Work Accidents
and
Air Pollution

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Abstract

We investigate the causal effect of air pollution on work accidents in Italy, a wealth country with strict environmental regulation. We employ unique administrative data on work accidents at daily frequency and detailed information on workers' location merged with air pollution concentrations. The causal identification of the effect is obtained by instrumenting air pollution with heating periods in specific municipalities and dates. We estimate that a ten unit increase in the Air Quality Index results in a 8.6% increase in the number of accidents. We do not find any effect of air pollution on the intensive margin, i.e. accident-related disabilities. Our results imply that, even at moderate air pollution concentrations, the safety of workers is not only under direct competence of employing and polluting firms but extents to the surrounding economy as a whole, affecting the public domain.

Keywords: air pollution, air quality index, work accidents, IV, winter heating.

JEL: I18, J28, J81, Q51, Q53

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1 Introduction

Air pollution is an important risk factor for human capital development (Dominici et al., 2014; Zivin and Neidell, 2018). While early empirical studies focused on mortality and morbidity effects, more recent evidence has showed that short-run fluctuations in air pollution concentrations produce more subtle effects, impairing labor supply (Hanna and Oliva, 2015), on-the-job productivity (Graff Zivin and Neidell, 2012; Chang et al., 2016; He et al., 2018), human behavior (Bondy et al., 2018), concentration and cognitive ability (Ebenstein et al., 2016; Zhang et al., 2018; Sunyer et al., 2017). These subtle effects have been shown to produce sizable costs in terms of economic growth and health expenditures. Yet, there could be other hidden impacts to explore that can be economically relevant.

In this paper we investigate for the first time the causal effect of air pollution on work accidents, a key outcome for the labor market. Building on recent literature, we conjecture that if air pollution reduces concentration and increases fatigue, workers exposed to bad air quality are more likely to make mistakes and, as a consequence, they are more likely to experience work accidents. We test this hypothesis using a unique administrative dataset containing the universe of daily accidents occurred in eight Italian regions from 2014 to 2018. With these data we analyze the effect of air pollution on the number of accidents and, since workers typically pay more attention when performing riskier tasks (Barnes and Wagner, 2009) and we also observe the severity of the accidents (disabilities and deaths), we also test whether air pollution produce differentiated effects.

Work accidents represent an important dimension of the labor market. In Europe the incident rate is about 1500 per 100,000 workers, with a stable trend in the previous years. These figures generate a substantial amount of social welfare expenditures and produces a loss of human capital and job skills, which in turn affect both economic and social development (Pouliakas and Theodossiou, 2013). According to recent estimates from the International Labor Organization (ILO), work-related injuries and illnesses result in the loss of 3.9% of all work-years globally and 3.3% of those in the European Union, equivalent to a cost of approximately 2,680 billion and 476 billion, respectively.[1] Despite the relevant economic implications, previous studies have investigated only the causes of accidents within the workplace environment (Galizzi, 2013), while the role of air pollution–a diffused externality that all workers face every day–remains virtually unknown.

[1]Cost to society 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.

Estimating the causal impact of air pollution on work accidents represents an empirical challenge for several 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 pollute more. To address this problem, we instrument air pollution with winter heating, which produces differential shocks in air pollution in specific municipality-period combinations without directly affecting the labor market. Our pollution measure consists in a four-pollutant Air Quality Index (AQI); this approach allows to capture independent effects of any single pollutant in the IV setting while reducing collinearity due to a multi-pollutant model approach (Dominici et al., 2010; Chang et al., 2018).

A second important identification challenge is that individuals differ for characteristics that are often unobserved to the econometrician, such as different predetermined health status, defensive investments or strategic behavior that may induce workers to sort into less polluted places or low pollution periods (Deschenes et al., 2017; Chang et al., 2016, among others). To mitigate these biases, we benefit of the unique features of our data; our identifying variation exploits high-frequency (day-by-day) fluctuations in air pollution within the municipality. In addition, we consider only accidents at the workplace during working days, controlling for holidays, strikes and weather conditions. By doing so, we estimate the effects in a setting where strategical sorting is negligible.

Our results show that a ten unit increase in the AQI (about a half s.d.) causes 0.22 additional accidents, approximately a 8.6% increase. We find no effects on disabilities. Our estimates are robust to different model specifications and robustness checks.

2 Data

2.1 Work-accidents data

In Italy work-related accidents (henceforth WRA) are defined as external traumatic events on the job that cause an injury (Legislative Decree 38/2000). The injury leads to temporary work disability (at least 3 working days lost), permanent work disability (complete or partial), or death. All Italian workers must be insured against WRA through the National Institute for Insurance against Accidents at Work (INAIL).[2] The mandatory enrollment in INAIL ensures

[2]INAIL is a public non-profit administration safeguarding workers against physical accidents and occupational diseases. For further information, visit: https://www.inail.it

that all the Italian WRA 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.[3]

We obtain data for any accident occurred between 2014 and 2018 in eight Italian regions (5201 municipalities): Lombardia, Veneto e Piemonte (North), Toscana and Lazio (Center), Campania, Puglia and Sicilia (South). This initial sample consists of about 2.1 million events (about 420,000 each year) and covers approximately 65% of the total number of work accidents in Italy during that period. The WRA data provide a richness of information which can be divided in three groups: worker's characteristics (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, compensation premium, no. of compensated days).

We restrict our sample to accidents occurred to individuals with working age, which we conventionally define as 16-67 years and to singleton events occurred at the workplace.[4] After this restriction, we obtain about 1.5 million observations. Since data provide worker's location at municipality level, we collapse the data by worker's municipality $\times$ day of event to ease the computational burden and to account for the fact that our identifying variation occurs at municipality (Isen et al., 2017); this procedure leads to a total of 874,328 observations (i.e. municipality $\times$ day-of-event cells).

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 unexpectedly they affect also 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 both accidents and disabilities are more likely to occur to men, and to domestic workers (panel d)).

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

[3]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."

[4]We exclude *in itinere* events since these mainly constitute traffic-related accidents and their analysis goes beyond the aim of this paper. For a recent investigation of the effect of road-safety and air pollution see Sager (2019).

holidays in Italy. 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 Environmental data

Air pollution data come from the European Air Quality Database (Airbase), which collects information on hourly concentrations registered by monitoring stations.[5] We collect concentration data for four pollutants, PM_{10}, CO, NO_2 and SO_2.[6]

Depending on which pollutant is considered, the number of monitoring stations varies across space and time, as some municipalities installed stations after the introduction of more stringent regulations on air quality and monitoring stations could not operate continuously. Since our period of analysis refers to recent years, we have a high number of operating monitors for each pollutant. Moreover, the collected data show at least 95% of correct readings in the period of analysis, which limits concerns about the endogeneity of monitor "births" and "deaths" (Bharadwaj et al., 2017). As in the case of WRA, we collapse air pollution data to municipality $\times$ day cells. For municipalities with more than one monitoring station, we assign the average pollution concentration registered in all the monitoring stations belonging to that municipality. With these concentration data we compute an air quality index (AQI) following the indications provided by the EEA. The AQI is a well-known indicator to measure the 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. For PM_{10}, NO_2 and SO_2, we calculate the AQI according to the EEA's indications, while for CO we follow the indication provided by the Environmental Protection Agency of the United States (US EPA) since the European AQI does not provide guidelines for CO.[7] The AQI computed with this procedure assumes values from 0 to 500 and over.

Because weather factors can independently affect worker's productivity (Deschênes et al., 2009) and the likelihood of work accident (Schifano et al., 2019), we include a full set of weather data available on a daily basis (Gridded Agro-Meteorological Data—GAMD). GAMD data are provided on a regular grid of approximately 20×20 km and cover all the municipalities for

[5]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.

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

[7]The complete AQI formula and calculation procedure is reported in Appendix.

which WRA data are available. We select maximum and minimum temperatures expressed in degrees Celsius (°C), wind speed expressed in m/s and total precipitation expressed in mm, computing daily measures at administrative municipality level following the same procedure described above for pollution data.

We match the WRA data with air pollutant concentrations and weather data, which leads to a final sample of 91,500 observations as identified by municipality $\times$ day cells for a total of 51 municipalities. Following Knittel et al. (2016); Moretti and Neidell (2011); Chay and Greenstone (2003), we extend this initial sample of municipalities with pollution stations to neighboring municipalities within a 18 km radius from each monitor's centroids. For municipalities where stations are present, we assign the original concentration measure, while for neighboring municipalities we weight the concentrations by the inverse distance. With this procedure, our final sample ranges from roughly 89,358 to 464,276 observations, respectively including 51 municipalities with stations, and 1857 municipalities in the most extended version.

Table 1 shows summary statistics for the relevant variables, while Figure 3 shows the geographical distribution of municipalities with monitoring stations (blue areas) and those of the extended sample up to 18 km (green areas). Even though our sample includes a relatively small fraction of the total municipalities for which we have accidents data, from this figure we observe that it is not affected by geographical sorting.

2.3 Additional data

We retrieve data on national holidays from the Italian Government website, and on single-day general strikes or transportation strike from the Italian strike commission and the Ministry of Infrastructures and Transport. We also collect population data from ISTAT, restricting to individuals between 16 and 67 years. Although this measure is affected by some limitation, it represents our best approximation of the active population in absence of more specific data. Summary statistics for these additional variables are reported in Table 1.

3 Econometric Framework

3.1 Baseline model

Our goal is to estimate the impact of air pollution on work-related accidents. We begin our econometric analysis by estimating the following fixed effects model:

$$Y_{ct} = \alpha + \beta AQI_{ct} + \mathbf{W}'_{ct}\gamma + \mu_c + \mathbf{T}_\tau + \varepsilon_{ct} \quad (1)$$

where the outcome Y_{ct} represents, respectively, the number of accidents and disabilities registered in the municipality c in day t; AQI_{ct} is the AQI, which is our indicator of air quality; $\mathbf{W}_{ct}$ contains a set of adjusting variables, namely individual characteristics of workers who underwent accidents (age, gender, and immigrant status), firm characteristics where the accident happened (NACE code), weather characteristics when the accident happened (up to fourth degree polynomials in minimum and maximum temperature, precipitations and wind speed) and dummies for national holidays and general strikes; finally, a distinctive feature of our model is a rich set of controls for unobserved heterogeneity like seasonal fixed effects (i.e. year, month, and day of week, denoted $\mathbf{T}_\tau$) and municipal fixed effects (μ_c); ε_{ct} represents an idiosyncratic error term. We also estimate a more demanding specification which includes an additional set of province $\times$ month-by-year fixed effects to account for differential growth trends. The coefficient of interest is β, which is the effect of one unit increase in the AQI on the outcome: a positive coefficient implies that as the air quality deteriorates the number of accidents/disabilities increases. Standard errors are robust to heteroschedasticity and clustered at province level (Wooldridge, 2003; Bertrand et al., 2004).

3.2 Quasi-experimental setting

Though the fixed effects included in model 1 purge a substantial part of time-invariant unobserved heterogeneity, the resulting estimates may still be biased. More intense economic activity in some geographical areas and days may co-vary with more intense air pollution release, leading to biased estimates. 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 pollute more. Similarly, if workers behave strategically and avoid high polluted days, the estimated effect of pollution from standard fixed effects model will be biased. In addition, the assignment of pollution exposure to workers may be imperfect as we move away from monitors; in this case fixed effects estimates would be *upward* biased. Therefore, it is difficult to establish *a priori* the direction of this bias. To purge from these possible sources of endogeneity we exploit an instrumental variable (IV) approach, using winter heating rules.

In numerous countries, winter heating both in private and public buildings is regulated by specific laws to reduce harmful emissions released from heating devices, especially traditional ones such as gas boilers and wood-burning and pellet stoves.[8] This feature has been recently exploited in a RDD setting by Fan et al. (2020) to analyze the effect of air pollution on mortality in China, a country with massive use of coal-based heating. Event though Italy benefits of more advanced heating technologies, fossil fuels still play the lion's share in the energy sources for residential heating. Natural gas and biomass represent approximately 85% of the total fuel, while cleaner sources such as electricity covers only 5% of the energy mix (ENEA, 2017). Therefore, winter heating results in a massive release of several harmful emissions during winter since burning natural gas and other fossil fuels generate several pollutants such as CO, NO_2 and PM_{10}.

In our setting, winter heating scheme consists in a classification of municipalities in six climate areas, 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 "F" are allowed to start heating in any day of the year due their severe and longer winter conditions. Figure 4 shows the map of in-sample municipalities classified according to the six climate zones, while Table A1 reports the share of in-sample municipalities across zones. Only 2.3% of municipalities belong to warm climate zones (A and B), where winter heating is allowed only from December to March. About 24% of municipalities is characterized by a longer winter, with heating allowed from November to early April (zones C and D), while the largest group is allowed to anticipate winter heating, which goes from mid October to mid April (zone E). Only 5% of municipalities is allowed to start heating in any day of the year (zone F).

Due to its regulation, winter heating produces differential shocks in air pollution concentrations in specific municipality-period groups while it does not affect the labor market and the firms' production processes. This represents an ideal IV in our setting since we can plausibly assume that work accidents do not significantly change during winter heating if not for heating-induced pollution shocks, once we control for weather factors. Controlling for weather is particularly important in our quasi-experimental setting; even though our IV captures both central heating systems (serving multiples homes) and independent heating systems (serving only one home), it could be possible that during severe cold conditions individuals with independent heating systems activate heating in advance, against the heating rules. Conversely, it could happen that if temperatures are mild during periods in which winter heating is al-

[8]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 than the half of that normally allowed.

lowed, individuals prefer not to activate heating. While we cannot explicitly observe these behaviors in our data, by accurately controlling for weather factors we rule out most of the weather-driven variation in air pollution, strengthening our exclusion restriction We estimate the following model by means of 2SLS:

$$AQI_{ct} = \alpha + \lambda D(Heat)_{ct} + \mathbf{W}'_{ct}\gamma + \mu_c + \mathbf{T}_\tau + \varepsilon_{ct} \tag{2}$$

$$Y_{ct} = \alpha + \beta \widehat{AQI}_{ct} + +\mathbf{W}'_{ct}\gamma + \mu_c + \mathbf{T}_\tau + \eta_{ct} \tag{3}$$

where $D(Heat)_{ct}$ is an instrumental dummy variable equal to 1 when the winter heating starts in each municipality-period group according to the six climate zones reported in Table A1 and $\widehat{AQI}_{ct}$ is the first stage predicted value of AQI_{ct}.

4 Results

In this section we present the main results, with additional checks discussed in Section 5. To begin with, the first stage results (see Appendix Table A2) indicate that winter heating generates substantial pollution shocks, increasing the AQI of approximately 1.5 units. This effect increases to 2.2 units (approximately a 10%) when controlling non-linearly for weather factors and province× year-month fixed effects.[9]

Table 2 and Table 3 report, respectively, estimates of the effects of air pollution on the number of accidents and disabilities. Each table includes both OLS-FE and 2SLS estimates and control for share of females, 5-year age classes, share of foreign workers and economic sectors (ATECO 1 digit). Non-linear controls for weather includes up to fourth degree polynomials in minimum and maximum temperatures, precipitations and wind speed. Moreover, columns (2) and (4) include additional province× year-month fixed effects. We cluster standard errors are clustered on provinces to account for dependencies in pollution shocks and labor market characteristics (Wooldridge, 2003; Bertrand et al., 2004).

OLS estimates are substantially lower of approximately 50% than 2SLS coefficients. This is not surprising since since simple OLS estimates suffer from multiple sources of endogeneity bias (see Section 1) (Deryugina et al., 2016; Sager, 2019). In the most demanding specification (column 4) the 2SLS coefficient is 0.22, corresponding to an increase of approximately 0.86% in the number of accidents for a one unit increase in the AQI. This coefficient is fully significant

[9]These comments refer to the sample for accidents. The results obtained when analyzing the effect on disabilities, based on a smaller sample, are larger (see column (4) of Appendix Table A2.

but much smaller than the one obtained without controlling for province-specific seasonality (column (3)).

5 Robustness checks

Avoidance behavior – In analyzing the effect of air pollution on humans, avoidance behavior represents a serious concern (Neidell, 2009; Moretti and Neidell, 2011; Knittel et al., 2016; Deschenes et al., 2017, among others). Individuals may adjust their exposure in response to changes in air pollution or adopt differential compensatory behavior, as for instance, by reducing the time spent outdoors. Nevertheless, the extent to which avoidance behavior affects the estimates depends also on the nature of the outcome analyzed and, more generally, on the nature of data employed. Event though we do not have information on workers' position in days before the accident, we directly observe their location (municipality) on the day of event. By excluding *in itinere* events, our sample includes only accidents occurred at the workplace. More importantly, we can plausibly assume that employed workers have hardly any option to adjust their location or postpone their tasks in response to changes in air pollution, at least on a daily basis. Since we employ daily data with events registered at the workplace, the endogeneity bias due to avoidance behavior is potentially very low.[10] Regarding possible omitted information on the predetermined health status of workers, even though we do not have explicit information on this, again we can assume that if a worker is present at the workplace on the day of accident, she is plausibly in a relatively good health status to carry out standard work tasks.

Independent effects of temperature – Temperatures may significantly alter the effect of air quality on work accidents. To address this important concern, we estimate a differences-in-differences (DiD) model to compare the effect of winter heating in cities with cold temperatures (treated) and with warm temperature (controls) during a time window $t = \{-5; +7\}$ days, with $t = 0$ being our pre-post variable, i.e. the day in which winter heating starts in any municipality. The DiD estimates presented in Appendix Table A3 reveal that when temperatures are colder, the effect of air pollution induced by heating does not significantly differ between treated and control groups.

The DiD results are further confirmed by another test presented in Figure 5, which shows the effect of minimum temperature on work accidents in cities with and without winter heating

[10] We cannot exclude, however, a differential response to air pollution in terms of defensive investments. For instance, we cannot observe in the data if, on high pollution days, some workers adopt specific devices to protect them.

using Regression Discontinuity (RD) estimates with cutoff set at 0 degree Celsius. Notice that these correlations already include controls for sample composition (age, sector etc.), other weather factors, and municipality fixed effects. When temperatures are low (around or even below the 0 cutoff) and winter heating is on (red line) there is no effect of temperature in affecting work accidents. Conversely, when temperatures are low but winter heating is off (blue line), the overall number of accidents is lower and there is a clear discontinuity around the 0 cutoff, since ice formation increases the risk of accidents.

Weighting – [Table to be included] To test the validity of our results, we also run our estimates using weights for the number of individuals living in each municipality-year cell. Even thought weighting by total population and year does not represent the best option, we do not have alternative data that allow to observe the exact number of individuals working in any municipality and day. Considering this limitation, our weighted estimates yield very similar results to those obtained without weights.

6 Conclusion

In this paper we find that air pollution, a diffuse externality, affects the labor market by increasing the number of work accidents. Since air pollution mostly depends on the economic activity, and productivity shifts can also affect air pollution concentrations even at a daily frequency, we exclude this important confounding channel by instrumenting for air pollution using winter heating rules. Even though we cannot provide with the data at hand a direct evidence of the mechanism through which air pollution increases the number accidents on the job, recent contributions highlight that air pollution, especially CO and PM_{10}, can alter concentration and mental alertness (Künn et al., 2019; Sager, 2019; Graff Zivin and Neidell, 2012). Moreover, these effects are contemporaneous and can also occur for daily fluctuations in air pollution. Therefore, a plausible explanation of our results is that workers exposed to higher pollution concentrations are likely to reduce their concentration and cognitive ability, resulting in a higher risk of accident on the job.

Our findings convey important implications for both firms and policy makers. Since firms and public administrations already sustain an "optimal" cost for workers' insurance against the risk of work accidents, if air pollution is found to increase this risk for factors that are beyond the control of the employers, it results that some workers could be sub-optimally insured.

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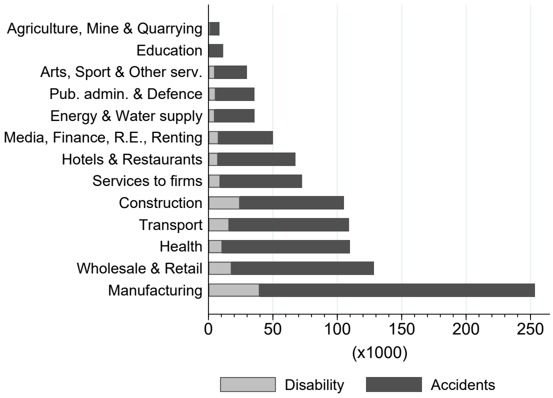
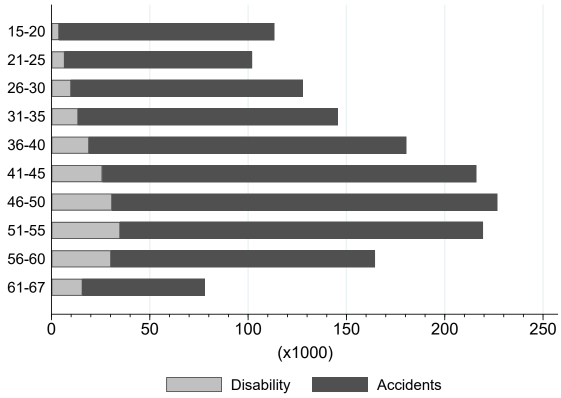
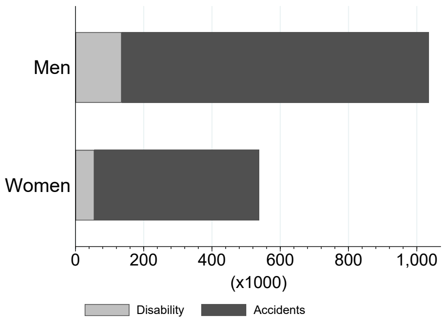
Figure 1: Accidents and disabilities by economic sector, age class, nationality and gender.



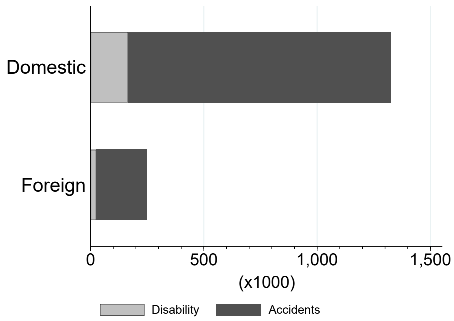
(a) Across economic sectors



(b) Across age classes

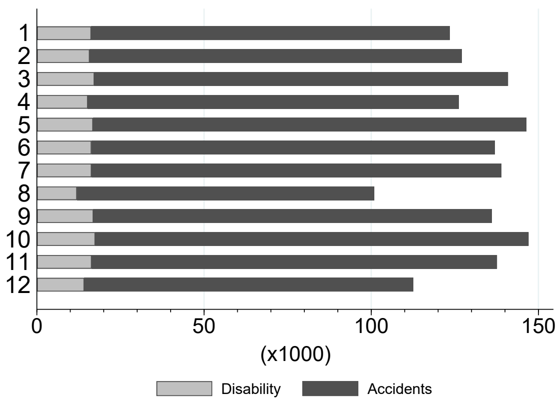


(c) Across gender

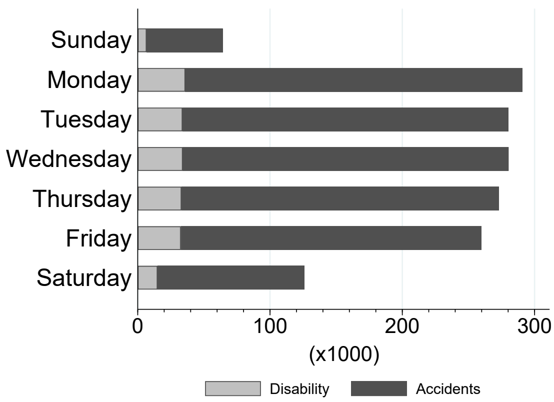


(d) Across nationality

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

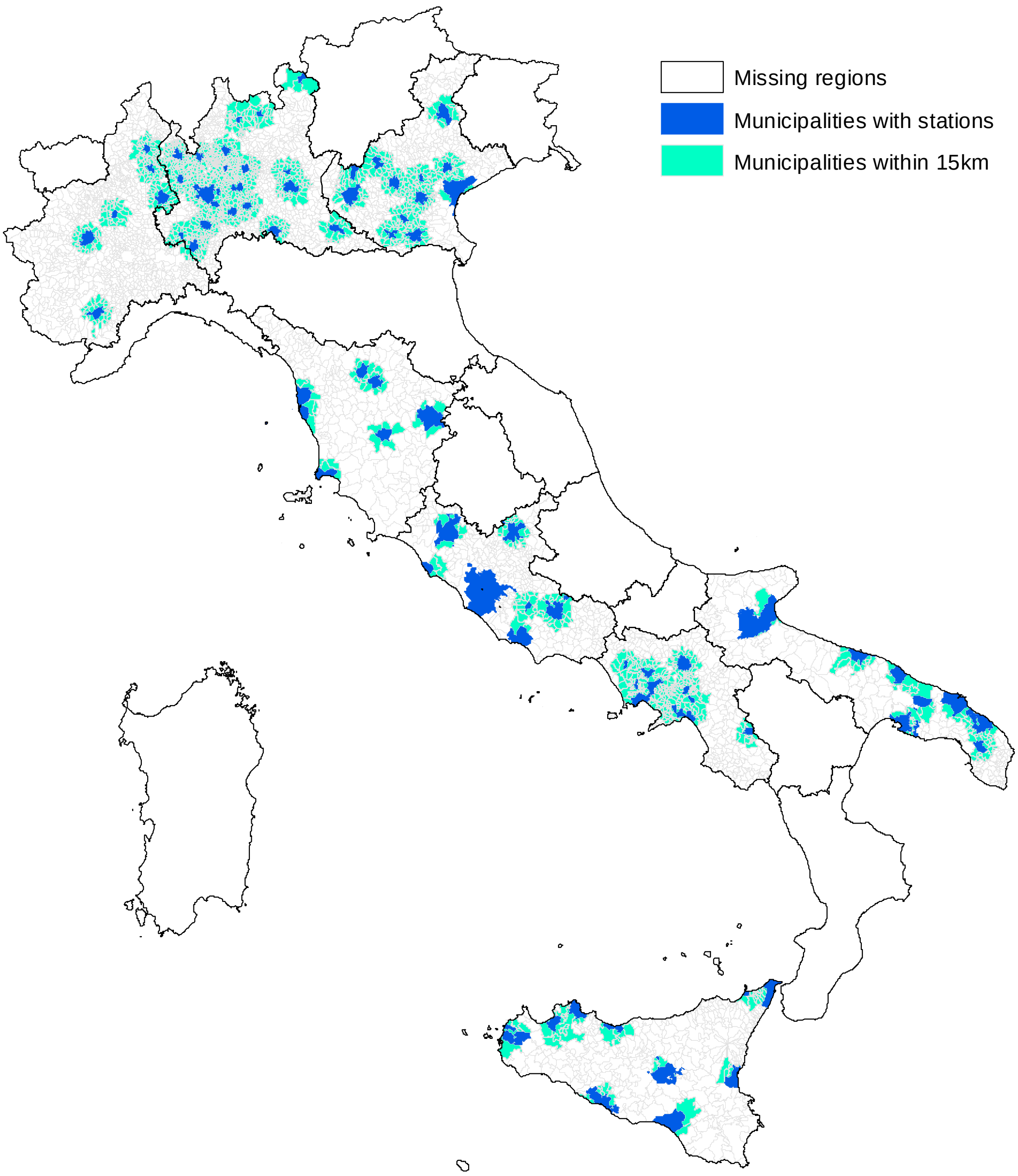


(a) Across months



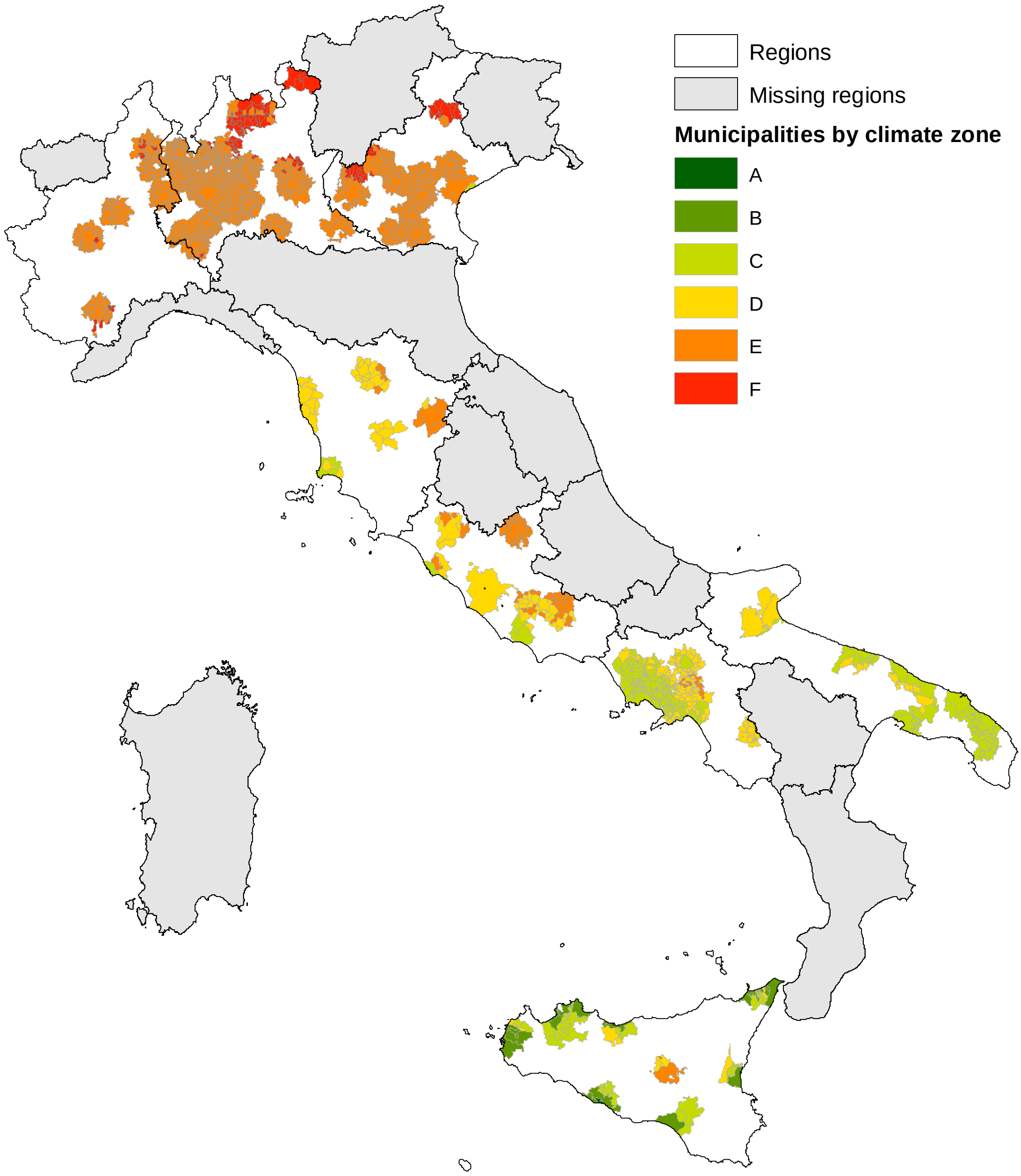
(b) Across day of week

Figure 3: Geographical location of municipalities with CO monitoring stations.



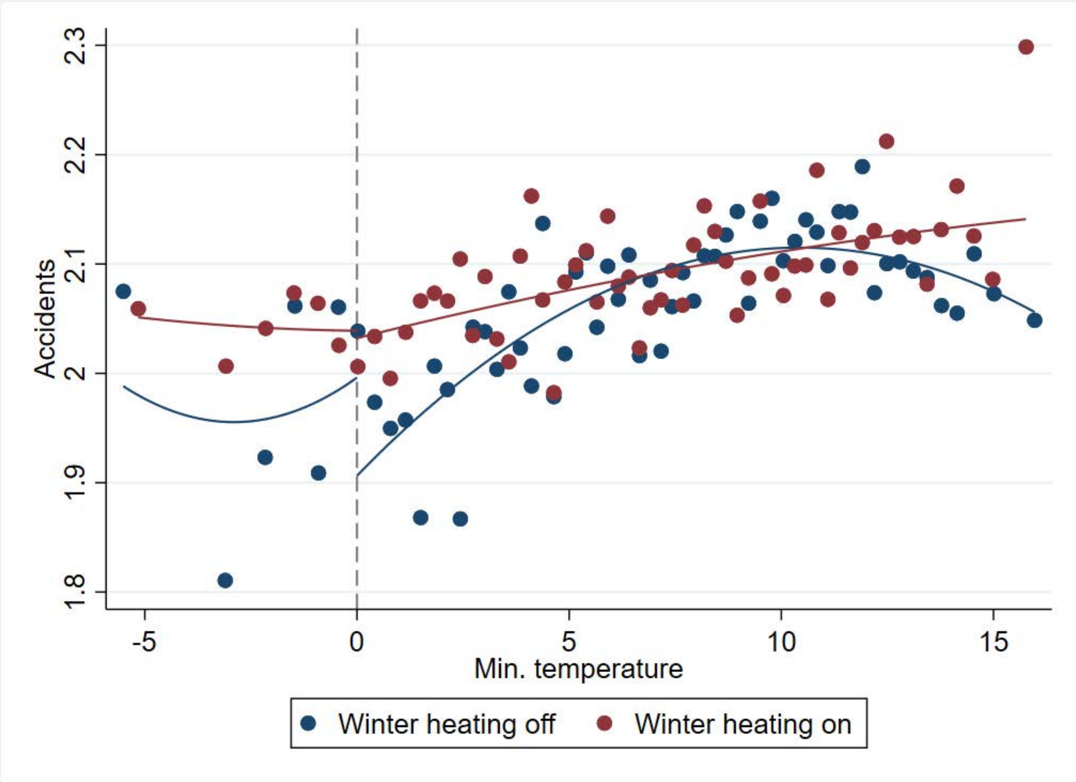
Notes : The figure shows the Italian municipalities where CO stations are present in the eight regions of analysis (blue areas) and municipalities within a 15 km radius from CO stations (green areas). Source: own elaboration based on the AirBase database.

Figure 4: Geographical distribution of in-sample municipalities 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.

Figure 5: Correlation between accidents and min. temperature with/without winter heating in an RD setting.



Notes : The figure is obtained using the `binscatter` Stata command by Michael Stepner (see https://michaelstepner.com/binscatter/). Source: own elaboration using Agri-4-cast and INAIL data.

Tables

Table 1: Summary Statistics

Variable	Mean	s.d.
Accidents	2.068	4.603
Disability	0.240	0.712
Female	0.298	0.414
Foreign workers	0.167	0.343
Age 21-25	0.070	0.234
Age 26-30	0.083	0.251
Age 31-35	0.095	0.267
Age 36-40	0.119	0.295
Age 41-45	0.141	0.317
Age 46-50	0.145	0.320
Age 51-55	0.137	0.313
Age 56-60	0.099	0.271
Age 61-67	0.045	0.189
AQI	9.812	15.096
Max. Temperature	19.851	8.205
Min. Temperature	10.496	7.203
Avg. Temperature	15.171	7.482
Wind speed	2.270	1.246
Total rainfall	2.362	7.268
Pop. (× 1,000)	35.926	137.154
Winter heating	0.349	0.477

Notes: Data are collapsed at municipality cells averaged over the period 2014-2018. Sample size (at 12 km) is 324,773 across 1,488 municipalities.

Table 2: Estimates of the Effect of Air Quality on Work Accidents

	Accidents			
	OLS		IV	
	(1)	(2)	(3)	(4)
AQI	0.011***	0.012***	0.059***	0.022***
	(0.003)	(0.003)	(0.018)	(0.007)
Municip. FE	x	x	x	x
Year FE	x	x	x	x
Day of week FE	x	x	x	x
Holidays + strike	x	x	x	x
Non-linear weather	x	x	x	x
Province × year-month FE		x		x
N	324,774	324,773	324,774	324,773
Effective F-stat.			15,41	39.00

Notes: N refers to the sample at 12 km (accidents mean=2.54, s.d.=5.82). All regressions control for share of females, 5-year age classes, share of foreigns and economic sectors (ATECO 1 digit). Non-linear controls for weather includes up to fourth degree polynomials in minimum and maximum temperatures, precipitations and wind speed. Standard errors, in parentheses, are clustered on provinces. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 3: Estimates of the Effect of Air Quality on Work Disabilities

	Disabilities			
	OLS		IV	
	(1)	(2)	(3)	(4)
AQI	0.003**	0.003**	0.003	-0.003
	(0.001)	(0.001)	(0.005)	(0.005)
Municip. FE	x	x	x	x
Year FE	x	x	x	x
Day of week FE	x	x	x	x
Holidays + strikes	x	x	x	x
Non-linear weather	x	x	x	x
Province × year-month FE		x		x
N	65.255	65.180	65.255	65.180
Effective F-stat.			15,43	31,08

Notes: N refers to the sample at 12 km (disability mean=1.44, s.d.=1.41). All regressions control for share of females, 5-year age classes, share of foreigns and economic sectors (ATECO 1 digit). Non-linear controls for weather includes up to fourth degree polynomials in minimum and maximum temperatures, precipitations and wind speed. Standard errors, in parentheses, are clustered on provinces. * significant at 10%; ** significant at 5%; *** significant at 1%.

Appendix

Table A1: Municipalities by Climate Zone

Climate Zone	No. of Municipalities	Share	Start/End Heating Period
A	1	0.001	Dec. 1/ Mar. 15
B	32	0.022	Dec. 1/ Mar. 31
C	219	0.147	Nov. 15 / Mar. 31
D	139	0.093	Nov. 1 / Apr. 15
E	1022	0.687	Oct. 15 / Apr. 15
F	75	0.050	Any day

Notes: Sample size (at 12 km) is 324,773 across 1,488 municipalities.

Table A2: First Stage Estimates of the Effect of Winter Heating on AQI

	First stage			
	Accidents		Disability	
	(1)	(2)	(3)	(4)
Winter heating	1.557***	2.198***	3.049***	3.336***
	(0.396)	(0.352)	(0.776)	(0.598)
Municip. FE	x	x	x	x
Year FE	x	x	x	x
Day of week FE	x	x	x	x
Holidays + strikes	x	x	x	x
Municip. x year-month FE		x		x
Non-linear weather		x		x
N	324,774	324,773	65,255	65,180
F-statistics	15.41	39.00	15.43	31.08

Notes: N refers to the sample at 12 km (for column 1-2, AQI mean: 20.81, s.d.: 21.17, for column 3-4, AQI mean: 13.65, s.d.: 17.28). All regressions control for share of females, 5-year age classes, share of foreign and economic sectors (ATECO 1 digit). Non-linear controls for weather includes up to fourth degree polynomials in minimum and maximum temperatures. Standard errors, in parentheses, are clustered on 54 provinces. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table A3: Differences-in-Differences Estimates

Winter Heating	0.084	0.072	0.114	0.088*
	(0.078)	(0.049)	(0.079)	(0.051)
N	10,245	10,216	10,245	10,216

Notes: All regressions include controls as in column (4) of Table 2. Standard errors, in parentheses, are clustered on 54 provinces. * significant at 10%; ** significant at 5%; *** significant at 1%.