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Labor Market Effects of Dirty Air. Evidence from Administrative Data*

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Labor Market Effects of Dirty Air. Evidence from Administrative Data*

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Abstract

We study the impact of air pollution on labor supply and wage compensations in Italy. Matching administrative data on the universe of Italian dependent employees with PM_{10} concentrations and weather data at monthly frequency, we exploit exogenous variation in wind speed to instrument for endogenous air pollution exposure. We find that a one standard deviation increase in PM_{10} level, leads to a 7.3% higher probability of sick leave and to an earning loss of 0.83 euros/worker/month. These figures generated total social excess expenditures of 755 million euro during the period 2011-2016 if we consider a pollution threshold set by the World Health Organization and extend the effects to the total workers population. The heterogeneity analysis shows that the impacts are larger for workers in constructions and services, for white and blue collars and for females and foreign workers, while we find no impact on managers. The sick wage received by exposed workers is not always aligned to the pollution exposure actually faced by different worker categories.

Studiamo l'impatto dell'inquinamento atmosferico sull'offerta di lavoro e le compensazioni salariali in Italia. Abbinando i dati amministrativi sull'universo dei dipendenti nel settore privato alle concentrazioni di PM10 e a dati meteorologici

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a frequenza mensile, sfruttiamo la variazione esogena della velocità del vento come variabile strumentale per l'esposizione endogena all'inquinamento atmosferico. Troviamo che un aumento di una deviazione standard nel livello di PM10, porta a un aumento di probabilità di congedo per malattia pari al 7.3%, corrispondente a una perdita di guadagno di 0.83 euro/lavoratore/mese. Queste cifre hanno generato un eccesso di spesa sociale totale di 755 milioni di euro nel periodo 2011-2016 se si considera una soglia di inquinamento fissata dall'Organizzazione Mondiale della Sanità e si estendono gli effetti alla popolazione totale dei lavoratori. L'analisi di eterogeneità mostra che gli impatti osservati sono maggiori per i lavoratori nel settore delle costruzioni e dei servizi, per gli impiegati e operai, e per le lavoratrici e lavoratori stranieri, mentre non troviamo alcun impatto sui dirigenti. Il salario percepito durante l'assenza da malattia non è sempre proporzionale all'esposizione all'inquinamento effettivamente affrontata dalle diverse categorie di lavoratori.

Keywords: air pollution, labor supply, sick leave, social cost of pollution

JEL: I18, J81, Q51, Q53

1 Introduction

It is widely documented that air pollution exposure has detrimental health effects, particularly in more vulnerable population groups (Chen et al., 2013; Dominici et al., 2014; Chay and Greenstone, 2003a; Wellenius et al., 2005; Giaccherini et al., 2019; Deryugina et al., 2016, among others). The literature has also unveiled less severe effects such as headaches, irritation in the nose and lungs that exacerbate asthma episodes, changes in blood pressure and changes in behavior (Pope, 2000; Auchincloss et al., 2008; Keet et al., 2018; Kampa and Castanas, 2008; de Prado Bert et al., 2018; Sager, 2019).

Recent studies have documented that air pollution affects labor supply and productivity (Hanna and Oliva, 2015; Isen et al., 2017; Kim et al., 2017; Montt, 2018). The effects found in these studies are large and generate sizable costs for the labor market, where net of direct effects on wages, pollution contributes to deteriorate health capital, a key ingredient for the labor market. Among the various types of pollutants, particulate matter (PM), which consists of particles of very small size, is of particular concern for policy makers because of its large diffusion and ability to penetrate indoors, affecting the work environment (Thatcher and Layton, 1995; Chang et al., 2019).

Motivated by this recent literature, we study the impact of particulate matter pollution on labor supply and wage compensations resulting from sick leaves episodes. Our analysis focuses on Italy, a country with a generous welfare system and strict environmental regulation, with pollution levels comparable with other advanced economies. We combine individual employment data on the universe of Italian dependent employees in the private sector with granular PM_{10} concentrations and weather data.

Estimating the causal effect of air pollution on labor supply is complicated by several empirical challenges that can lead to endogeneity (Dominici and Zigler, 2017; Moretti and Neidell, 2011, among others). These can include, for instance, measurement error in assigning pollution shocks, strategic behavior of individuals who avoid more polluted places and high pollution days, and other unobserved determinants of labor supply that can co-vary with ambient pollution. To rule out these sources of bias, we exploit exogenous variation in wind speed to instrument for endogenous air pollution exposure in an individual fixed effects model.

Our main findings show that a one standard deviation increase in PM_{10}, leads to a 0.147 percentage point increase in the probability of taking a sick leave, which represents a 7.3% increase with respect to the baseline average of sick leaves observed in the data. Similarly, the effect of a one standard deviation increase in PM_{10} on sick wage compensation represents a 7.7% increase in the average amount of sick wage compensation. When we analyze the effect of pollution on labor supply in different sub-samples of the data, we find that the effects are heterogeneous, with the impact being larger in constructions sector and for blue collar workers. By analyzing the effects through the lens of demographic variables, we find that female and foreign workers bear stronger negative impacts of pollution exposure. Finally, we find that the heterogeneity in the effect of PM_{10} on sick leaves are not always aligned with the heterogeneity found across the same groups for sick wage compensations received by affected workers.

This study offers important improvements with respect to the exiting literature. It is the first that considers the universe of private dependent employees and the heterogeneous pollution effects in an advanced economy with a well regulated environmental policy setting. Therefore, the implications deriving from our results can be valid also in other countries where individuals face comparable pollution levels. Along with the effects on labor supply, we estimate a direct measure of social cost of air pollution based on the wage compensations paid by the social security as a sick benefit. From these estimates we extrapolate the aggregated excess social expenditure for affected workers. It results that during the period 2011-2016 air pollution generated large social costs, which amount on average to 125 million euro/year if we consider the universe of private workers in Italy and a threshold of pollution concentrations based on the national average. This figure represents nearly 4.5% of the total annual social expenditure for sick leaves in terms of compensating wages.

2 Background

There is a flourishing and influential literature analyzing the effect of air pollution on labor supply and worker's productivity. Early observational studies by Ostro (1983, 1987) and Ostro and Rothschild (1989) represent pioneering attempts in the economics literature that find a robust correlation between particle pollution and labor supply. Some years later, Hansen and Selte (2000) study the effect of several pollutants on sick leaves using individual data from a large office in Oslo, finding a significant association between sick leaves and PM_{10} concentration, with more ambiguous findings for SO_2 and NO_2.

Though, measuring the causal effect of air pollution is challenging since the exposure may not be random across individuals and locations (Chay and Greenstone, 2003b), and this may lead to severely biased estimates. To address endogeneity in pollution exposure, more recent studies exploited sophisticated empirical techniques based on a quasi-experimental approach. For instance, Currie et al. (2009) use data from elementary and middle school children to investigate the causal effect of exposure to PM_{10} and carbon monoxide (CO) on school absenteeism in Texas, finding a significant drop in school attendance driven by higher CO concentrations. Hanna and Oliva (2015) study the impact of sulfur dioxide (SO_2) exposure on labor supply in Mexico City exploiting the closure of a large refinery as a natural experiment for exogenous pollution variation. They find that the closure led to a decline of about 20% in SO_2, which resulted in an increase of about 3.5% in work hours per week for workers in the surrounding neighborhoods.

Kim et al. (2017) estimate the short and long run effects of air quality on workers' productivity in Korea using the natural experiment of forest fires caused by farmers and transported from El Niño. The authors show that an important channel through which pollution reduces labor supply is due to caregiving for dependent people. Caregiving is found to be a key mechanism in reducing labor supply also in the study by Aragon et al. (2017), who find that the effect of air pollution is concentrated among households with more vulnerable dependents such as small children and the elderly. Similarly, analyzing a long panel of individual labor data and pollution concentrations in Santiago, Montt (2018) concludes that women with children, who need assistance if unable to attend school, are the most susceptible to air pollution exposure.

The long-run effects of air pollution on the labor market are analyzed by Isen et al. (2017), who use exogenous variation in pollution induced by the introduction of the Clean Air Act (CAA) in the United States in 1970. They estimate that the cohorts of individuals living in counties subject to the policy have experienced better later-life outcomes such as a higher wage and job participation.

More recently, an important strand of literature investigated the effects of milder fluctuations in air pollution on human capital, focusing on worker productivity. Graff Zivin and Neidell (2012a) study the impact of ambient ozone concentrations using data from a large farm in California. Controlling for individual labor supply and avoidance behavior, they find that a 10 parts per billion drop in ozone concentration increases worker productivity by 5.5%. Lichter et al. (2017) find significant negative effects of PM_{10} on soccer players' productivity using within-player variation. They show that a one standard deviation increase in the concentrations reduces the number of total passes played by a fraction of 0.4–2.4% of a standard deviation. Chang et al. (2016) and He et al. (2019) study the contemporaneous and cumulated effect of $PM_{2.5}$ – a pernicious pollutant that penetrates and persists in the indoor environment – on workers productivity respectively in the US and China, two settings with different compliance status with respect to the hazardous $PM_{2.5}$ concentration limits. Both studies find a decrease in productivity caused by higher $PM_{2.5}$ concentrations, with limited additional damages when the exposure accumulates over up to 30 days. Finally, Chang et al. (2019) consider a multi-pollutant setting to analyze the productivity effect of air pollution for Chinese call-center workers using the Air Pollution Index – a composite measure of air quality. Their results confirm the negative effects on worker productivity found in previous studies that focused on single pollutants and on more physical working activity.

Despite the well documented effects on labor supply and, more recently on on-the-job productivity, very few studies focus on the monetary costs associated with air pollution health impacts leading to reduced labor activity of those affected or increased labor supply for those avoiding exposure. A simple but insightful cost calculation is provided by Hanna and Oliva (2015), who show that the increase in the amount of work hours due to the closure of a refinery in Mexico City generated a total gain of 125 USD/worker. Yet, this calculation can be seen as conservative since it accounts only for the salary that the worker would not have taken if exposed to air pollution, while it does not consider the welfare costs born on the social security system for exposed workers.

3 Data

In this paper we combine national administrative data from the Italian National Institute of Social Security (Istituto Nazionale della Previdenza Sociale - INPS), air pollution concentrations from the European Centre for Medium-Range Weather Forecasts (ECMWF), and weather data from the Joint Research Centre of the European Commission. This section describes each data source in detail.

3.1 Labor data

We use a longitudinal administrative employer-employee dataset provided by INPS, one of the largest administrative organizations at the European level. INPS collects data on the universe of private sector employees in Italy, who represent more than 70% of Italian workers. The structure of the data resembles an unbalanced longitudinal sample at the individual (and firm) level and a monthly frequency. Together with earnings and employment histories, INPS data include socio-demographic information regarding age, sex, nationality as well as municipality of birth, and that of residence of both individuals and firms. In the period considered, we obverse in the data 7,561 Italian municipalities, which represent the finest level of administrative breakdown.

In terms of labor outcomes, the dataset contains information on earnings and qualifications defined on a hierarchical categorical variable. Most importantly, we exploit information on sick leaves and the amount of earnings loss due to the absence period. In particular, in INPS data a sick leave is defined as an absence from the workplace for a period longer than five working days, during which workers receive an extended sick absence benefit paid by social security system (INPS). The compensating wage amounts to 50% of forgone salary for documented sick leaves within a period between 4 and 20 days.[1] Unfortunately, we do not observe in the data the exact diagnosis for each sick leave, which means that our analysis has a limited capacity in unveiling the physiological mechanism of pollution exposure in reducing labor supply. Nevertheless, many clinical and epidemiological studies have established a well known link between exposure to particle pollution and specific diseases

[1] For sick leaves longer than 20 days, the compensation increases to 66.6% of forgone salary, for a maximum period of 180 days for each calendar year.

that can lead to sick leaves such as pulmonary or cardio-vascular diseases (Brunekreef and Holgate, 2002, among others). Yet, our individual fixed effects mitigate this limitation as they allow to account for any time-invariant factor, including chronic health diseases and individual-specific preferences for clean air.

Our analysis includes years in the between 2011 and 2016, a period compatible with the availability of pollution data. We restrict the sample to working age individuals (18-65) who worked at least 8 weeks in each year. Additionally we do not consider earnings falling outside the first and 99^{th} percentile of the yearly earnings distribution. This sample selection leaves us with a total of 440 million observations. Due to the computational burden, we select a random draw of 15% for a total of nearly 67 million observations (roughly one million individuals followed for a period of 72 months).

We exploit the information on municipality of the firm in order to assign pollution concentrations exposure to each worker. Our baseline specification is based at the individual and monthly level. Additionally, we carry out analysis of heterogeneous effects by each category of economic sector, gender, nationality and qualification. To do so, we construct sub-samples of individuals falling into each of the aforementioned categories and collapse the data at the municipality $\times$ month cells. This procedure comes at no cost of loss in precision in the air pollution variation, as the data originally come at this temporal and spatial grid.[2] The category-specific data sets consist in 510,604 municipality $\times$ month cells.

3.2 Environmental Data

We collect air pollution concentrations from the Copernicus Atmosphere Monitoring Service (CAMS), which is implemented by the ECMWF on behalf of the European Union. At the time of writing, CAMS validated data are available from 2011 to 2016. We consider

[2] While allowing for an easier computational setting and preserving precision in assigning pollution exposure, this procedure does not allow to fully capture potential individual-level confounding factors that may affect our outcomes of interest in each cell. A fruitful approach to overcome this limitation was employed, among others, by Isen et al. (2017) and Currie et al. (2015), who control for micro-level heterogeneity through a compositional adjustment procedure. Replicating this approach however would have required a richness of information available at cell level that we could not exploit both for data availability reason and privacy limitations in importing these data according with the rules of the VisitInps research program.

particulate matter with a diameter of 10 micrometers or less in aerodynamic diameter (PM_{10}) which is a mixture of solid and liquid particles suspended in the air originating from both natural and anthropogenic sources, mainly from fuel combustion for vehicles and heating EEA (2016). PM_{10} is considered one of the most diffused and harmful air pollutants (EEA, 2019; Chay and Greenstone, 2003c; OECD, 2019).

CAMS data are based on observations from satellites, monitoring stations and a reanalysis process, representing the state-of-the-science for air quality data in Europe.[3] Using a Geographic Information System, we assign daily level averages of PM_{10} concentrations to each Italian municipality. In the case of large urban centers that contain more than one grid cell, we compute the average for that area based on the cell's centroid.

As an alternative to satellite data, several studies that analyze air pollution impacts employ concentrations data based on monitoring stations. Yet, air pollution reanalysis data offer several improvements over monitoring stations measures. For instance, readings from monitoring stations are often discontinuous due to temporary interruptions or prolonged stops (Deschênes et al., 2017; Bharadwaj et al., 2017, among others), and missing values may contaminate monthly estimates derived from daily data (Auffhammer et al., 2013). Moreover, the number of monitoring stations is often limited and may vary in a non-random order, giving rise to potential sample selection (Grainger and Schreiber, 2019; Fowlie et al., 2019). Conversely, CAMS data are originally designed at hourly frequency over a regular grid of about 18×18 km, offering a substantial advantage of a homogeneous and consistent measures of PM_{10} concentrations over the entire period and area considered in this analysis.

Figure 1 shows the geographical distribution of PM_{10} concentration levels averaged over the period 2011-2016 in all Italian municipalities. Despite PM_{10} affects all the Italian territory, pollution levels are much higher in Northern areas corresponding to the Padana valley. This area is characterized by a large presence of industrial sites, intense economic activity and climate conditions that could favor the accumulation of pollutants due to a low air circulation. The pattern described in Figure 1 is confirmed and even sharper if

[3]Specifically, CAMS data combine observations from past and current satellite instruments and computer models for reanalysis. It is worth noting that mere satellite observations often have gaps due to instrumental failures or clouds obscuring the view, and inconsistencies may occur because of a difference in resolution between instruments. CAMS data do not suffer from this limitation.

we look at Figure 2, which shows the geographical distribution of high PM_{10} days, that is the total number of days exceeding the air quality standard for PM_{10} concentrations.[4] A high number of Northern Italian areas experienced a very high number of exceeding days, up to nearly 10% considering the period in between 2011 and 2016.

3.3 Weather data

Weather data come from the Gridded Agro-Meteorological dataset, collected by MARS AGRI-4-CAST and managed by the Joint Research Center of the European Commission. This database includes several meteorological parameters gathered by weather stations and interpolated on a 25×25 km grid. We obtain daily information on the level of precipitations expressed in millimeters, temperatures (minimum, maximum and average) in Celsius degrees and wind speed in meter per second (m/s). We repeat the same procedure described above in order to obtain municipality-specific weather measures. Following Deschênes and Greenstone (2011) and Deryugina et al. (2019), we discretize the daily temperature distribution into a fixed set of 5-degree bins for a total of 15 bins, to allow for a semi-parametric control for temperature. We calculate the number of days with temperature within each bin and then collapse the dataset at monthly level to be consistent with our labor market data. The same procedure is applied to calculate bins of total precipitations with an interval of 1 mm.

Descriptive statistics of selected variables are reported in Table 1. Roughly 60% of the individuals are men, most of whom aged 41 to 45. The probability of going on a sick leave amounts to 2% and workers accrue monthly on average 11 euro from sick days compensations, while the average monthly wage is 1,680 euro. When we look at aggregated data, there are on average 1,356 workers in each municipality × month cell, corresponding to 28 sick days on average. In terms of sectoral distribution, 38% of workers are in the private services, while 29% in manufacturing. In terms of qualifications, blue collar workers amount to 67% of the sample while 26% are white collar workers.

[4]The air quality standards are set by the European Commission for each pollutant. For PM_{10}, the daily concentration is 50 μg/m3. For further details, see https://ec.europa.eu/environment/air/quality/standards.htm.

4 Econometric strategy

Our goal is to estimate the causal relationship between PM_{10} exposure and a set of labor market outcomes which includes labor supply and the associated sick benefits paid by the social security institute. In this section we describe the empirical challenges arising in our setting and how we address them.

Individual health status and exposure to pollution are both likely to affect the probability of taking a sick leave. Additionally, individual health status determines individual vulnerability to a given level of air pollution exposure. This individual vulnerability together with socio-economic determinants give rise to different willingness to pay for clean air and results in different intensity of avoidance efforts (Neidell, 2009). For instance, the adverse effect of working in polluted zones can be offset by living in less-polluted areas or adoption of defensive behavior such as air filters. Therefore, there is a wide range of lifestyle adjustments that may independently affect the probability of taking a sick leave (Graff Zivin and Neidell, 2009). Moreover, measurement error in assigning pollution exposure represents another possible source of bias because pollution measures are available in locations that are often far from where individuals are actually exposed. Finally, air pollution is highly procyclical to the economic activity. This means that economic shocks may simultaneously affect both labor supply and pollution emissions even at a local level (Hanna and Oliva, 2015; Graff Zivin and Neidell, 2012b). In this setting simple OLS estimates are likely to be biased as pollution exposure assignment may be endogenous due to the aforementioned issues regarding sorting, avoidance, measurement error and concomitant seasonal factors often unobserved in the data (Schlenker and Walker, 2015; Deryugina et al., 2019).

In this perspective we adopt an individual fixed effects model, which allows us to control for individual observable confounding factors such as biological vulnerability, willingness to pay for clean air and the resulting sorting and avoidance time invariant attitudes. Therefore, we start from the following individual fixed effects model:

$$Y_{i,m,t} = \alpha + \beta \text{PM10}_{m,t} + W'_{m,t}\rho + \phi X_{i,t} + \eta_i + \theta_t + \mu_{i,m,t} \qquad (1)$$

where outcome $Y_{i,m,t}$ is, respectively, the predicted probability of taking a sick leave for a period of at least four working days, and the amount of earnings (in euro) paid by the social security system as a sick benefit for the individual i in municipality m and year-month t. $\mathrm{PM}_{10m,t}$ is the average PM_{10} concentration (in μg/m3), and $W_{m,t}$ is a matrix of semi-parametric controls for weather conditions which may independently affect labor supply; these include no. of days with 5 C° bins of maximum temperature and 1-mm bins of total precipitation. $X_{i,t}$ is the individual level percentage of part-time days, while η_i and θ_t are, respectively, individual and year-month fixed effects. Finally, $\mu_{i,m,t}$ is a normally-distributed error term clustered at the municipality level.[5]

Our parameter of interested is β, which represents the effect of one-unit increase in PM_{10} on the individual probability of taking a sick leave, and the amount of sick benefits received, respectively. In this model, individual fixed effects control for all time-invariant, unobserved individual specific characteristics such as predetermined health and differences opportunity cost of time of sick leaves, while year-month fixed effects control for time varying effects of factors such as national policy regulation, seasonal epidemics and other common shocks.

Event though our baseline individual fixed effects model purges the estimates from all time-invariant unobserved heterogeneity, it does not allow us to solve potential endogeneity issues arising from sorting and simultaneity between pollution and economic activity. To address these important concerns, we exploit as-good-as-random variation in local wind speed as an instrument for air quality proxied by PM_{10} concentrations. It is indeed well documented that weather factors, wind in particular, have the capacity to disperse air pollution (Czernecki et al., 2017; Chu et al., 2004; Zhang et al., 2012; Lu and Fang, 2002) while being random around a local mean. As discussed earlier in Section 2, while other studies exploit specific emission-generating episodes where wind moves air pollution between two specific areas, we adopt a generalization of this setting which allows to carry out a large-scale analysis including contiguous areas (municipalities). In this setting, we estimate the following 2SLS model:

$$\mathrm{PM10}_{i,m,t} = \alpha + \gamma V_{m,t} + W'_{m,t}\delta + \phi X_{i,t} + \eta_i + \theta_t + \epsilon_{i,m,t} \tag{2}$$

[5]Our baseline results are clustered at the municipality level, following the level of aggregation of our pollution “treatment” assignment (Bertrand et al., 2004).

$$Y_{i,m,t} = \alpha + \beta \widehat{\mathrm{PM10}}_{m,t} + W'_{m,t}\rho + \phi X_{i,t} + \eta_i + \theta_t + \varepsilon_{i,m,t} \quad (3)$$

where the term $\widehat{\mathrm{PM10}}_{m,t}$ is the first stage predicted value of PM_{10} instrumented by wind speed, conditional on the full set of fixed effects and other controls.

In addition to our baseline fixed effect model specification, when using cell-level data we also adopt a more demanding specification to account for time-varying determinants of province common to all individuals working in a particular municipality and year-month pair. We do so by including province $\times$ year-month linear trends.

Moreover, as the relationship between windspeed and pollution may extend beyond the administrative boundaries of municipalities, such as provinces, in our first-stage we use an alternative clustering for the standard errors (s.e.), which yields similar results.[6]

Finally, it is important to highlight that we do not consider a multi-pollutant model, yet, wind can affect also other air pollutants. In such a setting, a researcher faces a potential identification problem rooted in the violation of exclusion restriction. Since CAMS data are not available for all main pollutants during our period of analysis, we cannot explicitly deal with this issue. Nevertheless, the literature has highlighted as PM_{10} is highly correlated with other harmful pollutants such as $PM_{2.5}$, NO_2 and CO, being emitted from the same sources such as heating or transport. Therefore, while we cannot interpret our estimates as pollutant-specific impacts, we refer to PM_{10} concentration as a proxy for overall air quality (Chang et al., 2018; Dominici et al., 2010).

5 Results

We present the results of our analysis starting from the individual fixed effects model, followed by the 2SLS model in Section 5.1. Subsequently, in Section 5.2 we analyze the impact of particle pollution on the sick leaves across various population groups relevant in terms of potential exposure and vulnerability. We thus divide the data into three

[6]When clustering on provinces, we obtain a s.e. of 0.131, which is slightly larger than the one obtained with clusters on municipalities (s.e.: 0.092). Importantly, both inferences lead to obtain coefficients statistically significant at 1%.

major labor sectors, according to qualification, gender and migrant status, respectively. In Section 5.3 we then offer a back-of-the-envelope calculations of the aggregated social expenditures due to pollution exposure based on the estimates here carried out. Finally, in order to support the validity of our identification strategy, in Section 5.4 we show results based on a set of checks and alternative model specifications.

5.1 Main effects

Table 2 presents the results on the effect PM_{10} fluctuations on labor supply (column (1)) and on sick days compensation (column (2)), obtained from our baseline OLS estimates of the individual fixed effects model. The predicted probability of taking a sick leave due to a one $\mu g/m^3$ increase in PM_{10} pollution exposure causes an increase of 0.004 percentage points, which corresponds to a 0.2% increase in the average sick leave probability. If scaled up to a one standard deviation (s.d., equivalent to 6.14 $\mu g/m^3$), it amounts to an average increase of 0.024 percentage points, which more than doubles the sick leave probability. Column (2) shows that the effect of a one s.d. increase in PM_{10} on the sick compensation wage amounts to 0.10 euro/worker/month, or a 0.9% increase in the average compensation wage.

As already discussed, our baseline individual fixed effect model may suffer from omitted variable bias and other confounding factors, therefore the associated results are not likely to represent the true effect of pollution on sick leaves and associated sick wages compensations. Below we deal present the IV estimates based on Equation (3) of Section 4. To begin with, we discuss the first stage effect of wind speed on PM_{10} obtained in a 2SLS setting and presented in Table 3. After controlling for other weather factors and individual and year×month fixed effects, there is sufficient residual variation to estimate the effect of wind speed on monthly fluctuations of air pollution: for each additional speed unit (m/s) in wind, PM_{10} concentration decreases by about 0.7 g/m^3; the coefficient is statistically significant at 1%. We also run our first stage estimates by clustering standard errors at the province level. Provinces represent higher-level administrative units and include several local labor market areas in which pollution exposure is more homogeneous with respect to municipality boundaries. First stage results clustered on provinces are presented in Appendix Table A2 and confirm that our coefficient estimates remain significant at 1%

level. We also test for weak identification and report the F-statistics in any estimate table, which are always well above 10 according with the conventional significance levels suggested by Staiger and Stock (1997). The values of our F-statistics are robust also to more stringent identification conditions developed in more recent contributions (Bound et al., 1995, among others). Finally, in Section 5.4 we run a simple robustness check to show the monotonicity of our IV, where the effect of the wind speed increases affects PM_{10} always in the same direction.

The second-stage results, presented in column (1) of Table 4, show that the causal effect of air pollution on labor supply is much larger than OLS results previously presented in Table 2. Specifically, we find that one additional $\mu g/m^3$ in PM_{10} concentration causes an increase in the probability of an individual going on a sick leave by 0.024 percentage point, which represents an increase of 1.2% with respect to the baseline probability of sick leave. If scaled up to a one s.d., the effect amounts to 7.3% increase with respect to the average of sick leaves in the estimation sample. Similarly, the effect on sick wage compensation presented in column (2) of Table 4, indicates an additional 0.83 euro/worker/month for a one s.d. increase in PM_{10}, representing 7.7% of the average amount of sick wage compensation. When we cluster standard errors on provinces to account for errors correlation in larger geographical units, our results preserve full statistical significance (see Appendix Table A1).

The fact that our IV estimates are approximately 7-8 times larger with respect to the OLS estimates can be considered as a standard result in the literature that focuses on the effects of pollution in a quasi-experimental setting (Deryugina et al., 2019, among others). OLS fixed effects estimates are lower as variation in pollution is correlated with many unobserved factors that mitigate the detrimental effect of pollution on health. Selection issues and economic activity fluctuations are likely to bias the estimates, as workers exposed in large urban areas on high pollution days might actually be represent individuals with better socioeconomic status, which is likely to mitigate their potential pollution harm. Additionally, measurement error in pollution concentrations if not accounted for, is likely to cause a misclassification in exposure and a consequent attenuation bias.

5.2 Heterogeneous effects

The large dimension of the dataset employed in this study allows us to carry out a rich heterogeneity analysis without losing statistical power. We concentrate on a number of demographic and labor dimensions that are likely to drive the effects of pollution in a differentiated manner. For this purpose, as already introduced in then Section 3.1, we re-estimate our IV model specification for sub-samples defined by the following characteristics of workers: *i*) three economic sectors (manufacturing, construction and services), *ii*) four levels of workers' qualifications (blue collar, white collar, manager and apprentice), *iii*) gender, *iv*) nationality (Italian and foreign). As already described in Section 3, for each of the relevant sub-samples respectively, we transform the data into municipality×month averages. All the estimates are weighted by the number of workers in each municipality-month cell.

Table 6 presents the estimates of the effect of air pollution in three different economic sectors. We find that the impact of pollution on the probability of taking a sick leave is the highest for workers belonging to the constructions sector. For this group of employees, their penalty deriving from a one s.d. increase in PM_{10} amount to a 0.282 percentage point increase in the average probability of taking a sick leave. This coefficient estimate is twice as large as the effect found in the pooled individual level IV estimates. The direction of the differential is also in line with the potential exposure of construction workers to pollution, who are more likely to spend more time outdoors with respect to other economic sectors. Similarly, workers of private services are found to suffer relatively more from increase in PM_{10} concentrations, which is also likely to be driven by their persistent and cumulative exposure to pollution in urban areas with larger emissions from vehicles and heating systems.

It is important to highlight that the effect that we find is measured controlling for all demographic and labor market characteristics of workers in each municipality × month cell, hence accounting for differences in age and gender structure, qualification, contract type and average experience. In fact, the probability of taking a sick leave is higher in municipalities × months combinations where shares of older workers are higher, with the differential being the strongest for the 61-65 age category. Additionally, a major presence of blue collar workers is also correlated with a higher probability of sick leaves, while workers with managerial qualifications are associated with a lower probability of sick leaves.

As for sick wage compensations, our coefficient estimates for manufacturing and construction sectors are almost double the ones of the individual level model, and slightly higher with respect to the private sector. This might be due to the fact workers in construction and manufacturing that are traditionally considered risky sectors, benefit from more generous social security allowances. On the other hand, the sick wage compensation might be higher if workers spent more time home. Yet, with the data at hand we do not observe the length of the leave, hence we cannot unambiguously interpret the coefficient estimate on sick wage compensation in the direction of the intensive margin.

Subsequently, we focus on the differential impact of pollution across level of qualifications, namely white collars, blue collars, managers and apprentices. In Table 7 we show that that the effect of exposure to PM_{10} is disproportionally higher for blue-collar workers. A one s.d. increase in PM_{10} results in an increase in the probability that workers take a sick leave of 0.34 percentage points, which represents a 17% increase in the probability of a sick leave. This result is in line with the type of duties that blue collar workers are more likely to perform, as manual work is more prone to make them assimilate ambient impacts. Conversely, white collar workers and managers are more likely to work indoors and hence less exposed to environmental impacts. In fact, we find non statistically significant effects for managers. The results relative to the probability of taking a sick leave are in line with the estimates of the effect of PM_{10} on sick wage compensations. Specifically, among blue collar workers, those most at risk, a differential in sick wage compensations at the municipality $\times$ month level as a result of a one s.d. increase in PM_{10} amounts to 1.7 euro/worker/month. Conversely, among white collar workers, who face a relatively lower exposure at any given level of concentration, the sick wage compensation due to a one s.d. increase in PM_{10} is less than a half of the estimate for blue collar workers. In case of apprentices, the difference between the estimate on the sick leave probability is higher than that for white collar workers, and the respective estimates on compensations highlight that apprentices face weak employment contracts that are are not adequately compensated in relation to their work-related risks, including exposure to air pollution.

Table 8 presents the heterogeneous effects estimated in sub-samples aggregated by gender.

The estimates show that the impact of the increase in PM_{10} for females is twice as large as that of male workers. Specifically, the increase in the probability of a sick leave for female workers due to a one s.d. increase in PM_{10} is of 0.32 percentage point, compared to 0.16 percentage point for male workers. Therefore, ceteris paribus, women face a risk that more than double that faced by men. The fact that a higher pollution concentration exerts a larger effect on Italian women is in line with the literature on socioeconomic gradient in health inequalities among Italians. In a statistical meaning, labor characteristics represent stronger predictors of several health related outcomes for women with respect to men (Atella and Kopinska, 2014). Moreover, Pirani and Salvini (2015) shows that work related factors are more harmful for self-assessed health among females in Italy. This feature is common to Southern European countries, where women are more likely to work under shorter-term contracts, occupy less qualified jobs and earn lower pays (Smith et al., 2013). In line with these contextual findings, though much more susceptible of pollution damages, women perceive similar sick wage compensations to men, amounting to 1.15 euro/worker/month due to a one s.d. increase in PM_{10}.

When discussing the heterogeneous effects by gender it is worth discussing that they might be driven also by specific gender patterns such as caregiving. Several studies cited in Section 2 show that the effect of pollution on females is likely to take an indirect channel, as they are more likely to assist vulnerable dependents, mainly children and the elderly (Kim et al., 2017; Aragon et al., 2017). Regardless the reason, our results highlight the existence of environmental inequality that has the potential to exacerbate the already large gender gap existing in the labor market.

Finally, in Table 9 we present the results by nationality, distinguishing between Italian and foreign citizenship workers. While the effects are fully statistically significant in both categories considered, net of the full set of covariates which define several demographic and labor characteristics of the workers considered, the effect that pollution exerts on the the sick leave probability for foreign workers is greater. A one s.d. increase in PM_{10} causes a 0.32 percentage point increase in the likelihood of taking a sick leave among foreigners, and of 0.21 for Italians. Foreign workers receive also a higher sick wage compensation, roughly twice that of Italians. This differential is likely to be driven by a major baseline vulnerability that foreign nationality workers are likely to have.

5.3 Aggregated social security expenditure attributable to pollution

In order to offer a monetary quantification of the effect of PM_{10} on sick leaves, we carry out a simple back-of-the-enveloped calculation where we exploit the coefficient estimates obtained in the individual 2SLS model.[7] The scope of this exercise is to evaluate the expenditure attributable to excess PM_{10} concentrations, which delivers an idea of how economically relevant is the issue of pollution for the labor market. Indeed, this health-related excess expenditure borne by the social insurance system represents society's costs. We provide our health impact assessment under the assumption that there is a threshold concentration above which health effects occur. The existence of possible non-linearity or thresholds in the concentration-response functions is frequently advocated in epidemiological studies (Daniels et al., 2000, among others) and it also represents a basis for the pollution limits guidelines introduced by the Directive 2008/50 of the European Commission.

Our baseline scenario assumes a social security expenditure deriving from the actual PM_{10} concentration observed in the sample. We compare this scenario with two alternative ones. In the first alternative scenario we assume that all municipalities comply with the recommended PM_{10} concentration values provided by World Health Organization (WHO) (20 μg/m), which implies that PM_{10} concentrations exceeding WHO limits are censored to 20 μg/m. In the alternative second scenario instead we censor PM_{10} concentrations to the annual national average. This procedure boils down to comparing the baseline model predictions given actual PM_{10} levels, with two sets of predictions derived from the alternative scenarios above described. For each scenario, we calculate excess expenditures for both the analytical sample only (on average 1 million workers yearly) and for the entire Italian workers population (approximately 26.6 million workers yearly). In the latter case, we use official statistics from the Italian National Institute of Statistics (ISTAT) on

[7]It is worth noting that our 2SLS estimates deliver a Local Average Treatment Effect (LATE), in which the 'compliers' are workers in windy cities. While using high frequency data there could be cities where wind speed is almost zero in specific time intervals (days or hours) with no effect on pollution dispersion, this is not the case in our setting because we never observe wind speed dropping to zero using monthly wind data. Our analysis considers a period of six years during which all municipality-month pairs are affected to some extent by wind, hence we can plausibly interpret our LATE as an average treatment effect (ATE). With this assumption, we thus elaborate our back-of-the-envelope calculations based on the full sample.

province employment rates, which we apply to municipality specific population sizes in order to define potentially affected pools of individuals.

Our calculations, shown in Table 10, unveil that the expenditure sustained by the social security system attributable to excess PM_{10} in 2011 amounted to 4.3 million euro for the sample considered in the analysis and, if scaled up to the entire population of Italian workers, it amounted to 125 million euro. The temporal evolution of the expenditure is different according to the threshold with respect to which we benchmark the baseline scenario. Under the assumption that PM_{10} concentrations do not exceed the WHO standard, the actual excess expenditure deriving from the baseline scenario increases with time as a result of a consistent incremental trend in PM_{10} emissions in several Italian municipalities. Conversely, if in our benchmark we cap PM_{10} concentrations at the national average, we find a much more stable progression of expenditure attributable to excess PM_{10}. In fact, if we look at 2016, the in-sample expenditure computed with respect to the WHO standard accounted to 5.3 million euro, while with respect to the national average, we estimate an expenditure of 5.5 million euro. In a similar manner, the population level expenditure amounts to 151 million euro if we cap PM_{10} at the WHO standard, and to 146 million euro according to the national average.

The total expenditure generated by excess air pollution during the period 2011-2016 amounts to nearly 27 million euro for the INPS sample and 755 million euro for the total workers population, while if benchmarked to WHO standard, the excess expenditure decreases, respectively, to nearly 17 and 475 million euro. Considering the total working population, the incidence of these expenditures over the total social welfare expenditure for sick leaves range from 2.8% to 4.5%, considering respectively national average and WHO standards.[8]

5.4 Robustness checks

Reduced form - When examining the robustness of our results, an important concern may come from the fact that wind speed may not satisfy the exclusion restriction if, in

[8] According to recent INPS estimates, the total social welfare expenditures for sick leaves amounted to 2.8 billion/year in 2018. Source: Senate Hearing held by the INPS President in September 2018, available at: http://www.senato.it/application/xmanager/projects/leg18/attachments/documento_evento_procedura_commissione/files/000/000/291/Memorie_INPS.pdf

strong windy days, the labor supply is reduced for factors other than pollution. This may happen, for instance, if wind affects our the probability of sick leave through direct mechanisms of health deterioration. To address this issue, we show the reduced form of our 2SLS model. If wind is directly responsible of health deterioration, we would observe a positive effect of wind on the outcome, with the probability of taking a sick leave in days with strong wind being higher. The reduced form, showed in Table 5, points to an opposite direction. The estimated coefficient is negative and strongly significant, signaling that wind does not negatively affect the labor supply measured by sick leaves. It is worth noting that our estimates of effects heterogeneity are weighted by the number of workers in each municipality-month cell, accounting for overall labor supply.

IV monotonicy - If wind only moves pollution far away from where it is generated instead of lowering PM_{10} concentration through dispersion, the monotonicity assumption would be violated. Wind as a pollution mover has been already employed in several quasi-experimental studies that combine wind direction and speed (Schlenker and Walker, 2015; Deryugina et al., 2019; Anderson, 2019). A simple (though not conclusive) way to test if the dispersion effect of wind prevails when considering multiple contiguous municipalities is to divide the treatment effect of wind on pollution by quantiles. Figure 3 shows that the marginal first stage effects of wind on PM_{10} concentration by decile of wind speed, with the lowest decile representing the omitted category.[9] The direction of the wind effect is, on average, consistently negative, and it increases in higher wind speed deciles. Importantly, the effect is statistically significant at 1% level also when we include non-linear controls for precipitations and temperatures. Even though this test does account for different effects in any cell of our sample but it only account for the mean in each decile of the distribution, we show here that when considering a multitude of contiguous municipalities, the association between wind speed and particle pollution concentration is negative in each decile, i.e. the dispersion effect holds also at relatively low wind speed.

[9]We cannot test the dispersion effect for non-particle pollutants such as SO_2, NO_2 or O_3 as these pollutants were not fully available at the time of writing.

6 Conclusions

This paper offers a large-scale causal analysis of the effect of exposure to air pollution on labor supply by taking advantage of exogenous variation in concentrations induced by wind. We carry out the analysis using administrative individual data collected by the Italian social security institute (INPS) for the universe of Italian dependent employees in the private sector.

Our estimates show that higher PM_{10} concentrations cause an increase in the probability of taking a sick leave by workers, net of their individual time invariant characteristics. The large dataset at hand allows us to analyze to what extent the impacts affect differently specific subgroups of workers defined according to demographic and labor characteristics, such as gender, nationality, economic sector and level of qualification. When comparing the impact of PM_{10} on taking sick leaves and on the sick wage compensations, we find that the effects are particularly pronounced for females and for foreign workers. Moreover, within a selected set of labor market characteristics, we find that the impact of air quality on sick leaves and associated monetary compensations are higher for blue collar workers and for workers in the construction sector.

Our results deliver important indications for policy makers. The environmental inequality resulting from a disproportionate impact of pollution on specific workers categories is likely to reinforce typical socioeconomic gradients in health and in labor market participation. In fact, the groups that are found to be the most penalized in our study, such as females, foreigners and blue collar workers, are also the most disadvantaged groups on the labor market, with shorter-term contracts and lower pays. This dual disadvantage gives rise to a gap that deepens the relative vulnerability of these groups.

We compute the total social expenditure that, during the period in between 2011 and 2016, was likely to be accumulated due to sick leaves resulting from excessive PM_{10} concentrations with respect to the national average. These annual costs amount to approximately 125 million euro on average, with a total cost of 755 million euro accumulated over the period considered in our analysis. This total cost corresponds to about 4.5% of the total INPS expenditures in sick leave compensations dispensed during the same period.

Among the limitations of this study we highlight that it would be interesting to address absenteeism in more nuanced dimensions. Despite available for the universe of private workers, the measures we observe are monthly indicators of sick leaves without observing a medical diagnoses and the length of the leave. With more detailed information, it would be possible to understand the effect of PM_{10} on the complexity of such episodes. Moreover, as in the present setting we are not able to properly address potential impacts from co-emitted pollutants, the effects that we attribute to PM_{10} might represent the effect of a combination of pollutants. Yet, we can interpret our results on PM_{10} as a good proxy for overall air quality.

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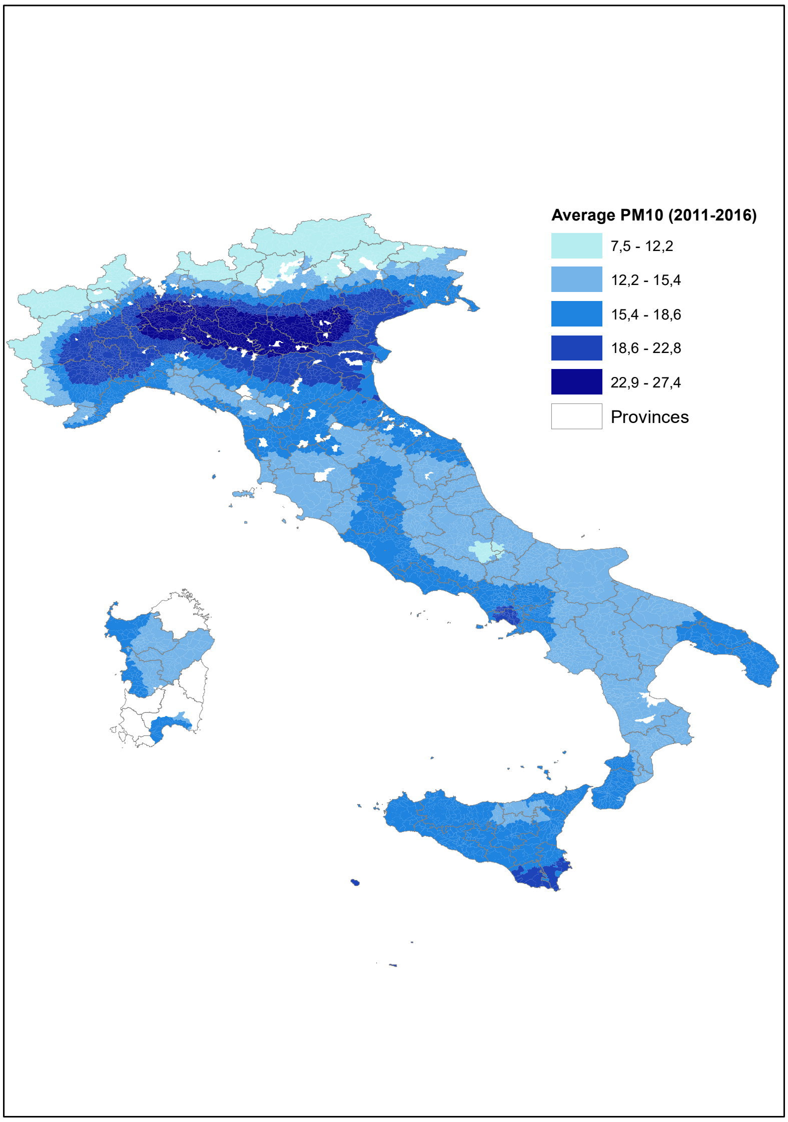
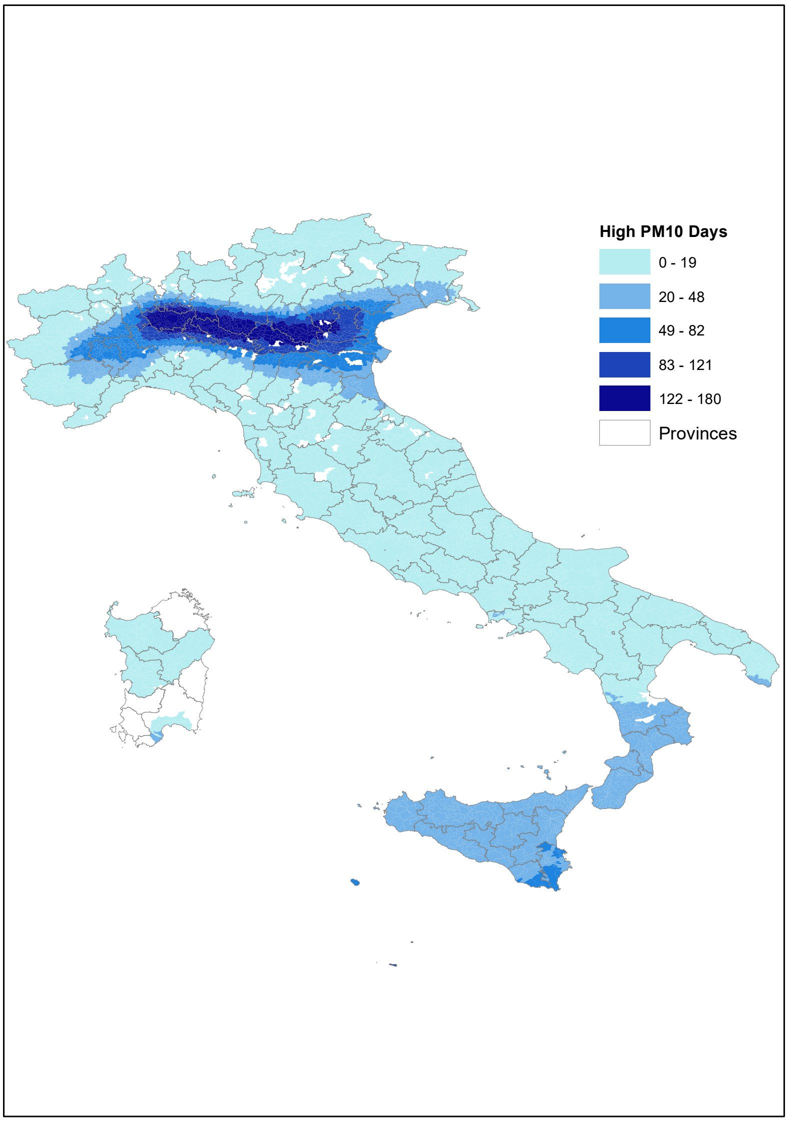
Figures

Figure 1: Average PM_{10} Concentration Level in Italian Municipalities between 2011 and 2016.



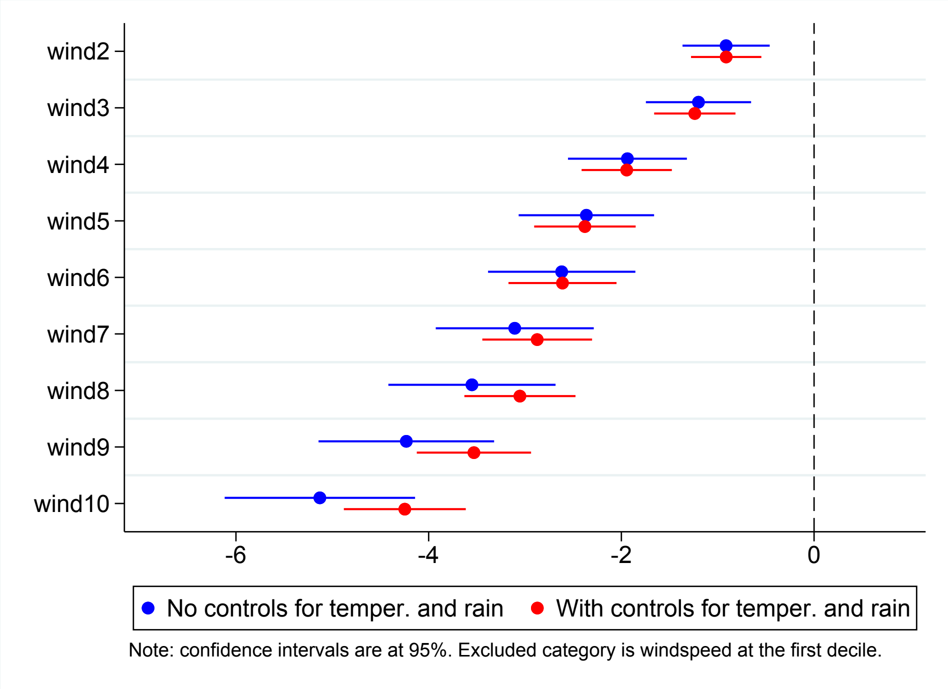
Notes: The figure shows the geographical distribution of average PM_{10} concentration levels between 2011 and 2016 in each Italian municipality. The figure is based on own elaborations using CAMS PM_{10} data.

Figure 2: Total Number of High PM_{10} Days in Italian Municipalities between 2011 and 2016.



Notes: The figure shows the geographical distribution of total number of days between 2011 and 2016 with PM_{10} concentration levels above the daily recommended limit of 50 μg/m3 set by the European Commission. The figure is based on own elaborations using CAMS PM_{10} data.

Figure 3: First Stage Effects of Wind Speed on PM_{10} Level, at Different Speed Deciles.



Notes: The graph shows the point estimates of the effect of wind speed on PM_{10} concentrations at different levels of wind speed deciles. Red markers show the effect of wind without controlling for rain and temperatures, while blue markers show the effect with full weather controls as in Table 2. The graph is obtained with the Stata command `coeffplot` by Ben Jann (http://repec.sowi.unibe.ch/stata/coefplot/index.html).

Tables

Table 1: Summary Statistics of Relevant Variables at Month and Municipality Level.

Variable	Mean	Standard deviation	Minimum	Maximum
Demographic variables (shares)				
Females	0.39	0.15	0	1
Foreigners	0.13	0.11	0	1
Age 16-20	0.02	0.03	0	1
Age 21-25	0.09	0.06	0	1
Age 26-30	0.12	0.06	0	1
Age 31-35	0.14	0.06	0	1
Age 36-40	0.15	0.06	0	1
Age 41-45	0.16	0.07	0	1
Age 46-50	0.14	0.07	0	1
Age 51-55	0.11	0.07	0	1
Age 56-60	0.05	0.05	0	1
Age 61-65	0.01	0.02	0	1
Labor variables				
Share of sick days	0.02	0.02	0	1
Sick days compensation (euro)	10.79	17.52	0	2058.00
Wage (euro)	1680.18	504.46	7.00	8432.00
Total workers	1355.48	11131.35	1.00	748054.00
Total sick days	28.71	221.65	0	19628.00
Share of part-time contracts	0.15	0.08	0	1
Share of Manufacturing (1039)	0.29	0.25	0	1
Share of Construction (4145)	0.13	0.15	0	1
Share of Private services (4582)	0.38	0.25	0	1
Share of Public services (8493)	0.06	0.11	0	1
Share of Blue collar workers	0.67	0.14	0	1
Share of White collar workers	0.26	0.13	0	1
Share of Managers	0.01	0.02	0	0
Share of Apprentice workers	0.06	0.06	0	1
Pollution and weather variables				
PM_{10} ($\mu g/m^3$)	17.12	6.14	3.44	55.37
Wind speed (m/s)	2.49	1.00	0.46	10.46
Temperature (min)	9.93	6.72	-15.70	26.12
Temperature ($mean$)	14.37	7.16	-9.66	30.00
Temperature (max)	18.80	7.75	-6.02	36.05
Total precipitations (mm)	72.19	64.66	0	689.80

Notes: The statistics are derived from an original sample of 440 million observations referring to workers observed between 2011-2016, aged between 18-65, with at least 8 weeks worked in each year, whose earnings falling inside the first and 99$^{\text{th}}$ percentile of yearly earnings distributions. Based on this sample a municipality × month sample is constructed corresponding to 510,551 observations.

Table 2: OLS Estimates of the Effect of PM_{10} on Labor Supply and Sick Wage.

	(1)	(2)
	Sick Leave	Sick Wage
PM_{10}	0.00004***	0.01636***
	(0.00001)	(0.00568)
Obs.	66,402,554	66,402,554
Worker FEs	YES	YES
Year-month FEs	YES	YES

Notes: Individual controls include age classes and part-time. Weather controls include bins of precipitations, minimum, average and maximum temperatures. Standard errors, in parentheses, are clustered on municipalities.

Table 3: First Stage Estimates of the Effect of Wind Speed on PM_{10} Concentration.

	(1)
	PM_{10}
Wind speed	-0.72326***
	(0.09293)
Obs.	66,402,554
Worker FEs	YES
Year-month FEs	YES

Notes: Individual controls include age classes and part-time. Weather controls include bins of precipitations, minimum, average and maximum temperatures. Standard errors, in parentheses, are clustered on municipalities.

Table 4: IV Estimates of the Effect of PM_{10} on Labor Supply and Compensation Wage.

	(1)	(2)
	Sick Leave	Sick Wage
PM_{10}	0.00024***	0.13630**
	(0.00009)	(0.05842)
Obs.	66,402,554	66,402,554
Worker FEs	YES	YES
Year-month FEs	YES	YES
F-statistics:	60.58	60.58

Notes: Individual controls include age classes and part-time. Weather controls include bins of precipitations, minimum, average and maximum temperatures. Standard errors, in parentheses, are clustered on municipalities.

Table 5: Reduced Form Estimates of the Effect of Wind Speed on Labor Supply and Compensation Wage.

	(1)	(2)
	Sick Leave	Sick Wage
Wind speed	-0.00018***	-0.09858**
	(0.00007)	(0.04262)
Obs.	66,402,554	66,402,554
Worker FEs	YES	YES
Year-month FEs	YES	YES

Notes: Individual controls include age classes and part-time. Weather controls include bins of precipitations, minimum, average and maximum temperatures. Standard errors, in parentheses, are clustered on municipalities.

Table 6: IV Estimates of the Effect of PM_{10} on Sick Leave and Sick Wage by Economic Sector

	Manufacturing		Construction		Private services	
	(1)	(2)	(3)	(4)	(5)	(6)
	Sick Leave	Sick Wage	Sick Leave	Sick Wage	Sick Leave	Sick Wage
PM_{10}	0.00032***	0.24990***	0.00046***	0.24510***	0.00040***	0.22475***
	(0.00008)	(0.07156)	(0.00012)	(0.09358)	(0.00007)	(0.03541)
Sex	0.00511***	-0.71532	-0.01934***	-16.18329***	0.00949***	2.42727***
	(0.00099)	(0.67227)	(0.00267)	(2.77034)	(0.00139)	(0.63551)
Foreign	-0.00637***	-3.54715***	-0.00583***	-4.30794***	0.00879***	3.68269***
	(0.00173)	(1.29212)	(0.00107)	(1.25224)	(0.00138)	(0.64667)
Part-time	-0.02521***	-21.33344***	-0.02858***	-28.63835***	0.01476***	-3.09679***
	(0.00218)	(1.62500)	(0.00318)	(2.62018)	(0.00137)	(0.80131)
Age 21-25	-0.00047	-1.97876	0.00621*	6.04615*	-0.01105***	-2.81127
	(0.00456)	(3.07579)	(0.00360)	(3.30848)	(0.00401)	(2.15103)
Age 26-30	0.00045	-1.76280	0.00623*	5.67293	-0.00524	-0.21240
	(0.00459)	(3.27400)	(0.00370)	(3.49825)	(0.00409)	(2.19815)
Age 31-35	-0.00115	-3.76543	0.01023**	8.10750**	-0.00137	2.01081
	(0.00439)	(3.01755)	(0.00397)	(3.52901)	(0.00355)	(1.93863)
Age 36-40	0.00522	1.34645	0.01333***	12.09027***	0.01446***	9.99774***
	(0.00447)	(3.17160)	(0.00396)	(3.69164)	(0.00383)	(1.99593)
Age 41-45	0.01256***	7.67465**	0.01628***	13.73782***	0.01750***	11.74526***
	(0.00476)	(3.38200)	(0.00387)	(3.55714)	(0.00389)	(2.14431)
Age 46-50	0.00791*	4.62782	0.02290***	19.04206***	0.01938***	12.06403***
	(0.00472)	(3.36128)	(0.00381)	(3.78678)	(0.00401)	(2.01594)
Age 51-55	0.02079***	13.78584***	0.03753***	32.18965***	0.01136***	9.51373***
	(0.00463)	(3.10327)	(0.00382)	(3.54291)	(0.00369)	(2.23064)
Age 56-60	0.02973***	20.65168***	0.05581***	49.50753***	0.00358	5.07421**
	(0.00448)	(3.59281)	(0.00426)	(4.02555)	(0.00402)	(2.45963)
Age 61-65	0.03759***	18.95692***	0.06744***	56.15392***	-0.00259	-3.72195
	(0.00737)	(5.38579)	(0.00708)	(6.65375)	(0.00630)	(3.63013)
Blue collars	0.03594***	16.60604***	0.02732	17.48013	0.02349***	8.81201***
	(0.00543)	(3.47669)	(0.01963)	(15.99386)	(0.00331)	(1.73589)
White collars	-0.00750	-6.15011	0.00176	3.32806	0.01741***	7.08131***
	(0.00536)	(3.77202)	(0.01972)	(16.10746)	(0.00340)	(1.82810)
Managers	0.00308	-1.52633	-0.03181	-4.43287	-0.03974***	-21.63039***
	(0.00594)	(5.39056)	(0.02260)	(25.58602)	(0.00678)	(3.90785)
Apprentices	0.00815	0.22143	0.02725	14.67262	0.00732	4.05532
	(0.00635)	(4.23487)	(0.01965)	(16.00375)	(0.00499)	(2.76686)
Experience	0.00012***	0.06966***	0.00007***	0.04446***	0.00008***	0.03567***
	(0.00000)	(0.00321)	(0.00000)	(0.00422)	(0.00000)	(0.00208)
Obs.	434,595	434,595	442,018	442,018	485,401	485,401
Municipality FEs	YES	YES	YES	YES	YES	YES
Year-month FEs	YES	YES	YES	YES	YES	YES
Province × year-month FEs	YES	YES	YES	YES	YES	YES
F-statistics	154.6	154.6	111.3	111.3	78.71	78.71

Notes: All controls are calculated as averages in each municipality× year-month cells. Additional controls (not showed in the table) include total precipitations and bins of temperatures. Estimates are weighted by number of workers in each municipality-month cell. Standard errors, in parentheses, are clustered on municipalities.

Table 7: IV Estimates of the Effect of PM_{10} on Sick Leave and Sick Wage by Qualification

	White collar		Blue collar		Managers		Apprentice	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Sick Leave	Sick Wage	Sick Leave	Sick Wage	Sick Leave	Sick Wage	Sick Leave	Sick Wage
PM_{10}	0.00024***	0.12427***	0.00055***	0.28166***	0.00005	0.01481	0.00034***	0.07958**
	(0.00005)	(0.02744)	(0.00009)	(0.06074)	(0.00004)	(0.04759)	(0.00007)	(0.03759)
Sex	0.00520***	3.04443***	0.00989***	1.17345	0.00011	-0.38792	-0.00246***	-1.35139***
	(0.00084)	(0.48595)	(0.00154)	(0.86666)	(0.00030)	(0.43970)	(0.00069)	(0.43197)
Foreign	0.04508***	22.95262***	-0.00476***	-2.49777**	0.00449**	3.17274	-0.00047	-0.90716**
	(0.00327)	(1.90548)	(0.00180)	(1.06865)	(0.00193)	(2.26092)	(0.00089)	(0.45979)
Part-time	0.02127***	1.62516*	-0.00909***	-16.41929***	0.00519***	-1.03026	0.00133	-2.80811***
	(0.00196)	(0.88921)	(0.00202)	(1.24740)	(0.00134)	(1.66489)	(0.00125)	(0.70948)
Age 21-25	0.00158	2.09812	-0.03163***	-22.31787***	0.00430	13.50243	-0.00170	1.53930***
	(0.00675)	(3.41540)	(0.00606)	(3.59576)	(0.01573)	(15.48279)	(0.00131)	(0.48814)
Age 26-30	-0.01509**	-6.41481**	-0.04485***	-28.84102***	0.01419	31.56929***	-0.00366***	0.99900
	(0.00659)	(3.22541)	(0.00617)	(3.76646)	(0.01231)	(10.54907)	(0.00137)	(0.72291)
Age 31-35	-0.01685***	-6.57358**	-0.03898***	-28.14742***	0.01389	29.86513***	0.00204	3.49567***
	(0.00624)	(3.20353)	(0.00612)	(3.75190)	(0.01218)	(10.08915)	(0.00170)	(0.94864)
Age 36-40	-0.01196**	-4.79056	-0.01807***	-14.82377***	0.01098	27.37072***	-0.00944	1.45465
	(0.00581)	(3.08003)	(0.00600)	(3.53279)	(0.01212)	(10.04508)	(0.00753)	(4.49650)
Age 41-45	-0.00780	-1.52000	-0.01457**	-12.62272***	0.01015	26.96510***	0.00045	6.95685
	(0.00573)	(2.97816)	(0.00577)	(3.56697)	(0.01209)	(10.03593)	(0.00805)	(4.97326)
Age 46-50	-0.00864	-1.83594	-0.01506***	-10.94461***	0.00974	25.69908**	0.00073	7.23025
	(0.00580)	(3.07451)	(0.00573)	(3.59180)	(0.01209)	(9.99075)	(0.00843)	(5.46390)
Age 51-55	-0.01120**	-2.74433	-0.00165	-3.90355	0.00873	24.82863**	-0.00539	4.62053
	(0.00557)	(2.95641)	(0.00586)	(3.48394)	(0.01208)	(9.97660)	(0.01005)	(6.22994)
Age 56-60	-0.01106**	-2.09150	0.01365*	7.03611	0.00814	23.99987**	-0.01896	-14.19854**
	(0.00533)	(2.87145)	(0.00732)	(4.33570)	(0.01207)	(10.05590)	(0.01161)	(5.77800)
Age 61-65	-0.00891	1.98748	-0.00351	-15.30825**	0.00753	22.45903**	-0.02619	-10.33824
	(0.00712)	(4.29756)	(0.01047)	(6.04689)	(0.01223)	(10.29226)	(0.01621)	(9.07428)
Manufacturing	-0.00639***	-4.06253***	0.00348***	1.69722***	-0.00205***	-3.33475***	0.00068	0.09053
	(0.00041)	(0.27251)	(0.00080)	(0.43863)	(0.00024)	(0.38114)	(0.00077)	(0.50731)
Construction	-0.01085***	-5.92327***	0.00673***	7.99312***	-0.00033	0.23228	0.00572***	4.35962***
	(0.00092)	(0.49722)	(0.00127)	(0.83066)	(0.00091)	(1.62131)	(0.00097)	(0.58400)
Private Services	0.00416***	2.19188***	0.00182**	1.10451**	0.00076***	0.65821*	-0.00169**	-0.72416
	(0.00041)	(0.29977)	(0.00092)	(0.51054)	(0.00023)	(0.37105)	(0.00076)	(0.44827)
Experience	0.00006***	0.03037***	0.00012***	0.06392***	-0.00003***	-0.06154***	0.00001***	0.00113
	(0.00001)	(0.00274)	(0.00000)	(0.00294)	(0.00000)	(0.00823)	(0.00000)	(0.00204)
Obs.	501,626	501,626	504,799	504,799	345,169	345,169	451,912	451,912
Municipality FEs	YES	YES	YES	YES	YES	YES	YES	YES
Year-month FEs	YES	YES	YES	YES	YES	YES	YES	YES
Province $\times$ year-month FEs	YES	YES	YES	YES	YES	YES	YES	YES
F-statistics:	68.80	68.80	112.2	112.2	51.19	51.19	111.1	111.1

Notes: All controls are calculated as averages in each municipality$\times$ year-month cells. Additional controls (not showed in the table) include total precipitations and bins of temperatures. Estimates are weighted by number of workers in each municipality-month cell. Standard errors, in parentheses, are clustered on municipalities.

Table 8: IV Estimates of the Effect of PM_{10} on Sick Leave and Sick Wage by Sex

	Females		Males	
	(1)	(2)	(3)	(4)
	Sick Leave	Wage Sick	Sick Leave	Wage Sick
PM_{10}	0.00052***	0.19957***	0.00026***	0.18695***
	(0.00008)	(0.03667)	(0.00007)	(0.04211)
Foreign	0.00601***	1.96910*	-0.00087	-0.65108
	(0.00202)	(1.01686)	(0.00153)	(0.92952)
Part-time	-0.00149	-11.45007***	-0.00724***	-15.04060***
	(0.00168)	(0.85193)	(0.00198)	(1.47544)
Age 21-25	-0.01474**	-5.43431**	-0.00043	-2.23076
	(0.00578)	(2.41776)	(0.00419)	(3.35381)
Age 26-30	-0.01898***	-8.54151***	0.00015	-3.98976
	(0.00538)	(2.26286)	(0.00432)	(3.03545)
Age 31-35	-0.01729***	-8.57053***	-0.00270	-6.58295**
	(0.00498)	(2.27364)	(0.00421)	(3.14374)
Age 36-40	-0.00223	-0.42222	0.00412	-0.18822
	(0.00510)	(2.25652)	(0.00430)	(3.22403)
Age 41-45	0.00132	1.71314	0.01194***	4.59844
	(0.00492)	(2.20056)	(0.00436)	(3.19027)
Age 46-50	0.00357	1.93763	0.01215***	5.41540*
	(0.00501)	(2.29475)	(0.00419)	(3.07938)
Age 51-55	0.00653	4.13004*	0.01878***	11.46463***
	(0.00480)	(2.34638)	(0.00400)	(3.28394)
Age 56-60	0.00531	2.75441	0.02887***	21.06089***
	(0.00568)	(2.59835)	(0.00435)	(3.19799)
Age 61-65	-0.00492	-10.13675**	0.02832***	13.97389***
	(0.00807)	(4.00635)	(0.00750)	(5.26634)
Manufacturing	0.00010	0.55092	0.00137**	0.16435
	(0.00081)	(0.41699)	(0.00057)	(0.34930)
Construction	-0.03682***	-16.21983***	0.00818***	8.15697***
	(0.00326)	(1.49961)	(0.00086)	(0.62099)
Private Services	0.00514***	3.07048***	-0.00014	0.09423
	(0.00073)	(0.39224)	(0.00061)	(0.42164)
Blue Collars	0.02529***	9.86120***	0.02035***	7.99889***
	(0.00679)	(3.57501)	(0.00341)	(1.93150)
White Collars	0.00790	3.47238	0.00226	-2.23086
	(0.00678)	(3.51789)	(0.00348)	(1.95860)
Managers	-0.04857***	-25.41940***	-0.02430***	-17.81829***
	(0.00884)	(4.62558)	(0.00546)	(3.50825)
Apprentices	-0.00746	-5.51996	0.00728*	-2.78736
	(0.00870)	(4.54863)	(0.00427)	(2.91554)
Experience	0.00013***	0.06005***	0.00009***	0.05124***
	(0.00001)	(0.00257)	(0.00000)	(0.00341)
Obs.	500,391	500,391	507,511	507,511
Municipality FEs	YES	YES	YES	YES
Year-month FEs	YES	YES	YES	YES
Province × year-month FEs	YES	YES	YES	YES
F-statistics:	100.6	100.6	96.93	96.93

Notes: All controls are calculated as averages in each municipality× year-month cells. Additional controls (not showed in the table) include total precipitations and bins of temperatures. Estimates are weighted by number of workers in each municipality-month cell. Standard errors, in parentheses, are clustered on municipalities.

Table 9: IV Estimates of the Effect of PM_{10} on Sick Leave and Sick Wage by Nationality

	Italian		Foreign	
	(1)	(2)	(3)	(4)
	Sick Leave	Sick Wage	Sick Leave	Sick Wage
PM_{10}	0.00034***	0.19327***	0.00053***	0.37879***
	(0.00006)	(0.03599)	(0.00009)	(0.07807)
Sex	0.00868***	1.76184**	0.01305***	4.03869***
	(0.00123)	(0.70302)	(0.00124)	(0.81609)
Part-time	0.00359*	-9.69837***	-0.02406***	-15.09818***
	(0.00187)	(1.09996)	(0.00166)	(1.40820)
Age 21-25	-0.00679	-2.04066	-0.00062	-2.40129
	(0.00512)	(3.12933)	(0.00303)	(2.29891)
Age 26-30	-0.00873*	-5.75499*	-0.00392	-6.03141**
	(0.00511)	(3.10850)	(0.00290)	(2.54231)
Age 31-35	-0.00951**	-8.17863***	-0.00419	-4.54894*
	(0.00454)	(3.06569)	(0.00301)	(2.52509)
Age 36-40	0.00285	0.49778	0.00176	-0.93515
	(0.00483)	(3.10978)	(0.00321)	(2.61704)
Age 41-45	0.01010**	4.77108	0.00586*	3.39313
	(0.00479)	(3.02290)	(0.00338)	(2.58792)
Age 46-50	0.00552	3.35245	0.00867**	5.37931**
	(0.00477)	(2.99047)	(0.00346)	(2.39201)
Age 51-55	0.01420***	8.92365***	0.01869***	9.71331***
	(0.00444)	(3.26827)	(0.00400)	(3.07282)
Age 56-60	0.02409***	15.95279***	0.02365***	15.13065***
	(0.00493)	(2.98678)	(0.00476)	(3.68530)
Age 61-65	0.00703	-0.20094	0.04473***	23.92821***
	(0.00853)	(5.49615)	(0.00844)	(8.13962)
Manufacturing	0.00200***	0.44017	0.00082	-0.80004
	(0.00056)	(0.32494)	(0.00081)	(0.60746)
Construction	0.00715***	7.30750***	0.00430***	4.24543***
	(0.00112)	(0.73490)	(0.00101)	(0.77606)
Private Services	0.00208***	1.44124***	0.00035	-0.82296
	(0.00059)	(0.35573)	(0.00078)	(0.71769)
Blue Collars	0.02471***	9.68382***	0.02168***	6.92798**
	(0.00446)	(2.52769)	(0.00511)	(3.15194)
White Collars	0.00940**	2.13761	0.00998**	5.80586*
	(0.00447)	(2.54763)	(0.00486)	(3.24672)
Managers	-0.02839***	-19.01491***	-0.01310	-20.43491
	(0.00689)	(3.84685)	(0.01027)	(48.86088)
Apprentices	-0.00094	-5.22841	0.01782***	5.77339
	(0.00627)	(3.94314)	(0.00551)	(3.70061)
Experience	0.00010***	0.05528***	0.00011***	0.05166***
	(0.00000)	(0.00338)	(0.00000)	(0.00439)
Obs.	510,516	510,516	473,045	473,045
Municipality FEs	YES	YES	YES	YES
Year-month FEs	YES	YES	YES	YES
Province × year-month FEs	YES	YES	YES	YES
F-statistics:	98.12	98.12	124.2	124.2

Notes: All controls are calculated as averages in each municipality× year-month cells. Additional controls (not showed in the table) include total precipitations and bins of temperatures. Estimates are weighted by number of workers in each municipality-month cell. Standard errors, in parentheses, are clustered on municipalities.

Table 10: Total Annual Costs of PM_{10} (in million Euro).

Year	INPS sample		Italian employees	
	Baseline *vs.* National average	Baseline *vs.*. WHO standard (20 $\mu g/m^3$)	Baseline *vs.* National average	Baseline *vs.* WHO standard (20 $\mu g/m^3$)
2011	4.31	2.20	125.41	65.39
2012	4.04	1.35	115.30	39.92
2013	4.20	2.43	118.46	70.78
2014	4.86	2.59	127.42	69.70
2015	4.33	2.69	121.57	77.30
2016	5.31	5.49	146.41	151.19

Notes: INPS sample refers to INPS data selected according to criteria enlisted in the data sample, and amounting to 1 million workers on average yearly. Italian employees are constructed by taking the employment shares with respect to municipality population sizes, as defined according to ISTAT statistics. National PM_{10} average refers to the all-period CAMS data average concentrations.

Appendix

Additional Tables

Table A1: IV Estimates of the Effect of PM_{10} with Standard Errors Clustered on Provinces.

	(1)	(2)
	Sick Leave	Sick Wage
PM_{10}	0.00024**	0.13629*
	(0.00011)	(0.07467)
Obs.	66,402,425	66,402,425
Worker FEs	YES	YES
Year-month FEs	YES	YES
F-statistics:	30.35	30.35

Notes: Individual controls include age classes and part-time. Weather controls include bins of precipitations, minimum, average and maximum temperatures. Standard errors, in parentheses, are clustered on provinces.

Table A2: First Stage Estimates With Standard Errors Clustered on Provinces

	(1)
	PM_{10}
Wind speed	-0.72326***
	(0.13128)
Obs.	66,402,425
Worker FEs	YES
Year-month FEs	YES

Notes: Individual controls include age classes and part-time. Weather controls include bins of precipitations, minimum, average and maximum temperatures. Standard errors, in parentheses, are clustered on provinces.