling for' refers to the additional controls in the main equation. All estimates include municipality, day-of-week and local labor market-by-calendar month fixed effects. We also control for non-linear weather (10 bins of minimum and maximum temperatures, solar radiation, humidity, precipitations and wind speed), dummies for national holidays and general strikes. The reference sample includes municipalities whose centroids are located within 5 km of an air pollution monitoring station, comprising 896,791 observations. Standard errors, in parentheses, are clustered on municipalities. Statistical significance: * 10 %; ** 5 %; *** 1 %.

we present compelling evidence that air pollution adversely affects workplace safety by increasing the number of work accidents. We do this by merging Italian air quality data with administrative data on WPA from all sectors of the economy. This data allows us to conduct a large-scale analysis at a daily frequency and a granular geographical level.

To address the potential endogeneity of pollution exposure, we employ an original combination of instruments for local air quality: winter heating regulations to capture pollution generation, and quasi-random variations in planetary boundary layer height to capture pollution dispersion. The combination of these instruments is new for the economic literature and represents a suitable IV setting for several pollutants. Our estimates show that a 10-unit increase in PM_{10} concentration results in 0.073 additional accidents, corresponding to an elasticity of 0.12.

Although the magnitude of the effects varies across groups, the increase in WPA is 'near-universal' (Cabral and Dillender, 2024). We find that prime-age workers (15-25 years old) suffer the most from bad air quality, likely because they have less work experience, weaker labor market attachment, and face more pressure on the job. However, air pollution negatively affects also very experienced workers and those who are approaching retirement (56-67 years old), although to a smaller extent. While their health status may make them more vulnerable, they are typically less exposed to frontline risks and benefit from greater experience in managing workplace hazards. Finally, the effects of air pollution are stronger in sectors considered high-risk, but they also extend to less risky sectors.

Given the significant risks associated with poor air quality, implementing additional workplace preventive measures could help reduce WPA. In line with a simple theoretical model, employers may have an incentive to invest in workplace safety to reduce workers' exposure to air pollution, despite the fact that pollution constitutes a 'public bad'. Our empirical analysis supports this claim in a setting where the risk carrier and compensation cost burden depend on the severity of accidents and the associated costs are split between employers and society through a public insurer. We further exploit our theoretical implications to derive the employer's optimal level of investment. Back-of-the-envelope calculation shows that the overall cost of accidents resulting from non-compliance with the European daily concentration limit for PM_{10} (50 mcg/m3) is approximately 32 million euros in 2015 real terms.

Our analysis carries important policy implications. First, policymakers should recognize that poor air quality has far-reaching effects on the labor market, extending beyond the well-documented impacts on labor supply and productivity. Pollution-induced WPA represents an additional obstacle to economic growth, as it undermines worker safety even in countries with relatively low pollution levels and strong occupational safety standards. In particular, the additional costs generated are nontrivial and can substantially reduce the opportunity cost of implementing stricter air quality regulations. This is especially important in densely urbanized areas, where the concentration of heating devices is high. In this regard, our findings are also relevant regarding pollution control policies in the residential sector, which have become increasingly important considering the growing number of individuals working from home (OECD, 2021). An additional policy stimulus to improve heating technologies could have positive spillover effects into the labor market by increasing workplace safety and reducing accident costs for both firms and society.

Moreover, our analysis helps quantify the health consequences of urban densification (Cicala et al., 2021), where air pollution is most concentrated due to the combined effects of heating intensity and high traffic volumes. These findings are particularly relevant, as poor air quality affects workers across all sectors and age groups, including younger workers. This group faces a higher risk of pollution-related accidents and greater job instability, underscoring that the burden of air pollution is broadly shared yet unevenly distributed within the labor force.

From an employer's perspective, considering that a significant fraction of the accident risk comes from air pollution, it could be economically profitable for firms to invest in defensive expenditures to reduce the accident risk arising from poor air quality, also in cases where this risk goes beyond their responsibility. Along with additional information on the risks that workers face at work, it would be desirable for employers to employ specific technologies and protective equipment to reduce workers' exposure, especially on days with high pollution. Technologies such as masks or air filter systems are effective and relatively low-cost compared to the costs of compensating workers in case of an accident.

Our work has also some limitations, mainly due to privacy reasons that prevented us from obtaining more detailed data. Ideally, we would like to know more about the injured workers and the characteristics of accidents. For instance, we do not observe the task during which the event occurs and some workers' relevant characteristics such as educational attainment, marital status, and sleeping behavior. Regarding costs, although our calculation provides a good approximation of the cost of air pollution exposure at the workplace, we cannot directly estimate accident costs at the employer level since we do not observe this information in the data.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A

Additional tables and figures

See Tables A1–A6 and Figs. A1–A4.

Table A1
Classification of municipalities by climate zone.

Climate zone	No. of municipalities	Share	Heating period
A	1	0.001	Dec. 1/ Mar. 15
B	17	0.03	Dec. 1/ Mar. 31
C	95	0.17	Nov. 15 / Mar. 31
D	68	0.12	Nov. 1 / Apr. 15
E	380	0.67	Oct. 15 / Apr. 15

Notes: Sample at 5 km. Climate zone "F", in which winter heating allowed in any day of the year, is excluded.

Table A2
Effect of PM_{10} on the number of accidents and disabilities.

	Accidents (1)	Disabilities (2)
PM_{10}	0.0726***	0.000190
	(0.0148)	(0.000246)
Solar radiation 1	0.0216*	0.00264
	(0.0116)	(0.00227)
Solar radiation 2	0.0639*	0.0107
	(0.0337)	(0.00677)
Solar radiation 3	0.0763	0.0138
	(0.0500)	(0.0102)
Solar radiation 4	−0.0404	−0.0103
	(0.0479)	(0.0131)
Solar radiation 5	−0.00505	−0.00358
	(0.0690)	(0.0174)
Solar radiation 6	−0.100	0.0188
	(0.128)	(0.0469)
Solar radiation 7	−0.672	−0.0758
	(0.542)	(0.0614)
Solar radiation 8	−0.533*	−0.181*
	(0.293)	(0.106)
Solar radiation 9	1.191***	−0.264***
	(0.220)	(0.0661)
Min. temperature 1	0.176**	0.0271*
	(0.0811)	(0.0140)
Min. temperature 2	0.152	0.0552***
	(0.100)	(0.0173)
Min. temperature 3	0.163	0.0510**
	(0.0993)	(0.0207)
Min. temperature 4	0.180*	0.0614***
	(0.105)	(0.0214)
Min. temperature 5	0.194*	0.0601***
	(0.106)	(0.0214)
Min. temperature 6	0.216*	0.0603***
	(0.110)	(0.0217)
Min. temperature 7	0.205*	0.0590***
	(0.109)	(0.0216)
Min. temperature 8	0.222**	0.0653***
	(0.111)	(0.0218)
Min. temperature 9	−0.416	0.403*
	(0.930)	(0.229)
Max. temperature 1	−0.0803	0.0583**
	(0.252)	(0.0276)
Max. temperature 2	−0.0150	0.0720*
	(0.178)	(0.0402)
Max. temperature 3	−0.0433	0.0635*
	(0.186)	(0.0377)
Max. temperature 4	−0.0486	0.0601
	(0.187)	(0.0378)
Max. temperature 5	−0.0554	0.0609
	(0.187)	(0.0380)

(*continued on next page*)

Table A2 *(continued)*

	Accidents (1)	Disabilities (2)
Max. temperature 6	−0.0422	0.0623
	(0.187)	(0.0380)
Max. temperature 7	−0.0596	0.0600
	(0.187)	(0.0381)
Max. temperature 8	0.0128	0.0661*
	(0.191)	(0.0387)
Max. temperature 9	0.0473	0.0611
	(0.203)	(0.0445)
Total precipitations 1	0.0239**	0.00425**
	(0.0116)	(0.00206)
Total precipitations 2	0.0414**	0.00809
	(0.0182)	(0.00522)
Total precipitations 3	0.00796	0.00667
	(0.0498)	(0.00705)
Total precipitations 4	0.147***	0.0173
	(0.0515)	(0.0134)
Total precipitations 5	−0.0328	−0.0192
	(0.0789)	(0.0128)
Total precipitations 6	0.0101	0.00143
	(0.111)	(0.0224)
Total precipitations 7	−0.181**	−0.0351*
	(0.0881)	(0.0188)
Total precipitations 8	−0.225**	−0.0490***
	(0.109)	(0.0127)
Total precipitations 9	−1.409***	0.236***
	(0.225)	(0.0630)
Wind speed 1	0.0313***	0.000959
	(0.00849)	(0.00135)
Wind speed 2	0.0562***	0.00386*
	(0.0163)	(0.00226)
Wind speed 3	0.0799***	−1.33e-05
	(0.0263)	(0.00428)
Wind speed 4	0.0408	−0.00247
	(0.0308)	(0.0112)
Wind speed 5	0.281*	0.0677**
	(0.155)	(0.0341)
Wind speed 6	0.00472	0.0155
	(0.165)	(0.0319)
Wind speed 7	−0.0641	−0.0650
	(0.147)	(0.0698)
Wind speed 8	−0.352	−0.160***
	(0.224)	(0.0420)
Wind speed 9	−0.0657	−0.0519*
	(0.0822)	(0.0265)
Relative humidity 1	−0.304	−0.119
	(0.277)	(0.147)
Relative humidity 2	−0.0903	−0.0818
	(0.229)	(0.143)
Relative humidity 3	−0.187	−0.0920
	(0.229)	(0.139)
Relative humidity 4	−0.186	−0.0874
	(0.231)	(0.140)
Relative humidity 5	−0.200	−0.0870
	(0.229)	(0.140)
Relative humidity 6	−0.202	−0.0865
	(0.229)	(0.139)
Relative humidity 7	−0.205	−0.0861
	(0.229)	(0.139)
Relative humidity 8	−0.215	−0.0856
	(0.228)	(0.139)
Relative humidity 9	−0.190	−0.0852
	(0.230)	(0.139)
N	896,794	896,794
Elasticity	0.118	0.0250

Notes: Estimates of the effect of 10 μg/m^3 PM_{10} increase on the number of accidents (column 1) and disabilities (column 2). N refers to the sample at 5 km. Estimates include municipality, day-of-week and local labor market by calendar month fixed effects. Controls for non-linear weather reported in the table include 10 bins of solar radiation, minimum and maximum temperatures, total precipitations, wind speed and humidity (omitted category is the last bin). We also include dummies for national holidays and general strikes. Standard errors, in parentheses, are clustered on municipalities. Statistical significance: * 10 %; ** 5 %; *** 1 %.

Table A3
Effect of air quality on the probability of accidents and disabilities.

	Accidents		Disabilities	
	OLS (1)	2SLS (2)	OLS (3)	2SLS (4)
AQI	0.00072***	0.00199***	0.00044***	0.00027
	(0.00006)	(0.00031)	(0.00005)	(0.00019)
Day of week	✓	✓	✓	✓
Municipality	✓	✓	✓	✓
Local Labor Market × Year-month	✓	✓	✓	✓
N	896,791	896,791	896,791	896,791
Elasticity	0.07	0.10	0.19	0.07
F-stat.		256.90		256.90
Outcome Mean	0.23	0.23	0.06	0.06
Outcome S.D.	0.42	0.42	0.23	0.23

Notes: Estimates of the effect of 1 unit increase in AQI on the predicted probability of accident (OLS estimates, columns 1 and 2) and disabilities (2SLS estimates, columns 3 and 4). The reference sample includes municipalities whose centroids are located within 5 km of an air pollution monitoring station, comprising 896,791 observations. Estimates include municipality, day of week and local labor market by calendar month fixed effects. We also control for non-linear weather (10 bins of minimum and maximum temperatures, solar radiation, humidity, precipitations and wind speed), dummies for national holidays and general strikes. Standard errors, in parentheses, are clustered on municipalities. Statistical significance: * 10 %; ** 5 %; *** 1 %.

Table A4
Probability of working in specific sectors by age class.

	Manufacturing	Construction	Services
Age 15–25	−0.01467***	−0.01668***	0.04213***
Age 26–35	−0.01593***	−0.00514***	0.03065***
Age 36–45	0.01704***	0.00272***	−0.01243***
Age 46–55	0.02964***	0.00489***	−0.03028***
N	5,088,389	5,088,389	5,088,389

Notes: OLS estimates based on administrative data from the social security registries held by INPS. The regression models estimate the probability that an individual works in the sector j as identified from the head of the column. The dependent variable is a dummy taking value equal to 1 if the individual works in sector j and 0 otherwise. Each model controls for year, region of residence, age, gender, part-time, working only part of the year, seasonal worker. For a simpler readability of the results, we only report the coefficients attached to the age classes, using the class 55+ as reference. Standard errors, in parentheses, are clustered at the provincial level. Statistical significance: * 10 %; ** 5 %; *** 1 %.

Table A5
Effect of PM_{10} on disabilities by gender and economic sector.

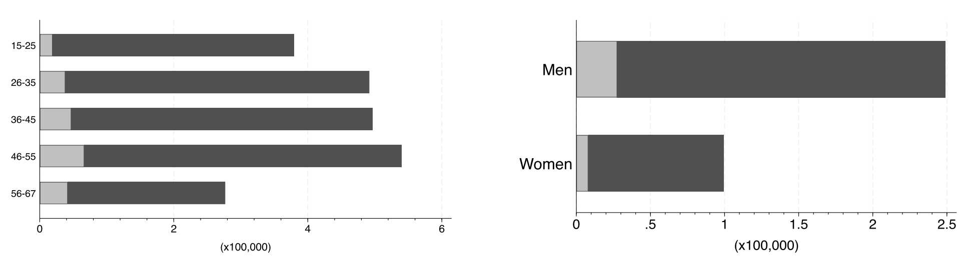
	Gender		Sectors				
	Males (1)	Females (2)	No manufacturing (3)	No construction (4)	Services (5)	Manufacturing (6)	Construction (7)
PM_{10}	0.00130	0.00060	0.00108	0.00217	0.00122	0.00184***	0.00179
	(0.00188)	(0.00145)	(0.00192)	(0.00201)	(0.00109)	(0.00067)	(0.00120)
N	895,054	880,678	896,791	895,054	856,221	858,702	886,469
Elasticity	0.03	0.02	0.02	0.03	0.07	0.11	0.09
F-statistic	388.10	386.73	416.12	415.48	379.15	404.34	293.03

Notes: 2SLS estimates of the effect of 10 $\mu g/m^3$ PM_{10} increase on the number of disabilities. The reference sample includes municipalities whose centroids are located within 5 km of an air pollution monitoring station, comprising 896,791 observations. Estimates include municipality, day-of-week and local labor market by calendar month fixed effects. We also control for non-linear weather (10 bins of minimum and maximum temperatures, solar radiation, humidity, precipitations and wind speed), dummies for national holidays and general strikes. Standard errors, in parentheses, are clustered on municipalities. Statistical significance: * 10 %; ** 5 %; *** 1 %.

Table A6
Reduced form effects of winter heating and PBL height on the number of workplace accidents.

	Number of workplace accidents					
	(1)	(2)	(3)	(4)	(5)	(6)
Winter Heating	0.0340***	0.0285***			0.0302***	0.0251**
	(0.01000)	(0.00992)			(0.0100)	(0.00994)
PBL Height			−0.0000594***	−0.0000586***	−0.000056***	−0.0000564***
			(0.0000129)	(0.0000119)	(0.0000129)	(0.0000119)
Weather controls	✓	–	✓	–	✓	–
N	896,791	896,794	896,791	896,794	896,791	896,794

Notes: OLS estimates (reduced forms) of the effect of winter heating regulation with and without full weather controls (columns 1 and 2), PBL height with and without full weather controls (columns 3 and 4), and their combined effect with and without full weather controls (columns 5 and 6) on the number of workplace accidents. Non-linear weather controls include 10 bins for solar radiation, minimum and maximum temperatures, total precipitation, wind speed, and humidity. All estimates include municipality fixed effects, day-of-week fixed effects, and local labor market by calendar month fixed effects. We also control for national holidays and general strike dummies. The reference sample includes municipalities whose centroids are located within 5 km of an air pollution monitoring station, comprising 896,791 observations. Standard errors, in parentheses, are clustered on municipalities. Statistical significance: * 10 %; ** 5 %; *** 1 %.



(a) Across age classes (b) Across gender

Fig. A1. Accident and disability rates by age class and gender. Notes: The figure shows the rates of workplace accidents and disabilities (per 100,000 workers), obtained by dividing the number of events over the total number of private-sector workers in each reference category, using administrative data from the National Institute for Social Security (INPS). Panel (a) reports accidents by age group, and panel (b) by gender. Source: own elaboration based on administrative accident data from INAIL.

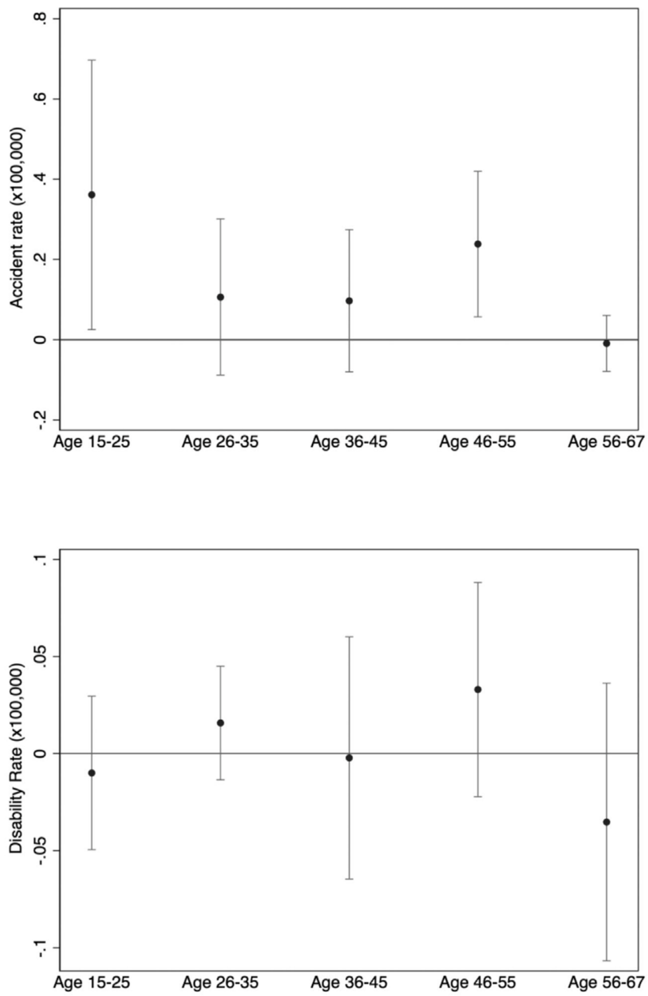


Fig. A2. Effect of PM_{10} on accident and disability rates by age group. Notes: the figure presents 2SLS estimates of the effect of a 10 µg/m^3 increase in PM_{10} on the workplace accident rate (top panel) and disability rate (bottom panel), by age group, per 100,000 workers. Estimates are weighted by the corresponding worker population in each group and include municipality, day-of-week and local labor market by calendar month fixed effects. We also control for non-linear weather (10 bins of minimum and maximum temperatures, solar radiation, humidity, precipitations and wind speed), dummies for national holidays and general strikes. The reference sample includes municipalities whose centroids are located within 5 km of an air pollution monitoring station, comprising 896,791 observations. Standard errors are clustered on municipalities. Confidence intervals are at 95 %.

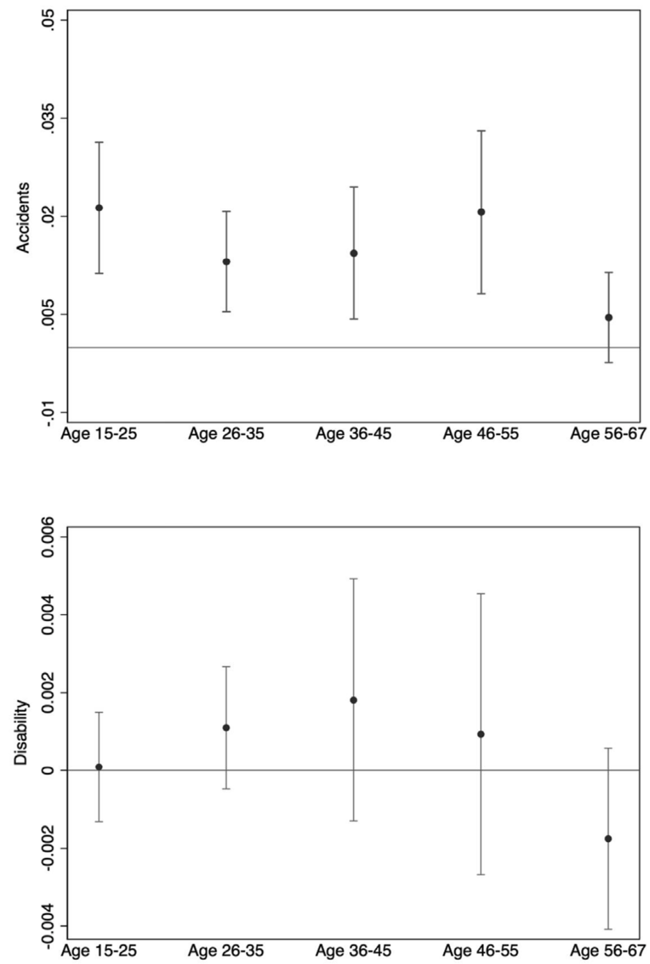


Fig. A3. Effect of PM_{10} on accidents and disabilities controlling for working population by age group. Notes: the figure presents 2SLS estimates of the effect of a 10 µg/m^3 increase in PM_{10} on the number of workplace accidents (top panel) and disabilities (bottom panel) by age group, controlling for the number of private workers in each age group. Estimates include municipality, day-of-week and local labor market by calendar month fixed effects. We also control for non-linear weather (10 bins of minimum and maximum temperatures, solar radiation, humidity, precipitations and wind speed), dummies for national holidays and general strikes. The reference sample includes municipalities whose centroids are located within 5 km of an air pollution monitoring station, comprising 896,791 observations. Standard errors are clustered on municipalities. Confidence intervals are at 95 %.

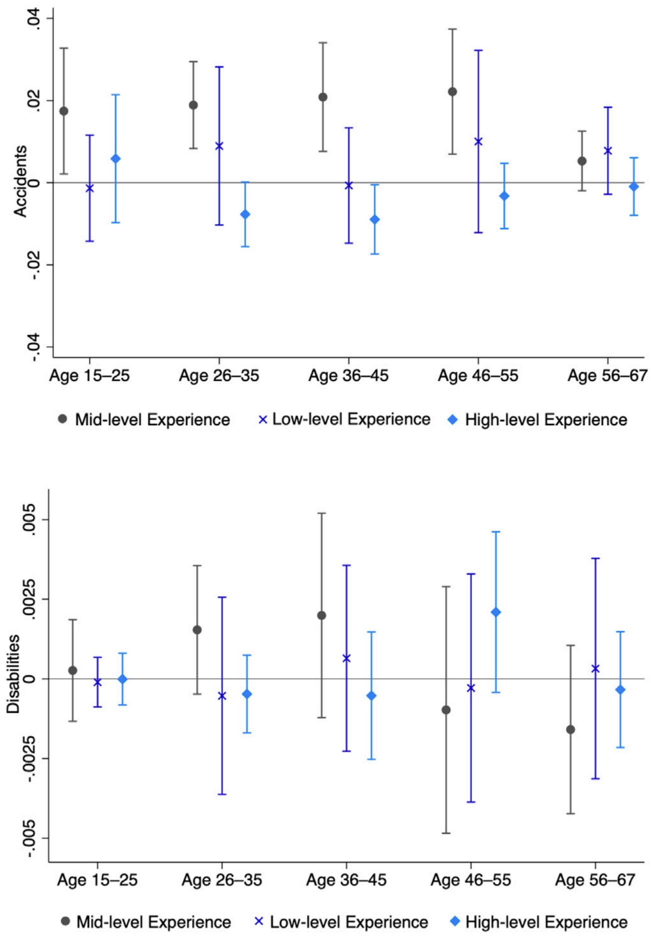


Fig. A4. Moderating role of work experience on accidents and disabilities. Notes: the figure presents 2SLS estimates of the effect of a 10 μg/m^3 increase in PM_{10} on the number of workplace accidents (top panel) and disabilities (bottom panel) by age group, by interacting PM_{10} with two experience categories, low (<2 years) and high (>7 years), with intermediate experience (2-7 years) as omitted category. Black circles denote baseline age-specific effects for workers with moderate experience, while blue squares and green crosses represent medium- and high-experience groups, respectively. Estimates include municipality, day-of-week and local labor market by calendar month fixed effects. We also control for non-linear weather (10 bins of minimum and maximum temperatures, solar radiation, humidity, precipitations and wind speed), dummies for national holidays and general strikes. The reference sample includes municipalities whose centroids are located within 5 km of an air pollution monitoring station, comprising 896,791 observations. Standard errors are clustered on municipalities. Confidence intervals are at 95 %. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Appendix B

Calculation of the Air Quality Index (AQI)

The AQI is divided into six categories, each one with a specific color. Each category corresponds to a different pollutant-specific threshold and associated level of health concern (see Figs. A5 and A6).

In calculating the AQI we follow the EEA guidelines.[34] We include stations with non-missing data for four pollutants: PM_{10}, NO_2, CO_3 and SO_2. The index is calculated for all monitoring stations with data for at least one pollutant. We consider hourly concentrations for NO_2, CO_3 and SO_2, while for PM_{10} we consider the 24-hour running means for the past 24 hours. For CO, the calculation follows the EPA guidelines as the EEA does not provide specific indications.[35]

The AQI is calculated as follows. For each pollutant, we consider the highest concentration value among all of the monitors within each municipality. Based on Fig. A5, we then find the two breakpoints that contain the maximum concentration values. Finally, we calculate the index following the formula:

$$I_p = \frac{I_{Hi} - I_{Lo}}{BP_{Hi} - BP_{Lo}}\left(C_p - BP_{Lo}\right) + I_{Lo} \tag{8}$$

where I_p is the index for pollutant p, C_p is concentration of pollutant p, BP_{Hi} is the concentration breakpoint that is greater than or equal to C_p, BP_{Lo} is the concentration breakpoint that is less than or equal to C_p, I_{Hi} is the AQI value corresponding to BP_{Hi}, I_{Lo} is the AQI value corresponding to BP_{Lo}. The index corresponds to the highest level for any of four pollutants considered, according to Fig. A5.

[34] Source: https://www.eea.europa.eu/themes/air/air-quality-index/index

[35] Source: https://www.airnow.gov/sites/default/files/2020-05/aqi-technical-assistance-document-sept2018.pdf.

Pollutant	AQI level (based on pollutant concentrations in µg/m3, (ppm for CO))					
	Good	Fair	Moderate	Poor	Very poor	Extremely poor
Particles less than 10 µm (PM_{10})	0-20	20-40	40-50	50-100	100-150	150-1200
Nitrogen dioxide (NO_2)	0-40	40-90	90-120	120-230	230-340	340-1000
Carbon Monoxide (CO)	0-4.4	4.5-9.4	9.5-12.4	12.5-15.4	15.5-30.4	30.5-50.4
Sulphur dioxide (SO_2)	0-100	100-200	200-350	350-500	500-750	750-1250

Fig. A5. Pollutant-specific thresholds, AQI values and levels of concern.

AQI	General population	Sensitive populations
Good	The air quality is good. Enjoy your usual outdoor activities.	The air quality is good. Enjoy your usual outdoor activities.
Fair	Enjoy your usual outdoor activities	Enjoy your usual outdoor activities
Moderate	Enjoy your usual outdoor activities	Consider reducing intense outdoor activities, if you experience symptoms.
Poor	Consider reducing intense activities outdoors, if you experience symptoms such as sore eyes, a cough or sore throat	Consider reducing physical activities, particularly outdoors, especially if you experience symptoms.
Very poor	Consider reducing intense activities outdoors, if you experience symptoms such as sore eyes, a cough or sore throat	Reduce physical activities, particularly outdoors, especially if you experience symptoms.
Extremely poor	Reduce physical activities outdoors.	Avoid physical activities outdoors.

Fig. A6. AQI thresholds and health implications.

Data availability

The authors do not have permission to share data.

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