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When Particulate Matter Strikes Cities: Social Disparities and Health Costs of Air Pollution

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Abstract

We investigate the heterogeneous effects of daily particular matter (PM) pollution on Italian hospitalizations and their costs. We exploit public transportation strikes as plausibly-exogenous shocks in PM. We find that young individuals, an arguably healthy age group, exhibit economically meaningful responses to changes in air pollution. A higher prevalence of pollution-induced hospitalizations also exists among the elderly, low educated individuals and migrants coming from low income countries. Our results imply a large role for differential avoidance behavior driving heterogeneous marginal effects. PM exposure also affects the intensive margin since pollution-induced hospitalizations are not only more frequent but they are characterized by a higher complexity, generating additional costs.

Keywords: health effects of air pollution, public transportation strikes, hospitalization costs, environmental inequality
JEL: I14, Q53, R41

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1 Introduction

Air pollution contributes to serious illness, premature death and lost productivity, especially in urban areas (Graff Zivin and Neidell, 2012, He et al., 2018, Isen et al., 2017, Schlenker and Walker, 2015, Simeonova et al., 2019, among others). While the health effects of air pollution are well documented, we know very little about how concentration-response functions vary across different groups and socio-economic status (SES). Exposure to air pollution translates into costs through an individual-specific damage function. According to Hsiang et al. (2019) the damage function is closely related to SES, raising concerns about environmental justice (Banzhaf et al., 2019, Lavaine, 2015, Neidell, 2004). Socio-economic factors interact with vulnerabilities through two major channels: heterogeneous sensitivity (i.e. baseline health) and heterogeneous compensatory behavior (i.e. avoidance and defensive investments (Deschenes et al., 2017, Moretti and Neidell, 2011)). Therefore, to properly quantify the welfare costs of air pollution, it is necessary to account for both baseline health and individual actions to avoid pollution exposure.

In this paper we estimate the heterogeneous health effects of particulate matter (PM), one of the most diffuse and harmful air pollutants, on urgent respiratory hospitalizations. We use these estimates to calculate the cost of PM exposure for various population groups in Italy, a country with strict environmental regulation and moderate air pollution levels. To derive marginal health effects net of avoidance behavior, we exploit public transportation (PT) strikes as an instrumental variable (IV) for endogenous air pollution. PT strikes are an ideal instrument in our setting: they create plausibly-exogenous shocks in air pollution concentration due to unexpected traffic congestion but do not prevent individuals from engaging in their daily routines. In addition, PT strikes in Italy are frequent and affect a very large portion of the at-risk population, allowing for a large-scale analysis.

Our paper improves on previous work in several ways. We first offer a simple conceptual framework to show how compensatory behavior may affect hospitalization costs of pollution for a given individual exposure and sensitivity. This framework allows us to clarify the channels through which our empirical findings should be interpreted, disentangling the different roles of heterogeneous sensitivity versus heterogeneous compensatory behavior. We analyze the costs of exposure to air pollution examining heterogeneity across educational attainment, migration status, and age. For this purpose, we consider the universe of hospitalizations rather than a subset of patients from a particular insurance plan or geographical area. The institutional context offers two benefits. First, the Italian health system is publicly provided, with minimum frictions for accessing the healthcare. Second, the cost of health treatment is largely homogeneous across individuals, so it is unlikely that differentials in the expected cost of treatment are generating sample selection. Importantly, our estimation procedure disentangles the extensive and the intensive margins of pollution effects, considering, respectively, the number of hospitalizations and their unit costs. We thus show that hospitalizations arising from higher PM concentrations are not only more likely to occur, but also more complex to deal with. Our large-scale empirical analysis uses data for all major Italian cities between 2013 and 2015 and employs state-of-the-science data on PM_{10} concentrations.

We find that particle pollution instrumented by PT strikes causes an increase in urgent respiratory hospitalizations: a one standard deviation (s.d.) increase in PM_{10} (corresponding to 10.37 micrograms per cubic meter) causes an additional 0.55 hospitalizations per 100,000 residents. Importantly, we find that moderately young populations (aged 15–44) exhibit economically meaningful and statistically significant responses to changes in air pollution, implying a large role for differential avoidance behavior driving heterogeneous marginal effects. Moreover, we find a higher prevalence of pollution-induced hospitalizations among low educated individuals and migrants coming from low income countries.

We then examine to what extent traffic-born adverse air quality affects the complexity of hospitalizations. We find that one additional s.d. in average PM_{10} concentration increases the average unit cost for asthma hospitalizations by 84.4%, suggesting that higher pollution levels make hospitalizations not only more frequent but also more complex. Likewise, one additional s.d. of PM_{10} causes an 18.6% increase in average unit cost for chronic obstructive pulmonary disease (COPD) hospitalizations. Considering both the extensive and the intensive margins, we estimate that a daily increase of one s.d in PM_{10} is associated with an additional 2,603 euros of medical spending per 100,000 individuals, representing a 45% increase in the average daily expenditure for respiratory hospitalizations. We find that for young people the spending increase is 4,837 euros per 100,000 individuals, while for the elderly it is 8,774. While the estimates might be downward biased for the elderly due to residual unobserved avoidance behavior, for the young they represent the true health cost of pollution exposure. We summarize the heterogeneity of these effects with a heat map showing how cities with different age structures and different PM exposures can face similar health costs.

Based on these results, we offer back-of-the-envelope calculations of the total daily monetary costs of a one s.d. increase in PM_{10} for the 17.8 million residents in the 111 municipalities we consider, which amounts to 331,843 euros. 85% of this spending increase comes from the extensive margin (hospitalization count); the remaining 15% comes from the intensive margin (increased complexity of hospitalizations). Overall, the total daily costs of a one s.d. increase in PM_{10} represent approximately 0.4% of the total daily health expenditure in Italy.

From a policy perspective, our results on health impacts for the 15–44 age group are the most novel and informative. While we do not explicitly estimate the distinct roles of heterogeneity in sensitivity and heterogeneity in compensatory behavior, for this age group we can infer their relative roles. The fact that the young, arguably the most healthy age group is significantly harmed by PM_{10} exposure suggests that they optimally respond to their low marginal health sensitivity, choosing low levels of defensive behavior. These novel results imply an important role for economic incentives determining defensive spending and compensatory behaviors, which may ultimately lower the exposure an individual faces, conditional on ambient conditions. Additionally, our findings concerning the extensive and the intensive margins unveil incremental complexity of hospitalizations, hence additional costs, in response to air pollution.

2 Particulate matter and health

Air pollution has well documented negative affects on human health. Most of the evidence on the health effects of air pollution relates to particulate matter (PM), ozone (O_3) and nitrogen dioxide (NO_2). Due to its large diffusion and ability to penetrate the lungs and blood stream, PM is considered "*the most pernicious form of air pollution*" (Chay et al., 2003). PM consists of pollution particles of different sizes and compositions directly emitted into the atmosphere. When inhaled, PM can cause cardiovascular and pulmonary disease, and premature death (WHO, 2013). In particular, PM_{10} consists of particles that are less than 10 micrometers (μm) in aerodynamic diameter, and originates from both natural and anthropogenic sources, though most particle pollution comes from fuel combustion from motor vehicles (diesel in particular) and heating (EEA, 2016). Many countries are trying to regulate PM levels, which requires an accurate assessment of the health effects of marginal pollution concentrations. Because of road traffic, with over 80% of trips made by private cars, particle pollution in Italy represents a major source of concern for policy makers and an important parameter for improving air quality (EC, 2019).[1]

Estimating the causal effect of PM on health is complicated by widely-documented methodological issues, including omitted variable bias and measurement error. Several quasi-experimental studies have tried to overcome these challenges by introducing plausibly exogenous sources of variation in pollution (Dominici et al., 2014). Recently, an influential body of literature has investigated the effect of air pollution on healthcare utilization, focusing on NO_2, CO and PM (Deryugina et al., 2019, Halliday et al., 2015, Schlenker and Walker, 2015, among others). These studies find that air pollution has a strong adverse effect on hospitalizations and mortality for young children and the elderly, and quantifies the costs of air pollution. While the literature has benefited immensely from their findings, each of these studies addresses a single subpopulation or

[1] Italy has failed to address air quality standards, especially for PM_{10}. As a consequence, the European Commission in 2017 requested Italy to take appropriate actions in order to ensure good air quality and safeguard public health (EC, 2017).

geographical area. Moreover, most studies take place in settings featuring frictions in access to healthcare and differential costs of treatment, where selection issues make it difficult to estimate the cost of pollution.

3 Heterogeneous effects of air pollution

There is a growing literature on the distributional consequences of environmental conditions and environmental policy (see Hsiang et al. (2019) for a recent review) that focuses on the distribution of the marginal effect of pollution. This distribution can be explained by two main mechanisms. First, individuals facing the same ambient conditions may exhibit differential health responses due to biophysical differences in vulnerability, such as age and baseline health. Second, individuals facing the same ambient conditions may exhibit differential health responses due to their optimal investments in defensive expenditures or compensatory behaviors, such as avoiding time spent outside during high pollution periods (Deschenes et al., 2017, Graff Zivin and Neidell, 2013). These two mechanisms have very different welfare implications. On the one hand, knowing the extent of biological effects makes it possible to design policies that can encourage optimal levels of avoidance behavior. On the other hand, knowing the extent of deliberate avoidance is necessary to properly quantify the economic impact of pollution, and to construct an optimal policy response. Although we do not explicitly estimate the two distinct effects, we lay out a theoretically-grounded framework that allows us to interpret our empirical results for various groups of individuals as a function of biological *versus* avoidance heterogeneity.

Avoidance behavior relates to transient actions that individuals take to reduce their realized exposure to pollution (Graff Zivin and Neidell, 2013). Given the lack of adequate data, avoidance behavior often constitutes an important source of endogeneity in empirical analysis. Avoidance responses in our setting are typically represented by non-market behavior, like spending time indoors (Hsiang et al., 2019, Moretti and Neidell, 2011). Since these behaviors are very difficult to measure, it is infeasible for us to explicitly quantify them. To estimate the health effect of air pollution net of avoidance behavior we make some simple assumptions. We first assume that avoidance is costly and, in our setting, its cost is mostly related to the disutility associated with reallocating time across activities, or to the opportunity cost of time. Then, we assume that this cost is heterogenous across groups of individuals. For instance, the most susceptible individuals are more likely to adapt to their sensitivity to air pollution and may optimally decide to avoid staying outdoors on high pollution days. Conversely, individuals engaged in working and schooling activities have limited scope for avoidance, since the labor and schooling supply is inelastic to relatively normal day-by-day fluctuations in air pollution. A similar argument holds for materially disadvantaged individuals, who are also less likely to compensate for the negative effects of bad air quality (Adler and van Ommeren, 2016, Cournane et al., 2017, Forastiere et al., 2007, Germani et al., 2014, Halliday et al., 2015, Isen et al., 2017, Lavaine, 2015, McCubbin and Delucchi, 1999, Sun et al., 2017, among others).

Based on Graff Zivin and Neidell (2013) and Deschenes et al. (2017), we formulate a simple framework, where we let e denote ambient pollution concentrations, $a \in [0, 1]$ captures avoidance behaviors, and $f[e(1-a)]$ indicates health damage as a function of the actual pollution experienced (i.e. if there is full avoidance, $a = 1$ and all ambient pollution exposure is avoided). Suppose each subpopulation k has a differential response to a given level of pollution, leading to different health damage functions $f_k[e(1-a)]$. Avoidance is costly and this cost differs across subgroups of individuals. A representative agent in population k will choose the amount of avoidance that minimizes total damages, including the cost of avoidance:

$$\min_a f_k[e(1-a)] + c_k(a). \tag{1}$$

First order conditions imply

$$-\frac{\partial f_k}{\partial \tilde{e}} = \frac{\partial c_k}{\partial a}, \tag{2}$$

where $\tilde{e} = e(1-a)$ is the actual pollution the agent experiences net of avoidance behavior. Optimal avoidance $a_k^*(e)$ satisfies the first order condition, and will differ across each subpopulation k if the sensitivity to effective pollution and/or the cost of avoidance differs across these k groups. If their avoidance costs are convex, given ambient concentrations e, populations that are less sensitive to effective pollution or that face a high avoidance cost will optimally choose a lower level of avoidance a_k^*. Whenever we observe a marginal effect of health outcomes with respect to a given level of pollution e, we measure the total derivative of health with respect to PM concentrations e, net of any avoidance behavior a, which differs across groups k:

$$\frac{df_k}{de} = \frac{\partial f_k}{\partial e} + \frac{\partial f_k}{\partial a}\frac{\partial a_k^*}{\partial e}. \tag{3}$$

The first term of this total derivative is the group specific sensitivity ($\frac{\partial f_k}{\partial e}$), which we assume has a positive sign. The interaction term is the optimal avoidance behavior ($\frac{\partial f_k}{\partial a}\frac{\partial a_k^*}{\partial e}$), where we assume the partial derivative of the health damage function with respect to avoidance behavior has a negative sign and the partial derivative of avoidance behavior with respect to pollution has a positive sign. Since health damage increases with sensitivity and decreases with avoidance behavior, $\frac{df_k}{de}$ is an underestimate of $\frac{\partial f_k}{\partial e}$. If avoidance behavior is sufficiently intense, it may entirely offset a high biological sensitivity, delivering negligible overall health effects; conversely, if there is no avoidance behavior, the biological effect and the overall health effect will coincide.

In this study we exploit this framework in order to offer a theoretically-grounded intuition for the interpretation of our results. While with the data at hand we are unable to directly observe optimal compensatory behavior a_k^*, we build on previous literature that documents a nonlinear gradient of $\frac{df_k}{de}$ with age, finding significant effect of pollution on health of infants and the elderly, and none or negligible effects for young adults. We thus exploit an empirical strategy that allows to make plausible assumptions about avoidance behavior on various age groups in relation to air pollution exposure. The exogenous source of variation in PM that we exploit are PT strike events, which deliver unexpected increases in traffic-born pollution on strike days. As we explain in Section 5, this strategy allows us to focus on time-varying behavioral responses to shocks in pollution, minimizing concerns about residential sorting and other structural responses to high levels of pollution. One should notice that while in our setting pollution peaks are modest and hard to notice, congestion is a visible and straightforward correlate of pollution, hence the resulting increase in pollution levels may be public knowledge, potentially motivating individuals to engage in avoidance behavior. Nevertheless, PT strikes occur on regular working/school days, and the associated avoidance behavior among working-age individuals and school-age children is negligible, as their opportunity cost of avoidance is very high. Therefore, even though we do not explicitly control for avoidance behavior, focusing on the 15–44 age groups within our empirical setting uncovers the effect of air pollution holding avoidance behavior fixed, i.e. the biological effect.

4 Data

We combined administrative data on urgent respiratory hospitalizations for the period from 2013 to 2015 with pollution concentration data and information on public transportation strikes at the day-municipality level. Our data is at the finest level of disaggregation, represented by 8,090 municipalities, even though we only use the 111 province capital cities for our core analysis (see Figure 4). For each of the 1,095 days between 2013 and 2015, and for each of the 111 administrative municipalities, we consider a balanced panel consisting of 121,545 observations. In this section we describe the main features of the data; see Appendix Table A.1 for additional information.[2]

[2]In January 2010 there were 8,090 Italian municipalities (corresponding to Local Administrative Units according to the European classification of territorial units), which were the building blocks of Italian provinces corresponding to the NUTS 3 level of the Eurostat classification. Each province is governed by a municipality. Following several administrative reorganizations, the number of municipalities dropped to 7,954 in 2018, with both the number of provinces and their capital cities undergoing organizational changes: the number of Italian provinces increased from 107 to 110; during the period between 2010 and 2018, these provinces were headed by 111 unique municipalities (in some cases the administration moved to a different municipality, e.g. the case of Cesena-Forlí). In our analysis, we

4.1 Hospitalization Data

The Hospital Discharge Data (SDO) from the Italian Ministry of Health is our main data source. These data provide information on the universe of hospitalizations delivered by public hospitals and publicly funded private hospitals. The universal provision of healthcare in Italy is a favorable setting for our analysis since the Italian health system is publicly provided, with minimum frictions for accessing the healthcare. In addition, the cost of health treatment is largely homogeneous across individuals, so it is unlikely that differentials in the expected cost of treatment are generating sample selection. The records contain socio-demographic information (age, gender, nationality, place of birth and residence, educational attainment) along with clinical information (diagnoses, procedures performed, hospital transfers, discharges) and hospitalization details (hospital type and specialty). We restrict the data to urgent hospitalization episodes, disregarding programmed or elective hospital stays.[3]

Hospital discharge records include information on the primary diagnosis determining each hospitalization, but they also list up to five secondary diagnoses describing other conditions. We limit our analysis to hospitalizations with a primary diagnosis for respiratory diseases following the International Statistical Classification of Diseases and Related Health Problems v.9 (ICD-9 codes).[4] This sample restriction is more stringent than the approach adopted by Schlenker and Walker (2015), who classify a patient as suffering from a specific illness if either the primary or one of the secondary diagnoses codes lists a respiratory illness, but it allows us to precisely identify pollution-induced events. For instance, since traffic congestion correlates not only with air pollution but also with driving safety, the hospitalization of a car accident victim who also suffers from asthma may be wrongly attributed to air pollution, violating the exclusion restriction

consider all 111 municipalities that constituted an administrative city in Italy at any point during our sample.

[3]We use programmed hospitalizations to test the robustness of our results (see Section 6.5).

[4]ICD-9 codes for Respiratory diseases: Acute respiratory infections (460-466), Other diseases of the upper respiratory tract (470-478), Pneumonia and influenza (480-488), Chronic obstructive pulmonary disease and allied conditions (490-496), Pneumoconioses and other lung diseases due to external agents (500-508), Other diseases of respiratory system (510-519).

of our IV strategy.

During the period 2013–2015, there were roughly 30 million hospitalizations in 8,090 municipalities in Italy, and approximately 11.2 million (39%) were urgent. Approximately 31% of the urgent hospitalizations were delivered to residents of the 111 municipalities we include in our sample. A subset of 11.7% of hospitalizations, corresponding to a total of 403,859 events, was due to primary respiratory disease diagnoses, which is the main outcome in our study.

In our core analysis, we count the number of daily hospitalizations when municipality of residence matches the municipality of hospitalization.[5] While Italian residents are free to seek healthcare anywhere in Italy, it is unlikely that patients with urgent cases of respiratory disease are traveling farther than necessary for medical care. Moreover, administrative towns are more likely to receive inflows of workers from minor surrounding towns than to generate worker outflows. According to our calculations based on individual surveys concerning aspects of daily living conducted by the Italian National Institute of Statistics (ISTAT), in 2013 only 11% of residents living in big Italian cities commuted outside their municipalities of residence each day; most of these workers are better educated and between 30 and 45 years old. We exclude hospitalizations delivered to non-residents of administrative towns and hospitalizations delivered to non-residents outside administrative towns.[6] While individuals commuting to administrative municipalities are also exposed to the environmental conditions in their host towns and, as a consequence, are more likely to be hospitalized in these towns, we are not able to convincingly make any assumption about their actual exposure to air pollution. We thus collapse the data by day of hospitalization $\times$ patient's municipality of residence cells, for a total of 121,545 observations covering 111 major Italian cities from 2013 to 2015.

In order to assess the heterogeneous effects of pollution exposure, we divide the data into five age groups (0–14, 15–24, 25–44, 45–64 and over 65), three educational

[5]The patient's municipality of residence matches the hospital's municipality in 98.7% of cases.

[6]Before applying this restriction, we carefully test for the mobility response of residents on PT strike days to see if strike episodes affect how likely individuals are to seek hospitalization outside their town of residence. Results are available upon request.

levels (primary, secondary and tertiary school attainment) and migrant status. We further distinguish between migrants from low vs. high income countries, based on the World Bank country classification.[7] We obtain daily counts of hospitalizations for the entire population and for each of the socio-economically relevant subgroups. Our final outcomes are daily municipality-level hospitalization counts expressed per 100,000 residents. When we consider specific age, education or migration groups, we adjust the relevant resident population to that particular group.

In order to quantify the economic burden of the pollution exposure on direct health expenditure, we calculate individual hospitalization costs. Based on patient primary and secondary diagnoses, surgical intervention, diagnostic and therapeutic procedures, and individual age and sex, an algorithm adopted by the Italian Department of Health assigns each hospitalization episode into a specific Diagnosis Related Group (DRG). DRGs classify hospital patients by assigning a cost and a standard length of hospital stay to each hospitalization .[8] Additionally, each DRG includes information on a supplementary cost applied to days exceeding the standard length of stay. We exploit this information to construct individual hospitalization costs by assigning the cost of the DRG to each individual, rescaled to account for any extra hospital stay days. This procedure allows us to capture a more accurate cost pattern based on the severity of each hospitalization episode. We then collapse the individual costs by municipality $\times$ day of hospitalization cells. We express the total costs in two ways: per hospitalization and per capita. In the first case, we calculate the average unit cost (AUC) of a respiratory disease hospitalization as the ratio of total costs of urgent cases of respiratory disease to the number of hospitalizations for each day/municipality. We calculate the unit costs for both the overall pool of respiratory disease and for each disease type. The average unit cost is a comprehensive measure of the average complexity of respiratory hospitalizations faced by a municipality on a given day. In the second case, we calculate

[7]According to World Bank (2014), high income countries are countries with per capita gross national income (GNI) in the previous year $> 12,746\$$, while those who fall below the threshold are in the low-middle income countries group. For further details see https://blogs.worldbank.org/opendata/updated-income-classifications.

[8]DRG prices are the key parameters through which hospitals are financed by the central administrations.

the per capita respiratory hospitalization costs as the ratio of total costs of urgent cases for respiratory disease to the number of residents for each municipality × day cell. This represents the total average cost (TAC) since it captures changes in both the unit cost and the count of hospitalizations. We refer to increased healthcare costs from a higher number of hospitalizations as the extensive margin (TAC), those arising from a higher unit cost of hospitalizations as the intensive margin (AUC), and the combination of the two as the total cost of pollution-induced hospitalizations.

Table 1 presents descriptive statistics for the full sample of hospitalizations and for each socio-economic subgroup separately. Since all the results come from aggregation procedures that reduce the relevant variables to rates, we weight observations by the size of the municipality population (Janke, 2014, Janke et al., 2009, Knittel et al., 2016, Schlenker and Walker, 2015, among others). We observe an average of two hospitalizations per day. Hospitalizations are highest for the elderly and children. Both the overall and group-specific counts are extremely variable, with s.d.s larger than the means. The number of hospitalizations for individuals with only primary education is higher than for other education attainment categories. Finally, the number of hospitalizations is lower for migrants, although citizens from low-income countries undergo hospitalization more frequently than those from high-income countries.

The average AUC for an urgent respiratory hospitalization is 2,856 euros, and this cost varies according to the specific respiratory problem: 1,648 euros for asthma, 2,237 euros for COPD, and 2,884 euros for pneumonia. The average TAC for urgent respiratory problems amounts to 0.05 euros/day per resident in the 111 municipalities we consider. For context, the total Italian healthcare expenditure amounts to 5 euros per resident/day, so urgent respiratory hospitalizations account for approximately 1%.[9]

[9] The public healthcare fund (FSN) amounts to 110,000 million euros/year for a population of about 60 million.

4.2 Air Pollution Concentrations

Our core analysis focuses on PM_{10}, particle air pollutants ten micrometers or smaller in aerodynamic diameter. This pollutant is the most relevant in our setting since a large fraction of PM_{10} is generated by road traffic, and PM_{10} is widespread in urban areas. PM_{10} is also relevant from a policy perspective since recent official statistics report that its concentration has decreased more slowly than other traffic-related pollutants such as carbon monoxide (CO) and nitrogen dioxide (NO_2) (EEA, 2019). Fuel combustion is the primary source of PM_{10}, and most fuel combustion comes from road traffic. Non-exhaust emission sources related to traffic, such as mechanical abrasion of brakes and tires and corrosion of vehicle components, also contribute to PM formation. These particles, often referred to as 'road dust', may be suspended or resuspended in the atmosphere as a result of tire shear and vehicle-generated turbulence. While our analysis focuses on PM_{10}, we also consider other traffic-related pollutants directly emitted from exhaust such as NO_2 and CO, and ozone (O_3), a secondary pollutant formed from a reaction between NO_2, hydrocarbons and sunlight. We use data on these additional pollutants in our robustness checks in Section 6.5.

Data on PM_{10} and O_3 concentrations come from the Copernicus Atmosphere Monitoring Service (CAMS) managed by the European Centre for Medium-Range Weather Forecasts (ECMWF).[10] These data come from a combination of direct observation from satellites, monitoring stations and reanalysis.[11] Air pollution reanalysis data offer three substantial improvements over monitoring stations measures. First, as discussed in Filippini et al. (2019), using monitoring stations data assumes that the pollution concentration is homogeneous within a given administrative unit, and this assumption is unlikely to hold especially in the Italian case. Therefore, individuals living far from the

[10] At the time we are writing, CAMS data are not available for CO and NO_2 during the period 2013–2015. In order to test if PM_{10} drives our main results in a multi pollutant model setting, we supplement CAMS data with monitoring station data for CO and NO_2.

[11] Reanalysis is a systematic process for estimating concentrations across a grid by combining different observational sources such as monitoring stations, satellites, aircraft, ship reports and other inputs with a climate model. This framework provides a dynamically consistent estimate of the climate and pollution at each time period and location.

monitoring stations are likely to be exposed to different pollution levels from those actually registered, generating a mismatch between the true pollution level and the assigned one. Second, these estimates are sensitive to the approach used to impute pollution at aggregate levels; since measurement error is not normally distributed, the direction of the bias is ambiguous (Lleras-Muney, 2010). Third, there are only a few monitoring stations and their number and location may vary over time in a non-random way (Fowlie et al., 2019, Grainger and Schreiber, 2019). CAMS data overcome all these limitations, providing homogenous information over time and space on a granular geographical area.

CAMS data are reported on a regular grid of about 18×18 km at the Italian latitudes. In order to obtain administrative-level concentrations for the 8090 Italian municipalities, we combine CAMS grids with administrative boundaries using a spatial join algorithm that assigns a grid point to a municipality if the point is contained within the municipality's boundary. When a municipality contains more than one grid point, as in the case of major urban centers, we assign the average value calculated for all the grid points within that municipality. On the contrary, in the few municipalities where no grid points fall within their boundaries, we assign a value averaged over the closest grid points.

To test the validity of our reanalysis data and test weather PM is driving our results, we also collect air pollution concentrations from monitoring stations. We obtain these data from the Airbase database of the European Environmental Agency (EEA), which includes validated concentration measures from monitoring stations in a large number of Italian municipalities (see Section 6.5). Figure 5 plots weekly trends of PM_{10} concentrations, averaged over the period 2013–2015, with data from both CAMS and monitoring stations. The two sources follow a similar trend even though concentration readings from monitoring stations are higher and more variable. The higher variance is due to the fact that monitoring stations only provide readings in the exact place where the station is placed, without accounting for air pollution dispersion near the monitor. Since monitoring stations are not randomly located, the resulting noise is likely to generate selection bias. Since CAMS data are processed on a regular grid, they provide a more reliable measure of pollutant concentrations over any geographical area. Table 3 presents descriptive statistics for the pollutant concentration levels from both sources.

4.3 Public transportation strikes

Italy has been consistently above the average in the European "country-strike league" (Vandaele, 2011). Indeed, even though transport is one of the essential services and strikes are explicitly regulated by Law no. 146/1990 and Law no. 83/2000, the Italian transport sector is strike-prone. Strikes are regulated by the Guarantee Authority (Commissione di Garanzia), which ensures that citizens' basic needs are satisfied during strikes.

We construct a public transportation (PT) strike database by combining information provided by the Italian strike commission[12] and the Ministry of Infrastructures and Transport. We use information on strikes that took place at the municipality level, excluding national and regional PT strikes, and day-long national general strikes. Italy faced 855 strike episodes in 91 municipalities over the study period, with only a few lasting for more than one day. When considering only the 111 administrative municipalities, we are left with 470 single-day strike episodes distributed across 72 municipalities.

The first three panels of Figure 1 show the distribution of one-day strike activity across years, months, and day of the week. Strikes tend to take place in all months, with a significant drop during the summer. Strikes are most likely to occur on Mondays and Fridays, and we observe a pronounced spike in strikes in 2015. The fourth panel plots the frequency of strikes with respect to their duration, showing a clear majority of single-day strikes. We leave out all multi-day strike episodes, due to their lower effectiveness and different nature. As observed by van Exel and Rietveld (2001), long strike episodes are likely to generate adaptive behavior, complicating our analysis.

PT strikes affect traffic congestion and pollution levels. This effect is larger for bigger municipalities where the resident population is more dependent on PT. Several studies highlight that PT strikes increase traffic density and road congestion as a result of the switch to private cars (Adler and van Ommeren, 2016, Anderson, 2014, Bauernschuster

[12]Commissione di Garanzia Sciopero https://www.cgsse.it/web/guest/home

et al., 2017, van Exel and Rietveld, 2001, among others). We expect the higher dependence on PT in administrative municipalities to generate a larger impact of strikes on traffic-related PM levels (Basagaña et al., 2018, Bauernschuster et al., 2017, Chaloulakou et al., 2005, Meinardi et al., 2008, Pereira et al., 2014). Conversely, in smaller municipalities where PT serves a limited share of the population, strikes are unlikely to cause a sufficient variation in traffic congestion and air pollution.

4.4 Local population

Data for the annual local population size are publicly available from ISTAT. Table 4 shows summary statistics for the Italian resident population in the 111 administrative cities. The total population for the period 2013–2015 amounts to 54,012,341 individuals, approximately 18 million per year.

4.5 Weather Conditions and Holiday Data

Air pollution concentration data are adjusted for dispersion factors such as weather conditions. Nevertheless, we still want to control for weather factors since adverse respiratory health problems are independently related to weather variability, especially temperature (Deschenes and Moretti, 2009). We therefore collect municipality-specific weather data from the Gridded Agro-Meteorological dataset managed by Mars-Agri-4-Cast[13]. In particular, we use daily average (mean of the minimum and maximum) measures of temperature, wind speed at 10 meter elevation, and total precipitation. This database contains meteorological parameters from weather stations interpolated on a 25×25 km grid.[14] We follow the same procedure we applied to air pollution data to guarantee a homogeneous measure of weather over space and time. We report descriptive statistics of selected weather parameters in Table 5, while Figure 6 shows trends of the weather parameters over time. Following Knittel et al. (2016), we flexibly control for

[13] http://agri4cast.jrc.ec.europa.eu/DataPortal/Index.aspx

[14] Meteorological data are available on a daily basis from 1975 to the last calendar year, covering EU Member States, neighboring European countries, and Mediterranean countries.

weather conditions by including second-order polynomials in our weather variables.[15]

We also employ data listing school and public holidays, both at the local and the national level, to control for days when commuting activity is systematically lower. School holiday data come from the Ministry of Education, Universities and Research; we retrieved the public holiday dates from a Google search. We then transformed holiday data into municipality-day dummy variables for when school/public holidays are in effect. Of the 121,545 day and municipality pairs, 9,657 observations, approximately 8%, refer to a school or a public holiday.[16]

5 Empirical strategy

Our main goal is to investigate the causal effect of PM_{10} on urgent respiratory hospitalizations. OLS fixed effects models in this setting are poorly identified, since variation in pollution is correlated with many unobservable determinants of health, even when exploiting within-location variation over time. Day-to-day fluctuations in pollution might be correlated with how residents choose their daily activities, leading to different health outcomes. For instance, good weather may encourage individuals to spend more time outdoors; this may give rise to more traffic congestion but also reduce health adversities. Therefore, if activity choices are correlated with changes in air pollution, we might see different health outcomes for reasons completely unrelated to pollution. This fundamental flaw leads to bias in simple OLS or fixed effects models and motivates our choice to use a quasi-experimental identification strategy.[17]

To identify the causal effect of air pollution, we leverage PT strike episodes to capture exogenous changes in air pollution concentrations due to shocks in traffic congestion. IV

[15]We also test alternative weather specifications by including third-order polynomials and by calculating quantiles of the overall daily distribution of each measure, which are equivalent to the following bins: for the temperature $\leqslant$8.5°C, 8.51–13 °C, 13.61–17.5 °C, 17.55–22.1°C, $\geq$ 22.11°C; for rain 0 mm, 0.0005–0.6 mm, 0.60–7.2 mm, 7.24–15 mm, $\geq$15.1 mm, and for wind $\leqslant$1.5 m/s, 1.51–2 m/s, 2.03–2.59 m/s, 2.60–3.5 m/s, $\geq$3.53 m/s. These alternative specifications deliver results (available upon request) that are very similar to our baseline estimates.

[16]There are 7,659 school holidays and 4,329 public holidays, which overlap in 2,331 cases.

[17]We report OLS fixed effects model estimates at municipality-day level, which serve as a benchmark for our quasi-experimental estimates, in Appendix Table A.2.

estimated has been used in a number of pollution-related studies to reduce bias caused by measurement error and non-random assignment of pollution exposure (Arceo et al., 2016, Currie and Walker, 2011, Halliday et al., 2015, Knittel et al., 2016, Schlenker and Walker, 2015). Recently, Lavaine and Neidell (2017) exploit the French oil refinery strike in October 2010 to estimate the impact of air pollution on birth outcomes and respiratory-related hospitalizations. Moreover, Bauernschuster et al. (2017) observe that transportation strikes in Germany have sizable effects on traffic congestion, increasing pollution, traffic accidents, travel time and emergency room (ER) respiratory disease visits.

In Italy, PT strike episodes are a particularly compelling IV. PT strikes in Italy are relatively frequent and represent a routine event that residents are used to coping with. Moreover, since the Guarantee Authority ensures that a limited amount of transportation is guaranteed during the so-called 'protected hours' on strike days, PT strikes do not represent a complete shutdown, but a substantial limitation of the PT network. This setup is valuable for our analysis because it downplays the possibility that labor supply or school activity is curtailed on strike days, while providing exogenous shocks to traffic congestion since a large number of commuters turn to private and rental vehicles. Traffic congestion results in fuel combustion with tailpipe emissions of PM. Moreover, the friction resulting from wheel-to-road contact further increases PM levels. Formally, we specify our two-stage least squares (2SLS) model as

$$P_{irdwy} = \alpha + \beta PTStrike_{irdwy} + \zeta W_{irdwy} + h_{irdwy} + \gamma_d + \delta_w + \eta_y + \theta_i + \phi Z_{id} + \rho_{ry} + \varepsilon_{irdwy} \qquad \text{First stage} \tag{4}$$

$$H_{irdwy} = \alpha + \lambda \widehat{P}_{irdwy} + \zeta W_{irdwy} + h_{irdwy} + \gamma_d + \delta_w + \eta_y + \theta_i + \phi Z_{id} + \rho_{ry} + \mu_{irdwy} \qquad \text{Second stage} \tag{5}$$

where H_{irdwy} denotes the number of urgent respiratory hospitalizations per 100,000 citizens in city i, in region r, on day of the week d, in week of the year w, and in year y. P_{irdwy} is the endogenous air pollutant concentration expressed in $\mu g/m^3$, and $PTStrike_{irdwy}$

is the strike dummy variable. $\widehat{P}_{irdwy}$ is the first stage predicted value of P_{irdwy}, while W_{irdwy} and h_{irdwy} are controls for weather conditions (up to a second-order polynomial in rain, wind-speed and average temperature), and a set of dummies indicating school and public holidays. Moreover, θ_i, γ_d, δ_w, η_y are city, day of week, week of year and year fixed effects that account for time-invariant differences between municipalities, seasonal fluctuations in exposure due to commuting and time spent outdoor during the week and effects or recurrent episodes of specific epidemics common to all municipalities.

It is plausible that municipalities or regions experienced different changes in the likelihood of striking due, for instance, to differential changes in economic opportunities, while also experiencing differential trends in pollution and baseline health. Moreover, seasonality in health, pollution, and striking probability may be different across municipalities or regions. We thus include an additional set of municipality-specific time trends Z_{id}, and region×year fixed effects ρ_{ry} that control for spatially-varying secular temporal effects. We weight all estimates by municipality population size and cluster standard errors on municipalities to allow for correlation within municipalities exposed to similar levels of air pollution (Cameron and Miller, 2015).[18]

An important concern for our IV setting is the potential correlation between various pollutants co-emitted from the same source. Other than PM, transport vehicles emit CO and NO_2. One might argue that if PT strikes change the concentrations of more than one pollutant simultaneously, the exclusion restriction is violated. We thus directly test this hypothesis in a multi-pollutant model. Finally, to further support our identification strategy, in Section 6.5 we present an extensive set of falsification tests and alternative model specifications.

[18]We also test alternative weights including the number of hospitalizations at the municipality level. We obtain similar results (available upon request).

6 Results

6.1 Public Transportation Strikes and PM_{10}

To begin with, we analyze the relationship between PM_{10} and PT strikes in an event study framework. We augment our empirical strategy in Equation 4 with distributed lags and leads constructed according to Figure 7. PT strikes are indexed on a time scale τ, where we define $\tau = 0$ as the event date, $\tau = [-3, -1]$ as the pre-event window, and $\tau = [+1, +4]$ as the post-event window. We frame the actual timing of each strike on this synthetic timeline and estimate the following equation:

$$P_{irdwy} = \sum_{\tau=-3|\tau\neq-1}^{4} \beta_\tau PTStrike_\tau + \zeta W_{irdwy} + h_{irdwy} + \gamma_d + \delta_w + \eta_y + \theta_i + \phi Z_{id} + \rho_{ry} + \varepsilon_{irdwy}, \tag{6}$$

where P_{irdwy} denotes the endogenous PM_{10} concentrations, $\tau = [-3, +4]$ represents the time scale, the vector W_{irdwy} controls for weather conditions, h_{irdwy} is a set of dummies indicating school and public holidays, γ_d, δ_w, η_y and θ_i are a set of fixed effects, Z_{id} contains municipality-specific time trends and ρ_{ry} are region-year fixed effects, as described in Equation 4 and Equation 5. Finally, ε_{irdwy} is an idiosyncratic error term. On a PT strike day ($\tau = 0$), we observe an average increase of 0.90 $\mu g/m^3$ in PM_{10} and a gradual leveling off in the next 3 days. These results use the sample of all municipalities where a strike event takes place and are not directly comparable with the first-stage results obtained from the full sample of the 111 administrative municipalities in the IV setting.

Table 6 presents first stage results across different model specifications, controlling for holidays (columns (3) and (4)) and weather conditions (columns (2) and (4)).[19] In the most demanding specification in column (4), which includes dummies for public and school holidays and weather controls, the PM_{10} coefficient is 0.83 $\mu g/m^3$ with fully statistically significance. Larger coefficients obtained in less demanding specifications

[19]The first-stage F-statistics (calculated using the Cragg-Donald F-test) are well above 10, clearing the rule-of-thumb hurdle for a weak first stage (Staiger and Stock (1997) and Stock and Yogo (2002)).

(column (1)-(3)) are not surprising since PM_{10} is highly responsive to weather conditions and to programmed daily holidays when economic activity is reduced (Knittel et al., 2016, Schlenker and Walker, 2015). These estimates are in line with the generalized differences-in-differences estimates of Bauernschuster et al. (2017), who show that strikes significantly increase PM_{10} concentration peaks. Even though these authors find a larger increase in PM_{10} levels on strike days (5 $\mu g/m^3$ during peak hours), their results refer to more rare and harsh strike events occurring in Germany.

6.2 Effects of PM_{10} on respiratory hospitalizations

Table 7 reports second stage coefficients, i.e the effect of PM_{10} on total urgent respiratory hospitalizations. Our most complete specification (Column 4) shows that one additional unit of $\mu g/m^3$ in PM_{10} increases the number of hospitalizations by 0.074 units per 100,000 residents. This result is in line with recent causal evidence on the effect of air pollution on similar health problems (Halliday et al., 2015, Knittel et al., 2016, Schlenker and Walker, 2015, e.g.), but larger than the estimates obtained from other identification strategies. If we consider causal estimates of particle pollution (PM_{10} or $PM_{2.5}$), Halliday et al. (2015) have the most comparable results. They find that a unit increase in PM_{10} causes a 5.7% increase in ER hospitalizations which, in our case, amounts to 3.6%. This difference is likely caused by our different focus: Halliday et al. (2015) analyze the impact of volcanic particle pollution, whereas our estimates relate to PM_{10} directly emitted from exhaust and road dust. The authors offer a broad discussion of possible differences between pollution originating from various sources and regions, concluding that direct comparisons of relative toxicity of PM likely depend on other characteristics of local industrial activity, weather factors, and concomitant air pollutants. Moreover, Ward (2015) find that a one s.d. increase in PM concentration causes a 4% increase in children hospitalization, which is close to our estimate. Other direct comparisons should be interpreted with caution since we address the contemporaneous health response, whereas most of the literature focuses only looks at mortality, which captures only the most severe health damage.

6.3 Heterogeneous effects of PM_{10}

Our results so far refer to the overall population, without accounting for heterogeneity in how exposure to air pollution shocks affects individual health. There is abundant evidence that adverse health effects of air pollution are larger for infants and the elderly. Indeed, early childhood is a period of rapid growth when organ systems are particularly susceptible to health shocks (Beatty and Shimshack, 2014, Mudway et al., 2018, Schwartz, 2004), whereas in the elderly, co-existing chronic disease and cumulative exposure to air pollution increase susceptibility, hospitalization and the risk of mortality (Janke et al., 2009, Simoni et al., 2015).

We analyze the heterogeneous effects of air pollution on the young and adults, a topic rarely addressed in the literature. According to our conceptual framework, our estimated marginal effects recover the total derivative of hospitalization rate with respect to pollution exposure, which includes the age specific health sensitivity to PM_{10} net of the optimal amount of compensatory behavior. While heterogeneous biophysical vulnerability is likely to be lowest among the 15–44 age group, they are the most involved in the labor market and schooling; this attachment limits their scope for avoidance behavior on strike days. Therefore, our marginal effects capture age-specific health sensitivity to PM_{10} for this age group. Similarly, we explore the health effects of pollution on socio-economically disadvantaged groups. If lower education and lower income give rise to major vulnerability due to greater heterogeneous sensibility or weaker compensatory behavior, the marginal effect on hospitalization rates will capture this group's heterogeneous sensitivity to pollution.

Our heterogeneous effects analysis therefore isolates distinct groups of the population, based on their age, education and migration status, and evaluates whether their health penalties, resulting from similar exposure to air pollution, are significantly different. To capture the heterogeneous effects of PM_{10}, we aggregate hospitalizations into distinct categories, and for each category we create an outcome measure, i.e. the count of hospitalizations for 100,000 residents in each group. To prevent our estimates from conflating age heterogeneity with heterogeneity that is actually driven by the group characteristics, we include controls for the age structure of each subpopulation. This allows us to account for the fact that the primary education level population is systematically younger than the tertiary education level population. The same argument holds for migrants from low income countries.

Table 8 presents second-stage results for five age subgroups following Equation 5, weighted by the size of municipality population for each age group. We find significant and positive effects in young adults aged 15–24 and 25–44, with a one s.d. increase in PM_{10} causing one additional urgent hospitalization for the first group, and 0.44 for the second group. In interpreting these results, we refer to our conceptual framework, trying to disentangle sensitivity and compensatory actions. If young individuals are less sensitive to respiratory consequences and choose their avoidance behavior level in line with their low biophysical perception and a high avoidance cost faced on strike days, the positive effect on hospitalization rate is likely to materialize mainly through the biological effect because of the lack of avoidance actions. In fact, lifestyle patterns are likely to be inelastic to traffic congestion in the short run due to schooling or work life. The young thus seem to respond to their low marginal sensitivity and high avoidance costs by neglecting compensatory investments. The parameter estimate thus confirms the intuition that the healthiest age group shows evidence of a significant pollution effect on health likely because it engages in the least avoidance behavior. This suggests an important role for economic incentives determining compensatory behavior. Conversely, we find no effects for the 45–64 age group, which might be the result of greater avoidance by these individuals, offsetting the health damage specific to this age group.

In Table 8 we also observe an increase of 0.24 hospitalizations (statistically significant at 1%) in the number of urgent respiratory cases for individuals aged 65 and older for a 1 $\mu g/m^3$ increase in PM_{10}. If this coefficient is scaled up to one s.d., the effect amounts to 2.5 additional daily hospitalizations for a one s.d. increase in PM_{10}. This result is economically meaningful and highly statistically significant. In view of the heterogeneous sensitivity, the elderly are frequently found to bear clinically relevant consequences of pollution. Additionally, this estimate might represent an underestimate of the true differential sensitivity, as individuals belonging to this age group choose their optimal level of avoidance behavior in line with their high sensitivity and low avoidance cost.

Disadvantaged individuals are likely to suffer from worse baseline health and are also likely to bear very high avoidance costs on work days, with related health inequalities representing the consequences of differences that are largely beyond individual control (Neidell, 2004, among others). To offer a deeper understanding of the unequal health response to air pollution spikes, we estimate PM_{10} hospitalizations in relation to SES proxied by educational attainment and migrant status.

Our estimates in Table 9 show a particularly pronounced effect of PM_{10} on urgent hospitalizations among individuals with only primary education attainment; a one s.d. increase in PM_{10} leads to 1.5 additional respiratory hospitalizations for this subpopulation. The same estimate for the subpopulation with a secondary education is 0.40 hospitalizations and is only weakly statistically significant. Under the assumption that our the marginal effect for the low-educated individuals, net of their age, is to a narrow extent affected by avoidance behavior, our estimates are close to the biological sensitivity of this particular socio-economic group. The steep slope of the damage function caused by PM_{10} for low educated individuals implies that a policy aimed at reducing air pollution or promoting compensatory behaviors is likely to have sizable effects for this group. Conversely, the flat slope for the secondary and tertiary education groups is not informative about the heterogeneous sensitivity of these two subpopulations to air pollution, since their biological response might be mitigated by avoidance behavior that the two groups are better able to adopt in order to minimize their health damage.

Finally, we address disparities in the adverse impact of air pollution on health for migrants. We report our results in Table 10 and point to the non-significant effects of PM_{10} on urgent respiratory hospitalizations when considering foreign citizens from countries with low-middle and high income based on the World Bank classification (see Section 4). Since the low-middle income group aggregates countries with substantially different socio-demographic characteristics, we provide a deeper analysis focusing on the group of African migrants who come from Morocco, Egypt, Nigeria, Senegal and Tunisia and represent the vast majority of low-income migrants in Italy. Although our estimates are only weakly statistically significant, this particular group of nationalities seems to be adversely affected by air pollution, with a one s.d. increase in PM_{10} causing 0.53 additional hospitalizations. When interpreting the coefficient estimate, it is important to underline that the number of daily hospitalizations for migrants is, on average, much lower than for the general population, i.e. 0.30 *vis-à-vis* 2.05. The damage caused by air pollution is thus larger for migrants since a one s.d. increase in PM_{10} doubles their hospitalization rate. Nonetheless, a potential caveat of this result is that a large group of migrants has limited access to healthcare. Full healthcare coverage in Italy is only granted to foreign citizens who register with the national healthcare service (SSN), which is not possible without formal residency. Since low-income migrants tend to be in the country informally, they face major difficulties in obtaining residency status and consequently healthcare coverage. Considering this differential cost of treatment, hospitalizations of migrants that we observe in the data might be a severe underestimate of the actual healthcare demand.

6.4 Health costs of air pollution

In this part of the analysis we quantify the costs from the strike-induced increases in PM concentrations. Costs are the ultimate policy parameter and the recent literature has focused on quantifying them (see Section 3). We expand the analysis of the health consequences of air pollution by measuring hospitalization complexity proxied by the average unit cost (AUC) reported in Table 2, which represents a novel margin for quantifying the health costs of air pollution. The literature has often focused on extensive margin measures, such as the number of hospitalizations for specific diagnoses, and the associated total costs calculated by multiplying the differential by an average of DRG tariffs. In our analysis we study the true cost of each discharge, which allows us to capture the heterogeneous complexity of hospitalizations. While the impact of PM on the number of hospitalizations is an obvious cost of air pollution, the complexity of hospitalizations represents the intensive margin, a cost that has been overlooked so far.

Table 11 shows the impact of PM_{10} on the AUCs of an urgent hospitalization with primary diagnosis related, respectively, to any respiratory problem, asthma, pneumonia or COPD. While we find no statistically significant effects on the complexity in the overall group of respiratory problems, in the case of hospitalizations for asthma one additional $\mu g/m^3$ in PM_{10} concentration increases the unit cost by 194 euros which, represents approximately 11.8% of the baseline AUC of asthma episodes. We find no effect on the complexity of urgent hospitalizations for pneumonia, which is in line with the clinical literature analyzing the long-term effects of air pollution on pneumonia, though evidence on contemporaneous effects is scant (Ji et al., 2017). We find a significant impact on COPD costs, where a one $\mu g/m^3$ increase in PM_{10} rises the hospitalization cost by 65 euros, which represents a 2.9% increase compared with the baseline COPD AUC.

These results lead us to conclude that exposure to higher PM_{10} concentration levels not only generates more hospitalizations, but it also increases the complexity, hence the costs, of hospitalizations for asthma and COPD, two important respiratory diseases. The heterogeneous evidence across various hospitalization types is similar to findings in the clinical literature (DeVries et al., 2016, Soriano et al., 2017). Moreover, the evidence on hospitalization complexity suggests that previous studies solely analyzing expenditures deriving from the increase in the number of hospitalizations are likely to underestimate the total health costs of particle pollution.

Finally, considering both the extensive and intensive margins, we estimate the effect of PM on total per capita healthcare costs. Table 12 shows that a daily increase of one $\mu g/m^3$ in PM_{10} is associated with an additional 251 euros of spending per 100,000 individuals. If scaled up to one s.d., these figures correspond to 45% of the average daily expenditure on urgent respiratory hospitalizations.

Moreover, in Table 13 we report the same set of results for each age group, showing that the costs from air pollution are unequally distributed across age groups. These estimates are in line with the evidence on the extensive margin presented in Table 8. In particular, we find that a daily increase of one $\mu g/m^3$ in PM_{10} causes an additional 466 euros of spending per 100,000 individuals for the 15–24 age group, and 163 euros for the 25–44 age group. Again, these estimates refer to the marginal healthcare cost defined as the difference between biological sensitivity specific to each age group, and net of the avoidance behavior adopted by individuals. Sizable health costs of pollution for young individuals are a novel finding. The low investments in avoidance that we expect for the younger individuals suggest that the cost estimates are the true health costs of pollution for the 15–44 subpopulation; their economically relevant and statistically significant magnitudes highlight the scope for policy interventions promoting compensatory actions. Finally, we find the largest effect for the elderly, with one additional $\mu g/m^3$ of PM_{10} causing an increase of 846 euros of spending per 100,000 individuals.

To better appreciate the heterogeneity of the total costs for urgent respiratory hospitalizations resulting from PM_{10} exposure, in Figure 3 we plot excess hospital costs corresponding to a one s.d. increase in PM_{10} at the municipality level. For each municipality we obtain predictions from the age-specific model estimates (Table 13), computed at one s.d. increase in PM_{10} and the demographic structure observed in 2015. We smooth the predictions on a regular grid of age/s.d. combinations. The resulting figure is a heat map, where darker tones signal higher excess costs.[20] Figure 3 shows how different ages, in combination with different average PM_{10} concentration levels, impose similar costs on the health system. For instance, a one s.d. increase in PM_{10} among young individuals in the age group 15–24 in the most polluted municipalities yields comparable healthcare costs as a one s.d. increase in PM_{10} for the elderly exposed in the least-polluted municipalities.

Based on these results, we carry out back-of-the-envelope calculations of total daily monetary costs of air pollution for the 17.8 million residents in the 111 municipalities

[20] Our predictions are based on semi-elasticities of total urgent respiratory hospital costs. We compute predictions at each municipality-specific s.d. for the average PM_{10} concentration. We then apply our estimates to age-specific averages of total costs and expand them according to the demographic structure of the 111 municipalities. We smooth the estimates across ages by applying a moving average to the coefficient estimates. Each age/PM_{10} combination is then assigned to a tone corresponding to the specific level in excess expenditure.

considered, which amount to 462,737 euros of additional spending for a one s.d. increase in PM_{10}; this accounts for approximately 0.51% of total public health expenditure in Italy. Overall, our quantification of the health cost burden of PM pollution represents a lower bound of the total health costs, since it does not account for the long run and cumulative effects of pollution. Moreover, daily fluctuations in hospitalizations do not account for individuals who experience less severe health issues related to pollution, relying on their primary care physician or staying home sick. Nevertheless, the costs of hospital care represent an important policy parameter since health expenditures devoted to hospitalizations represent approximately 60% of the national healthcare budget in Italy and are the least cost-effective healthcare service.

6.5 Robustness checks

In addition to the main set of estimates we presented above, we carry out a number of sensitivity checks to confirm the robustness of our empirical findings. To begin with, we validate our results based on pollution reanalysis data by comparing our estimates with estimates based on PM measurements from monitoring stations. We subsequently construct a multi-pollutant model to address possible threats to the exclusion restriction in our IV setting due to co-emission of other pollutants. We develop a number of parallel tests. We first falsify the treatment variable, then the outcomes and, finally, the treatment assignment. Then, we alter our identification strategy by looking at multi-day strikes and a larger estimation sample including all Italian municipalities. Moreover, we check that our analysis is insensitive to alternative weighting schemes. We also correct our findings for multiple hypotheses testing. Finally, we run our IV estimates in a Poisson regression setting. All these tests validate our identification strategy and confirm our main results.

Estimates based on pollution data from monitoring stations. In order to validate the reanalysis air pollution data employed in our study, we perform a benchmarking exercise in which we replicate the baseline results using air pollution data from monitoring stations. Data from monitoring stations have several limitations. Nevertheless, they are used in much of the existing literature (Janke, 2014, e.g.). We collect data from the European Environmental Agency (EEA) AirBase database, which includes concentration measures for traffic-related pollutants and the time span in our analysis. We aggregate the data by municipality and day to obtain concentration averages that are consistent with our original dataset. Our final sample is limited to municipalities in which at least one monitoring station operates on a regular basis, which results in 66 administrative cities. Given this data limitation, in order to provide a direct comparison we also present results of our IV framework using reanalysis data restricted to the same sample of 66 administrative cities with monitoring stations. When multiple stations are present in the same municipality, we average their readings. Given the granular texture of Italian municipalities, we assume that measurement error in pollution assignment is limited and allows for comparison with our original dataset.[21] In the baseline specification presented in Appendix Table A.11 we weight our estimates by the municipality population.[22] Our findings, presented in Appendix Table A.11 and Table A.12, suggest that the effect of a strike is larger when PM is measured by monitoring stations. This discrepancy is likely driven by the higher concentration values measured by point monitors (see Figure 5). On the contrary, the second stage results are slightly smaller and less statistically significant than the second stage results from our estimates using CAMS data. One potential explanation is that measurement error in the standard approach based on monitoring stations is not negligible when assigning air pollution exposure, and this measurement error constitutes an attenuation bias.

Multi-pollutant model. As widely discussed in pollution and health papers (Deschenes et al., 2017, Schlenker and Walker, 2015, among others), it is challenging to isolate the impact of a single pollutant on health effects, because pollutants tend to be highly correlated with each other. Since PT strikes causes an increase in PM through

[21]The average area of an Italian municipality is only 37.3 km^2.

[22]We also weight by the number of monitoring stations in each municipality. These additional results, though similar in sign and magnitude, are only weakly statistically significant, and are available upon request.

increased traffic congestion due to changes in commuting behavior, it is plausible that other pollutants emitted by vehicles, such as NO_2 and CO, also rise, violating the exclusion restriction. To address this concern we construct a multi-pollutant model where we test how the traffic congestion related pollutants affect our health outcome. We collect additional data on other types of emissions and construct a multi-pollutant model. Since CAMS reanalysis data do not include complete information on all these pollutants, we employ data from monitoring stations including concentration readings for the three main traffic-related pollutants, PM_{10}, NO_2 and CO.

We construct an alternative IV framework where, in order to simultaneously identify our 2SLS model with three endogenous pollutants, we interact $PTStrike$ event dummies with a variable describing the per capita demand for PT. Per capita demand is the number of passengers served by PT each year relative to the resident population. Cities relying more on PT are likely to suffer a bigger response in commuting behavior and, consequently, traffic congestion. Conversely, municipalities making a limited use of PT are much less exposed to increased pollution levels on PT strike days. We create a 3-level ranking of PT dependence based on the 50^{th} and 75^{th} percentile cutoffs of the PT demand level variable.[23]

Since monitoring readings are not available for the full set of 111 municipalities, we employ two alternate approaches. The first approach uses all available monitoring readings for an unbalanced panel of day-municipality observations (Panel A), while the second approach uses only a subsample of municipalities containing all three pollutant readings available for all 1095 days in only 54 municipalities (Panel B). Appendix Table 14 shows the estimates for four model specifications, where column (1) represents the single pollutant model for PM_{10}, columns (2) and (3) add CO and NO_2 one at a time, and column (4) reports the results for a three-pollutant model. The estimates of the effect of PM_{10} are comparable to the results in our baseline specification. These findings

[23] Precisely, based on the distribution of PT demand registered in the three years of the analysis weighted by the number of residents of each municipality, we divide each municipality in each year into *below median PT users*, *between median and third quartile PT* users and *highest quartile PT users*. We have tried various alternatives to this ranking without substantially changing the results. These alternative specifications are available upon request.

suggest that the urgent respiratory health effects are mainly attributable to PM_{10}, and not to CO and NO_2. This is not surprising since we focus on respiratory health damages, which are mainly responsive to PM_{10} (WHO, 2006, for a review), while CO impairs the oxygen carrying capacity of the blood and produces cerebrovascular and cardiovascular health problems (WHO, 2004).[24]

Falsification of Treatment—O_3 as a Placebo Pollutant. We can check our identification strategy by exploiting pollutants that are not likely to be significantly affected by daily fluctuations in traffic. We thus consider the effect of strikes on O_3 as a placebo pollutant. As in Figure 2, in Figure 8 we present the relationship between PT strikes and O_3 in an event study framework. We observe a non-statistically significant decrease of ozone on strike days. O_3 is indirectly generated by emissions but it is created by a series of chemical reactions between substances present in the atmosphere (precursors), which are present in urban areas regardless of traffic levels on a given day (i.e. Graff Zivin and Neidell, 2012). There are several motivations that allow us to use O_3 as a placebo. First, O_3 levels are strongly dependent on sunlight and ambient temperature, with O_3 concentrations following strong seasonal patterns. Hence, even when there is major traffic congestion, weather factors can strongly affect the formation of O_3. Second, O_3 has a life span of several days, so higher O_3 concentrations can be found in regions distant from precursor emission sources because of wind. Third, several chemical O_3 destruction mechanisms found in cities are absent from rural areas (Saitanis, 2003). Consequently, O_3 concentrations are often lower in urban areas even though high levels of precursors are emitted from vehicles (Pires et al., 2012). Finally, O_3 levels are much lower in the morning, when most of the effects of PT strikes take place. We estimate our baseline specification by substituting PM_{10} with O_3. The results are presented in

[24]The World Health Organization reports that "Community population studies on carbon monoxide in ambient air have not found any significant relationship with pulmonary function, symptomatology and disease" (WHO, 2004, p. 7). While Schlenker and Walker (2015) find effects of CO on respiratory urgent hospitalizations, is important to highlight that the authors also label hospitalizations for cardiovascular health of individuals who have concomitant respiratory conditions as respiratory hospitalizations, making it difficult to distinguish between the two health issues, which are often correlated. Our results, which isolate respiratory health problem, might diverge because of our narrower focus.

Appendix Table A.5 and show non-significant effects of PT strike on O_3.

Falsification of Outcome I—Placebo diseases. We also investigate the effect of pollution on other diseases that are unlikely to be affected by air pollution. We focus on Diseases and Disorders of the Nervous System, Diseases and Disorders of the Musculoskeletal System and Connective Tissue, and Diseases and Disorders of the Endocrine, Nutritional and Metabolic System. The IV estimates are reported in Appendix Table A.6 and do not provide any statistically significant results.

Falsification of Outcome II—Programmed Hospitalizations for Respiratory Diseases. An important indirect test for the validity of our identifying assumption is whether PT strikes also affect programmed hospitalizations for pollution-induced diagnosis. We thus run our baseline specification on a sample of 132,317 day-hospital programmed hospitalizations for respiratory disease, singled out according to primary diagnosis records. The resulting IV estimates are reported in Appendix Table A.7 and point to no statistically significant effects of PM_{10} on elective cases. Taken together, the two falsification tests on the disease type and the hospitalization type reinforce the identification strategy we use, confirming that a higher PM_{10} concentration level is the mechanism through which PT strikes increase respiratory hospitalizations.

Falsification of IV assignment—Placebo Strikes in Unaffected Municipalities. We conduct a falsification test where we randomly move the strike episodes across municipalities. After assigning strikes to municipalities that did not witness strikes on those days, we rerun our baseline estimation. The results are presented in AppendixTable A.8, showing no significant effects on PM_{10} in the non-affected cities.

Multi-Day Strikes and Adaptive Response. Following Bauernschuster et al. (2017), we test the effects of PT strikes lasting longer than one day. We thus substitute our IV of one-day strikes with multi-day strike dummy variables. As shown in Appendix

Table A.9, the first stage effect of multi-day strikes on pollution is weaker than single-day strikes (0.94 instead of 1.20). This result is in line with the hypothesis of a change in travel patterns after the first day of a strike since individuals are likely to adapt to persistent PT stops. At the margin, a multi-day PT strike generates less additional PM compared with the first day. The second stage results suggest, however, that the effect of air pollution on urgent respiratory hospitalizations is larger (0.0651 *vis-à-vis* 0.0527). This difference may be driven by the cumulative deviation from average levels of pollution, where a prolonged increase of 1 $\mu g/m^3$ in PM_{10} could generate larger adverse effects on health if it persists over several days.

Estimates on All Italian Municipalities Along with the robustness checks presented above, we estimate our model specification by considering all Italian municipalities, including non-administrative small towns. We construct a balanced panel dataset for all Italian municipalities. The initial sample has 1,267,367 urgent respiratory hospitalizations defined in the primary diagnosis, and a population of 181,601,025 (an average of 60 million per year) individuals distributed across 8,090 municipalities over 1095 days (*obs.*= 8,858,550; n=8,090, t=1,095). The resulting IV estimates, presented in Appendix Table A.10, confirm the results of our preferred specification using the sample of 111 administrative municipalities.

Additional Checks. Since our dependent variable is initially measured as hospitalization count in a given municipality and day, we also estimate an IV Poisson regression model (Cameron and Trivedi, 2013, Mullahy, 1997, Windmeijer and Santos Silva, 1997) to account for the non-negative and discrete nature of the data. While in this setting a Poisson regression model might be more appropriate than a linear model (Park and Oh, 2018, Winkelmann, 2008), it may underestimate the dispersion of the observed counts because there are too many zeroes in the dependent variable. For the sake of completeness, we still provide the Poisson estimates. Following Schlenker and Walker (2015), we include the residuals from our Equation 4 (i.e. the effect of PT strikes on pollution) as a control variable in Equation 5. In contrast with the baseline model, we do not employ weights. The results, available upon request, confirm that respiratory disease hospitalizations are sensitive to PM fluctuations.

We confirm that our results are robust to alternative weighting schemes. We use specifications without weights and an alternative weighting scheme that includes the number of hospitalizations at the municipality level instead of municipality population size. The results, available upon request, are consistent with our main results.

Worker mobility is also a concern in our empirical setting. If traffic congestion is drives the demand for healthcare away from the affected areas, residents in administrative towns may be willing to access hospitals outside their residence area. In this case, we may underestimate the treatment exposure, especially for the extensive margin of hospitalization, since the treated individuals may access healthcare in areas not included in our identification strategy. However, our results show no evidence in favor of differential hospital mobility on strike days in strike towns. All these considerations suggest that our IV is unlikely to cause any sort of endogenous mobility since the out-of-town flows of residents are negligible and not correlated with any *ad-hoc* individual actions.

Finally, since different null hypotheses arise in our setting from the heterogeneity of the effect of pollution across various SESs and age groups, we provide a step down bootstrap-based procedure for simultaneously testing multiple null hypotheses (Clarke, 2016, Romano and Wolf, 2016). The effects of PM persist significantly under this demanding criterion for testing the significance of our results. This last set of evidence is available upon request.

7 Conclusions

In this study we provide a quasi-experimental investigation of the short-term negative health effects of exposure to air pollution for different groups. We identify the causal effect of air pollution by leveraging PT strike episodes occurring in specific city-day combinations that generate traffic shocks with higher PM_{10} concentrations.

We find that an increase in PM_{10} induced by PT strikes leads to more hospitalizations for urgent cases of respiratory disease. Our data allow us to explore the heterogeneity of this effect in terms of exposure and vulnerability differentials by testing if air pollution disproportionately affects individuals characterized by lower SES. By disentangling the impact of age, educational attainment and migrant status, we find that the young and the elderly generate high hospitalization costs for urgent cases of respiratory disease. Moreover, the impact of air pollution is–*ceteris paribus*–stronger for individuals with only elementary education and is attenuated for individuals with higher education, whereas it disappears for those with tertiary education. When considering migrant status, we find weak evidence of additional detrimental effects of air pollution for migrants from low-income African countries.

From a policy perspective, our results on health impacts for moderately young individuals (aged 15–44) are the most novel and informative. While we do not explicitly estimate the distinct roles of heterogeneity in sensitivity *vis-à-vis* heterogeneity in compensatory behavior, the fact that the young, healthiest age group is found to be harmed from PT strike-induced PM_{10} exposure suggests that they optimally respond to their low marginal health sensitivity, choosing low levels of avoidance behavior. Quantifying this differential is of directly policy relevance. Since deliberative avoidance is costly, controlling for it in the estimation of health costs of air pollution leads to a proper characterization of the associated social welfare cost.

Overall, our results imply that policy makers should perceive air pollution not only as a technological issue, but also as a socio-economic phenomenon. Therefore, the strict and reinforcing gradient between air pollution and SES stresses the role of complementary policies aimed at improving the "boundary conditions" that are able to substantially reduce or amplify these effects, particularly for younger individuals. Economic incentives determining defensive spending and compensatory behaviors may ultimately lower the exposure an individual faces, conditional on ambient conditions.

A pivotal part of our analysis decomposes healthcare costs into the extensive and intensive cost margins of respiratory hospitalizations caused by PM_{10}. We find that pollution not only causes additional costs due to more hospitalizations, but we also show that hospitalizations tend to be more complex and expensive, costing approximately 8% more than an average hospitalization for asthma for a one μg/m3 increase in PM_{10}. These findings imply that quantifying the healthcare burden deriving from PM should take into account not only the number of healthcare services accessed, but also the complexity of the services.

Our study has some limitations. One of them is common to all studies relying on hospital data. Because the opportunity cost of time differs across individuals, for a given health impact, different groups may differentially choose to take the time to go to the hospital to get treatment. For example, a retired elderly patient may be more likely to go to the hospital than a younger working-age individual, whose time cost is higher. Nevertheless, in our setting we can plausibly assume that the differential expected cost of treatment does not constitute an issue, at least for the non migrant population. In this respect, while our estimates of the effect of air pollution on migrants represent a novel finding, this result should be interpreted with caution. Migrants from low-income African countries, who represent a large fraction of migrant inflows in Italy, face important barriers to accessing healthcare since their irregular status precludes them from applying for public healthcare. Although our results suggest that SES plays an important role both in the biological effect and economic cost of air pollution, our evidence on migrants should be interpreted as a lower bound estimate of the true effect.

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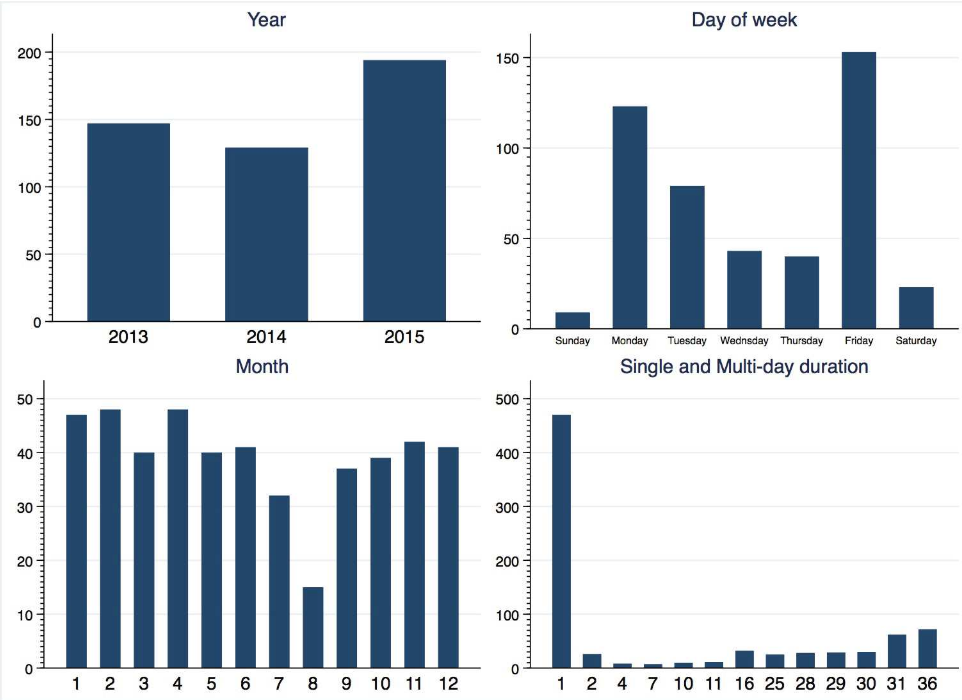
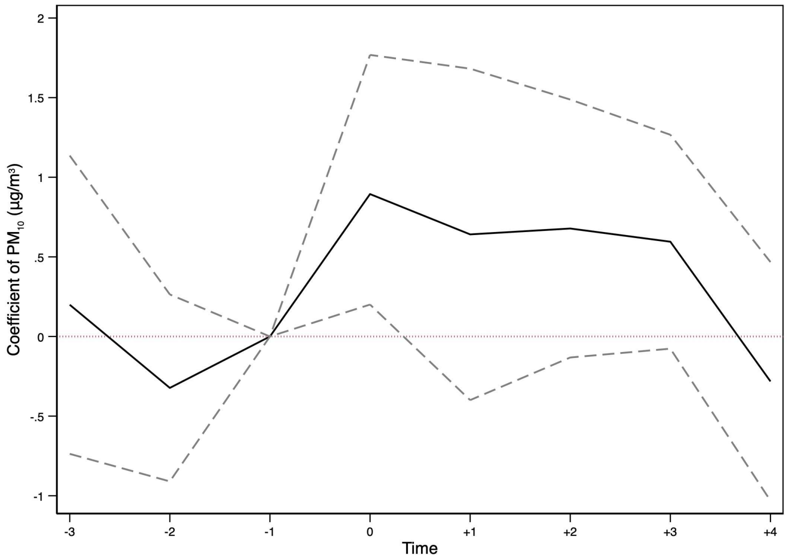
Figures

Figure 1: Distribution of Strike Events Across Time.



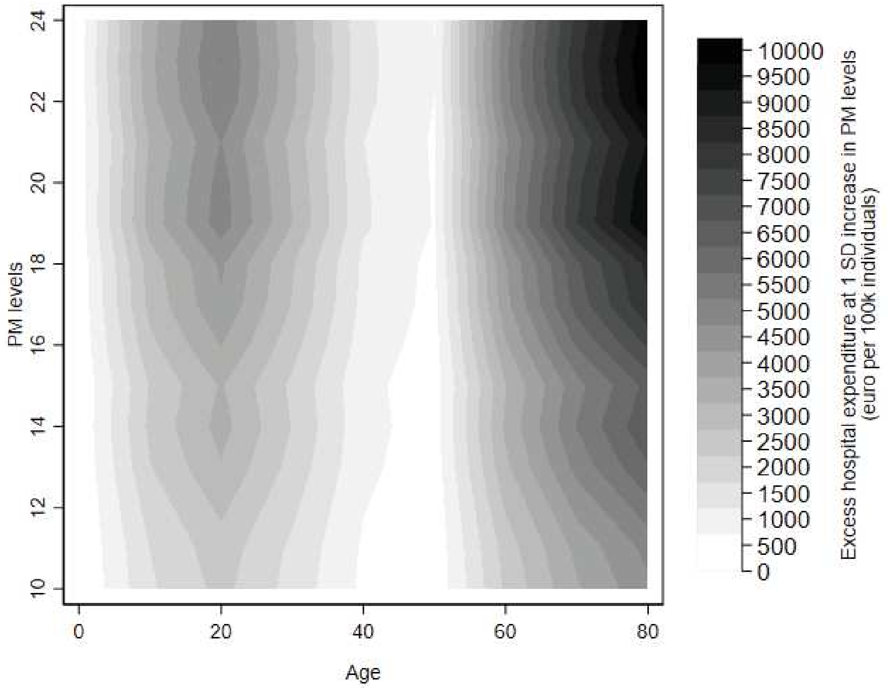
Notes: The data come from Commissione di Garanzia Sciopero https://www.cgsse.it/web/guest/home and the Ministry of Infrastructures and Transport. The figures refer to municipality level PT strikes, excluding national and regional PT strikes, and amount to 470 single-day PT strike episodes distributed across 72 municipalities.

Figure 2: The effects of PT strikes on PM_{10} in an event study framework.



Notes: The figure presents coefficient estimates from Equation 6. We regress the daily PM_{10} concentrations on a PT strikes indexed in event time $\tau = 0$, controlling for up to a second-order polynomial in weather conditions, holiday dummies, municipality and time fixed effects (day-of week, week-of-year and year), municipality specific time trends and region-year fixed effects. Estimates are weighted by municipality population size. The dashed lines represent 95 percent confidence intervals. The results refer to 4,156 observations covering 72 municipalities for 470 strike events.

Figure 3: Heat Map of Excess Hospitalization Costs By Age and PM_{10} level.



Notes: The figure shows excess hospitalization costs at the municipality level, for different PM_{10} increases (in s.d.) and ages. Predictions are based on semi-elasticities of total urgent respiratory hospital costs.

Figure 4: Map of the 111 Italian Municipalities

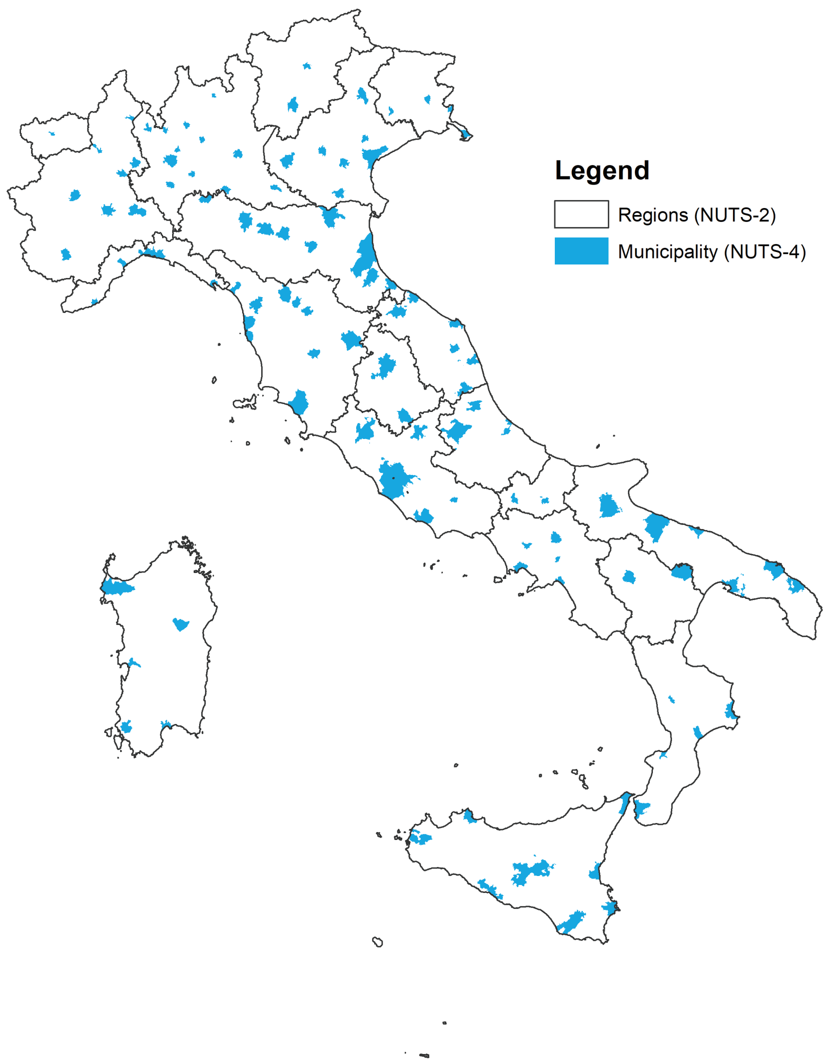


Figure 5: Comparison of PM_{10} Weekly Average Levels from CAMS and Monitoring Stations Data

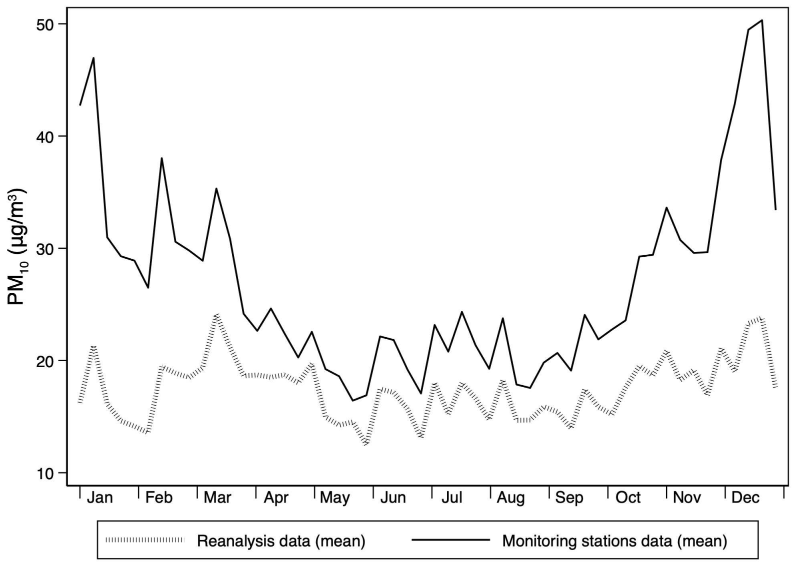


Figure 6: Trends of Weekly Respiratory Hospitalization Rate and Weather Conditions.

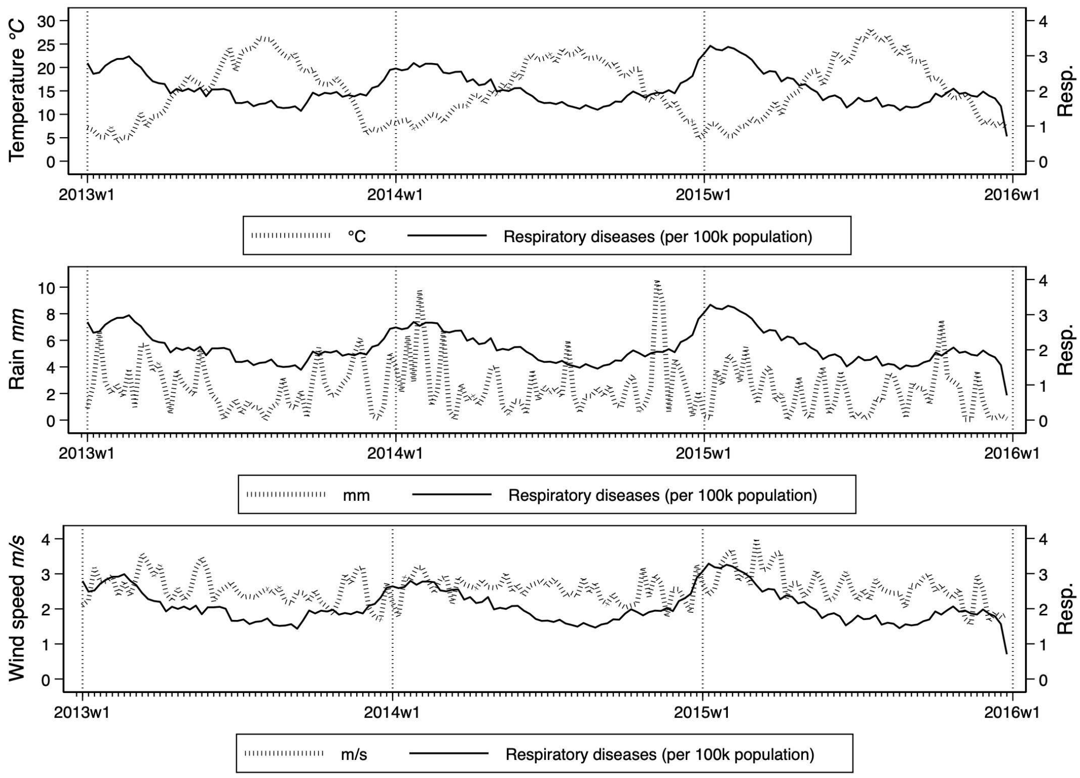


Figure 7: Timeline for the Event Study

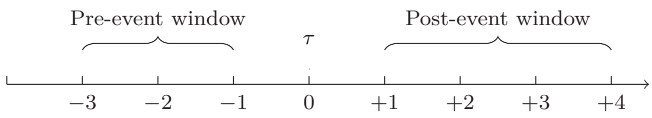
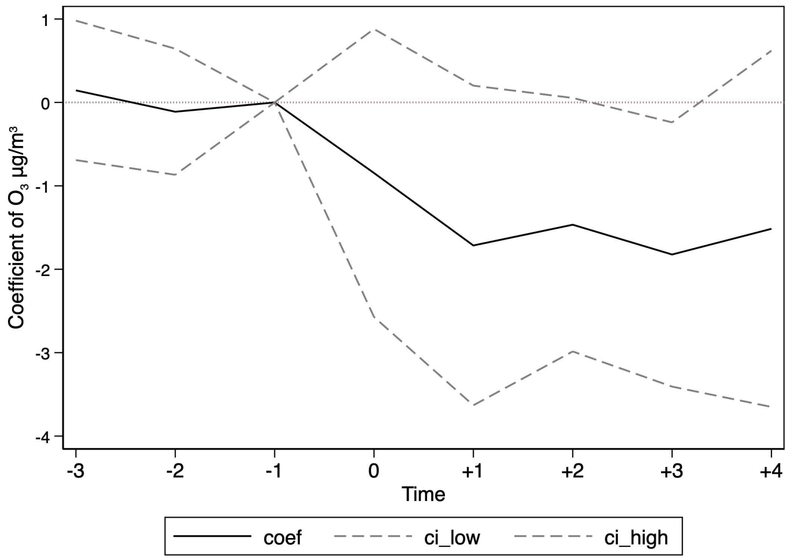


Figure 8: The Effects of PT Strikes on O_3 in an Event Study Framework



Tables

Table 1: Summary Statistics - Hospitalization Data

	Mean	Std. Dev.	Min	Max
All ages	2.05	1.30	0	26.35
Ages below 14	2.12	3.52	0	102.24
Ages 15 - 24	0.39	1.66	0	74.34
Ages 25 - 44	0.35	0.94	0	33.25
Ages 45 - 64	0.82	1.35	0	46.58
Ages 65 and above	6.05	4.51	0	105.45
Primary education	3.18	2.11	0	46.16
Secondary education	0.58	1.12	0	28.67
Tertiary education	0.46	1.88	0	85.06
Low income countries	0.30	0.78	0	63.45
High income countries	0.05	0.50	0	53.79

Notes: Sample size is 121,545 (111 municipalities $\times$ 1095 days). Numbers represent daily municipality level urgent respiratory hospitalization rates expressed for 100,000 individuals; they refer to an initial sample of 403,859 urgent respiratory hospitalizations defined in the primary diagnosis and to a population of 54,012,341 individuals distributed across 111 municipalities over 1095 days. Statistics are weighted by the relevant municipality population size. In case of each age/education/migration specific group, the resident population is adjusted to that particular group.

Table 2: Summary Statistics - Costs of Municipality Level Urgent Respiratory Hospitalizations

	Mean	Std. Dev.	Min	Max
	Unit cost (per-hospitalization)			
Respiratory	2855.85	785.81	703.04	6054.17
Asthma	1647.69	1345.53	299.50	5898.48
Pneumonia	2884.10	550.46	1724.17	3373.38
COPD	2237.03	330.46	299.50	2404.23
	Total cost (per capita)			
Respiratory all ages	0.05	0.05	0	0.74

Notes: The values are in euros. Sample size is 121,545 (111 municipalities ÃŮ 1095 days). Statistics are weighted by the relevant municipality population size.

Table 3: Summary Statistics - Air Pollutants

Air pollutants ($\mu g/m^3$)	Mean	Std. Dev	Min	Max	N
CAMS data					
PM_{10}	17.48	10.72	1.03	203.63	121,545
O_3	61.02	24.52	0.54	150.16	121,545
Monitoring stations					
PM_{10}	26.98	18.06	0	273.00	92,447
O_3	38.04	30.40	0	167.28	81,998
CO	0.60	0.40	0	4.90	74,184
NO_2	29.95	15.57	.04	156.00	94,991

Notes: CAMS sample includes 111 municipalities. Monitoring stations sample refers to 66 municipalities.

Table 4: Summary Statistics of the Local Population.

	Mean	Std. Dev.	Min	Max	Total
All ages	162,199.2	312,356.6	15,176	2,872,021	54,012,341
By age					
Ages below 14	21,328.79	42,314.34	1,884	388,795	7,102,486
Ages 15 - 24	15,166.10	28,474.25	1,286	256,054	5,050,312
Ages 25 - 44	42,566.48	84,244.52	3,757	786,239	14,174,639
Ages 45 - 64	45,771.51	88,358.71	4,293	832,142	15,241,914
Ages 65 and above	37,366.34	69,811.02	3,726	620,912	12,442,990
By education levels					
Pop. with primary ed. (p.c. rate)	0.60	0.04	0.48	0.69	30,841,632
Pop. with secondary ed. (p.c. rate)	0.30	0.03	0.24	0.35	16,654,839
Pop. with tertiary ed. (p.c. rate)	0.10	0.02	0.07	0.17	6,515,870
Migrants					
All ages	32,390.44	78,888.19	642	727,126	10,786,018

Notes: The data refer to the resident population counts by age, education level and migrant status in the 111 administrative cities in the period 2013-2015.

Table 5: Summary Statistics for Selected Weather Variables

Weather conditions	Mean	Std. Dev	Min	Max
Temperature (°C)	15.766 (15.990)	6.964 (6.381)	-15.1 (-3.9)	33.3 (31.1)
Precipitation (mm)	2.437 (2.171)	7.489 (7.730)	0 (0)	264 (66)
Wind speed (m/s)	2.660 (3.090)	1.418 (1.544)	0 (0.3)	20.3 (10)

Notes: Sample size is 121,545 (111 municipalities ÃŮ 1095 days). Statistics are weighted by municipality population size. Descriptive statistics computed on a sample of, corresponding to 1-day strike day-municipality combinations, are reported in parentheses.

Table 6: First Stage Estimates of the Effect of PT Strikes on Average PM_{10} Concentration Level.

First stage				
	PM_{10} level			
	(1)	(2)	(3)	(4)
PT Strike	1.239 [0.252]	0.874 [0.204]	1.166 [0.257]	0.828 [0.207]
Weather		YES		YES
Holidays			YES	YES
Time FE	YES	YES	YES	YES
Municipality FE	YES	YES	YES	YES
Region×year FE	YES	YES	YES	YES
F-statistics	31.17	18.80	27.62	16.88
N	121,545	121,545	121,545	121,545

Notes: All estimates include day-of-week, week-of-year, year and municipality fixed effects, municipality specific time trends and region-year fixed effects. Additional controls include dummies for school holidays and public holidays as well as up to a second-order polynomial in atmospheric temperature, precipitation and wind speed. Standard errors (in brackets) are clustered at the municipality level. PT Strike is an indicator dummy variable equal to unity when a strike is in effect and zero otherwise. Estimates are weighted by municipality population size.

Table 7: IV Estimates of the Effect of PM_{10} on Total Respiratory Hospitalizations.

	Total Respiratory Hospitalizations			
	(1)	(2)	(3)	(4)
PM_{10}	0.055 [0.013]	0.075 [0.022]	0.054 [0.014]	0.074 [0.024]
Weather		YES		YES
Holidays			YES	YES
Time FE	YES	YES	YES	YES
Municipality FE	YES	YES	YES	YES
Region×year FE	YES	YES	YES	YES
N	121,545	121,545	121,545	121,545

Notes: The numbers refer to an initial sample of 403,859 urgent respiratory hospitalizations defined in the primary diagnosis, and to a population of 54,012,341 individuals distributed across 111 municipalities over 1095 days. All estimates include day-of-week, week-of-year, year and municipality fixed effects, municipality specific time trends and region-year fixed effects. Additional controls include dummies for school holidays and public holidays as well as up to a second-order polynomial in atmospheric temperature, precipitation and wind speed. Standard errors (in brackets) are clustered on municipalities. Estimates are weighted by municipality population size.

Table 8: IV Estimates of the Effect of PM_{10} on Respiratory Hospitalizations in Different Age Groups.

	Respiratory Hospitalizations			
	(1)	(2)	(3)	(4)
Panel A. Age below 14				
PM_{10}	0.036	0.050	0.040	0.060
	[0.058]	[0.084]	[0.061]	[0.088]
Panel B. Age 15 - 24				
PM_{10}	0.068	0.096	0.070	0.097
	[0.035]	[0.054]	[0.038]	[0.057]
Panel C. Age 25 - 44				
PM_{10}	0.028	0.041	0.030	0.042
	[0.012]	[0.019]	[0.014]	[0.021]
Panel D. Age 45 - 64				
PM_{10}	-0.009	-0.012	-0.012	-0.017
	[0.015]	[0.021]	[0.016]	[0.022]
Panel E. Age 65 and above				
PM_{10}	0.175	0.242	0.172	0.236
	[0.047]	[0.067]	[0.050]	[0.071]
Weather		YES		YES
Holidays			YES	YES
Time FE	YES	YES	YES	YES
Municipality FE	YES	YES	YES	YES
Region×year FE	YES	YES	YES	YES
N	121,545	121,545	121,545	121,545

Notes: The numbers refer to an initial sample of 403,859 urgent respiratory hospitalizations defined in the primary diagnosis, and to a population of 54,012,341 individuals distributed across 111 municipalities over 1095 days. All estimates include day-of-week, week-of-year, year and municipality fixed effects, municipality specific time trends and region-year fixed effects. Additional controls include dummies for school holidays and public holidays as well as up to a second-order polynomial in atmospheric temperature, precipitation and wind speed. Standard errors (in brackets) are clustered on municipalities. Estimates are weighted by municipality population size in each age group.

Table 9: IV Estimates of the Effect of PM_{10} on Respiratory Hospitalizations by Educational Attainment.

	Respiratory Hospitalizations			
	(1)	(2)	(3)	(4)
Panel A: PM_{10} - Primary ed. lev.	0.101	0.140	0.101	0.140
	[0.030]	[0.051]	[0.033]	[0.055]
Panel B: PM_{10} - Secondary ed. lev.	0.028	0.039	0.028	0.039
	[0.013]	[0.019]	[0.014]	[0.020]
Panel C: PM_{10} - Tertiary ed. lev.	-0.002	-0.003	-0.005	-0.007
	[0.029]	[0.042]	[0.032]	[0.045]
Age classes	YES	YES	YES	YES
Weather		YES		YES
Holidays			YES	YEs
Time FE	YES	YES	YES	YES
Municipality FE	YES	YES	YES	YES
Region×year FE	YES	YES	YES	YES
N	121,545	121,545	121,545	121,545

Notes: The numbers refer to an initial sample of 403,859 urgent respiratory hospitalizations defined in the primary diagnosis, and to a population of 54,012,341 individuals distributed across 111 municipalities over 1095 days. All estimates include day-of-week, week-of-year, year and municipality fixed effects, municipality specific time trends and region-year fixed effects and age controls. Additional controls include dummies for school holidays and public holidays as well as up to a second-order polynomial in atmospheric temperature, precipitation and wind speed. Standard errors (in brackets) are clustered on municipalities. Estimates are weighted by municipality population size in each age group.

Table 10: IV Estimates of the Effect of PM_{10} on Respiratory Hospitalizations for Migrants by Origin Countries.

	Respiratory Hospitalizations			
	(1)	(2)	(3)	(4)
Panel A: High income Countries				
PM_{10}	0.004	0.004	0.004	0.005
	[0.010]	[0.015]	[0.011]	[0.016]
Panel B: Low-middle income Countries				
PM_{10}	0.024	0.036	0.024	0.036
	[0.021]	[0.035]	[0.022]	[0.037]
Panel C: African countries				
PM_{10}	0.032	0.049	0.034	0.051
	[0.018]	[0.029]	[0.019]	[0.031]
Age classes	YES	YES	YES	YES
Weather		YES		YES
Holidays			YES	YEs
Time FE	YES	YES	YES	YES
Municipality FE	YES	YES	YES	YES
Region×year FE	YES	YES	YES	YES
N	121,545	121,545	121,545	121,545

Notes: The numbers refer to an initial sample of 403,859 urgent respiratory hospitalizations defined in the primary diagnosis, and to a population of 54,012,341 individuals distributed across 111 municipalities over 1095 days. All estimates include day-of-week, week-of-year, year and municipality fixed effects, municipality specific time trends and region-year fixed effects and age controls. Additional controls include dummies for school holidays and public holidays as well as up to a second-order polynomial in atmospheric temperature, precipitation and wind speed. Standard errors (in brackets) are clustered on municipalities. Estimates are weighted by municipality population size in each age group.

Table 11: IV Estimates of the Effect of PM_{10} on Average Unit Costs (AUC) for Hospitalizations in Four Distinct Respiratory Problems.

	Unit Cost			
	All respiratory	Asthma	Pneumonia	COPD
PM_{10}	16.395	193.842	10.020	64.564
	[19.601]	[107.509]	[40.756]	[30.927]
N	121,545	121,545	121,545	121,545

Notes: The numbers refer to an initial sample of 403,859 urgent respiratory hospitalizations defined in the primary diagnosis, and to a population of 54,012,341 individuals distributed across 111 municipalities over 1095 days. All estimates include day-of-week, week-of-year, year and municipality fixed effects, municipality specific time trends and region-year fixed effects, dummies for school holidays and public holidays as well as up to a second-order polynomial in atmospheric temperature, precipitation and wind speed. Standard errors (in brackets) are clustered on municipalities. Estimates are weighted by municipality population size.

Table 12: IV Estimates of the Effect of PM_{10} on Total Health Costs for Respiratory Hospitalizations.

	Total Health Cost			
	(1)	(2)	(3)	(4)
PM_{10}	183.401 [48.496]	254.270 [72.491]	180.985 [52.397]	251.056 [77.882]
Weather		YES		YES
Holidays			YES	YES
Time FE	YES	YES	YES	YES
Municipality FE	YES	YES	YES	YES
Region×year FE	YES	YES	YES	YES
N	121,545	121,545	121,545	121,545

Notes: The numbers refer to an initial sample of 403,859 urgent respiratory hospitalizations defined in the primary diagnosis, and to a population of 54,012,341 individuals distributed across 111 municipalities over 1095 days. All estimates include day-of-week, week-of-year, year and municipality fixed effects, municipality specific time trends and region-year fixed effects. Additional controls include dummies for school holidays and public holidays as well as up to a second-order polynomial in atmospheric temperature, precipitation and wind speed. Standard errors (in brackets) are clustered on municipalities. Estimates are weighted by municipality population size.

Table 13: IV Estimates of the Effect of PM_{10} on Total Health Costs for Respiratory Hospitalizations by Age Group.

	Total Health Costs				
	(0-14)	(15-24)	(25-44)	(45-64)	(65-100)
PM_{10}	105.324 [124.449]	466.401 [194.565]	163.171 [93.317]	162.645 [101.921]	846.114 [253.654]
N	121,545	121,545	121,545	121,545	121,545

Notes: The numbers refer to an initial sample of 403,859 urgent respiratory hospitalizations defined in the primary diagnosis, and to a population of 54,012,341 individuals distributed across 111 municipalities over 1095 days. All estimates include full controls: day-of-week, week-of-year, year and municipality fixed effects, municipality specific time trends and region-year fixed effects, dummies for school holidays and public holidays as well as up to a second-order polynomial in atmospheric temperature, precipitation and wind speed. Standard errors (in brackets) are clustered on municipalities. Estimates are weighted by municipality population size.

Table 14: IV Estimates of the Effect of PT Strike on Respiratory Hospitalizations in a Multi-pollutant Model.

	Respiratory Hospitalizations			
	(1)	(2)	(3)	(4)
Panel A - Unbalanced panel:				
PM_{10}	0.064	0.051	0.063	0.051
	[0.017]	[0.019]	[0.031]	[0.021]
CO		0.498		0.495
		[0.513]		[0.586]
NO_2			0.030	0.001
			[0.064]	[0.054]
F-stat. PM_{10}	59.22	66.52	59.49	66.72
F-stat. CO		26.12		26.12
F-stat. NO_2			3.49	3.27
N	92,447	74,184	94,991	73,845
Panel B - Balanced panel:				
PM_{10}	0.066	0.053	0.066	0.052
	[0.023]	[0.021]	[0.026]	[0.023]
CO		0.547		0.481
		[0.525]		[0.681]
NO_2			0.023	0.009
			[0.044]	[0.051]
F-stat. PM_{10}	72.18	72.18	72.85	72.92
F-stat. CO		26.15		26.16
F-stat. NO_2			3.87	3.85
N	59,130	59,130	59,130	59,130

Notes: The coefficients indicate effects for 100,000 residents. The numbers refer to urgent respiratory hospitalizations defined in the primary diagnosis for the population of 54 municipalities over 1095 days. All estimates include full controls: day-of-week, week-of-year, year and municipality fixed effects, municipality specific time trends and region-year fixed effects, dummies for school holidays and public holidays as well as up to a second-order polynomial in atmospheric temperature, precipitation and wind speed. Standard errors (in brackets) are clustered on municipalities. Estimates are weighted by municipality population size.

Appendix A For Online Publication

Additional Tables

Table A.1: Data Sources

Variable	Source
Hospital urgent hospitalizations	Hospital Discharge Data (SDO) - Italian Ministry of Health
Air pollution reanalysis data	Copernicus Atmosphere Monitoring Service (CAMS)
Air pollution data from monitoring stations	Airbase database of the European Environmental Agency
Weather data	MARS-Agri4Cast - European Commission, Joint Research Center
Public Transport Strikes	Italian Strike Comm. and Italian Min. of Infrastructure and Transport
Demand per capita of Public Transportation	Italian National Institute of Statistics (ISTAT)
Local population	Italian National Institute of Statistics (ISTAT)

Table A.2: OLS Estimates on the Effect of PM_{10} on Respiratory Hospitalizations.

	Respiratory Hospitalizations			
	(1)	(2)	(3)	(4)
PM_{10}	-0.001	-0.001	-0.000	-0.001
	[0.000]	[0.000]	[0.000]	[0.000]
Weather		YES		YES
Holidays			YES	YES
Time FE	YES	YES	YES	YES
Municipality FE	YES	YES	YES	YES
Region×year FE	YES	YES	YES	YES
N	121,545	121,545	121,545	121,545

Notes: The numbers refer to an initial sample of 403,859 urgent respiratory hospitalizations defined in the primary diagnosis, and to a population of 54,012,341 individuals distributed across 111 municipalities over 1095 days. All estimates include day-of-week, week-of-year, year and municipality fixed effects, municipality specific time trends and region-year fixed effects and age controls. Additional controls include dummies for school holidays and public holidays as well as up to a second-order polynomial in atmospheric temperature, precipitation and wind speed. Standard errors (in brackets) are clustered on municipalities. Estimates are weighted by municipality population size.

Table A.3: IV Estimates of the Effect of PM_{10} on AUC for Hospitalizations for Four Distinct Respiratory Problems.

	Unit Cost			
	(1)	(2)	(3)	(4)
Panel A - Tot. respiratory				
PM_{10}	12.992	17.145	12.223	16.395
	[13.867]	[18.833]	[14.528]	[19.601]
Panel B - Asthma				
PM_{10}	128.219	182.424	137.034	193.842
	[69.436]	[101.150]	[74.262]	[107.509]
Panel C - Pneumonia				
PM_{10}	8.182	11.034	7.010	10.020
	[27.396]	[38.357]	[29.593]	[40.756]
Panel D - COPD				
PM_{10}	44.228	62.001	46.137	64.564
	[21.298]	[28.957]	[22.815]	[30.927]
Weather		YES		YES
Holidays			YES	YES
Time FE	YES	YES	YES	YES
Municipality FE	YES	YES	YES	YES
Region×year FE	YES	YES	YES	YES
N	121,545	121,545	121,545	121,545

Notes: The numbers refer to an initial sample of 403,859 urgent respiratory hospitalizations defined in the primary diagnosis, and to a population of 54,012,341 individuals distributed across 111 municipalities over 1095 days. All estimates include day-of-week, week-of-year, year and municipality fixed effects, municipality specific time trends and region-year fixed effects and age controls. Additional controls include dummies for school holidays and public holidays as well as up to a second-order polynomial in atmospheric temperature, precipitation and wind speed. Standard errors (in brackets) are clustered on municipalities. Estimates are weighted by municipality population size.

Table A.4: IV Estimates of the Effect of PM_{10} on Total Health Costs for Respiratory Hospitalizations by Age Group.

	Total Cost			
	(1)	(2)	(3)	(4)
Panel A: age below 14				
PM_{10}	62.186	91.275	69.400	105.324
	[80.703]	[118.714]	[85.517]	[124.449]
Panel B: age 15-24				
PM_{10}	319.682	453.598	333.761	466.401
	[119.087]	[178.563]	[131.752]	[194.565]
Panel C: age 25-44				
PM_{10}	107.649	157.093	112.759	163.171
	[54.315]	[86.697]	[58.968]	[93.317]
Panel D: age 45-64				
PM_{10}	121.364	169.763	117.960	162.645
	[65.516]	[96.684]	[69.791]	[101.921]
Panel E: age 65 and above				
PM_{10}	615.046	854.092	614.659	846.114
	[176.774]	[240.027]	[187.970]	[253.654]
Weather		YES		YES
Holidays			YES	YES
Time FE	YES	YES	YES	YES
Municipality FE	YES	YES	YES	YES
Region×year FE	YES	YES	YES	YES
N	121,545	121,545	121,545	121,545

Notes: The numbers refer to an initial sample of 403,859 urgent respiratory hospitalizations defined in the primary diagnosis, and to a population of 54,012,341 individuals distributed across 111 municipalities over 1095 days. All estimates include day-of-week, week-of-year, year and municipality fixed effects, municipality specific time trends and region-year fixed effects and age controls. Additional controls include dummies for school holidays and public holidays as well as up to a second-order polynomial in atmospheric temperature, precipitation and wind speed. Standard errors (in brackets) are clustered on municipalities. Estimates are weighted by municipality population size.

Table A.5: IV Estimates of the Effect of O_3 on Respiratory Hospitalizations.

First stage				
	O3			
	(1)	(2)	(3)	(4)
PTStrike	-0.151	-0.015	-0.147	0.025
	[0.366]	[0.506]	[0.366]	[0.502]
F-stat	0.170	0.001	0.161	0.002
Second Stage				
	Respiratory Hospitalizations			
	(1)	(2)	(3)	(4)
O_3	-0.450	-4.526	-0.427	2.446
	[1.069]	[157.049]	[1.042]	[49.090]
Weather		YES		YES
Holidays			YES	YES
Time FE	YES	YES	YES	YES
Municipality FE	YES	YES	YES	YES
Region×year FE	YES	YES	YES	YES
N	121,545	121,545	121,545	121,545

Notes: The numbers refer to an initial sample of 403,859 urgent respiratory hospitalizations defined in the primary diagnosis, and to a population of 54,012,341 individuals distributed across 111 municipalities over 1095 days. All estimates include day-of-week, week-of-year, year and municipality fixed effects, municipality specific time trends and region-year fixed effects and age controls. Additional controls include dummies for school holidays and public holidays as well as up to a second-order polynomial in atmospheric temperature, precipitation and wind speed. Standard errors (in brackets) are clustered on municipalities. Estimates are weighted by municipality population size.

Table A.6: IV Estimates of the Effect of PM_{10} on Placebo Diseases.

Nervous System Hospitalizations (ICD09 320-359)				
	(1)	(2)	(3)	(4)
PM_{10}	-0.004 [0.012]	-0.006 [0.017]	-0.007 [0.013]	-0.010 [0.017]
Musculoskeletal Hospitalizations (ICD09 710-739)				
PM_{10}	-0.006 [0.005]	-0.009 [0.007]	-0.009 [0.005]	-0.012 [0.005]
Endocrine Systems Hospitalizations (ICD09 240-279)				
PM_{10}	-0.008 [0.009]	-0.012 [0.012]	-0.010 [0.009]	-0.014 [0.013]
Weather		YES		YES
Holidays			YES	YES
Time FE	YES	YES	YES	YES
Municipality FE	YES	YES	YES	YES
Region×year FE	YES	YES	YES	YES
N	121,545	121,545	121,545	121,545

Notes: The numbers refer to hospitalizations distributed across 111 municipalities over 1095 days. All estimates include day-of-week, week-of-year, year and municipality fixed effects, municipality specific time trends and region-year fixed effects and age controls. Additional controls include dummies for school holidays and public holidays as well as up to a second-order polynomial in atmospheric temperature, precipitation and wind speed. Standard errors (in brackets) are clustered on municipalities. Estimates are weighted by municipality population size.

Table A.7: IV Estimates of the Effect of PM_{10} on Programmed Respiratory Hospitalizations.

	Programmed Respiratory Hospitalizations			
	(1)	(2)	(3)	(4)
PM_{10}	-0.015 [0.016]	-0.021 [0.021]	-0.020 [0.015]	-0.028 [0.020]
Weather		YES		YES
Holidays			YES	YES
Time FE	YES	YES	YES	YES
Municipality FE	YES	YES	YES	YES
Region×year FE	YES	YES	YES	YES
N	121,545	121,545	121,545	121,545

Notes: The numbers refer to hospitalizations distributed across 111 municipalities over 1095 days. All estimates include day-of-week, week-of-year, year and municipality fixed effects, municipality specific time trends and region-year fixed effects and age controls. Additional controls include dummies for school holidays and public holidays as well as up to a second-order polynomial in atmospheric temperature, precipitation and wind speed. Standard errors (in brackets) are clustered on municipalities. Estimates are weighted by municipality population size.

Table A.8: IV Estimates of the Effect of PM_{10} on Respiratory Hospitalizations in Non-Affected Cities.

First stage				
	PM_{10}			
	(1)	(2)	(3)	(4)
$FakePTStrike$	0.478	0.257	0.498	0.272
	[0.646]	[0.644]	[0.652]	[0.650]
F-stat.	0.424	0.149	0.462	0.166
Second Stage				
	Respiratory Hospitalizations			
	(1)	(2)	(3)	(4)
PM_{10}	-0.047	-0.086	-0.041	-0.074
	[0.208]	[0.446]	[0.195]	[0.404]
Weather		YES		YES
Holidays			YES	YES
Time FE	YES	YES	YES	YES
Municipality FE	YES	YES	YES	YES
Region×year FE	YES	YES	YES	YES
N	121,545	121,545	121,545	121,545

Notes: The numbers refer to an initial sample of 403,859 urgent respiratory hospitalizations defined in the primary diagnosis, and to a population of 54,012,341 individuals distributed across 111 municipalities over 1095 days. All estimates include day-of-week, week-of-year, year and municipality fixed effects, municipality specific time trends and region-year fixed effects and age controls. Additional controls include dummies for school holidays and public holidays as well as up to a second-order polynomial in atmospheric temperature, precipitation and wind speed. Standard errors (in brackets) are clustered on municipalities. Estimates are weighted by municipality population size.

Table A.9: IV Estimates of the Effect of PM_{10} on Respiratory Hospitalizations with Multi-Day Strike.

First stage				
	PM_{10}			
	(1)	(2)	(3)	(4)
$Multi - DayPTStrike$	1.026	0.603	0.920	0.537
	[0.195]	[0.177]	[0.194]	[0.176]
F-stat.	27.762	10.279	22.538	9.301
Second Stage				
	Respiratory Hospitalizations			
	(1)	(2)	(3)	(4)
PM_{10}	0.064	0.106	0.066	0.111
	[0.014]	[0.034]	[0.016]	[0.040]
Weather		YES		YES
Holidays			YES	YES
Time FE	YES	YES	YES	YES
Municipality FE	YES	YES	YES	YES
Region×year FE	YES	YES	YES	YES
N	121,545	121,545	121,545	121,545

Notes: The numbers refer to an initial sample of 403,859 urgent respiratory hospitalizations defined in the primary diagnosis, and to a population of 54,012,341 individuals distributed across 111 municipalities over 1095 days. All estimates include day-of-week, week-of-year, year and municipality fixed effects, municipality specific time trends and region-year fixed effects and age controls. Additional controls include dummies for school holidays and public holidays as well as up to a second-order polynomial in atmospheric temperature, precipitation and wind speed. Standard errors (in brackets) are clustered on municipalities. Estimates are weighted by municipality population size.

Table A.10: IV Estimates of the Effect of PM_{10} on All Italian Municipalities.

First stage				
	PM_{10}			
	(1)	(2)	(3)	(4)
PTStrike	1.181 [0.308]	0.866 [0.300]	1.101 [0.310]	0.826 [0.301]
Second Stage				
	Respiratory Hospitalizations			
	(1)	(2)	(3)	(4)
PM_{10}	0.049 [0.015]	0.067 [0.025]	0.048 [0.016]	0.064 [0.025]
Weather		YES		YES
Holidays			YES	YES
Time FE	YES	YES	YES	YES
Municipality FE	YES	YES	YES	YES
Region×year FE	YES	YES	YES	YES
N	8,858,550	8,858,550	8,858,550	8,858,550

Notes: The numbers refer to an initial sample of 1,267,367 urgent respiratory hospitalizations defined in the primary diagnosis and to a population of 54,012,341 individuals distributed across 8,090 municipalities over 1095 days. All estimates include day-of-week, week-of-year, year and municipality fixed effects, municipality specific time trends and region-year fixed effects and age controls. Additional controls include dummies for school holidays and public holidays as well as up to a second-order polynomial in atmospheric temperature, precipitation and wind speed. Standard errors (in brackets) are clustered on municipalities. Estimates are weighted by municipality population size.

Table A.11: IV Estimates of the Effect of PM_{10} on Respiratory Hospitalizations Using Monitoring Station Data.

First stage				
	PM_{10}			
	(1)	(2)	(3)	(4)
PTStrike	1.606	1.008	1.499	1.290
	[0.770]	[0.699]	[0.752]	[0.774]
F-stat	16.583	7.883	14.459	12.62
Second Stage				
	Respiratory Hospitalizations			
	(1)	(2)	(3)	(4)
PM_{10}	0.037	0.057	0.036	0.056
	[0.014]	[0.034]	[0.015]	[0.027]
Weather		YES		YES
Holidays			YES	YES
Time FE	YES	YES	YES	YES
Municipality FE	YES	YES	YES	YES
Region×year FE	YES	YES	YES	YES
N	72,270	72,270	72,270	72,270

Notes: The numbers refer to an initial sample of 316,109 urgent respiratory hospitalizations defined in the primary diagnosis and to a population of 41,852,702 individuals distributed across 66 municipalities over 1095 days. All estimates include day-of-week, week-of-year, year and municipality fixed effects, municipality specific time trends and region-year fixed effects and age controls. Additional controls include dummies for school holidays and public holidays as well as up to a second-order polynomial in atmospheric temperature, precipitation and wind speed. Standard errors (in brackets) are clustered on municipalities. Estimates are weighted by municipality population size.

Table A.12: IV Estimates of the Effect of PM_{10} on Respiratory Hospitalizations Using CAMS Data.

First stage				
	PM_{10}			
	(1)	(2)	(3)	(4)
PTStrike	1.222	0.819	1.141	0.774
	[0.244]	[0.209]	[0.250]	[0.216]
F-stat	25.185	15.290	20.837	12.836

Second Stage				
	Respiratory Hospitalizations			
	(1)	(2)	(3)	(4)
PM_{10}	0.048	0.070	0.048	0.068
	[0.011]	[0.021]	[0.013]	[0.024]
Weather		YES		YES
Holidays			YES	YES
Time FE	YES	YES	YES	YES
Municipality FE	YES	YES	YES	YES
Region×year FE	YES	YES	YES	YES
N	72,270	72,270	72,270	72,270

Notes: The numbers refer to an initial sample of 316,109 urgent respiratory hospitalizations defined in the primary diagnosis and to a population of 41,852,702 individuals distributed across 66 municipalities over 1095 days. All estimates include day-of-week, week-of-year, year and municipality fixed effects, municipality specific time trends and region-year fixed effects and age controls. Additional controls include dummies for school holidays and public holidays as well as up to a second-order polynomial in atmospheric temperature, precipitation and wind speed. Standard errors (in brackets) are clustered on municipalities. Estimates are weighted by municipality population size.

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