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The Dirtier You Breathe, The Less Safe You Are. The Effect of Air Pollution on Work Accidents

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Abstract

We estimate the effect of air pollution on work-related accidents and disabilities using administrative data from Italy in a setting characterized by strict air pollution and work safety regulations. Leveraging on winter heating rules to address the endogeneity of air quality, we find that a one unit increase in PM_{10} causes 0.014 additional accidents and 0.0014 disabilities. These results are robust to different model specifications and when we extend the geographical scale of the analysis using an alternative instrumental variable based on the height of planetary atmospheric boundary layer. We explore the theoretical implications of these findings and empirically confirm that firms have an incentive to deploy defensive investments also when the risk of accidents derives from external factors such as air quality. Our back-of-the-envelope calculation shows that each additional unit in PM_{10} concentration would increase the total cost of an accident by about 1.7%.

Keywords: air pollution, workplace safety, work accidents, instrumental variable, winter heating

JEL: I18, J28, J81, Q51, Q53

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1 Introduction

Work-related accidents (WRAs, hereafter) represent an important dimension of the labor market and a major source of concern for policy makers. The International Labour Organization (ILO) reports that every 15 seconds about 151 workers have a WRA in the world and one worker dies, which result in about 320 million non-fatal occupational accidents and two million deaths per year.[1] These figures generate large social costs and, most importantly, produce a dramatic loss in human capital and job skills, which in turn affect both economic and social development (Pouliakas and Theodossiou, 2013).[2]

WRAs can occur for a variety of reasons. Causes of accidents deriving from specific production processes and originating within the workplace environment have been extensively scrutinized (Galizzi, 2013, among others), and this has helped increase the safety at work substantially.[3] However, the role of environmental factors, for which single firms are not directly responsible, are still largely unknown. A clearer understanding of these factors would assist policy makers in enhancing job safety and more accurately assessing the costs associated with air pollution externalities.

Air pollution represents a major risk factor for both health and human capital development (Dominici et al., 2014; Zivin and Neidell, 2018). Despite efforts to improve air quality, particle pollution remains a significant environmental risk, particularly in densely populated areas, with a high potential for policy regulation (Carozzi and Roth, 2023; Giaccherini et al., 2021; Simeonova et al., 2018; Pestel and Wozny, 2021). Although early empirical studies have extensively investigated the health consequences of air pollution, focusing primarily on mortality and morbidity outcomes, more recent contributions have focused on its less visible impacts. These include negative effects on labor supply (Hanna and Oliva, 2015), on-the-job productivity (Graff Zivin and Neidell, 2012; Chang et al., 2016a; He et al., 2018; Fu et al., 2021), and cognitive ability (Künn et al., 2019; Ebenstein et al., 2016), to name a few. These more subtle impacts affect a large fraction of the population and result in sizable losses for economic growth and excess health expenditures. A

[1] https://www.ilo.org/global/about-the-ilo/newsroom/media-centre/issue-briefs/WCMS_206117/lang--en/index.htm

[2] According to recent ILO estimates, WRAs and illnesses result in the loss of 3.9% of all work-years globally, equivalent to a cost of approximately 2,680 billion USD. Cost to society are calculated in terms of disability adjusted life years (DALY) rate (years per 100,000 workers) and in terms of contribution to work-years lost expressed as percentage equivalent of total GDP (%). Source: https://visualisation.osha.europa.eu/osh-costs/, accessed on April, 9 2020.

[3] For instance, in the U.S. the Department of Labor reports that between 1972 and 2019, WRA decreased from 10.9 to 2.8 per 100 workers.

recent study by Lavy et al. (2022a) found that high concentrations of NO_2 are associated with a greater number of accidents at construction sites in Israel. However, we still have limited knowledge on the effects and costs of air pollution on workplace safety in other less risky sectors of the economy. This is particularly important for particle pollution, which has the ability to penetrate indoor (Chang et al., 2016a). Our paper expands the literature by presenting evidence of additional hidden impacts of air pollution on the labor market by considering accidents occurred in any sector of the economy and in a setting where both air quality and work safety are well regulated.

A growing body of experimental and quasi-experimental studies has showed that air pollution can significantly impair brain activity, altering human behavior, mental alertness and concentration capacity (de Prado Bert et al., 2018; Zhang et al., 2018a; Sunyer et al., 2017; Archsmith et al., 2018; Sager, 2019; Bondy et al., 2018). Based on these evidence, we conjecture that workers exposed to bad air quality can face a reduced concentration, overexertion and fatigue, which are likely to increase their risk of accidents on the job. We test this hypothesis using a unique administrative dataset containing the universe of daily accidents occurred in eight Italian regions from 2014 to 2018, aligned with air pollution concentrations from monitoring stations. With this data we analyze the number of accidents and their severity, i.e. disabilities, as well as their associated costs. To the best of our knowledge, this is the first comprehensive study that provides a causal relationship between air pollution and workplace safety for the entire workforce.[4]

Estimating the causal impact of air pollution on work accidents represents an empirical challenge for two main reasons. First, fluctuations in air pollution concentrations may co-vary with economic activity. For instance, a sudden increase in the economic demand may induce workers to be more productive and to work faster, increasing the probability of accident. At the same time, if workers produce more, they also pollute more. This simultaneity generates endogeneity, overestimating the effect of air pollution. A second challenge is that workers may adopt strategic behavior and sort into less polluted places or low pollution periods (Deschenes et al., 2017; Chang et al., 2016a, among others). To address these biases, we use two instrumental variable (IV) approaches that enable us to disentangle the effects at different local scales.[5] Our main IV strategy employs

[4] Marinaccio et al. (2019) analyze the role of environmental factors in affecting occupational injuries in Italy from 2006 to 2010. However, their analysis does not account for potential endogeneity in temperature exposure and does not consider air pollution.

[5] Alternative IV strategies to identify the geographical patterns of the effect of air pollution have been recently used by

winter heating rules as a plausibly exogenous source of variation in pollution exposure. Winter heating in Italy largely relies on the combustion of fossil fuels and is strictly regulated by a law that defines both periods and municipalities in which heating is allowed. This IV allows to capture effects at a very local scale as winter heating rules find maximum compliance in densely populated areas. Our alternative IV strategy use as-good-as-random variation in pollution exposure deriving from changes in the height of planetary atmospheric boundary layer (PBL), which varies at a larger spatial scale and is largely controlled by atmospheric meteorological dynamics.

Our study provides two main contributions. Firstly, we estimate the effects of air pollution in any sector of the economy and not only in traditionally risky ones such as construction, manufacturing and agriculture, disentangling the impacts between less and more severe accidents, i.e considering associated disabilities. Our estimates show that a one unit increase in PM_{10} causes from 0.018 additional accidents in densely populated areas to 0.0029 when considering a larger geographical scale. In addition, the administrative data employed allows us to conduct a heterogeneous analysis across age groups, which is an important proxy for work experience. Our findings suggest that young and very young workers, who have a weaker labor market attachment and limited job experience, are more affected by accidents caused by air pollution. On the other hand, disabilities are more likely to occur among middle-age workers (46-55 years old), who have a more vulnerable baseline health.

Secondly, we explore the theoretical implications deriving from our main empirical findings. The fact that air pollution constitutes a significant external risk factor and causes additional accidents has implications for cost calculation, as in many countries, the compensation for injured workers is typically shared between private firms and the social security system (e.g., through a mandatory national insurance plan). This means that both the firms and the social security system could potentially bear the compensation costs in the case of an accident. In the Italian setting, private firms are responsible of compensation costs for less severe WRAs that result in sick leaves up to three days, while for more severe events that imply longer leaves the compensation process bears on a national insurance plan. Theoretically, if firms have full information on the risks associated with air pollution externalities, they should alter their investment patterns by

Bondy et al. (2020), even though they focus on a much smaller spatial scale.

allocating more resources to address pollution-specific risks, up to the point where the cost of addressing these risks balances the cost of additional accidents due to a poor air quality. To determine who bears the costs of accidents specifically caused by air pollution, we conduct an empirical test using the rule that imposes the division of costs based on the severity of the events. We found that air pollution has the strongest effect on less severe work-related accidents (WRAs), indicating that private firms bear most of the compensation costs of pollution-induced accidents. Our back-of-the-envelope calculation indicates that this cost amounts to about 55 euros (1.7%) for each one unit increase in PM_{10} concentration.

The remainder of the paper proceeds as follow. In Section 2 we describe the data and in Section 3 we present the econometric framework. We comment the empirical results in Section 4, while in Section 5 we calculate the costs of pollution-induced accidents. In section 6 we present a battery of robustness checks and alternative model specifications to validate our results. Section 7 concludes with some policy implications.

2 Data

2.1 Work related accidents

We obtain data on the universe of accidents occurred in Italy from the Italian National Institute for Insurance against Accidents at Work (INAIL). WRAs 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. With very few exceptions (e.g. policemen), all workers must be insured against WRA through INAIL, which is a public sector agency. The mandatory enrollment in INAIL ensures that all the Italian WRAs are recorded. Moreover, INAIL registers an accident no matter how the information is collected, e.g. through newspaper, limiting the possibility of losing information for undeclared workers.[6] We obtain data from 2014 to 2018 that cover all the municipalities in eight Italian regions (5,201 municipalities): Lombardia, Veneto e Piemonte (North), Toscana and Lazio (Center), Campania, Puglia and Sicilia (South). The initial sample consists of more than 2.1 million events (about

[6]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."

421,000 each year) and covers approximately 65% of the total number of work accidents in Italy during that period.

WRA data provide information about: worker's characteristics (anonymized worker identifier, age, sex, 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*, accident with or without transport means, degree of disability, no. of compensated days).

We restrict our sample to accidents occurred at the workplace 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 this restriction, 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 $\times$ day of 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 is within a radius of up to 20km from with air pollution monitoring stations; this procedure leads to a total of 5,215,136 municipality$\times$day-of-event cells. We mainly focus on municipalities with centroids at 5 km or less from monitoring stations, which result into 841,798 observations.[7] From Table 1, we observe that on average in each municipality$\times$day cell about 0.85 accidents and 0.095 disabilities occur.

[7] Samples at different distances, up to 20 km, are used for robustness checks.

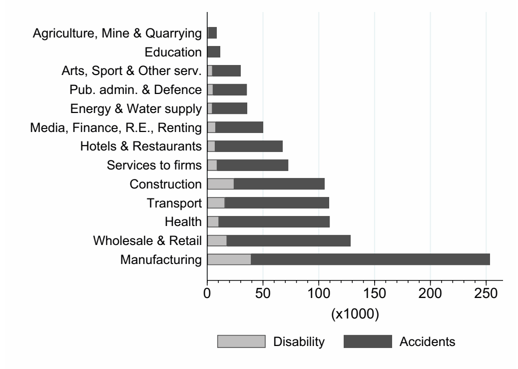
Table 1: Summary Statistics

Variable	Mean	s.d.
Outcomes:		
Accidents	0.845	3.871
Disabilities	0.095	0.540
Characteristics of injured workers:		
Female	0.346	0.388
Foreign workers	0.147	0.295
Age 15-20	0.076	0.215
Age 21-25	0.066	0.206
Age 26-30	0.082	0.224
Age 31-35	0.093	0.239
Age 36-40	0.116	0.264
Age 41-45	0.139	0.285
Age 46-50	0.143	0.286
Age 51-55	0.137	0.281
Age 56-60	0.102	0.246
Age 61-67	0.047	0.173
Air pollution and weather:		
PM_{10}	15.128	15.577
AQI	28.871	27.251
Max. temperature	19.509	8.239
Min. temperature	10.130	7.204
Wind speed	2.275	1.169
Total rainfall	2.404	7.448
Extreme rain events	0.0002	0.013
Extreme hail events	0.00009	0.009
Extreme wind events	0.0002	0.013
Instrumental Variables:		
Winter Heating	0.370	0.483
Highly urbanized cities	0.436	0.496
Planetary Boundary Layer Height	367.601	217.838

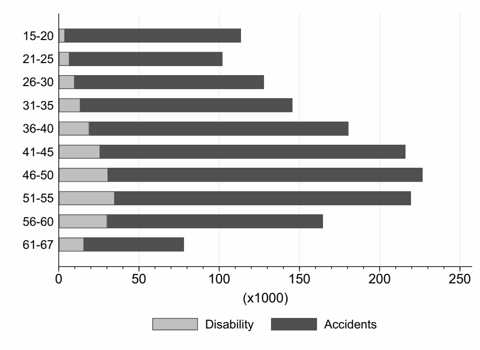
Notes: Data are collapsed at municipality cells averaged over the period 2014-2018. Sample is at 5km (N=841,798).

Figure 1 presents the distribution of accidents and disabilities across economic sectors and individual characteristics of injured workers such as age class, gender and nationality. Panel a) shows that work accidents not only occur in traditionally risky sectors such as construction, manufacturing and transport, but also in less risky sectors, stressing 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; both are lower in younger individuals. Finally, panel c) shows that men are more likely to incur in accidents and disabilities than women.

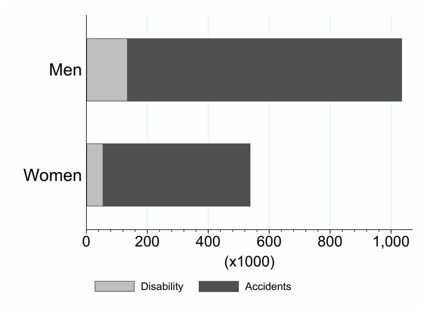
Figure 1: Accidents and Disabilities by economic sector, Age Class, Nationality and Gender



(a) Across economic sectors

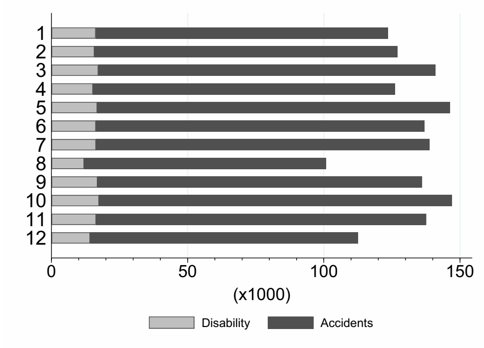


(b) Across age classes

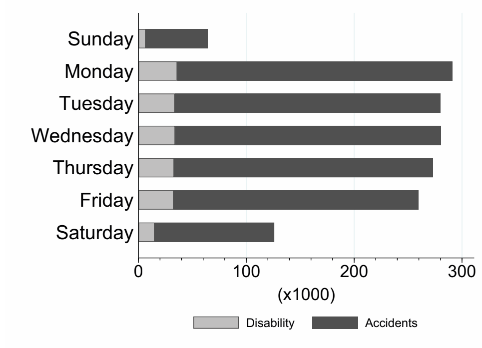


(c) Across gender

Figure 2: Accidents and Disabilities Across Months and Day of Week



(a) Across months



(b) Across day of week

Figure 2 shows the distribution of accidents across months and day of the week. Accidents occur in any month of the year, with a substantial drop in August, the typical period of summer vacations in Italy, and in December, during Christmas holidays. Within days of the week, the number of accidents is slightly decreasing from Monday (the highest number of occurrences) to Friday; the lowest number of events occur on Sunday and, to a letter extent, on Saturday.

2.2 Air quality

We collect air pollution data come from the European Air Quality Database (Airbase), which contains information on hourly concentrations registered by monitoring stations.[8] In addition to PM_{10}, we collect concentration data for three pollutants: CO, NO_2 and SO_2.[9] 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. Considering the increasing number of operating monitors for each pollutant in the most recent years, we mainly focus on PM_{10}, whose stations have a larger coverage than other pollutants.[10]

Following the same procedure for WRAs, we collapse air pollution data to municipality$\times$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.[11] We also calculate the AQI following the indications provided by the EEA and the Environmental Protection Agency (EPA, hereafter). The AQI is a well-known indicator to measure air quality in a multi-pollutant setting (Dominici et al., 2010; Cheng et al., 2007; Chang et al., 2018), allowing to account for the independent effect of any single pollutant included in the index. Details on the calculation of the AQI are provided in the Appendix.

After matching WRA and pollution data, our initial sample includes 197 'core' municipalities where air pollution monitoring stations are located. Following a standard procedure (Schlenker and Walker, 2015; Moretti and Neidell, 2011a; Chay and Green-

[8]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.

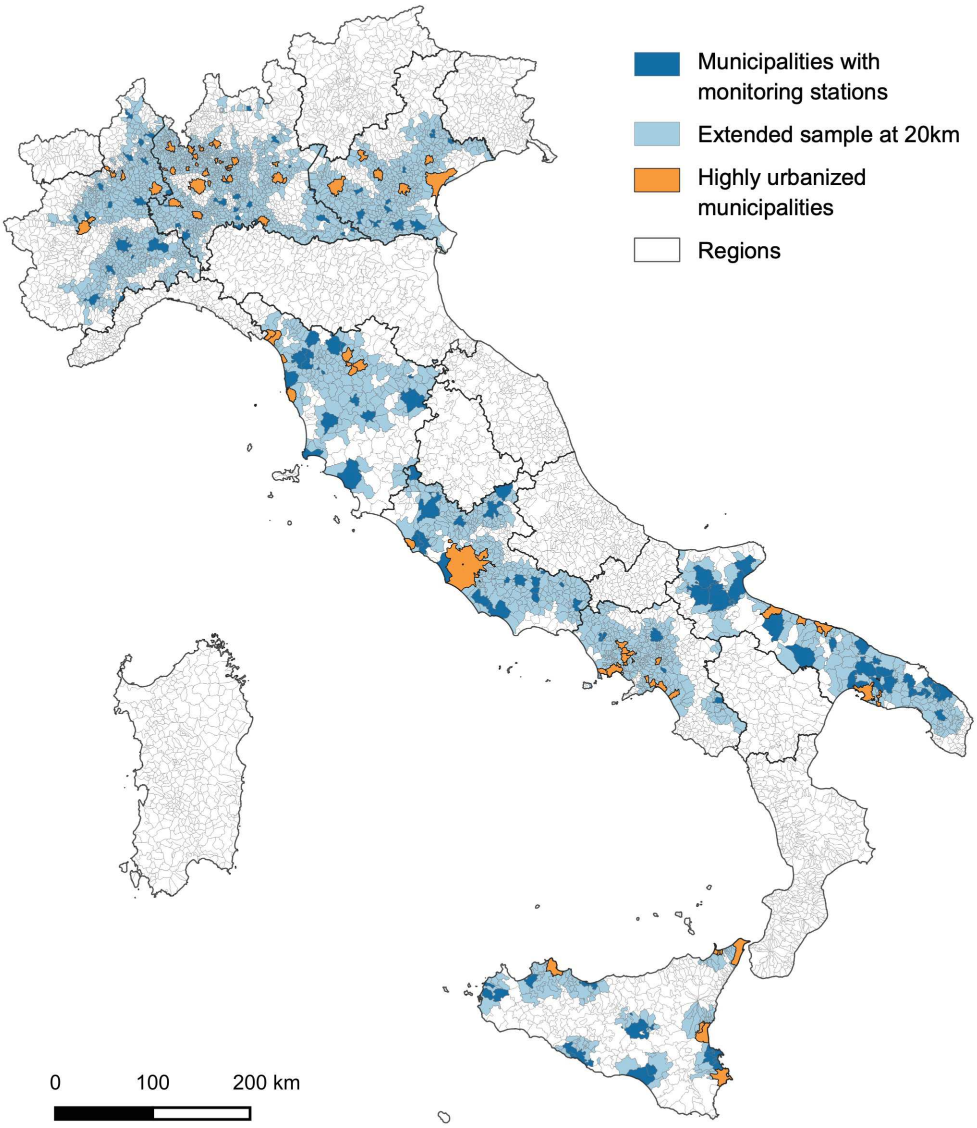
[9]We exclude O_3 and $PM_{2.5}$ since $PM_{2.5}$ is monitored only by few stations. However, $PM_{2.5}$ is highly correlated with PM_{10}. We also exclude ground-level O_3, a highly seasonal pollutant whose formation process in the atmosphere strongly depends on chemical reactions between PM, NO_2, other compounds and sunlight.

[10]Collected data show that at least 95% of readings in the period of analysis 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).

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

stone, 2003), we extend the sample to neighboring municipalities up to a 20-km radius from each monitor's centroids weighting the pollutants' concentrations by the inverse distance. With this procedure, our final samples include up to 5,215,136 observations (3,283 municipalities) and cover from about 40 (0-km radius) to 78 (20-km radius) per cent of the total accidents occurred in the eight regions available. Figure 3 displays the geographical distribution of municipalities with monitoring stations and the one with the extended sample at 20 km. We mainly focus on municipalities with centroids at 5 km or less from monitoring stations, which result into 841,798 observations.

Figure 3: Geographical Distribution of Municipalities Included in the Sample



Notes : The figure shows the Italian municipalities with monitoring stations in the eight regions of analysis (dark blue areas), municipalities within a 15 km radius from core monitoring stations (light blue areas) and municipalities within a 30 km radius from core monitoring stations (light green). Source: own elaboration.

From Table 1 we observe that the average concentration level of PM_{10} is 15 mcg/m^3, and the average level of AQI is 28; even though these are relatively low values and indicate a good air quality in our sample of municipalities, we also observe very high standard deviations (s.d.), signaling that some municipalities experience very poor air quality.

2.3 Weather and extreme events

Weather factors can independently affect both worker's productivity (Deschênes et al., 2009) and the likelihood of work accident (Behrer et al., 2021). Therefore, we include a full set of weather variables available on a daily basis from the Gridded Agro-Meteorological Database (GAMD hereafter). GAMD data are provided on a regular grid of approximately 25×25 km and cover all the municipalities for which accident data are available. For each municipality×day cell, we calculate 30-bin dummy variables for maximum and minimum temperatures (degrees Celsius, °C), wind speed (m/s) and total precipitation (mm of rain) to accurately control for non-linear effects of weather factors.

Along with standard weather variables, we include information on extreme weather events from the European Severe Weather Database (ESWD, henceforth) provided by the European Severe Storms Laboratory. This data includes information on severe wind, large hail and heavy rain events. For each event, we know the exact geographical location and time.[12] We use this information to compute event-specific dummy variables that take value of 1 when the event occurs. This set of dummies accurately controls for events that can significantly alter the risk of work accidents and affect pollution concentration at the same time, such as ice formation, lightning or extreme wind, but are not captured by standard weather data.

Lastly, we collect data on on the height of the planetary atmospheric boundary layer (PBL) from Copernicus ERA-5. Since this data comes at a resolution of 0.1×0.1 degrees (about 9×9 km), we collapse PBL data at municipality and daily level. PBL data turns out to be useful in our robustness check section, in which we employ an alternative IV strategy to instrument for air pollution concentration.

[12] Data include also 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 GC0.

2.4 Other data

We obtain administrative employer-employee data from the National Institute for Social Security (INPS). For each worker, we observe demographic information (age, gender, working municipality), contract duration, type of contract (full time, part-time, fixed term, open end), qualification (blue collar, white collar, managers, apprentices) and economic sector (NACE). Controlling for workforce composition is an important test in our setting to rule out potential bias due to labor market dynamics that may affect differential response to air pollution fluctuations (Hanna and Oliva, 2015; Graff Zivin and Neidell, 2012; Lavy et al., 2022b, among others). Even though we do not have information at daily frequency, INPS data enable us to control for labor supply (the total number of dependent employees in the private sector) in additional robustness estimates presented in Section 6. We also 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). Lastly, we retrieve from the web the official classification of municipalities by climate zone.[13] Summary statistics for all the relevant variables are reported in Table 1.

3 Econometric Framework

3.1 Baseline model

We begin our econometric analysis by estimating the following model specification:

$$Y_{cltm} = \alpha + \beta PM10_{ct} + \mathbf{W}'_{ct}\gamma + \mu_c + \mathbf{T}_\tau + \phi_{lm} + \varepsilon_{cltm} \tag{1}$$

where the outcome Y_{cltm} represents a dummy equal to one when an accident or disability occurs (extensive margin) in the municipality c of local labor market l in calendar day t of month m, or the number of accidents and disabilities (intensive margin). $PM10$ is the concentration level of PM_{10} in $\mu g/m^3$ and $\mathbf{W}_{ct}$ contains a set of controls at the municipality×day level, specifically dummies for 25 bins of minimum and maximum temperatures, precipitations and wind speed, and dummies for national holidays and general

[13] http://www.unicmi.it/UX57/html/ux57_2.php, accessed in 2021.

strikes.

A distinctive feature of our baseline model is the rich set of fixed effects to control for seasonal unobserved heterogeneity. In addition to municipality (μ_c) and day-of-week ($\mathbf{T}_\tau$) fixed effects, we include local labor market×month-by-year fixed effects (ϕ_{lm}) to account for differential growth trends. ε_{cltm} represents an idiosyncratic error term. The coefficient of interest is β, which is the effect of one unit increase in PM_{10} concentration on a dummy equal to one when an accident or disability occurs (extensive margin) and on the number of accidents and disabilities (intensive margin). A positive coefficient implies that, as the air quality deteriorates with higher PM_{10} concentration, the probability or the number of accidents with and without disabilities increases.

Although the β identified from the OLS-fixed effect model purges from a relevant part of time-invariant unobserved heterogeneity, 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, leading to endogeneity. Similarly, standard fixed effects estimates may be biased if workers behave strategically and avoid workplaces or periods with high pollution. In addition, the assignment of pollution exposure to workers may become less accurate as we move away from monitors: in this case the parameter of interest would be biased from the measurement error.

To address these possible sources of endogeneity at different geographical scales, we exploit two instrumental variable (IV) approaches. The first approach, based on winter heating rules, primarily captures the local-scale effect of air pollution, particularly in urban areas. The second approach confirms the effects on a larger geographical scale by utilizing the height of the planetary boundary layer and leveraging exogenous variation resulting from atmospheric dynamics. We present estimates from the second approach in Section 6.

3.2 Quasi-experimental setting: winter heating rules

In Italy winter heating is regulated by specific laws to reduce harmful emissions released from heating devices, especially from traditional ones such as gas boilers, wood-burning and pellet stoves.[14] Despite Italy benefits from relatively more advanced heating tech-

[14]In Italy, winter heating is regulated by the Presidential Decree Law no. 412/1993. Exceptions on this law are allowed only in case of exceptional climate conditions, by a specific Municipal law, and for a daily duration that must be lower

nologies, 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 such as electricity covers only 5% of the energy mix (ENEA, 2017). When winter heating is permitted, it leads to a significant discharge of various harmful pollutants, primarily composed of PM_{10} and CO. According to an official report of the National 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).

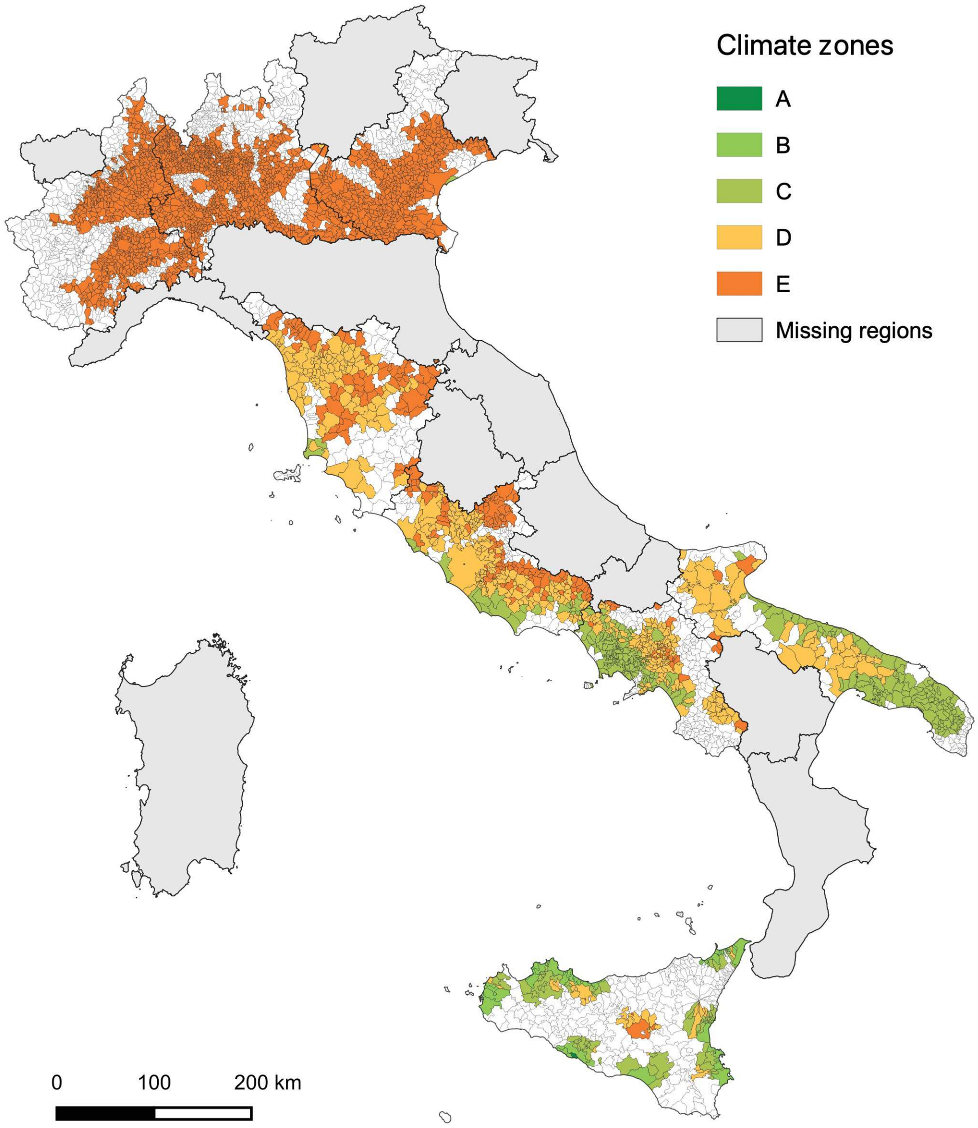
While in essence our IV is similar to the one used by Almond et al. (2009) and Fan et al. (2020), our setting is staggered since winter heating scheme consists in a classification of municipalities in six climate areas from 'A' to 'F', each one characterized by specific periods in which winter heating is allowed. For instance, 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 to March 31, while municipalities classified as 'E' are allowed to start heating from October 15 to April 15 due their severe and longer winter conditions. Municipalities belonging to climate zone 'F', which are allowed to use heating in any day of the year and are mainly located in mountain areas of Northern Italy, are excluded from the sample. Figure 4 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.

Because of this regulation, winter heating produces differential shocks in air pollution concentrations in specific municipality-period groups that are beyond the control of both employers and workers. Our IV captures both central heating systems (serving multiples homes) and independent heating systems (serving only one home). While in central heating systems the risk of manipulating winter heating dates is negligible, independent heating might be activated in advance during severe cold conditions against the heating rules. Conversely, if temperatures are mild during periods in which winter heating is allowed, individuals might prefer not to activate heating to save money. However, controlling for weather conditions strongly mitigates this confounding factor since heating is expensive and a colder outdoor temperature is the main factor affecting winter heating

than the half of that normally allowed.

decisions in non-compliance with the law. In addition, considering that central heating systems are largely concentrated in highly urbanized cities, to gain precision we also interact heating rules with a dummy variable to identify municipalities officially classified as 'highly urbanized' by ISTAT, in which the concentration of central heating systems is much larger and the possibility to manipulate the heating rules is low.[15] Highly urbanized municipalities, displayed in Figure 3, represent about 20% of the total municipalities in our sample.

Figure 4: Municipalities Included in the Sample by Climate Zone



Notes : The figure shows the in-sample municipalities classified by six climate zones (from A to F). Each climate zone is characterized by a different period in which winter heating is allowed. Source: own elaboration.

[15]Eurostat classifies municipalities according to three degrees of urbanization–high, medium and low–by considering the population density and the number of inhabitants within regular grids with cells of one square kilometer.

To sum up, our main 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 reported in Table A1, and an additional vector of dummies identifying highly-urbanized cities interacted with the winter heating indicators. Our identifying assumption is that winter heating is unrelated to work accidents except through its influence on air quality, after controlling for weather conditions, fixed effects, national holidays and strikes. Formally, we estimate the following 2SLS model:

$$PM10_{cltm} = \alpha + \lambda_1 D(Heat)_{ct} + \lambda_2 D(Heat \times Urban)_{ct} + \mathbf{W}'_{ct}\gamma + \mu_c + \mathbf{T}_\tau + \phi_{lm} + \eta_{cltm} \quad (2)$$

$$Y_{cltm} = \alpha + \beta \widehat{PM10}_{ct} + +\mathbf{W}'_{ct}\gamma + \mu_c + \mathbf{T}_\tau + \phi_{lm} + \varepsilon_{cltm} \quad (3)$$

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

4 Results

We first document the impact of winter heating on air quality. Table 2 shows that winter heating generates a strong first stage effect, increasing on average the level of PM_{10} concentration of about 6.2 units (respectively, for the two instruments, 2.43 and 3.75 units), which represents an increase of nearly 50% of the PM_{10} mean.

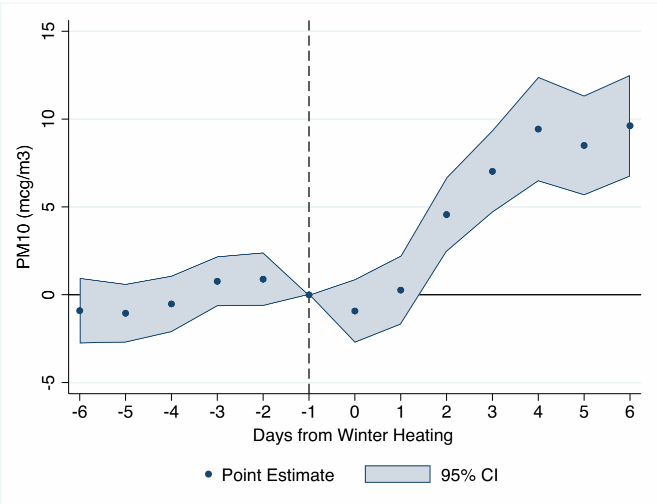
Table 2: First Stage Estimates of the Effect of Winter Heating on PM_{10}

	PM_{10} (1)	AQI (2)
Winter heating	2.429***	1.275**
	(0.512)	(0.520)
Winter heating × Urban	3.750***	4.145***
	(0.835)	(0.986)
Day of week	✓	✓
Municipality	✓	✓
LLM × Year-month	✓	✓
N	841,798	841,798

Notes: N refers to the sample at 5 km. All regressions control for non-linear weather (30 bins of minimum and maximum temperatures, precipitations and wind speed), dummies for national holidays and strikes. Standard errors, in parentheses, are clustered on municipalities. Statistical significance: * 10%; ** 5%; *** 1%.

The F-statistic is 74.34, consistent with the most recent research on valid IV inference (Lee et al., 2022), and the overidentification p-values reported at the bottom of Table 3 and 4 are mostly far from conventional significance levels. These figures reassure on the fact that our 2SLS model is not affected by weak identification issues and that the instruments are valid. The first stage effect remains strong and significant at 1% level also when we consider the AQI, which increases on average by 6 units, or 21% with respect to its sample mean. To further support the relevance of winter heating rules on PM_{10}, we also present an event study analysis that considers a small time window around the date when heating is allowed. We consider a bandwidth of ±6 days, controlling for all weather factors and for seasonal and municipality fixed effects. Figure 5 shows that air quality worsens in the days following the allowance of winter heating, with PM_{10} steadily increasing up to 10 units after six days.[16]

Figure 5: Event Study Analysis of the Effect of Winter Heating on PM_{10} in a 12-Day Window



Notes : The event study regression includes controls as in Table 4. The temporal interval considered is 12 days, omitted category is the day before winter heating. Standard errors are clustered on municipalities and confidence intervals (blue area) are at 95%.

We now turn to the effect on WRAs. For all estimates, we calculate the coefficients based on a 5-km radius surrounding each core municipality's centroid, where the monitoring stations are situated. We begin by examining the extensive margin and assessing the likelihood of accidents and disabilities. 2SLS estimates reported in Column 2 and 4 of Ta-

[16]The observed delay of approximately two days before PM_{10} levels begin to rise significantly is probably because the decline in air quality caused by heating devices is not immediate.

ble 3 show that for a one unit increase in PM_{10} level the probability of accident increases by 0.0016, corresponding to 0.7% of the sample average, while the one of disability by 0.00069 percentage points, corresponding to more than 1% of the sample average; OLS coefficients, reported in column 1 and 3, also point to a probability increase for both accidents and disabilities (significant at 1% level), but, compared with 2SLS estimates, the magnitude is approximately five times smaller for accidents, and four times smaller for disabilities. This means that OLS estimates suffer from attenuation bias, coherently with most of the literature analyzing the effect of air pollution in similar settings (Deryugina et al., 2016; Sager, 2019; Giaccherini et al., 2021).

Table 3: Effect of PM_{10} on the Probability of Accident and Disability

	P(Accident)		P(Disability)	
	OLS	2SLS	OLS	2SLS
	(1)	(2)	(3)	(4)
PM_{10}	0.000309***	0.001628***	0.000169***	0.000691***
	(0.000046)	(0.000422)	(0.000035)	(0.000215)
Day of week	✓	✓	✓	✓
Municipality	✓	✓	✓	✓
LLM X Year-month	✓	✓	✓	✓
N	841,798	841,798	841,798	841,798
Elasticity	0.01	0.04	0.03	0.09
F-stat.	–	74.34	–	74.34
Over-id.	–	1.6	–	0.7
P-value(Over-id.)	–	0.20	–	0.45
Outcome Mean	0.24	0.24	0.06	0.06
Outcome S.D.	0.43	0.43	0.24	0.24

Notes: N refers to the sample at 5 km. All regressions control for non-linear weather (30 bins of minimum and maximum temperatures, precipitations and wind speed), dummies for national holiday and strikes. Standard errors, in parentheses, are clustered on municipalities. Statistical significance: * 10%; ** 5%; *** 1%.

In Table 4 we present intensive margin estimates of the effects of air pollution. In column 2 we estimate that a one unit increase in PM_{10} causes 0.014 additional accidents (elasticity of 0.23). We detect a significant effect also for the number of disabilities (column 4), which increases by 0.0014 units (elasticity of 0.18). OLS estimates, reported in column 1 and 2, appear once again downward biased and signal that, even in setting with high-frequency data, non-experimental studies can severely underestimate the effects of pollution exposure.

Taken together, this set of results allows us to conclude that air pollution not only

Table 4: Effect of PM_{10} on the Number of Accidents and Disabilities

	Accidents		Disabilities	
	OLS	2SLS	OLS	2SLS
	(1)	(2)	(3)	(4)
PM_{10}	0.00240***	0.01431***	0.00032***	0.00136**
	(0.00063)	(0.00408)	(0.00008)	(0.00064)
Day of week	✓	✓	✓	✓
Municipality	✓	✓	✓	✓
LLM X Year-month	✓	✓	✓	✓
N	841,798	841,798	841,798	841,798
Elasticity	0.04	0.23	0.04	0.18
F-stat.	–	74.34	–	74.34
Over-id.	–	1.9	–	3.5
P-value(Over-id.)	–	0.16	–	0.060
Outcome Mean	0.84	0.84	0.10	0.10
Outcome S.D.	3.87	3.87	0.54	0.54

Notes: N refers to the sample at 5 km. All regressions control for non-linear weather (30 bins of minimum and maximum temperatures, precipitations and wind speed), dummies for national holiday and strikes. Standard errors, in parentheses, are clustered on municipalities. Statistical significance: * 10%; ** 5%; *** 1%.

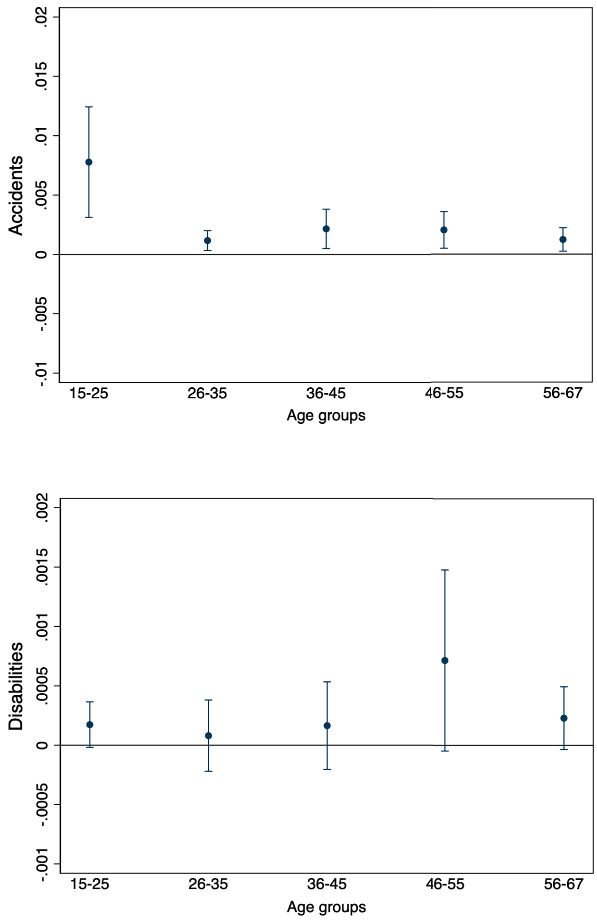
significantly increases the overall number of accidents, but it does also cause a workers' permanent health loss by increasing the number of injuries that cause disabilities.

4.1 Heterogeneous effects across age groups

In this section we test whether PM_{10} generates differential impacts across ages. There is evidence to suggest 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., 2019), and this latter strongly depends on the workers' career, which is essentially a function of age. To explore this margin, we split the sample in 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), senior workers and workers closed to the retirement age (56-67 years old). Figure 6 graphically presents 2SLS estimates for both accidents (top panel) and disabilities (bottom panel) across these age groups.

Interestingly, we find a much larger effect of PM_{10} for very young workers, in which a one unit increase in PM_{10} causes 0.075 additional accidents (significant at 1% level), while for other age groups the coefficients do not exceed 0.003 (all significant at 5%

Figure 6: Effect of PM_{10} on Accidents and Disabilities by Age Group



Notes : The figure displays the effect of PM_{10} on work accidents (top) and disabilities (bottom) by age group. All regressions include controls as in Table 4. Confidence intervals are at 95%.

level). The larger impact of air pollution on very young workers can be explained by the fact that this age group represents the most vulnerable class of workers, including those under the legal age (Barnes and Wagner, 2009). The International Labour Organisation provides several characteristics that make them more at risk than others. Firstly, they lack the skills and experience needed not only to do their job but also to be aware of the risks associated with their tasks. Secondly, they have a weaker labor market attachment as young workers are more likely to be employed informally or with unstable contracts, which are associated with lower salaries. Finally, their precarious conditions make them more susceptible to social pressure due to their desire to fit in and respond to employer's expectations. Therefore, they are more likely to face harsher worker conditions (ILO, 2018). As documented in other studies, all these socio-economic characteristics exacerbate the effects of air pollution exposure (Currie et al., 2023; Deryugina et al., 2021; Persico and Marcotte, 2022).

We observe a contrary pattern and less significant coefficients (at the 10% level) when we consider the effects on disabilities. The largest effect is for high-experience workers (46-55 years old), with 0.0007 additional disabilities for a unit increase in PM_{10}. This group is followed by workers closed to the retirement age (56-67 years old), who still show a much lower impact. The effects on other age groups show a similar magnitude, which is about three times smaller that the one we find for workers 45-55 years old. The larger effects on older workers may be explained by their more vulnerable health conditions, which exacerbates the impact of air pollution.

4.2 Mechanism and benchmark of results

An increasing number of health and economic studies consistently demonstrate that short-term exposure to high pollution concentration, especially PM and CO, not only increases the risk of cardiovascular and pulmonary diseases, but it has also significant impacts on brain activity, altering concentration and mental alertness that translate into subclinical effects. Although the physiological pathways are less clear for these 'non-health' effects, they can be explained by two main mechanisms.[17] Firstly, inflammation and oxidative stress processes occur in the brain, affecting the central nervous system (Kleinman and Campbell, 2014; Genc et al., 2012). Secondly, pollution particles can directly move to the circulatory system, affecting 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). Recent studies analyzing *in vivo* effects using neuroimaging document that cerebral white matter, cortical gray matter, and basal ganglia are affected by air pollution on the human brain, causing cognition changes (de Prado Bert et al., 2018). When individuals are performing job tasks, these physio-pathological mechanisms can lead to memory disturbances, fatigue, loss of concentration and judgment, decrease in memory and attention deficit. These mechanisms align with recent empirical studies that examine the causal effects of short-term air pollution exposure on the labor market. Such studies report a significant reduction in labor supply and worker productivity as a

[17] The non-health effects of air pollution have been recently review by Aguilar-Gomez et al. (2022).

result of pollution exposure (Graff Zivin and Neidell, 2012; Chang et al., 2019a, 2016b; Hanna and Oliva, 2015).

Other studies focus on cognitive ability and education outcomes. For instance, Ebenstein et al. (2016) document a causal relationship between air pollution and reduced cognitive ability by studying the effect of pollution exposure during high-stakes tests in Israeli schoolchildren, with similar effects confirmed by Zhang et al. (2018b), Marcotte (2016) and (Duque and Gilraine, 2022).

A third group of papers focuses on the performance 'on-the-job' by looking at the quality of speech (Heyes et al., 2019), risk attitude in financial investments and trading activities (Heyes et al., 2016; Huang et al., 2020), and performance of professional sport workers (Archsmith et al., 2018). A precise quantification of air pollution effect in reducing cognitive tasks is recently provided by Künn et al. (2019) and Nauze and Severnini (2021). The first study uses data on players' performance exposed to particle pollution during official chess tournaments and estimates that a ten unit increase in the indoor concentration of $PM_{2.5}$ increases a player's probability of making an erroneous move by 26.3%. They find larger effects with rising time pressure, an evidence consistent with the medical literature. The second work employs data from brain-training games to document the negative effect of $PM_{2.5}$ transported by wind on a rich set of cognitive domains that include verbal skills, attention, flexibility, memory, math, speed, and problem solving.

Looking at more severe impacts, Sager (2019) analyzes the causal effect of air pollution on road safety in the United Kingdom in a setting that is closely related to ours. Indeed, driving is a high-risk activity that requires high concentration as many job tasks. He finds that higher levels of particle pollution lead to an increase in the number of vehicles involved in accidents per day, concluding that bad air quality lowers safe driving performance by reducing drivers' cognitive performance by either reducing drivers' cognitive performance (resulting in lower attention span or longer reaction time) or changing drivers' behavior (resulting in more aggressive driving). The results obtained in these studies deliver two important results that corroborate our findings. First, all the documented effects reduce task performance because the worker's body experiences a stronger health stress and she has more difficulty to access their cognitive capacity; both mechanisms are compatible with a higher risk of WRA. Notice that these effects are significant and large even at levels below the EPA and WHO air quality standards, a setting very similar to ours.

The benchmarking of our results with other previous studies is not straightforward due to the absence of causal evidence on the effect of air pollution on work-related accidents. To the best of our knowledge, the very few papers related to ours are the ones by Sager (2019), by Chambers (2021) and by Lavy et al. (2022a). Each of these studies focuses on different sectors and pollutants, therefore our benchmarking exercise should be interpret with caution. In analyzing the effect on car accidents, Sager (2019) estimates an elasticity of 0.06 to $PM_{2.5}$ and 0.17 to AQI. Lavy et al. (2022a) focuses on accidents occurred at construction sites, using NO_2 concentrations but also considers 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.). Finally, the study by Chambers (2021), which is the most closely related to ours, analyzes the effect of $PM_{2.5}$ on accidents in the agricultural and manufacturing sectors; the reported elasticity is 0.65 for agricultural workers and 0.25 for workers in the manufacturing, with no information on the effect of overall air quality.

In our study, we estimate that an increase of one unit in PM_{10} concentration leads to a 0.0014 increase in the number of accidents, which corresponds to an elasticity of 0.23. Therefore, our elasticities are in line with the findings of Sager (2019) and fall within the range of values estimated by Chambers (2021) (0.57 *vis-á-vis* 0.25-0.67). Although our effects may appear smaller than those obtained in similar studies, it is important to consider that our study examines accidents occurring in all economic activities, not just those in traditionally high-risk sectors such as construction, agriculture, and manufacturing, which are the focus of our benchmark studies. To conclude, it is also worth comparing our estimates of the effects on accidents with those obtained from other quasi-experimental studies that have previously looked at the impact on workers' productivity (Graff Zivin and Neidell (2012); Chang et al. (2016a) and Chang et al. (2019a)). These studies have implied elasticities ranging from 0.02 to 0.26, and in this case, our estimates for accidents and disabilities fall within this range.

5 Implications and costs

In modern economies, employers must guarantee that the workplace meets minimum safety requirements and that workers who are injured receive their normal salary during their sick leave. The compensation schemes vary depending on the institutional setting, which determines the amount of risk carried by public and private actors. This means that the cost burden varies according to different risk-sharing schemes. In the Online Appendix, we provide a simple theoretical framework that helps interpret our cost calculations in a setting where private firms are responsible, at least partially, for compensating injured workers.

In Italy, as in many other countries, firms fully bear the compensation costs only for less severe accidents, i.e. those with sick leaves below four days, while the costs of more severe accidents are compensated through a national insurance plan. However, how pollution-specific accidents and their costs are actually distributed between private firms and public insurance remains an empirical issue that we address by conditioning the sample to the specific requirements set by the law in terms of sick leave days, which determine the distribution of risk carriage and compensation costs. Column (1) of Table 5 shows the results for less severe accidents, whose costs are paid by private firms. For this category we estimate 0.011 additional accidents for a one unit increase in PM_{10}, representing about 82% of the total pollution effect (0.011 vis-à-vis 0.014). Column (2) shows that the remaining 18% of the effect of PM_{10}, corresponding to a coefficient of 0.003 (significant at 1%) can be attributed to more severe accidents that result in longer sick leaves paid by the state.

This decomposition reveals that most of the accidents caused by air pollution are not severe, but the compensation costs for them are fully borne by private firms that are not directly responsible for the overall air quality. In contrast, pollution-related accidents with more severe consequences generate costs that are fully paid by the state, and firms only face the indirect cost of a reduced workforce without incurring any monetary spending to compensate their injured workers.

We now provide a back-of-the-envelope calculation of the costs of pollution-induced accidents based on our setting; in doing so, we consider all the cost components, both

Table 5: Effect of PM_{10} on Mild and Severe Accidents

	Accidents	
	With sick leaves <4 days	With sick leaves ≥4 days
	(1)	(2)
PM_{10}	0.0115***	0.0028***
	(0.0034)	(0.0009)
Municipality	✓	✓
Year	✓	✓
Day of week	✓	✓
LLMs × Year-month	✓	✓
N	840,051	840,051
Elasticity	0.342	0.092
F-stat.	74.143	74.278

Notes: N refers to the sample at 5 km. All regressions control for non-linear weather (30 bins of minimum and maximum temperatures, precipitations and wind speed), dummies for national holiday and strikes. Standard errors, in parentheses, are clustered on municipalities. Statistical significance: * 10%; ** 5%; *** 1%.

direct and indirect (Dolan, 2000).[18] Aggregate cost data for Italy are based on INAIL, which is the same data source we use in our analysis. In particular, EU-OSHA (2019, Table 2.2.2b) estimates that the total economic burden for work-related injuries in Italy is 3,239 euros per employed person (Table 6, col. 1; 2015 real term euros), with this amount including the direct, indirect, and the intangible component.

Table 6: Per-Worker Costs for Total and Pollution-Induced Accidents

	Total cost/worker (1)	Cost of air pollution (2)
By stakeholders:		
State	421	7
Employer	648	11
Employee	2,170	37
Total	3,239	55

Notes: Costs are in euros. Column 1 shows the total per-worker marginal costs of one accident split across the employer, employees and the state, based on the European Agency for Safety and Health at Work (EU-OSHA, 2019). Column 2 shows the fraction of cost of air pollution deriving from a one unit increase in PM_{10}.

Direct costs amount to 246 euros and 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 cost amount to 1,899 euros and include the loss in terms of market output, the related output/earning loss, payroll and fringe benefits

[18] EU-OSHA (2019); Tompa et al. (2021) employ this definition for Italy and other EU countries (Finland, Germany, Netherlands, Poland)

to adjust for full wage, and the associated administration costs and home production loss costs. Finally, intangible costs amount to 1,094 euros and include the loss in terms of quality adjusted years of life (QALY), assuming a retirement age at 65 years old.

Based on previous figures, we firstly calculate the total costs of pollution exposure. According to EU-OSHA (2019), the estimated total average cost of an accident in Italy in 2015 was approximately 55,000 euros, assuming a retirement age of 65 years. Considering that the yearly average number of accidents during the period 2014-2018 was 315,000, the total cost of pollution-induced accidents (net of *in itinere* events) was approximately 248 million euros/year for a one unit increase in PM_{10} level ($55,000 \times 0.0143 \times 315,000$, in real terms as of 2015, where 0.0143 is the value of the estimated coefficient in column 2 of Table 4).

Next to this calculation, we quantify the fraction of economic cost of air quality deterioration sustained by the state and employers, and by the employees. According to our estimates, a one additional unit in PM_{10} concentration would correspond to a total additional cost of about 55 euros per employed/person per year (1.7% of 3,239)[19] caused by pollution-induced accidents, of which 7 euros rest on the state, 11 on the employers, and remaining 37 euros on the employees, as shown in column 2 of Table 6.

In summary, our back-of-the-envelope calculation shows that, although the cost of pollution-related accidents is substantial for all the parties involved, employers bear a large portion –about 20%– of these costs.

6 Robustness checks

Alternative specifications – In Table 7 we present a set of additional estimates to validate our baseline results. First, in column 1 we account for the differential effect of single pollutants by using the AQI; the estimated coefficient is slightly larger but in line with the one obtained using PM_{10} (0.017 *vis-á-vis* 0.014) and significant at 1% level. This is also consistent with the fact that in largely urbanized areas, PM constitutes the major source of air pollution. The F-statistic is about 49, signaling that the first-stage estimates using AQI does not suffer from weak identification. For comparability

[19] If scaled up to a standard deviation (s.d.) increase in PM_{10} level, this calculation yields an additional total cost of about 838 euros (the s.d. of PM_{10} in our sample at 5km is 15.23.)

purposes, additional estimates of the effect of air quality using the AQI on the probability of accident and disability are reported in Appendix Table A2 (see Section 4.2).

Next, column 2 reports estimates of the effect of PM_{10} including a set of control dummies that account for extreme weather events (hail, ice formation, extreme wind and rain), with results that are fully significant and virtually identical to our baseline estimates.

In column 3 we account for the discrete nature of the accident distribution by estimating an IV Poisson model; estimates yield similar coefficients also in this case.[20]

In column 4 we test whether our results are driven by pollution emissions from specific economic activities that may include highly polluting industries; we do so by excluding the manufacturing sector from our full sample. The results obtained are, again, virtually identical to our baseline estimates, meaning that overall air quality emitted by building heating—and not specific industries—are driving our results.

Next, in column 5 we control for labor supply and its composition.[21] While geographical avoidance in our setting is not an issue (we observe the exact location of workers in the day of accident event and we exclude *in-itinere* events), temporal avoidance may be more problematic as workers may behave strategically and avoid high pollution days. Therefore it is necessary to test whether labor supply alters our results even though this control may appear endogenous considering the evidence that air pollution can directly affect the labor supply (Hanna and Oliva, 2015; Graff Zivin and Neidell, 2012). However, in our case controlling for labor supply does not alter our baseline estimate, implying that temporal avoidance is implicitly controlled for by our IV strategy.

Finally, in column 6 we account for predetermined characteristics of injured workers by including controls for age, sex and nationality. These additional variables are available only for events occurred, so that the available sample is necessarily smaller and likely suffers from sample selection. The estimated effects is larger than our baseline specification (0.024 *vis-á-vis* 0.014), albeit qualitatively similar.

[20]Standard errors are bootstrapped with 500 replications.

[21]We use administrative data provided by the Italian National Institute of Social Security (INPS), which provides this information at the municipality level and monthly frequency.

Table 7: Alternative Specifications Using Winter Heating Rules as IV

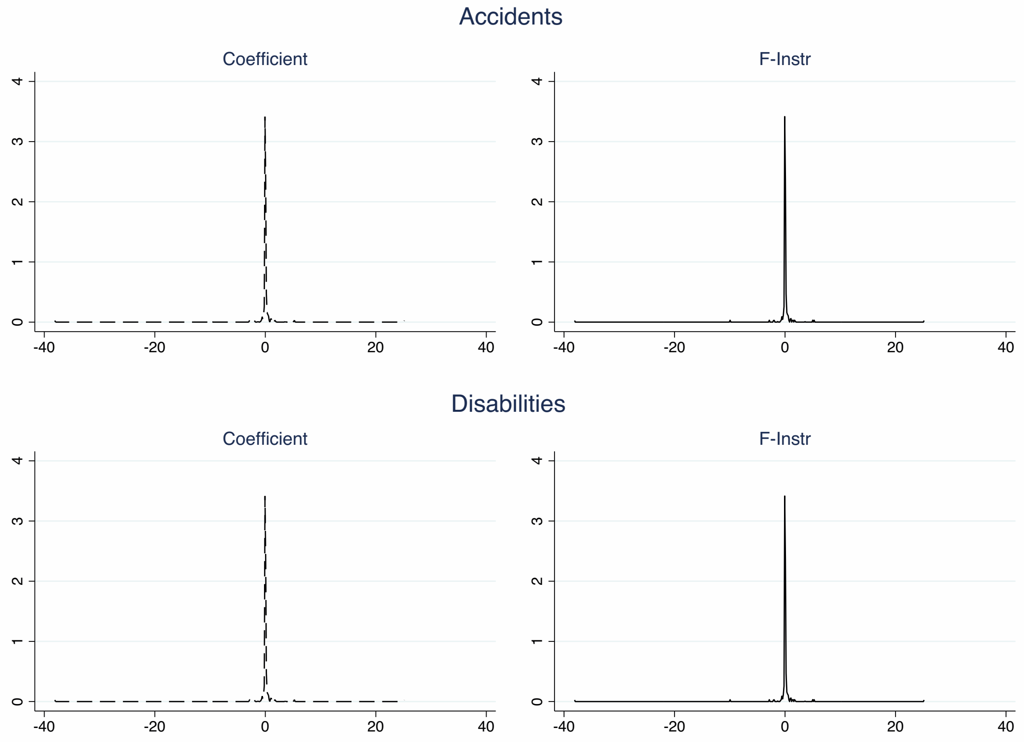
	Overall Air Quality (1)	Extreme events (2)	Poisson (3)	Excluding Manufacturing (4)	Including labor force composition (5)	Including composition of the injured workers (6)
PM_{10}		0.01429***	0.01071***	0.01431***	0.01475***	0.02432***
		(0.00408)	(0.00178)	(0.00408)	(0.00437)	(0.00633)
AQI	0.01684***					
	(0.00512)					
N	841,798	841,798	828,294	841,798	791,209	200,299
F-stat.	48.89	74.34	74.34	74.34	67.05	124.12

Notes: N refers to the sample at 5 km. All regressions control for non-linear weather (30 bins of minimum and maximum temperatures, precipitations and wind speed), dummies for national holidays and strikes. Standard errors, in parentheses, are clustered on municipalities. In column 6 the number of observations does not include zeros. Statistical significance: * 10%; ** 5%; *** 1%. S.e. in column (4) are bootstrapped with 500 replications.

Falsification of winter heating rules – We also present a falsification test to verify the relevance of our instrument. By randomly assigning winter heating dates we expect that our IV is no longer relevant for air quality. We proceed in two steps: first, we drop all the dates where winter heating may be switched on from the policy rules; second, we randomly assign the days when heating may be allowed. We based our test on 500 replications. For each draw, we run the 2SLS model specification (column 2 of Table 4) on this newly defined sample, reporting the F-statistic from the first stage, which tests the relevance of the instrument. Figure 7 shows that when the winter heating dates are randomly assigned to municipalities, we obtain both point estimates and F-statistics that are virtually zero. We take this result as an additional confirming evidence that our research design is credible.

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. Therefore, winter heating IV estimates can be sensitive to this issue because when extending the sample we are also capturing more rural areas with a prevalence of independent houses; this increases the fuzziness of our design and the measurement error in pollution assignment as we move farer from densely populated areas. To address this issue we proceed in two steps. First, we present a sensitivity check based on winter heating rules that shows how the effect of air pollution remains

Figure 7: IV Falsification Test



Notes : The test is obtained by dropping all the dates where winter heating may be switched on from the policy rules and randomly reassign the days when heating may be allowed. For each draw, we run the 2SLS model specification as in column 2 of Table 4. The test is based on 500 replications.

fully significant, though smaller in magnitude, as we move away from the municipalities with monitoring stations. We consider three samples, with distance from core municipalities' centroids of 0, 5 and 10 km. We do not further extend the sample since our main empirical strategy based on winter heating rules captures compliers in areas characterized by a prevalence of centralized heating systems and more densely populated; these areas are not likely to extend beyond a radius of five km. The results, presented in Table 8, show that the strongest effect is found on the sample that includes only municipalities with monitors, with a coefficient of 0.019. When we extend the sample from 0 to 10 km, the magnitude of the coefficients monotonically decrease with distance from 0.018 to 0.012, signaling the presence of attenuation bias.

Secondly, we present additional estimates based on a different IV strategy that does not depend on specific geographical locations or periods, expanding the fraction of IV compliers. Specifically, we use the thickness of the planetary atmospheric boundary layer (PBL), the lowest part of the troposphere, to instrument for air pollution exposure. PBL

Table 8: Effect of PM_{10} on Accidents at Different Distances

	Km		
	0	5	10
	(1)	(2)	(3)
Panel A: Accidents			
PM_{10}	0.01886***	0.01431***	0.01225***
	(0.00567)	(0.00408)	(0.00333)
Elasticity	0.236	0.230	0.205
Obs.	300,063	841,798	2,672,790

Notes: All regressions include day of week, municipality and Local Labor market × year-month fixed effects, along with controls as in Table 4. Standard errors, in parentheses, are clustered on municipalities. Statistical significance: * 10%; ** 5%; *** 1%.

thickness defines the volume of air through which the pollution is mixed and is a key factor in predicting near-surface pollutants concentrations (Akimoto, 2003).[22] PBL thickness is rarely constant and can change hour by hour: we use this as-good-as-random variation in PBL height to estimate predicted values of PM_{10}. In this case, the exclusion restriction is that PBL does not affect WRAs except through an increase in PM_{10} concentration. This is reasonable to believe as the thickness of the PBL is independent of economic activity and cannot be detected by the naked eye, making it difficult to sort out the effects of PBL changes.

Table 9: Effect of PM_{10} on Accidents Using Different IVs

	IV - Winter Heating	IV - PBL Height		
	10 km	10 km	15 km	20 km
	(1)	(2)	(3)	(4)
PM_{10}	0.01225***	0.00327***	0.00300***	0.00293***
	(0.00333)	(0.00083)	(0.00073)	(0.00069)
Day of Week	✓	✓	✓	✓
Municipality	✓	✓	✓	✓
LLM X year-month	✓	✓	✓	✓
N	2,672,790	2,605,072	4,101,057	4,966,929
Elasticity	0.20	0.05	0.05	0.04
F-Stat.	76.4	1,153.4	1,404.1	1,461.2
Outcome mean	0.35	0.35	0.26	0.23
Outcome S.D.	2.22	2.24	1.80	1.65

Notes: All regressions control for non-linear weather (30 bins of minimum and maximum temperatures, precipitations and wind speed), dummies for national holiday and strikes. PBL height is the thickness of the planetary boundary layer calculated in meters in each municipality and day. Standard errors, in parentheses, are clustered on municipalities. Statistical significance: * 10%; ** 5%; *** 1%.

Table 9 presents the results using the two IV strategies, i.e. using winter heating rules

[22] PBL thickness ranges from a few meters to several kilometers and it depends on its direct interaction with the earth's surface.

with a sample at a 10-km radius from monitors' centroids (column 1), and using PBL height at a radius of 10, 15 and 20 km (columns 2, 3 and 4). Both sets of coefficients point to a highly significant effect of PM_{10} on WRAs. However, when directly comparing the results on a 10-km radius, IV estimate using PBL height appears about four times smaller in magnitude. This because winter heating identifies a highly localized treatment effect since compliers are defined as individuals working in limited areas that, in most cases, are within few kilometers from largely populated areas and experience both more accidents and higher levels of air pollution. Conversely, IV estimates using PBL height extend the set of compliers to a larger spatial scale, in which the population density and pollution levels are relatively lower. Overall, this set of results confirms that air pollution exerts a negative impact on workplace safety by increasing the number of accidents, and that this effect holds at different spatial scales and using different IVs strategies. More specifically, our IV estimates using winter heating may be interpreted as an upper bound of the effect of PM_{10}.

7 Conclusions

The negative impacts of air pollution have been extensively investigated across several dimensions, especially given its highly visible effects. However, recent studies have documented less severe but more diffuse impacts that can generate significant costs for society. Building on recent contributions that establish a causal link between air pollution and reduced cognitive ability and other less visible health effects, we present compelling evidence that air pollution affects workplace safety by increasing the number of work accidents. We do this by merging Italian air quality data with administrative work accident data that allow us to conduct a large-scale analysis at a daily frequency and a granular geographical level.

To address potential endogeneity in pollution exposure and simultaneity from pollution release and productivity shifts, we instrument for local air pollution using winter heating rules, which produce differential pollution shocks across different combinations of municipalities and periods. We then consider the effects at a larger spatial scale using a different instrument based on the height of the planetary atmospheric boundary layer. Our estimates show that the magnitude of the effects of PM_{10} range from 0.003 to 0.014

additional accidents for a one unit increase in PM_{10} concentration. These effects are stronger among young and very young workers (15-25 years old), who are more likely to suffer from less work experience, have a weaker labor market attachment and face more pressure on the job.

Given that air quality poses a significant risk for WRAs, implementing additional preventive measures could help reduce this risk. Theoretically, this implies that in settings where the compensation burden is shared between public and private insurers, private firms may have an incentive to invest in work safety to minimize workers' exposure to air pollution, even if they are not directly responsible for overall air quality. Our empirical analysis supports this assumption in the Italian context, where the risk carrier and compensation cost burden depend on the severity of accidents and are split between private firms and society through a national insurance plan. Using per-employee costs deriving from EU-OSHA (2019), our back-of-the-envelope calculation shows that a one unit (s.d.) increase in the PM_{10} level would increase the total cost of accidents by about 1.7%. Notice that this figures include direct, indirect, and intangible components.

Our analysis conveys important policy implications. First, policy makers should consider that air quality constitutes an additional barrier for economic growth and human development even in countries with relatively low pollution levels and good work safety standards. The additional costs generated by pollution-induced accidents are economically relevant and, if accounted for in the policy design process, they could substantially lower the opportunity cost of a stricter air quality regulation, especially in highly urbanized areas, where there is the maximum concentration of heating devices. In this respect, our results are also relevant for what concern the pollution control policies in the residential sector, which have assumed a growing importance after the mobility restrictions due to the Covid-19 pandemic and the increased 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 also helps quantify the consequences associated with densification of cities, in which the concentration of air pollution from heating sources is systematically higher considering the large presence of vehicles.

From an employer's perspective, considering that a significant fraction of the accident risk comes from air pollution and firms have to face additional costs to compensate injured workers, it could be economically profitable for firms to invest in defensive expenditures to reduce the accident risk arising from poor air quality, even though this risk goes beyond their responsibility. Along with additional information on the risks that workers face at work, it would be desirable for firms to employ specific technologies 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 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, even though our calculation provides a good approximation of the cost of air pollution exposure at the workplace, we cannot directly estimate accident costs at the firm level since we do not observe this information in the data.

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Online Appendix

Theoretical framework

Since air pollution affects safety at work, we would expect an informed firm to internalize its effect in order to make the optimal decision on the level of defensive investment. Notice that this can happen even though air quality is not determined by the firm's activity, as the contribution of each firm to overall air quality is often negligible and emissions dispersion mostly depends on weather factors that are difficult to predict (Chang et al., 2019b).[23] For the same reason, firms are likely to be ignorant about the existence of the risk of accident due to bad air quality, therefore their defensive investment decisions might not be optimal. In absence of information on pollution risks, the firm sets the optimal safety level s by minimizing the following cost function:

$$\min_{s} CA[\gamma(s)] + CS(s) \tag{4}$$

where $s \in (0, \infty)$ is the level of safety at the workplace, with $\underline{s} > 0$ being the minimum level set by the law and $\bar{s}$ the maximum safety level achievable by current technology such that $\underline{s} < \bar{s}$; γ is a function that represents all risk factors known to the firm, $\gamma(\cdot) > 0$ and $\gamma'(\cdot) < 0$; CA is the cost of accidents, which is continuous, differentiable and non-decreasing in γ; finally, CS is the cost of defensive investments aimed at increasing safety within the work environment, which is continuous and differentiable in s, with $CS' > 0$ and $CS'' > 0$.

The firm chooses the optimal level of safety $\tilde{s}$ by balancing out the marginal cost (MC) of defensive investments and the related marginal benefit (MB) in terms of work accidents reduction. However, in no case the firm can choose a level of s that is lower than $\underline{s}$, the minimum safety level set by the law. Optimal $\tilde{s}$ satisfies the following first-order condition (FOC):

$$\frac{\partial CA(\tilde{s})}{\partial \gamma}\frac{\partial \gamma}{\partial s} = -\frac{\partial CS(\tilde{s})}{\partial s}. \tag{5}$$

[23] For instance, in our case air pollution shocks derive from winter heating and atmospheric meteorological dynamics, but other studies exploit other sources of variation such as road transport (Bauernschuster et al., 2017; Giaccherini et al., 2021), air transport (Schlenker and Walker, 2015) or boat traffic (Moretti and Neidell, 2011b).

We consider now the case in which the firm is aware that pollution is one of the risk factors affecting the cost of accidents. We denote by ϕ a function that describes the level of exposure to pollution at work in relation to different safety levels, assumed to be continuously differentiable and non-decreasing in s, with $\phi(\bar{s}) \geq 0$. Indeed, under the condition that the firm owns the necessary technology to reduce the exposure of workers to a bad air quality, it can reduce the cost of pollution-induced accidents by increasing the level of defensive investments. This implies that $CA(\cdot) = CA[\gamma(s), \phi(s)]$ and the firm minimizes the following cost function:

$$\min_{s} CA[\gamma(s), \phi(s)] + CS(s) \tag{6}$$

From eq. 6 we derive the following FOC for optimal safety level s^* in the case air pollution constitutes an additional risk factor causing accidents on the job:

$$\frac{\partial CA(s^*)}{\partial \gamma}\frac{\partial \gamma}{\partial s} + \frac{\partial CA(s^*)}{\partial \phi}\frac{\partial \phi}{\partial s} = -\frac{\partial CS(s^*)}{\partial s} \tag{7}$$

The LHS of Eq. 5 and Eq. 7 represent the MB curves, which consist in the marginal reduction in accident costs owing to a marginal increase in the level of safety. While the RHS curve is unchanged, in Eq. 7 the MB curve has shifted to the right with respect to Eq. 5, leading to a higher equilibrium safety level as $\tilde{s} < s^*$. This implies that defensive investments are sub-optimal if the firm does not consider that workplace exposure to air pollution is a risk factor. Therefore, the firm should optimally increase s if specific technologies are available to mitigate the exposure to bad air quality at the workplace.

Additional Tables

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 Air Quality on the Probability of Accident and Disability

	Accidents		Disabilities	
	OLS (1)	2SLS (2)	OLS (3)	2SLS (4)
AQI	0.00067***	0.00165***	0.00042***	0.00079***
	(0.00006)	(0.00051)	(0.00005)	(0.00025)
Day of week	✓	✓	✓	✓
Municipality	✓	✓	✓	✓
LLM X Year-month	✓	✓	✓	✓
N	841,798	841,798	841,798	841,798
Elasticity	0.07	0.09	0.18	0.20
F-stat.	–	48.88	–	48.88
Outcome Mean	0.24	0.24	0.06	0.06
Outcome S.D.	0.43	0.43	0.24	0.24

Notes: N refers to the sample at 5 km. All regressions control for non-linear weather (20 bins of minimum and maximum temperatures, precipitations and wind speed), dummies for national holiday and strikes. Standard errors, in parentheses, are clustered on municipalities. Statistical significance: * 10%; ** 5%; *** 1%.

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 Figure A1 and A2).

Figure A1: Pollutant-Specific Thresholds, AQI Values and Levels of Concern

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

Figure A2: AQI Thresholds and Health Implications

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.

In calculating the AQI we follow the EEA guidelines.[24] We include stations with non-missing data for four pollutants: PM_{10}, SO_2, NO_2 and O_3. 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} and $PM_{2.5}$ 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.[25]

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 Figure A1, we

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

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

then find the two breakpoints that contain the maximum concentration values. Finally, we calculate the index following the formula:

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

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 Figure A1.

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