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

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Abstract

We investigate unequal effects of daily particulate matter (PM) concentrations on Italian hospitalizations by exploiting daily episodes of public transportation strikes as an instrumental variable for pollution exposure. We show that hospitalizations resulting from higher pollution are not only more likely to occur (extensive margin), but are also more complex to deal with (intensive margin). This penalty is larger for the young, the elderly, the less educated and migrants from low income countries. In order to appreciate the heterogeneity of our results, we show how municipalities with different age structures and PM exposure face similar hospitalization costs.

JEL: I14, Q53, R41

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1 Introduction

Air pollution represents a global, increasing concern that contributes to serious illnesses, premature deaths and loss of productivity, especially in urban areas (Deryugina et al., 2016, Isen et al., 2017, Salvo et al., 2018, Schlenker and Walker, 2015, Zivin and Neidell, 2018, among others). While the consequences of air pollution *per se* are well documented, much less is known about their costs and distributional impacts. Both lethal and non-lethal effects are likely to depend on the socio-economic status (SES) of individuals (Lavaine, 2015, Neidell, 2004), raising the issue of environmental inequality. If poor air quality affects individuals differently, public policies aimed at mitigating the impact of air pollution should incorporate these differentials in order to optimally compensate individuals for the damage caused.

In this paper we provide causal estimates of the differential effect of particulate matter (PM), one of the most diffused and harmful air pollutants, on urgent respiratory hospitalizations. Since hospitalizations resulting from higher air pollution concentrations may be more likely to occur and more complex to deal with, we estimate the effect of PM_{10} on the number of hospitalizations (extensive margin), the average unit costs of hospitalizations (intensive margin) and the associated total costs, offering a large- scale analysis relative to all major Italian cities for the period 2013-2015. Although the distinction between the extensive and intensive margin is of significant policy interest, so far the literature has been limited to quantifying only the former.

An important contribution of this paper is that the data at hand allow us to explore the heterogeneity of these effects through the lens of age, educational attainment and migration status. Moreover, state-of-the-science environmental data employed in this study enables us to circumvent the non-random distribution over space and time, and the phenomenon of "births" and "deaths" of air quality monitoring stations. We link the data to an administrative hospital discharge dataset which includes the universe of Italian daily hospital admissions and their costs in both public and private providers.

The endogeneity issue due to non-random pollution exposure is carefully addressed by framing the analysis using an instrumental variable (IV) approach. More specifically, we leverage episodes of public transportation (PT) strikes, which unexpectedly generate traffic congestion increasing air pollution levels on specific day-municipality combinations. PT strikes represent a unique application in our setting since the at-risk population is potentially very large. Unlike countries such as Austria, Germany or the Netherlands where strikes are only singular events, PT strikes in Italy are relatively frequent and represent a common pattern that residents are used to coping with. Significantly, since the Guarantee Authority ensures that on strike days a limited amount of transportation is guaranteed in the so-called protected hours, PT strikes do not represent a complete shutdown, but a significant limitation of the PT network. Finally, the universalistic nature of the Italian healthcare system offers a favorable setting for this type of analysis, since individuals face no barriers to accessing hospital healthcare.

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We show that higher particle pollution instrumented by PT strikes causes an increase in urgent respiratory hospital admissions: one standard deviation increase in PM_{10} (corresponding to 10.37 micrograms per cubic meter) causes an additional 0.55 hospital admissions per 100 thousand residents and this penalty is particularly pronounced for the young and the less educated. Moreover, we extend the heterogeneity analysis to the migrant status, finding evidence of disparity for pollution-induced hospitalizations among migrants from low income countries. Taken together, our findings of unbalanced impacts of air pollution point to the existence of large environmental inequality since those who do not contribute the most to the formation of air pollution are the most affected. This evidence suggests that air pollution is not only a technological issue, but it also constitutes a socio-economic phenomenon due to the limited adaptive or affordable capacity of the most vulnerable population groups.

We then examine to what extent traffic-born adverse air quality affects the complexity of hospitalizetions proxied by unit average costs. We find that one additional standard deviation of PM_{10} increases the average unit cost for asthma admissions by 84.4%, suggesting that hospitalizations are not only more frequent, but are also more complex. We also find differentials for COPD hospitalizations in which a one additional standard deviation causes a 18.6% increase in average COPD admission costs. Overall, considering both extensive and intensive margins, we estimate that a daily increase of one standard deviation in PM_{10} is associated with an additional 1873 euros per 100,000 individuals, representing a 32.05% increase in the average daily per capita expenditure on respiratory hospitalizations. It should be noted that this differential ranges from 3,526 euros for young patients and 6,440 euros for elderly patients. We summarize the heterogeneity of these effects through a heat map which shows how populations with different age structures combined with different PM exposures can face similar health costs: young patients in cities with the lowest PM_{10} levels generate healthcare costs which are comparable with middle-aged individuals in the most polluted cities.

Based on these results, we do back-of-the-envelope calculations of total daily monetary costs relative to a one standard deviation increase in PM_{10} for the 17.8 million residents in the 111 municipalities considered which amount to 331,843 euros, 85% of which is represented by the extensive margin (admission count) and the remaining 15% by the intensive margin (major complexity of admissions). Overall, total daily costs of a one standard deviation increase in PM_{10} represent 0.37% of the total daily health expenditure in Italy.

To test the validity of our main findings, we provide a wide set of robustness checks and an additional set of results for $PM_{2.5}$, a finer particulate which throughout all steps of the analysis points to more severe health effects and higher hospitalization costs.

The remainder of the paper is organized as follows. In section 2 we provide an overview of the effects of air pollution, describe the institutional background and the issue of environmental disparity. section 3

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describes the data sources and the dataset construction. section 4 and section 5 presents, respectively, the estimation strategy and the econometric results, respectively. Finally, section 6 discusses the implications of our findings and concludes. The Appendix includes additional research material and the robustness checks.

2 Adverse effects of particulate matter

When considering the different types of air pollutants, most of the evidence of health effects relates to particulate matter (PM), ozone (O_3) and nitrogen dioxide (NO_2). Due to its large diffusion and ability to easily penetrate the lungs and blood stream, PM is considered "*the most pernicious form of air pollution*" (Chay et al., 2003). PM embraces pollution particles of different sizes and compositions directly emitted into the atmosphere that when inhaled can cause cardiovascular and pulmonary diseases, and premature death (WHO, 2013). PM_{10} consists of particles that are less than 10 micrometers (μm) in aerodynamic diameter, whereas $PM_{2.5}$ consists of particles with an even smaller diameter (less than 2.5 μm). Both PM_{10} and $PM_{2.5}$ originate from natural and anthropogenic sources, even though most of particle pollution derives from fuel combustion from motor vehicles (diesel in particular) and heating (EEA, 2016).

Although air pollution represents a "public bad", it does not affect everyone to the same extent. Indeed, the unequal distribution of the impact of air pollution closely reflects socio-demographic differences within society. A pioneering study by Neidell (2004), who studied the differential impact of air pollution on child hospitalizations, introduced the 'double jeopardy' hypothesis, according to which low SES individuals are more severely harmed by the same dose of pollution exposure. Individual characteristics, such as education, income, employment status, age or initial health conditions, may determine how sensitive individuals are to air pollution health hazards. This implies that while wealthier individuals can partially compensate for the negative effects of bad air quality in a medium and long run perspective (Halliday et al., 2015, Isen et al., 2017, McCubbin and Delucchi, 1999, Sun et al., 2017), the elderly, children, those experiencing material disadvantage and those in bad health are more vulnerable to air pollution and are also less responsible for its formation (Adler and van Ommeren, 2016, Cournane et al., 2017, Forastiere et al., 2007a, Germani et al., 2014, Lavaine, 2015, among others).

Some epidemiological studies also point to differential impact across ethnic groups in the US, with larger effects for Whites and Hispanics (Ostro et al., 2006) and African Americans (Apelberg et al., 2005, Bell and Dominici, 2008). A recent study on New Jersey residents found that the risk of dying early from long-term exposure to PM was higher in communities with larger African-American populations (Wang et al., 2016). However, the ethnic dimension in relation to exposure to air pollution has been overlooked so far. In Europe, growing inflow migration from low-income countries, in particular from Africa, is

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increasing the share of the at-risk population since migrants from low-income countries are often among the most marginalized. If there is a socio-economic gradient in the way air pollution hits individuals, a precise calculation of these differentials and the compensation gap may foster effective policy design to mitigate the environmental inequalities.

Recently, a small but influential group of studies investigated the effect of air pollution on healthcare utilization, focusing on NO_2, CO and PM. Using s variation in daily airport congestion, Schlenker and Walker (2015) estimate the health costs associated with air pollution exposure for communities surrounding twelve large airports in California. They use diagnosis-specific reimbursement rates offered to hospitals through Medicare and find that a one standard deviation (s.d.) increase in daily pollution led to an additional $540,000 per day in hospitalization costs for respiratory and heart-related admissions of individuals within 10 km of one of the twelve largest airports considered. Focusing on the elderly in the United States, Deryugina et al. (2016) estimate the causal effect of daily $PM_{2.5}$ on three-day hospitalization rates and associated total medical spending. They find that a one μ/m3 increase in daily $PM_{2.5}$ caused an increase in emergency room (ER) inpatient spending of 16 thousand per million US dollars. According to their calculations, progressively lower $PM_{2.5}$ concentrations experienced in the United States during the period 1999-2001 led to a decrease in the number of elderly deaths by 55,000 per year and the number of life years lost by 150,000 per year, for a corresponding monetary benefit of $15 billion per year. Finally Halliday et al. (2015) estimate the impact of increased SO_2 and PM induced by volcanic eruptions in the state of Hawaii using the total amount charged for patient care as a measure of healthcare cost. Their results show that a one s.d. increase in particulate pollution led to a 23-36% increase in expenditure on ER visits for pulmonary-related diseases. Even though these studies find strong adverse effects of air pollution on access to healthcare and quantify the overall cost for the underlying populations (total costs), treatment complexity and a systematic analysis of the differential effects of air pollution have been overlooked so far.

3 Data

We combine administrative data on hospital admissions for the period from 2013 to 2015 aligned with pollution concentrations data and information on public transportation strikes at day- municipality level. We rely on the finest territorial disaggregation of the Italian territory relative to 2010, represented by 8,090 municipalities, even though our core analysis is carried out on data for all the 111 province capital cities (see Figure B.1 in Appendix B). For each of the 1,095 days between 2013-2015 and the 111 administrative municipalities, we consider a balanced panel consisting of 121,545 observations. This section describes

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the data, with some of the additional data features included in Appendix A (Table A1).[1]

3.1 Hospital admissions

The Hospital Discharge Data (SDO) of the Italian Ministry of Health constitute our main data source. They provide information on the universe of hospitalization episodes delivered by public hospitals and publicly funded private hospitals. The universal provision of health-care in Italy guarantees a favorable setting for the analysis, where hospitalizations are largely free at point of delivery for all Italian residents. The records contain important socio-demographic information (age, gender, nationality, place of birth and residence, educational attainment), together with clinical information (diagnoses, procedures performed, in and out hospital transfers, discharges) and hospitalization details (hospital type and specialty where the patient received treatments).

Considering the aim and the setting of our study, we restrict the data to urgent hospitalization episodes, disregarding programmed or elective hospital stays.[2] For the same purpose, we further restrict the cases to hospitalization episodes relative to respiratory diseases based on the primary diagnosis of each hospitalization (codes ICD-9[3]). This choice is more stringent than the analysis by Schlenker and Walker (2015), who count a patient as suffering from an illness if either the primary or one of the secondary diagnosis codes list a respiratory illness under scrutiny. For instance, if an individual is hospitalized for a leg fracture but is also an asthmatic patient, hospitalization could be attributed to air pollution whereas it may be causally related to traffic congestion.

During the period 2013-2015, there were roughly 30 million hospital admissions in 8,090 municipalities in Italy and approximately 11.2 million (39%) were of an urgent nature. Of the urgent hospitalizations, 31% are delivered to residents of the 111 municipalities considered. A subset of 11.7% of hospitalizations, corresponding to a total of 403,861 hospitalizations, is due to primary respiratory disease diagnoses, which represents the main outcome in this study.

In our core analysis, we determine counts of daily admissions by considering only municipalities of residence and disregarding the municipalities where hospitalizations take place which do not match for 1.32% of urgent respiratory admissions. While Italian residents are free to seek healthcare anywhere in Italy, accessing hospitals that are outside the municipalities of residence represents an unlikely practice

[1] 1In 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 administratively governed by a municipality. Following several administrative reorganizations, the number of municipalities dropped down to 7,954 in 2018, with both the number of provinces and their capital cities undergoing organizational changes: Italian provinces increased from 107 to 110, and overall, during the period between 2010 and 2018, they were headed by 111 municipalities (in some cases the administration moved to a different municipality, e.g. the case of Cesena-Forlí). In our analysis, we consider all the 111 municipalities which at any point in time constituted an administrative city in Italy.

[2] Programmed admissions will turn out to be useful to test the robustness of our results (see Section 5.5).

[3] 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).

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in urgent cases of respiratory disease. Administrative towns are more likely to receive inflows of workers from minor surrounding towns, rather than generate worker outflows. According to our calculations based on individual level surveys concerning aspects of daily living conducted yearly by the Italian National Institute of Statistics, in 2013, only 11% of residents living in big Italian cities commute daily outside their municipalities of residence, with this number being driven prevalently by workers with higher education and an age comprised between 30 and 45 years. We make no assumptions about the commuting style of non-resident citizens who conversely are more likely to commute outside their municipalities (27% on average in 2013). While individuals commuting from outside to administrative municipalities are also exposed to the environmental conditions of the host towns and, as a consequence, more likely to be hospitalized in these towns in urgencies, we are not able to convincingly make any assumption about their actual exposure to pollution. For this reason, we disregard hospitalizations delivered to non-residents of administrative towns. Moreover, by disregarding hospitalizations delivered to non-residents, we also do not consider hospitalizations delivered to residents outside administrative towns.[4] We thus aggregate the data by day of admission and the patient's municipality of residence.

In order to gage the heterogeneous effects of pollution exposure, we further perform the aggregation by five age groups (0-14, 15-24, 25-44, 45-64 and over 65), three educational levels (primary, secondary and tertiary school attainment) and migrant status, as inferred from non-Italian citizenship. We further distinguish between migrants from low vs. high income countries, based on the World Bank country classification.[5] According to this procedure, we obtain daily counts of hospitalizations for the entire population as well as for each of the socio-economically relevant subgroups. Our final outcomes are represented by daily municipality-level admission counts expressed per 100,000 residents. When specific age, education or migration groups are considered, the relevant resident population is adjusted 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 diagnosis, surgical intervention, diagnostic and therapeutic procedures, and individual age and sex, an algorithm aggregates each hospitalization episode into a specific Diagnosis Related Group (DRG). DRGs classify hospital patients into homogenous groups by assigning to each hospitalization a relative cost and a standard length of hospital stay.[6] 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 to each individual a cost relative to the hospitalization DRG, rescaled to account

[4] Before applying this restriction, we carefully test for the mobility response of residents on PT strike days to see if strike episodes affect the likelihood of individuals to seek hospital admissions outside their town of residence (see 5.5).

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

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

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for the extra hospital stay days. We are therefore able to capture a more accurate cost pattern based on the severity of each hospitalization episode. Following the setup of our analysis, we then aggregate individual costs by municipality and day of hospitalization. We then express the total costs in a twofold manner: per admission and per capita terms. In the first case, we calculate the average unit cost (AUC) of respiratory disease as the ratio of total costs of urgent cases of respiratory disease to the number of admissions for each day/municipality. We calculate the unit costs for both the overall pool of respiratory disease, as well as for each disease type. The average unit cost represents a comprehensive measure of the average complexity of respiratory hospitalizations faced by a municipality on a given day. In the second case, we calculate the per capita respiratory admission costs as the ratio of total costs relative to urgent cases of respiratory disease to the number of residents for each municipality/day. This represents the total average cost (TAC) since it captures changes in both the unit cost and the count of admissions. Throughout the analysis, we will refer to healthcare costs accruing from a higher number of admissions as the extensive margin (TAC), those relative to a higher unit cost of admissions as the intensive margin (AUC), and the combination of the two as the total cost of pollution-induced hospitalizations.

Table 1: Descriptive statistics - daily municipality level urgent respiratory admission counts x 100k population (primary diagnosis)

	Mean	Std. Dev.	Min	Max
all ages	2.049	1.308	0	26.357
Ages below 14	2.126	3.526	0	102.249
Ages 15 - 24	0.390	1.661	0	74.349
Ages 25 - 44	0.358	0.949	0	33.25
Ages 45 - 64	0.829	1.351	0	46.587
Ages 65 and above	6.055	4.514	0	105.457
Primary education	3.186	2.116	0	46.164
Secondary education	0.582	1.125	0	28.678
Tertiary education	0.464	1.880	0	85.069
Low income countries	0.301	0.789	0	63.452
High income countries	0.057	0.502	0	53.792
Obs.=121,545; n=111; t=1095				

Notes: The numbers refer to an initial sample of 403,861 urgent respiratory hospital admissions defined in the primary diagnosis and to a population of 54,012,341 individuals distributed across 111 municipalities over 1095 days. All descriptive statistics are weighted by the relevant municipality population size. Admission counts are expressed as the number of hospital admissions per 100,000 residents. In case of each age/education/migration specific group, the resident population is adjusted to that particular group.

Table 1 presents descriptive statistics for the full sample of admissions considered and 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, as is standard practice in several related studies (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, with this number being the highest for the elderly and for individuals of pediatric age. Both the overall and group-specific

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counts are extremely variable with standard deviations being larger than the means. The number of admissions among individuals with primary education is disproportionally higher than the remaining education attainment categories. Finally, the number of admissions is on average lower for migrants, although citizens from low-income countries undergo hospitalization more frequently than those from high-income countries.

The AUC for an urgent respiratory admission is 2,856 euros, and this amount varies according to the specific respiratory problem. The AUC for an admission for asthma is 1,648 euros, chronic obstructive pulmonary disease (COPD) 2,237 euros and pneumonia, 2,884 euros. The TAC related to urgent respiratory problems amount to 0.06 euros/day per resident in the 111 municipalities. To gauge the magnitude of this estimate, we should bear in mind that the overall Italian healthcare fund amounts to an average of 5 euros per resident/day, thus representing approximately 1.2%.[7]

Table 2: Descriptive statistics - costs of municipality level urgent respiratory admissions (euros)

	Mean	Std. Dev.	Min	Max
Unit cost (per-admission)				
Respiratory	2855.857	785.8157	703.04	6054.17
Asthma	1647.695	1345.537	299.50	5898.48
Pneumonia	2884.100	550.4634	1724.17	3373.38
COPD	2237.036	330.4629	299.50	2404.23
Total cost (per capita)				
Respiratory all ages	0.0564	0.0539	0	0.7459
Obs.=121,545; n=111; t=1095				

Notes: The numbers refer to an initial sample of 403,861 urgent respiratory hospital admissions defined in the primary diagnosis and to a population of 54,012,341 individuals distributed across 111 municipalities over 1095 days.

3.2 Air pollution concentrations

Our core analysis focuses on PM ten micrometers or smaller in aerodynamic diameter (PM_{10}), being the most applicable to our setting and relevant from a policy perspective. We also check the robustness of our results using PM 2.5 micrometers in size or smaller ($PM_{2.5}$), which is much less frequently examined in the existing literature and, as a consequence, less considered in the policy debate up until now.[8]

Automobile fuel combustion creates mainly PM and CO, although to a lesser extent, it also contributes to the production of nitrogen oxides, and benzene. While comparable CO and NO_2 data are not available for the pollutants analyzed in the dataset at hand, we additionally exploit the information on ozone (O_3), which is a secondary pollutant produced by a reaction between NO_2, hydrocarbons and

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

[8] For instance, at the time of writing, the European Commission has not yet set the hazard daily concentration limits for $PM_{2.5}$. Moreover, an important 2013 WHO report in collaboration with the European Commission specifically declares the need for additional evidence on the effects of short-term exposure to $PM_{2.5}$ on both mortality and morbidity (WHO, 2013).

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sunlight, and serve as a placebo exercise in our IV setting.

Air pollutants concentrations come from the Copernicus Atmosphere Monitoring Service (CAMS) managed by ECMWF[9]. These data derive from a combination of direct observation from satellites, monitoring stations and reanalysis[10]. So far, reanalysis data have received limited attention in economic studies, also due to the burden of data management and storage (see among others Dell et al., 2014, Deschênes and Greenstone, 2007). In relation to air pollution concentrations, reanalysis data offer three substantial improvements over monitoring stations measures. To begin with, as discussed in Filippini et al. (2019), using monitoring stations data entails assuming that the dispersion of concentration is homogenous within a given administrative unit, and this assumption is unlikely to hold especially in the Italian case due to its heterogeneous landscape and geographical factors that affect pollution dispersion. Therefore, individuals living far from the monitoring stations are likely to be exposed to higher pollution levels than those actually registered, generating a mismatch between the true pollution level and the assigned one. To obtain information for locations far from the monitoring stations, several authors interpolate data points using weights of different nature (Currie and Neidell, 2005, Knittel et al., 2016, Lagravinese et al., 2014, Schlenker and Walker, 2015, among others). However, interpolating using simple distance weights neglects weather and geographical factors which play a key role in pollution dispersion. Second, estimates are sensitive to the approach used to impute pollution at aggregate levels and given that the measurement error is not normally distributed, the direction of the bias on estimates is ambiguous (Lleras-Muney, 2010). Third, the number of monitoring stations is limited and varies over space and time in a non-random order. This issue has been recently investigated by Grainger and Schreiber (2019), who demonstrate that local regulators strategically avoid pollution hotspots when siting monitors. Given that the attainment status of an area in relation to environmental policy standards depends on the concentration levels registered by the monitoring stations, their ad hoc placement can alter the actual compliant status of an area, with significant policy implications (Fowlie et al., 2019).

In their original format, CAMS concentration data cover a regular grid of about 20x20 km at the Italian latitudes. In order to obtain administrative-level concentrations for all 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 municipalities where no grid points fall within their boundaries because of their small area, we assign we assign value of the

[9] https://www.ecmwf.int/en/about/media-centre/focus/ecmwf-copernicus-atmosphere-monitoring-service-cams-applications-and

[10] Reanalysis is a systematic process to estimate data variables across a grid by combining different observational sources such as monitoring stations, radiosonde, satellite, aircraft, ship reports and other inputs with a climate model. This unchanging framework provides a dynamically consistent estimate of the climate and pollution states at each time period and location.

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closest grid points.

To test the validity of our reanalysis data, we also collect air pollution concentrations from monitoring stations. We obtain these data from the air quality database of the European Environmental Agency (EEA), which includes validated measures of PM concentrations for a large number of municipalities in Italy (see Section 5.5).

Figure B.2 in Appendix B plots weekly trends of PM_{10}, averaged over the period 2013-2015, from both CAMS satellite data and Italian monitoring station data. The two sources follow a similar trend even though concentration readings from monitoring stations are characterized by higher and more variable values. The higher variance is probably 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 in places near the reading monitor. Given that monitoring stations are spread in a non-random order over the area, the resulting noise is not normally distributed. On the contrary, being processed on a regular and granular grid, CAMS data account for a homogenous and accurate dispersion representation of pollutant concentrations with a normally distributed measurement error.

Table 3: Descriptive statistics - Air pollutants

Air pollutants ($\mu g/m^3$)	Mean	Std. Dev	Min	Max
PM_{10}	18.628	10.370	1.034	203.630
$PM_{2.5}$	13.660	9.255	0.603	93.514
O_3	59.640	25.359	0.540	150.168
Obs.=121,545; n=111; t=1095				

Notes: All descriptive statistics are weighted by municipality population size.

Table 3 presents descriptive statistics of the analyzed pollutants concentration levels. According to the WHO air quality standards (WHO, 2006), which establish limits for both PM_{10} and $PM_{2.5}$ in terms of daily means at 50 and 25 $\mu g/m^3$, respectively, 1.2% and 8% of our day/municipality combinations exceeded these thresholds during the period of analysis.

Figure 1 plots weekly averages of PM and O_3 concentrations versus a moving average of weekly means of urgent hospital admission rates (Figure B.3 in Appendix B shows the relative weekly averages, maximums and minimums). PM_{10} and $PM_{2.5}$ follow a similar pattern of seasonal variation, while the seasonal cycle of O_3 is inverse. Moreover, PM_{10} and $PM_{2.5}$ feature a positive correlation with respiratory admissions, with gentle downward slopes between March and September, followed by rising rates in the run up to the winter months. Consistent with the literature, we find that O_3 exhibits only very noisy and weak unconditional associations with particle pollution (Figure B.4 in Appendix B reports the correlation matrix between pollutants). This evidence will turn out to be useful in Section 5.5 and supports the single-pollutant setup adopted in this study, as opposed to a multi-pollutant approach which is highly unstable

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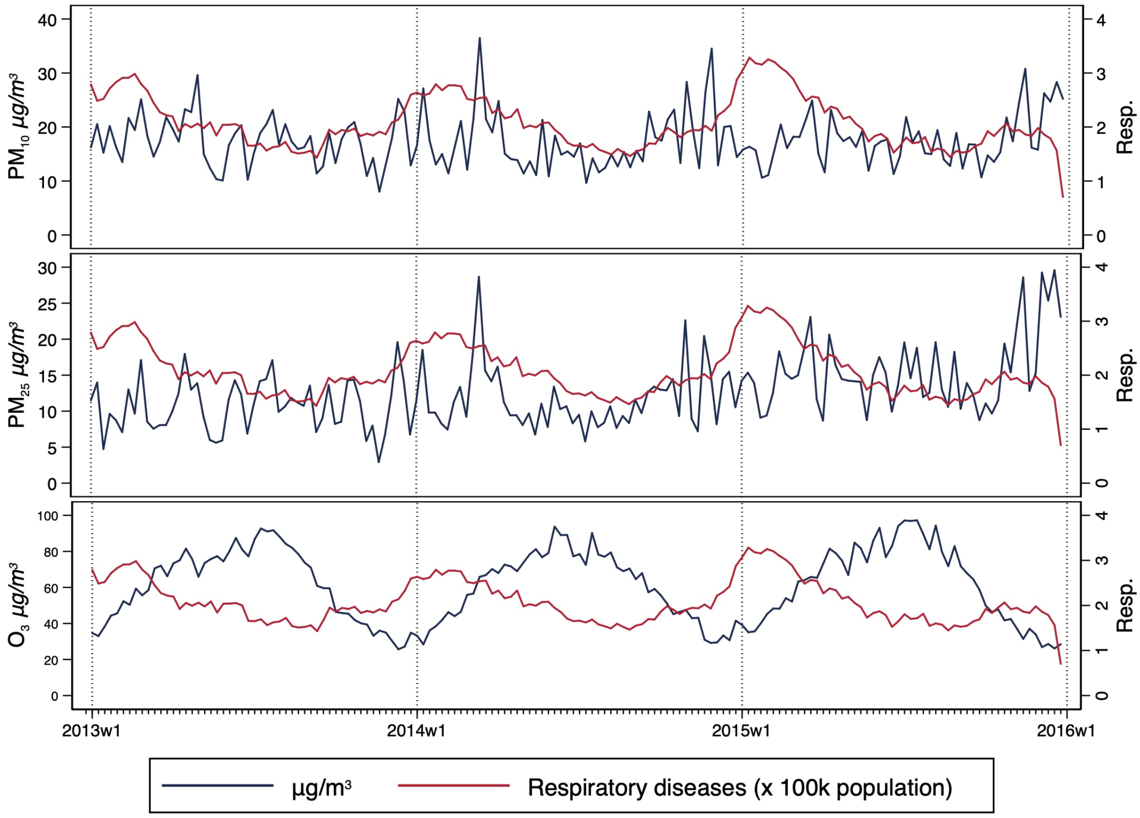
when incorporating pollutants that are highly correlated (Dominici et al., 2010, Halliday et al., 2015).

Figure 1: Weekly Respiratory diseases rate and Air pollutants trends (2013–2015)



3.3 Public transportation strikes

Together with Greece and Spain, 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 complemented by Law no. 83/2000, the Italian transport sector is traditionally strike-prone. Legislation regulates strikes in essential services sectors through the Guarantee Authority (Commissione di Garanzia) which ensures that citizens' basic needs are satisfied during strikes.

We construct a public transportation (PT) strike database merging information provided by the Italian strike commission[11] 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 affecting only to a narrow extent urban and residential centers and day-long national general strikes. Overall, Italy faced 855 strike episodes in 91 municipalities over the study period, with only a few of them lasting for more than one day. When considering only administrative municipalities, we are left with 470 single-day strike

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

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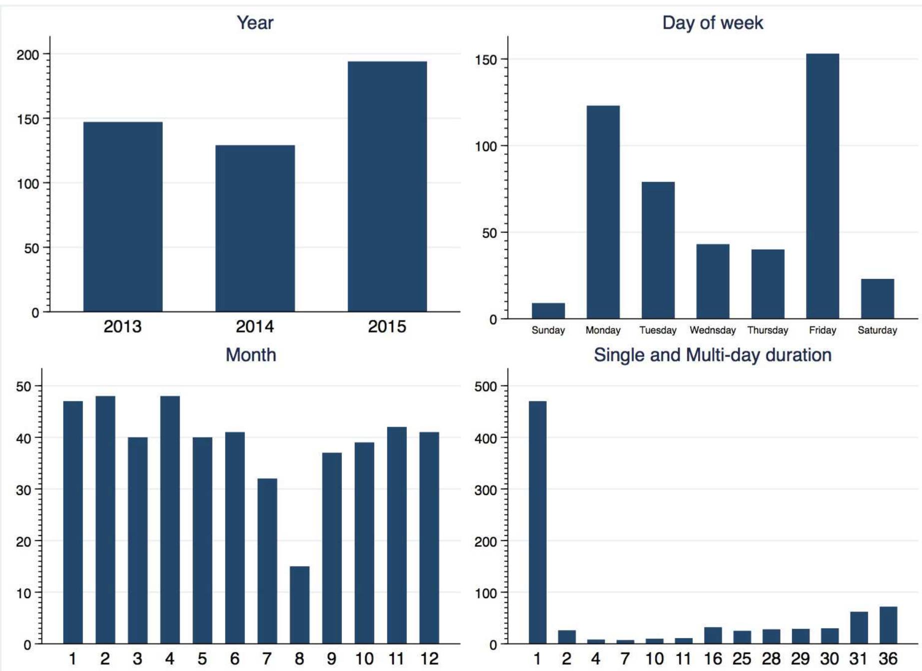
episodes distributed across 72 municipalities.

The first three panels of Figure 2 illustrate the distribution of one-day strike activity across years, months of year and days of the week. Strikes tend to take place in all months of the year, with a significant drop during the summer period. They are most likely to occur on Mondays and Fridays, and we observe a pronounced spike in strike activity in 2015. The fourth panel provides the frequency of strikes with respect to their duration, showing a clear majority of single-day strikes, with only a few of them lasting longer than one day. We leave out all multi-day strike episodes, due to their lower effectiveness and different nature. In fact, as observed by van Exel and Rietveld (2001), long strike episodes are likely to generate adaptive capacity with the possible adoption of new travel patterns.

PT strikes affect traffic congestion and pollution levels and the magnitude of this effect is more pronounced for bigger municipalities where the resident population is sufficiently dependent on PT. Several studies highlight that PT strikes increase traffic density as well as road congestion as a result of the induced switch to the use of private cars belonging to the PT users (Adler and van Ommeren, 2016, Anderson, 2014, Bauernschuster et al., 2017, van Exel and Rietveld, 2001, among others). As a consequence, with a higher rate of dependence on PT experienced in administrative municipalities, we expect a greater 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 minor municipalities where PT serves a small share of the population, a strike episode is unlikely to cause a sufficient variation in traffic congestion and consequent air pollution.

Figure 2: Distribution of strikes across time.



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3.4 Local population

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

Table 4: Descriptive 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					
% with primary ed.	0.60	0.04	0.48	0.69	30,841,632
% with secondary ed.	0.30	0.03	0.24	0.35	16,654,839
% with tertiary ed.	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
Obs.=121,545; n=111; t=1095					

3.5 Weather conditions and holiday data

Although our data on air pollution concentrations are intrinsically adjusted for weather conditions, we still want to control for weather factors since adverse respiratory health problems are independently related to weather variability (Deschenes and Moretti, 2009). We therefore employ municipality-specific weather data from the Gridded Agro-Meteorological dataset managed by MARS-AGRI4CAST[12]. In particular, we use daily average (mean of the minimum and maximum) measures of temperature and wind speed at 10m and the sum of precipitations expressed, respectively, in Celsius degrees, meters per second and mm of rain. This database contains meteorological parameters from weather stations interpolated on a 25x25 km grid[13]. We follow the same procedure applied in air pollution data in order to guarantee a homogeneous measure of weather over space and time. Descriptive statistics of the weather parameters are reported in Table 5 (Figure B.5 in Appendix A shows the weather condition trends). We flexibly model weather conditions by including a series of indicator variables for 5-degree temperature bins ($\leqslant$8.5°C, 8.51 - 13 °C, 13.61-17.5 °C, 17.55-22.1°C, $\geq$ 22.11°C), 5-degree rain bins (0 mm, 0.0005-0.6 mm, 0.60-7.2 mm, 7.24-15 mm, $\geq$15.1 mm) and 5-degree wind bins ($\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).

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

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

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Table 5: Annual mean of temperature and sum of precipitations (2013-2015)

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
Obs.=121,545; n=111; t=1095				

Notes: All descriptive statistics are weighted by size of municipality population. Descriptive statistics computed on a sample of 470 observations of 1-day strikes are reported in brackets.

We also employ data enlisting school and public holidays, both at the local and national level, to control for days during which the commuting activity is systematically reduced. The school holiday data come from the Ministry of Education, Universities and Research, whereas the public holiday dates were retrieved from a Google search. The holiday data are then combined into municipality-day dummy variables equal to unity when school/public holidays are in effect

4 Empirical strategy

4.1 Baseline OLS model

Our main goal is to investigate the causal effect of PM on urgent respiratory health problems on the overall population as well as on specific socio-economic groups. We begin by estimating a simple OLS fixed effects model at municipality-day level which serves as a benchmark for our quasi-experimental estimates. The baseline fixed-effects model including the full set of controls is as follows:

$$H_{idwy} = \alpha + \beta PM_{idwy} + \zeta W_{idwy} + h_{idwy} + \gamma_d + \delta_w + \eta_y + \theta_i + \mu_{idwy} \tag{1}$$

where H_{idwy} denotes the number of urgent respiratory admissions per 100,000 citizens in city i, day of the week d, week of the year w and year y, PM_{idwy} is the air pollutant concentration represented by PM_{10}. W_{idwy} and h_{idwy} represent, respectively, control variables for weather conditions (precipitations 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 in order to account for differences between municipalities, fluctuations in exposure due to commuting and time spent outdoor during the week and seasonal effects or recurrent episodes of specific epidemics.

A causal interpretation of these estimates relies on the assumption that hospitalizations are not correlated with any unobserved municipal and time characteristics. In our setting, the most serious concern is the non-random assignment of air pollution. If individual activity is related to air quality, there may be different sorting mechanisms that expose people at places and periods with systematically

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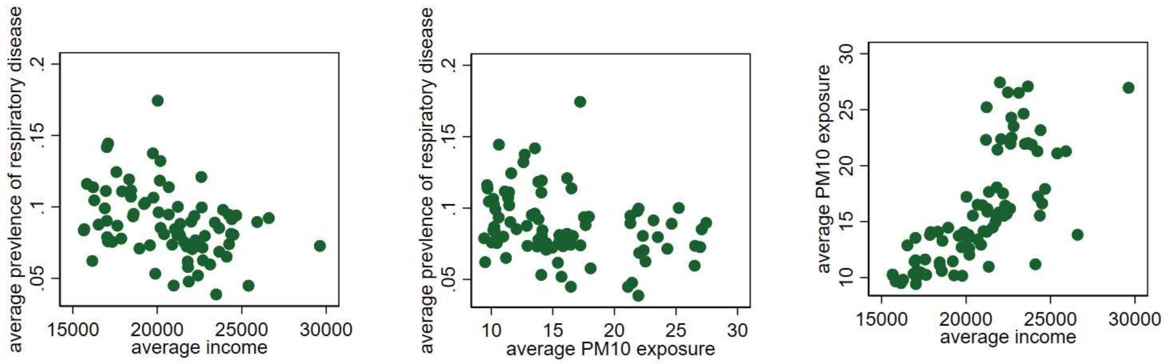
different pollution levels. The same sorting mechanisms are likely to correlate with differences in health and SES. Indeed, better educated individuals are likely to earn more and consume more preventive healthcare, as well as being more aware and cautious in dealing with air quality y (Almond et al., 2009, Chay and Greenstone, 2005, McCrary and Royer, 2011, among others). Moreover, regional growth increases air pollution concentration which also correlates with a higher income and better health and healthcare. Evidence of these associations is provided in Figure 3, which describes correlations between average municipality income, prevalence of respiratory disease and PM_{10} concentrations. Individuals living in municipalities with higher income are also more likely to be exposed to higher pollution levels, but at the same time, are less likely to suffer from respiratory disease.

Figure 3: Correlations between income, respiratory disease and PM_{10} exposure.



Notes: The figure presents averages for the period between 2013-2015. Income data come from the municipality level data on income from the Ministry of Economics and Finance, pollution data come once again from the Copernicus Atmosphere Monitoring Service (CAMS) managed by ECMWF, whereas respiratory disease prevalence data come from the Health Search (HS) dataset (Mazzaglia et al., 2009) run by a representative sample of general practitioners in Italy.

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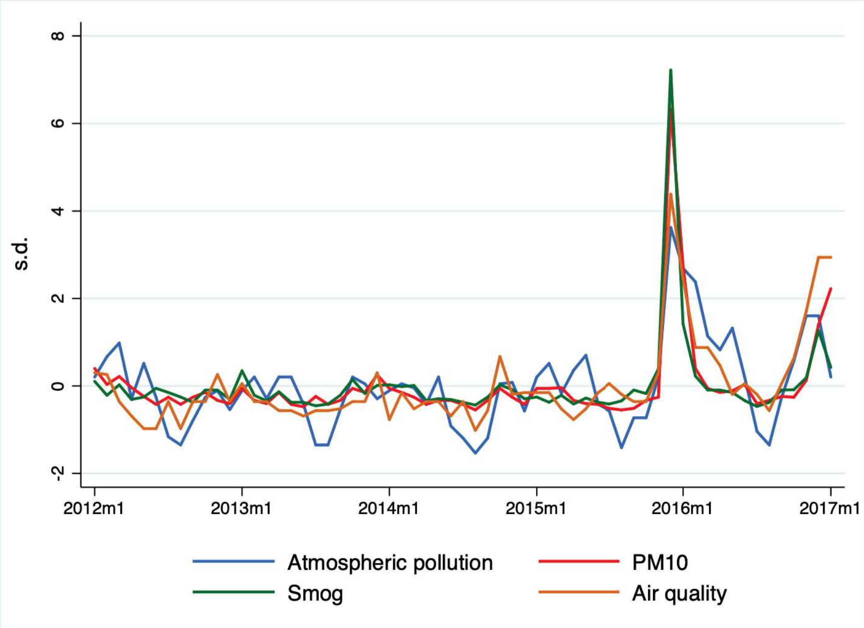
Figure 4: Google trends and interest in atmospheric pollution, PM10, smog and air quality (2012-2017)



Notes: The graph is taken from the Google Trends website accessed in April 2019. We calculate demeaned standardized values from the search frequencies in each month and topic as provided by Google. The query was restricted to Italy and research topics with the following keywords: "inquinamento atmosferico", "pm10", "smog", "qualità dell'aria".

On top of these cross-sectional relationships, day-to-day fluctuations in pollution may have a different impact on different groups of individuals due to their avoidance behavior. While we are not able to explicitly control for this potential confounder, we argue that the issue of air quality in Italy has not been present in the public domain until recent times. The number of Google searches in terms of air pollution, PM_{10}, smog and air quality shown in Figure 4 demonstrates how Italians' interest in air pollution-related issues was negligible prior to 2016. To the extent Google is able to map the individual search preferences, there are no compelling reasons to consider significant avoidance patterns in individuals' daily activities in response to air pollution levels once the seasonality that affects our Google searches is controlled for. On the contrary, it is plausible to assume that individuals involved in the labor market or in schooling are exposed to ambient pollution on a regular basis, with a limited possibility to avoid or downplay their daily activities. Conversely, vulnerable individuals with chronic respiratory problems are more likely to suffer respiratory symptoms during prolonged periods of heavy pollution which may prevent them from going out on days when pollution levels peak. In this setting, the OLS fixed-effects estimates are likely to be severely downward biased relative to the true causal effect. We therefore decide to frame our analysis in a quasi experimental setting.

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4.2 PT strikes as a quasi-experimental setting

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 analysis has found application in a number of pollution-related studies, thus reducing bias caused by measurement error and non-random 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 oil refinery strike occurred in October 2010 in France to estimate the impact of air pollution on birth outcomes and respiratory-related hospital admissions. Moreover, Bauernschuster et al. (2017) observe that transportation strikes in Germany have sizable effects on traffic congestion, increasing the levels of pollution, traffic accidents, travel time and emergency room respiratory disease visits.

In Italy, PT strike episodes constitute a particularly valuable IV setting. Unlike countries such as Austria, Germany or the Netherlands where strikes are rare and singular events, 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 on strike days a limited amount of transportation is guaranteed in the so-called protected hours, PT strikes do not represent a complete shutdown, but a substantial limitation of the PT network. This aspect 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 a relative tailpipe emissions of PM. Moreover, the physical act of friction resulting from wheel-to-road contact exacerbated by frequent acceleration and breaking further contribute to increasing PM levels. As such, not only are there more cars on the roads on heavy traffic days, but the efficiency of engines in each car is severely reduced through additional brake and gear wear. Formally, we specify our two-stage least squares (2SLS) model as follows:

$$P_{idwy} = \alpha + \beta STR_{idwy} + \gamma_d + \delta_w + \eta_y + \theta_i + \varepsilon_{idwy} \qquad \text{First stage} \tag{2}$$

$$H_{idwy} = \alpha + \lambda \hat{P}_{idwy} + \gamma_d + \delta_w + \eta_y + \theta_i + \mu_{idwy} \qquad \text{Second stage} \tag{3}$$

where H_{idwy} denotes the outcome variable, P_{idwy} is the endogenous air pollutant concentration represented by PM_{10} in our core specification, whereas STR_{idwy} is the strike dummy variable equal to unity when a strike is in effect and zero otherwise and $\hat{P}_{idwy}$ is the first stage predicted value of PM_{idwy}. We also include the same set of controls as in our baseline OLS model specification (Equation 1) to address potential threats to our identification strategy which may affect air pollution on strike days for reasons other than strikes being in effect. All estimates are weighted by municipality population size, while

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standard errors are clustered at the municipality level to allow for correlation between municipalities exposed to similar levels of air pollution concentrations (Cameron and Miller, 2015)[14]. To support our identification strategy, in Section 5.5 we present an extensive set of falsification tests as well as alternative model specifications.

5 Results

5.1 OLS estimates

We begin by presenting in Table 6 the OLS estimates of the effects of PM10 on hospitalizations. In column (1) we report the most parsimonious model specification, with time and municipality fixed effects, which are augmented in the next three columns with dummies for holidays (column (3)) and weather controls (columns (2 and 4)).

Table 6: OLS estimates on the effect of PM_{10} on respiratory disease.

	(1) Respiratory (all patients)	(2) Respiratory (all patients)	(3) Respiratory (all patients)	(4) Respiratory (all patients)
PM_{10}	-0.007 [0.040]	-0.011 [0.050]	-0.007 [0.040]	-0.010 [0.050]
CONTROL (weather)		YES		YES
CONTROL (holiday)			YES	YES
TIME FEs	YES	YES	YES	YES
MUNICIPALITY FEs	YES	YES	YES	YES
N	121,545	121,545	121,545	121,545

$^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$

Notes: The numbers refer to an initial sample of 403,861 urgent respiratory hospital admissions defined in the primary diagnosis and to a population of 54,012,341 individuals distributed across 111 municipalities over 1095 days. All regressions include day-of-week, week-of-year, year and municipality fixed effects. Additional controls include dummies for school and public holidays as well as weather controls (5-degree bins for average temperature, amount of precipitation and wind speed). Standard errors (in parentheses) are clustered at the municipality level. Estimates are weighted by municipality population size.

The OLS estimates show noise and no statistically significant effect of PM_{10} on hospital admissions. As explained earlier in Section 4, our baseline model suffers from severe underestimation because of different sources of bias. This evidence is largely consistent with several studies that deal with causal estimates of the effect of air pollution on health (Deryugina et al., 2016, Dominici et al., 2003, Goldman et al., 2011, Halliday et al., 2015, Künzli and Tager, 1997, Sheppard et al., 2012).

[14] We also test alternative weights including the number of hospitalizations at the municipality level. These strategies lead to similar results, which are available upon request.

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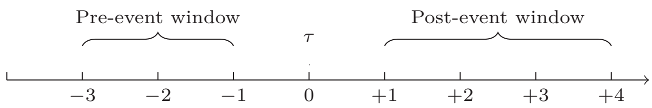
5.2 IV estimates

5.2.1 Public transportation strikes and PM_{10}

In order to understand the dynamics between PT strikes and air pollution, we graphically present the evidence of the first-stage relationship between PM_{10} and PT strikes in an event study framework. We thus augment our empirical strategy presented in Equation 2 with distributed lags and leads constructed according to Figure 5. PT strikes are indexed on time scale τ, defining $\tau = 0$ as the event date, $\tau = [-3, -1]$ as the pre-event window and $\tau = [+1, +4]$ as the post-event window, as shown in the timeline in Figure 5.

Figure 5: Timeline for the event study



We frame the actual timing of each strike on this synthetic timeline and estimate the following reduced-form equation:

$$P_{idwy} = \sum_{\tau=-3|\tau\neq-1}^{4} \beta_\tau PT_\tau + \gamma_d + \delta_w + \eta_y + \theta_i + \varepsilon_{idwy} \tag{4}$$

where P_{idw} denotes the endogenous PM_{10} concentrations, $\tau = [-3, +4]$ represents the time scale, with $\tau = 0$ corresponding to PT strike days, and γ_d, δ_w, η_y and θ_i are a set of fixed effects as described in Equation 2 and Equation 3. Finally, ε_{idwy} is an idiosyncratic error term.

On a PT strike day ($\tau = 0$), we observe an average increase of 1.5 $\mu g/m^3$ in PM_{10} and a decline in the days following the strike event. These results are obtained using the sample of all municipalities where a strike event takes place (see Section 3.3) and are consistent with the first-stage results performed on the entire sample of the 111 administrative municipalities. Indeed, in our core IV specification presented in Table 7, we find that PT strikes lead to an average increase in PM_{10} of 1.20 $\mu g/m^3$ (column (1)).

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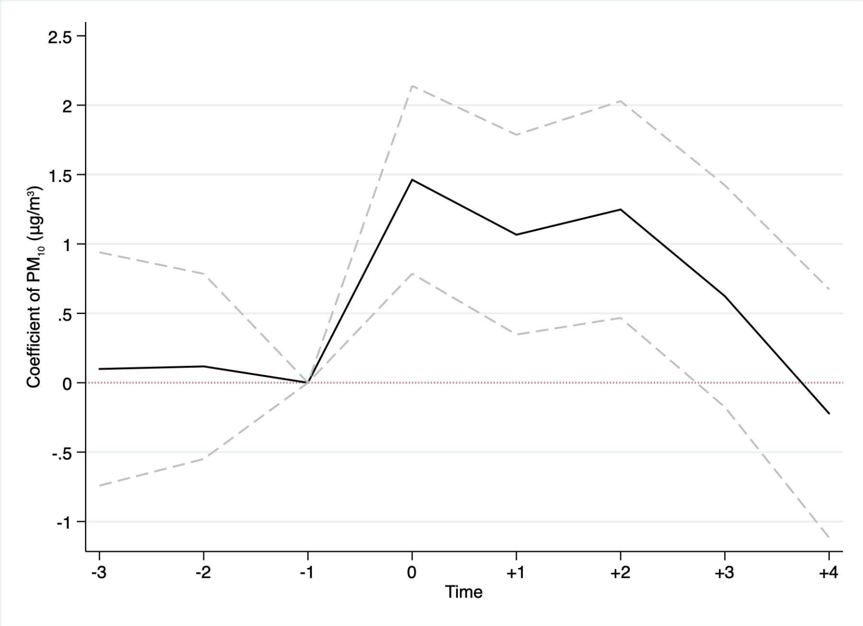
Figure 6: The effects of PT strikes on PM_{10} in an event study framework.



Notes: The figure presents coefficient estimates from Equation 4. We regress the daily PM_{10} concentrations on a PT strikes indexed in event time $\tau = 0$, controlling for municipality fixed effects and time fixed effects (day-of week, week-of-year and year). The estimates are weighted by municipality population size. The dashed lines represent 95 percent confidence intervals. Standard errors are clustered at the municipality level. The results refer to 4,156 observations covering 72 municipalities for 470 strike events.

In qualitative terms, our first stage estimates are in line with the generalized differences-in-differences estimates of Bauernschuster et al. (2017) who show that strikes have a significant and positive effect on PM_{10} concentration peaks. It is important to stress that the authors find a greater increase in PM_{10} levels on strike days (5 $\mu g/m^3$ on peak hours), but their results refer to more rare and harsh strike events occurring in Germany, as opposed to more frequent and less stringent Italian strike episodes. Our results are also robust to alternative model specifications when we control for holidays (column (3) and (4)) and weather conditions (column (2) and (4))[15]. These controls may be useful since on rainy days individuals may modify their daily activities, thus being less affected by strikes (Bauernschuster et al., 2017). However, heavier traffic congestion experienced on sunny strike days may generate higher pollution concentrations than those on rainy strike days[16]. In line with our expectations, when including these controls the magnitude of our first-stage coefficient estimates for PM_{10} slightly decreases. In the most demanding specification where both dummies for public and school holidays and weather controls are included (column (4)), the PM_{10} coefficient decreases to 1.01 $\mu g/m^3$ but still maintains full statistical significance.

[15]The first-stage F-statistics coefficients (calculated using the Cragg-Donald F-test) are well above 10 according to the rule-of-thumb proposed by Staiger and Stock (1997) and Stock and Yogo (2002).

[16]Rain has an attenuation effect of particle pollution concentrations due to its ability to clean the air by way of the "wash-out" effect (Ardon-Dryer et al., 2015, Guo et al., 2016).

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Table 7: First Stage estimates of the effect of PT strikes on PM_{10} concentration.

	First stage			
	(1)	(2)	(3)	(4)
Panel A.	PM_{10}	PM_{10}	PM_{10}	PM_{10}
PT Strike	1.20***	1.05***	1.12***	1.01***
	[0.30]	[0.31]	[0.30]	[0.32]
CONTROL (weather)		YES		YES
CONTROL (holiday)			YES	YES
TIME FEs	YES	YES	YES	YES
MUNICIPALITY FEs	YES	YES	YES	YES
F-stat	28.821	25.037	25.239	23.264
N	121,545	121,545	121,545	121,545

$^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$

Notes: All regressions include day-of-week, week-of-year, year and municipality fixed effects. Additional controls include dummies for school holidays and public holidays as well as weather controls (5-degree bins for atmospheric temperature, amount of precipitation and wind speed) are clustered at the municipality level. PT Strike is the strike dummy variable equal to unity when a strike is in effect and zero otherwise. Estimates are weighted by municipality population size.

5.2.2 Effects of PM_{10} on respiratory hospitalizations

Table 8 reports second stage coefficients (Panel A) and associated semi-elasticities (Panel B). Unlike the baseline OLS model presented in 5.1, the quasi-experimental estimates show a positive and statistically significant relationship between PM_{10} and the number of hospitalizations for urgent respiratory problems. Panel A (column 1) shows that one additional unit of $\mu g/m^3$ in PM_{10} increases the number of urgent respiratory admissions by 0.05 units per 100,000 residents. Similarly, a one standard deviation (s.d.) increase, which corresponds approximately to a10.3 $\mu g/m^3$ increase in PM_{10}, results in a 26% increase in respiratory hospitalizations. The coefficient estimates preserve both magnitude and statistical significance also in the most demanding specification (column 4), where both dummies for public and school holidays as well as weather variables are included.

Our results on hospitalizations are 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 in magnitude than those obtained from less precise identification strategies. Of the studies providing causal estimates of particle pollution, perhaps the most comparable is the one by Halliday et al. (2015), who find that a unit increase in PM_{10} causes a 5.7% increase in ER admissions which, in our case, amounts to 2.6%. Such a difference is likely to result from the fact that Halliday et al. (2015) analyze the impact of volcanic particle pollution, whereas our estimates relate to smog. The authors offer a broad discussion on possible differences between pollution originating from various sources and regions, concluding that direct comparisons of relative toxicity of PM are likely to depend on other general characteristics of the local industrial activity, weather, concomitant air pollutants and other factors.

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Although less comparable, the study by Ward (2015) finds that a one s.d. increase in PM concentration causes a 4% increase in children hospitalization. A direct comparison of our results with other studies is difficult since we address contemporaneous health problems, whereas most literature focuses on mortality which captures only the most severe manifestation of health issues, at least in terms of day-to-day air pollution fluctuations.

Table 8: IV estimates of the effect of PM_{10} on respiratory disease (all patients)

	(1) Respiratory (all patients)	(2) Respiratory (all patients)	(3) Respiratory (all patients)	(4) Respiratory (all patients)
Panel A - Marginal effects:				
PM_{10}	0.0527***	0.0599**	0.0523***	0.0578**
	[0.0174]	[0.0232]	[0.0190]	[0.0239]
Panel B - Semi-elasticities:				
PM_{10}	0.0257***	0.0293***	0.0255***	0.0282**
	[0.00846]	[0.0113]	[0.00921]	[0.0116]
CONTROL (weather)		YES		YES
CONTROL (holiday)			YES	YES
TIME FEs	YES	YES	YES	YES
MUNICIPALITY FEs	YES	YES	YES	YES
N	121,545	121,545	121,545	121,545

$^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.
Notes: The numbers refer to an initial sample of 403,861 urgent respiratory hospital admissions defined in the primary diagnosis and to a population of 54,012,341 individuals distributed across 111 municipalities over 1095 days. All regressions include day-of-week, week-of-year, year and municipality fixed effects. Additional controls include dummies for school holidays and public holidays as well as weather controls (5-degree bins for atmospheric temperature, amount of precipitation and wind speed) are clustered at the municipality level. Estimates are weighted by municipality population size.

5.3 Heterogeneous effects of PM_{10} on respiratory hospitalizations

The results discussed so far refer to the overall population, without accounting for heterogeneity in how exposure to air pollution shocks affects individual health. As discussed earlier, there is evidence that the adverse health effects of air pollution are stronger for the very young and the elderly. Indeed, childhood and adolescence are periods of rapid growth during which organ systems are particularly susceptible to health shocks (Beatty and Shimshack, 2014, Mudway et al., 2018, Schwartz, 2004), whereas in elderly people, co-existing chronic disease together with a cumulative exposure to air pollution, increases susceptibility, hospitalization and the risk of mortality (Janke et al., 2009, Simoni et al., 2015).

An important contribution made by our paper is that we extend the analysis of heterogeneous effects of air pollution to disadvantaged socio-economic groups. If lower education and lower income generate weaker health endowment, any additional health shock suffered by disadvantaged individuals is likely to give rise to greater health damage (Forastiere et al., 2007b, Neidell, 2004, O'Neill et al., 2003, among others). A quantification of these differentials is pivotal from a policy perspective since in universal healthcare systems which are adopted by many European countries, the financial burden of air pollution

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damage is directly transferred to public finance with a larger burden on healthcare expenditures. We therefore isolate distinct groups of population, based on their age class, education attainment and migrant status, and evaluate whether the relative health penalties deriving from similar exposure to air pollution are intrinsically different. In order to quantify these differences in relation to PM_{10}, we aggregate hospital admissions into five age-specific bins, and create distinct outcome measures, i.e. the count of admissions for 100,000 residents in each age group. Table 9 presents second-stage results for five age subgroups separately following Equation 3, weighted by the size of municipality population for each age group.

Table 9: IV estimates of the effect of PM_{10} on respiratory diseases in different age groups.

	Respiratory (1)	Respiratory (2)	Respiratory (3)	Respiratory (4)
Panel A: ages below 14				
PM_{10}	0.042	0.048	0.049	0.055
	[0.070]	[0.082]	[0.074]	[0.084]
Panel B: ages 15 - 24				
PM_{10}	0.072*	0.082	0.0740	0.082
	[0.041]	[0.053]	[0.045]	[0.055]
Panel C: ages 25 - 44				
PM_{10}	0.029**	0.033*	0.030*	0.034*
	[0.014]	[0.018]	[0.016]	[0.019]
Panel D: ages 45 - 64				
PM_{10}	-0.007	-0.008	-0.011	-0.012
	[0.015]	[0.017]	[0.016]	[0.018]
Panel E: ages 65 and above				
PM_{10}	0.167***	0.191***	0.165***	0.183***
	[0.050]	[0.060]	[0.053]	[0.062]
CONTROL (weather)		YES		YES
CONTROL (holiday)			YES	YES
TIME FEs	YES	YES	YES	YES
MUNICIPALITY FEs	YES	YES	YES	YES
N	121,545	121,545	121,545	121,545

$^{***}p < 0.01,^{**}p < 0.05,^{*}p < 0.1$.

Notes: The numbers refer to an initial sample of 403,861 urgent respiratory hospital admissions defined in the primary diagnosis and to a population of 54,012,341 individuals distributed across 111 municipalities over 1095 days. All regressions include day-of-week, week-of-year, year and municipality fixed effects. Additional controls include dummies for school holidays and public holidays as well as weather controls (5-degree bins for atmospheric temperature, amount of precipitation and wind speed) are clustered at the municipality level. Estimates are weighted by municipality population size by age group.

In Figure 7 we also present the results shown in Table 9 which account for the variability of the estimates due to the different number of ages that each age group includes. We do so by calculating the within effect of pollution for a given group, following Halliday et al. (2015): effects/(no. of ages in group)×1000, where higher values indicate larger effects. We observe an increase of 0.17 admissions (statistically significant at 1%) in the number of urgent respiratory cases for individuals aged 65 and over, for 1 $\mu g/m^3$ increase in PM_{10}. If this coefficient is scaled up to s.d., the effect amounts to 1.8 additional daily admissions for a one s.d. increase in PM_{10}. Interestingly, we also find significant and positive effects also in young adults, with a one s.d. increase in PM_{10} causing 0.75 additional urgent admissions. The adjusted estimates in Figure 7 show that young adults are disproportionately affected by particle pollution, with the penalization per year of age being larger than the one for the elderly as a

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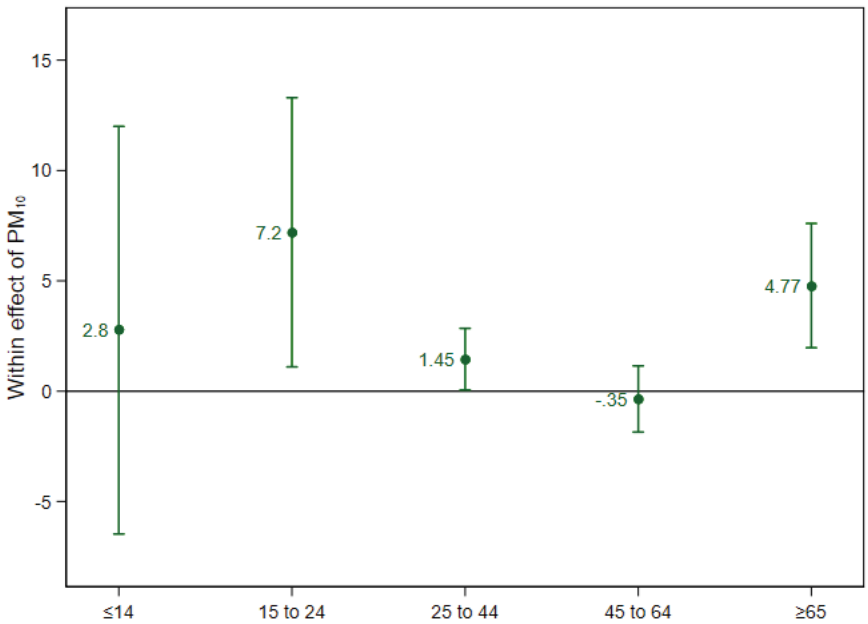
whole. A possible explanation channel for the magnitude of this result is likely to be related to lifestyle patterns of the young. As discussed earlier, according to official statistics (Istat, 2013), 73.1% of Italian individuals aged between 15 and 24 are engaged on a daily basis in commuting with public transportation or walking. If one accounts for the additional amount of time spent outdoors in relation to other daily activities, the exposure to air pollution concentrations for this age group is larger and persistent.

Figure 7: IV estimates of the effect of PM_{10} in different age groups.



Notes: The within effect of PM_{10} for a given age group is calculated following Halliday et al. (2015): effect/(no. of ages in group)×1000. Confidence intervals are set to 95%.

While age-related responses to adverse health shocks have been more frequently studied in the existing literature, there are other important mechanisms related to individual vulnerability to air pollution. Socio-economic disadvantage, as represented by education or income, has long been linked to higher infant mortality, shorter lives, higher smoking and obesity rates, propagating overall health inequality (Forastiere et al., 2007b, O'Neill et al., 2003, among others). As far as environmental aspects are potentially affected by public policy, the related health inequalities represent consequences of differences that are largely beyond individual control (Neidell, 2004, among others). In order to offer a deeper understanding of the unequal health response to air pollution, we also estimate the effects in relation to SES proxied by educational attainment. Our estimates in Table 10 show a particularly pronounced effect of PM_{10} on urgent admissions among individuals with primary education attainment, in particular, a one s.d. increase in PM_{10} leads to one additional increase in the number of respiratory hospitalizations (statistically significant at 1%). The same estimates are weaker in both statistical significance and magnitude in the case of secondary attainment. For individuals with tertiary education, additional PM_{10}

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concentrations induced by public PT strikes are no longer responsible for any increase in urgent respiratory admissions. Under the assumption that our IV estimates are not biased by avoidance behavior (see Section 4), the mechanisms driving these differentials are plausibly linked to a better overall health status of individuals with the highest education level which downplays the adverse effects of daily fluctuations in PM_{10} concentrations.

Table 10: IV estimates of the effect of PM_{10} on respiratory disease by educational attainment.

	Respiratory (1)	Respiratory (2)	Respiratory (3)	Respiratory (4)
Panel A: Primary ed. lev.				
PM_{10}	0.094***	0.108**	0.095**	0.106**
	[0.036]	[0.047]	[0.039]	[0.049]
Panel B: Secondary ed. lev.				
PM_{10}	0.032**	0.036**	0.032**	0.035*
	[0.014]	[0.017]	[0.015]	[0.018]
Panel C: Tertiary ed. lev.				
PM_{10}	-0.002	-0.003	-0.005	-0.006
	[0.030]	[0.034]	[0.033]	[0.035]
CONTROL (weather)		YES		YES
CONTROL (holiday)			YES	YES
TIME FEs	YES	YES	YES	YES
MUNICIPALITY FEs	YES	YES	YES	YES
N	121,545	121,545	121,545	121,545

$^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

Notes: The numbers refer to an initial sample of 403,861 urgent respiratory hospital admissions defined in the primary diagnosis and to a population of 54,012,341 individuals distributed across 111 municipalities over 1095 days. All regressions include day-of-week, week-of-year, year and municipality fixed effects. Additional controls include dummies for school holidays and public holidays as well as weather controls (5-degree bins for atmospheric temperature, amount of precipitation and wind speed) are clustered at the municipality level. Estimates are weighted by municipality population size by age group.

Finally, we address the disparities in the adverse impact of air pollution on health for migrants. The results are shown in Table 11 and point to non-significant effects of PM_{10} on urgent respiratory hospitalizations when considering foreign citizens from countries with a low-middle and high income based on the World Bank classification (see Section 3).

Since the former group aggregates countries with substantially different socio-demographic characteristics, we provide a deeper analysis focusing on the sole group of African migrants who mainly come from Morocco, Egypt, Nigeria, Senegal and Tunisia and represent the vast majority of low-income migrants in Italy. Although only weakly statistically significant, this particular group of nationalities seems to be adversely affected by air pollution, with one additional s.d. increase in PM_{10} causing 0.30 additional admissions. When interpreting the coefficient estimate, it is important to underline that the number of daily hospitalizations for migrants is, on average, much lower than the one for the general population, namely 0.30 vis-à-vis 2.05. Air pollution penalization is thus disproportionally 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 have limited access to healthcare. Due to normative regulations,

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full healthcare coverage in Italy is only granted to foreign citizens once they have registered with national healthcare service (SSN) which is not guaranteed without formal residency. Since these foreign citizens often live in informal rentals or illegally sublet, they often face difficulties in obtaining the residency status which also provides access to healthcare coverage. As a result, hospital admissions of migrants that we observe in the data may represent a severe underestimation of the actual healthcare demand. Indeed, the omitted unobserved healthcare needs of irregular migrants may be much larger than the one observed in our administrative data. We thus argue that our estimates can be interpreted as a lower bound of the true causal effect and, at the same time, we caution against taking this result as conclusive and definitive.

Table 11: IV estimates of the effect of PM_{10} on respiratory diseases for migrants from different groups of origin countries.

	Respiratory (1)	Respiratory (2)	Respiratory (3)	Respiratory (4)
Panel A: High income Countries				
PM_{10}	0.003	0.003	0.003	0.003
	[0.010]	[0.010]	[0.010]	[0.011]
Panel B: Low-middle income Countries				
PM_{10}	0.016	0.017	0.016	0.017
	[0.018]	[0.020]	[0.019]	[0.021]
Panel C: African countries				
PM_{10}	0.026*	0.029*	0.027*	0.029*
	[0.014]	[0.016]	[0.015]	[0.017]
CONTROL (weather)		YES		YES
CONTROL (holiday)			YES	YES
TIME FEs	YES	YES	YES	YES
MUNICIPALITY FEs	YES	YES	YES	YES
N	121,545	121,545	121,545	121,545

$^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.
Notes: The numbers refer to an initial sample of 403,861 urgent respiratory hospital admissions defined in the primary diagnosis and to a population of 54,012,341 individuals distributed across 111 municipalities over 1095 days. All regressions include day-of-week, week-of-year, year and municipality fixed effects. Additional controls include dummies for school holidays and public holidays as well as weather controls (5-degree bins for atmospheric temperature, amount of precipitation and wind speed) are clustered at the municipality level. Estimates are weighted by municipality population size by age group.

5.4 Health costs of air pollution

In this last part of the analysis we focus on the quantification of costs relative to the strike-induced increases in PM concentrations. Costs are the ultimate policy parameter and the recent literature has increasingly focused on their quantification (see Section 2. We expand the analysis of the health consequences of air pollution by measuring hospitalization complexity proxied by AUC which represents a novel policy parameter for an optimal design of environmental and health policies. While the impact of PM on the number of admissions can be seen as the extensive margin of the effect of air pollution on healthcare utilization, the complexity of hospitalizations represents the intensive margin.

Table 12 shows the impact of PM_{10} on four outcomes referring to AUCs of an urgent hospital ad-

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mission with the primary diagnosis related, respectively, to any respiratory problem, asthma, pneumonia and COPD. While we find no statistically significant effects on the complexity in the overall group of respiratory problems, in the case of hospitalization admissions for asthma, one additional $\mu g/m^3$ in PM_{10} concentration increases the relative unit cost by 133 euros which represents 8.1% of the AUC of asthma episodes. We find no effect on the complexity of urgent admissions for pneumonia. This seems to be in line with the clinical literature which has frequently shown the association between long-term exposure to air pollution and pneumonia, but evidence on the contemporaneous effects is scant (Ji et al., 2017). On the contrary, we find a detrimental impact of PM_{10} concentrations on COPD costs, with a one $\mu g/m^3$ increase leading to a rise in admission costs of an additional 45 euros, which represents a 1.8% increase compared with the COPD AUC. This set of results leads us to conclude that exposure to higher PM_{10} concentrations is not only responsible for a greater number of hospitalizations, but it also increases the complexity, hence costs, of admissions for asthma and COPD, two important and largely diffused respiratory diseases. The heterogeneous evidence across various admission types is closely related to what the clinical literature points to (DeVries et al., 2016, GBD et al., 2017). Moreover, the impact of PM on admission complexity suggests that previous studies analyzing the sole expenditures deriving from the increase in the number of hospitalizations are likely to underestimate the health costs of particle pollution.

Table 12: IV estimates of the effect of PM_{10} on average unit costs for hospital admissions for four distinct respiratory problems.

	Unit Cost (All respiratory)	Unit Cost (Asthma)	Unit Cost (Pneumonia)	Unit Cost (COPD)
PM_{10}	12.66	133.0*	3.878	44.73*
	[12.81]	[74.96]	[27.24]	[22.76]
TIME FEs	YES	YES	YES	YES
MUNICIPALITY FEs	YES	YES	YES	YES
N	121,545	121,545	121,545	121,545

$^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

Notes : The numbers refer to an initial sample of 403,861 urgent respiratory hospital admissions defined in the primary diagnosis and to a population of 54,012,341 individuals distributed across 111 municipalities over 1095 days. All regressions include day-of-week, week-of-year, year and municipality fixed effects and standard errors are clustered at the municipality level. Estimates are weighted by municipality population size by age group.

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Table 13: IV estimates of the effect of PM_{10} on total health expenditure costs for respiratory hospital admissions.

	Cost (1)	Cost (2)	Cost (3)	Cost (4)
Panel A - Marginal effects:				
PM_{10}	180.6***	205.9**	180.5***	200.0**
	[61.2]	[78.6]	[66.6]	[81.1]
CONTROL (weather)		YES		YES
CONTROL (holiday)			YES	YES
TIME FEs	YES	YES	YES	YES
MUNICIPALITY FEs	YES	YES	YES	YES
N	121,545	121,545	121,545	121,545

$^{***}p < 0.01,^{**} p < 0.05,^{*} p < 0.1$.
Notes : The numbers refer to an initial sample of 403,861 urgent respiratory hospital admissions defined in the primary diagnosis and to a population of 54,012,341 individuals distributed across 111 municipalities over 1095 days. All regressions include day-of-week, week-of-year, year and municipality fixed effects. Additional controls include dummies for school holidays and public holidays as well as weather controls (5-degree bins for atmospheric temperature, amount of precipitation and wind speed) are clustered at the municipality level. Estimates are weighted by municipality population size.

Finally, considering both extensive and intensive margins, we estimate the effect of PM on total per capita healthcare costs. Table 13 shows that a daily increase of one $\mu g/m^3$ in PM_{10} is associated with an additional 180 euros per 100,000 individuals. If scaled up to s.d., these figures correspond to 32% of the average daily expenditure on urgent respiratory admissions.

Moreover, in Table 14 we deliver the same set of results based on age groups, showing that the cost resulting from air pollution is unequally distributed across various age groups. These estimates are in line with the implications concerning the extensive margin presented in Table 9. In particular, we find that a daily increase of one $\mu g/m^3$ in PM_{10} causes an additional 340 euros per 100,000 individuals aged between 15 and 24 years old. For hospitalizations of individuals aged between 25 and 64, the results are slightly weaker in magnitude though still statistically significant. Finally, we find the largest effect for the elderly, with one additional $\mu g/m^3$ of PM_{10} causing an increase of 608 euros per 100,000 individuals.

Table 14: IV estimates of the effect of PM_{10} on total health costs for respiratory hospital admissions by age groups.

	Respiratory (0-14)	Respiratory (15-24)	Respiratory (25-44)	Respiratory (45-64)	Respiratory (65-100)
PM_{10}	70.9	338.6**	111.7*	126.0	608.6***
	[104.3]	[148.7]	[62.3]	[76.5]	[193.4]
TIME FEs	YES	YES	YES	YES	YES
MUNICIPALITY FEs	YES	YES	YES	YES	YES
N	121,545	121,545	121,545	121,545	121,545

$^{***}p < 0.01,^{**} p < 0.05,^{*} p < 0.1$.
Notes: The numbers refer to an initial sample of 403,861 urgent respiratory hospital admissions defined in the primary diagnosis and to a population of 54,012,341 individuals distributed across 111 municipalities over 1095 days. All regressions include day-of-week, week-of-year, year and municipality fixed effects and standard errors are clustered at the municipality level. Estimates are weighted by municipality population size by age group.

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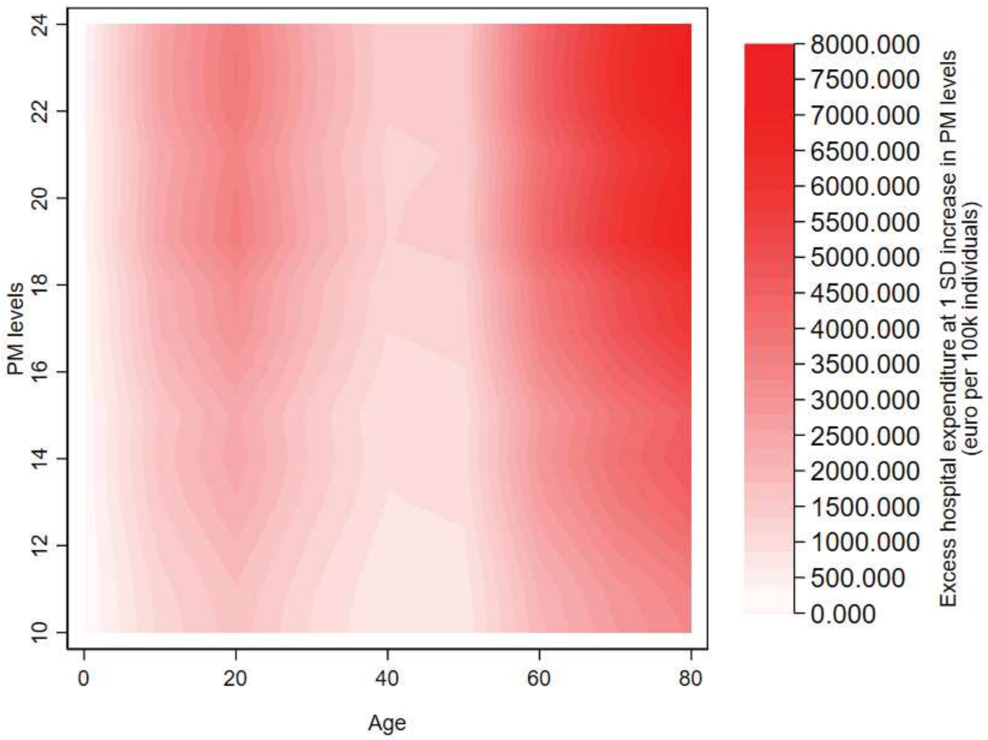
To better appreciate the heterogeneity of the total costs for urgent respiratory hospital admissions resulting from PM_{10} exposure, in Figure 8 we plot excess hospital expenditures relative to a one s.d. increase in PM_{10} at the municipality level. More specifically, for each municipality we obtain predictions from the age-specific model estimates (Table 14), computed at one s.d. of PM_{10} and demographic structure as observed in 2015. We smooth out the predictions on a regular grid of age/s.d. combinations. The resulting figure is structured as a heat map, where red tones signal higher excess expenditure levels[17]. The overall reading of the figure shows how different ages, in combination with different PM_{10} concentrations, deliver similar health costs. For instance, a one s.d. increase in PM_{10} among young individuals aged between 15 and 24 in the least polluted municipalities is responsible for comparable healthcare costs faced by middle-aged individuals exposed to the highest PM_{10} levels. The highest cost is accumulated for young adults at pronounced levels of PM_{10}, and the elderly.

Figure 8: Heat map of excess hospitalization costs for urgent respiratory problems by age and PM_{10} level.



Based on these results, we carry out back-of-the-envelope calculations of total daily monetary extra costs of PM for the 17.8 million residents in the 111 municipalities considered which amount to 332,000 euros for a one s.d. increase in PM_{10}; this accounts for approximately 0.37% of total public health

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

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expenditure in Italy. Overall, our quantification of health cost burden still represents a lower bound of the total health costs since it does not account for the long run and cumulative effects of pollution on health. Moreover, day-to-day fluctuations in hospital admissions do not account for individuals who experience less severe health issues related to pollution and limit themselves to seeing their primary care physician or staying home sick. However, the costs of hospital care represent an important policy parameter since health expenditures devoted to hospital admissions represent approximately 60% of the national healthcare budget in Italy and are the least cost-effective healthcare service.

5.5 Robustness checks

In addition to the main set of estimates presented above, we carry out a number of sensitivity checks to warrant the robustness of our empirical findings. To begin with, we examine the reduced form (RF) of the 2SLS model, which estimates the direct effect of PT strikes on urgent respiratory hospitalizations, to further explore potential mechanisms driving our main results on hospitalization outcomes. We then run our model specifications on a finer particulate matter, $PM_{2.5}$, which provides a valid setting for a robustness check of all the estimates proposed in terms of PM_{10}. We then develop a number of parallel tests. We first switch the treatment variable, then the outcomes and finally, the treatment assignment. Then, we alter our identification strategy by addressing multi-day strike episodes, municipality level demand for public transportation and a larger estimation sample including all the Italian municipalities. Moreover, in order to validate the use of pollution reanalysis data, we benchmark our analysis with estimates based on PM measurements from monitoring stations. We also check the sensitivity of our analysis to alternative weighting schemes. In addition, we correct our findings for multiple hypotheses testing. Finally, we run our IV estimates in a Poisson regression setting. All these tests consistently point to a correct identification strategy and validate our main results.

Reduced form analysis

The analysis of the reduced form (RF) is not only useful as a robustness test of weak identification (Chernozhukov and Hansen, 2008), but it also provides an important policy parameter (Heissel et al., 2019) since it represents the increase in urgent respiratory hospitalizations caused by the overall increase in air pollution emitted by vehicles on PT strike days. The RF estimates are obtained by the following model specification:

$$H_{idwy} = \alpha + \beta STR_{idwy} + \gamma_d + \delta_w + \eta_y + \theta_i + \varepsilon_{idwy}, \tag{5}$$

where the parameter of interest is β, which provides the causal effect of PT strikes on respiratory hospital-

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izations in all the 111 Italian municipalities. The effects are presented in Table 15 and are approximately only 2% larger than our second stage estimates on PM_{10} in the most demanding specification. As discussed also in Lavaine and Neidell (2017), a reasonable explanation is that β in Equation 5 is also likely to capture residual effects of other pollutants such as NO_2 and CO in addition to PM[18]. Unfortunately, data on NO_2 and CO not available for the period and municipalities covered in the analysis, which limits the possibility of testing the impact of PT strikes on other pollutants. Another important PM emission source is central heating in buildings. However, in addition to being uncorrelated with PT strikes, the variation in heating emissions is highly seasonal and well controlled for by including fixed effects.

Table 15: Reduced Form Estimates of the Effect of PT Strikes on Respiratory Hospitalizations.

	(1) Respiratory (all patients)	(2) Respiratory (all patients)	(3) Respiratory (all patients)	(4) Respiratory (all patients)
PT Strike	0.063***	0.063***	0.059***	0.059***
	[0.016]	[0.016]	[0.016]	[0.016]
Weather		YES		YES
Holidays			YES	YES
TIME FEss	YES	YES	YES	YES
MUNICIPALITY FEss	YES	YES	YES	YES
N	121,545	121,545	121,545	121,545

$^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$

Notes: The numbers refer to an initial sample of 403,861 urgent respiratory hospital admissions defined in the primary diagnosis and to a population of 54,012,341 individuals distributed across 111 municipalities over 1095 days. All regressions include day-of-week, week-of-year, year and municipality fixed effects. Additional controls include dummies for school holidays and public holidays as well as weather controls (5-degree bins for atmospheric temperature, amount of precipitation and wind speed). Standard errors (in parentheses) are clustered at the municipality level. Estimates are weighted by municipality population size.

Effects of finer particulate matter ($PM_{2.5}$)

The existing literature investigating the causal link between PM and health focuses by and large on PM_{10}, which represents a widespread measurement of particle pollution with precise policy indications in terms of daily/annual concentration limits. Nonetheless, epidemiological studies signal that finer PM is able to produce more harmful effects given its capacity to penetrate deeper into the lungs and blood stream as well as reach indoor building environments (Chang et al., 2016). In the spirit of Arceo et al. (2016), we offer a validity check for our main set of results pertaining to PM_{10} by running all model specifications also for $PM_{2.5}$, a pollutant for which no daily concentration limit currently exists in Europe. When presenting these results, we benchmark the estimates obtained for $PM_{2.5}$ with those obtained for PM_{10}. Figure 9 and Figure 10 show the estimates by age groups and educational attainments, while we additionally show the full set of estimates for $PM_{2.5}$ in Table A4 in Appendix A.

[18]Total emissions in urban road transport are mainly driven by PM, NO_2 and CO. According to the regional emissions inventory of Milan, one of the largest Italian cities, approximately 68% of NO_2, 45% of PM (including both exhaust and non-exhaust particulate) and 57% of CO emissions are generated by the transport sector (ARPA, 2016).

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Figure 9: IV estimates of the marginal effects of PM_{10} and $PM_{2.5}$ on respiratory diseases by age groups.

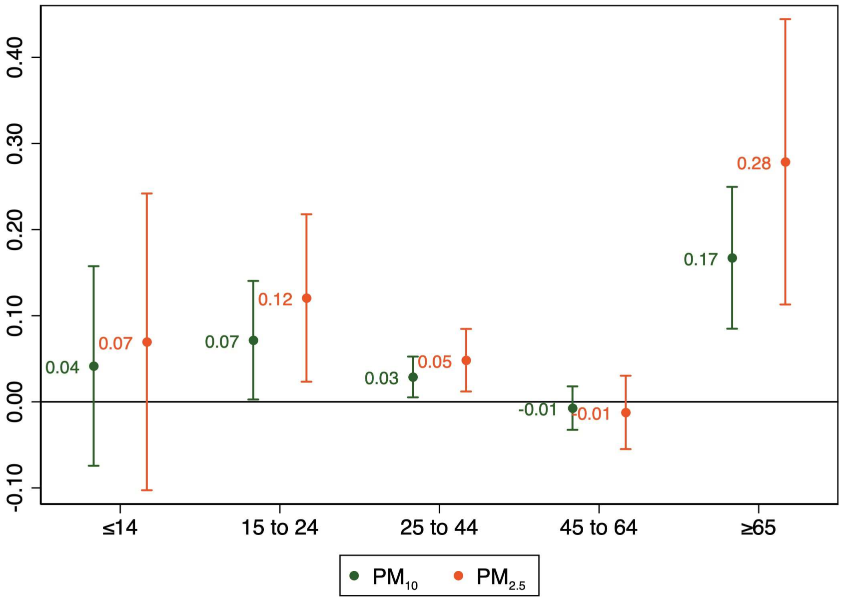
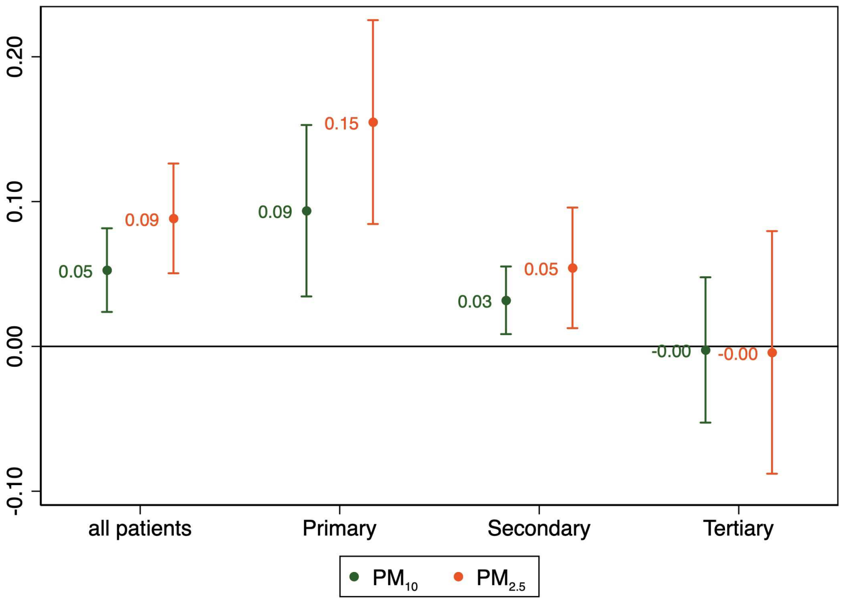


Figure 10: IV estimates of the marginal effects of PM_{10} and $PM_{2.5}$ on respiratory diseases by educational attainment.



As presented in Table A4 in Appendix A, the adverse health effects of $PM_{2.5}$ are stronger than those for PM_{10}, with one additional unit of $PM_{2.5}$ causing a 0.09 increase in urgent respiratory admissions which amounts to a 5.44% increase in hospitalization. This is in line with the results obtained by Halliday et al. (2015) who consider volcanic fine PM and find an increase of 7% for a one $\mu g/m^3$ increase. Also in the case of $PM_{2.5}$, the results are heterogeneous across ages and education attainment groups (Figure 9 and Figure 10), in all cases being roughly 40% larger in magnitude than the effects of PM_{10}. Moreover,

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even though not fully comparable, our estimated effects for the elderly are also consistent with those obtained by Deryugina et al. (2016), who find that each additional $\mu g/m^3$ of $PM_{2.5}$ causes an increase in hospital admissions of 2.3 each million of population, whereas our calculation points to a 2.8 increase for the same age group[19].

Falsification of treatment - O_3 as a placebo pollutant

An important check for our identification strategy consists of exploiting pollutants that are not likely to be significantly affected by day-to-day fluctuations in traffic. We thus consider potential effects of strikes on O_3 as a placebo pollutant. As in subsection 5.2, in Figure B.6 we present the relationship between PT strikes and O_3 in an event study framework. We observe a non-statistically significant decrease of 0.75 $\mu g/m^3$ of ozone on strike days. As mentioned above, O_3 is indirectly generated by emission sources but it derives from a series of chemical reactions between substances present in the atmosphere (precursors) which are largely present in urban areas. However, we provide 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 higher O_3 concentrations following strong seasonal patterns (see Figure B.3). Hence, even when there is major traffic congestion, weather factors can strongly affect the formation of O3. Second, this pollutant has a life span of several days and, consequently, higher O3 concentrations can be found in regions distant from precursor emission sources because of wind. Third, several chemical O_3 destruction mechanisms existing in cities are absent from rural areas (Saitanis, 2003). Consequently, O_3 concentrations are often lower in urban areas where, on the contrary, 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 places, and peak in the afternoon. We estimate our baseline specification by substituting PM_{10} with O_3. The results are presented in Table A9 in Appendix A 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 not likely to be affected by air pollution. Out of the classification of Major Diagnostic Categories (MDCs), we include those that are the most likely to satisfy the exclusion restrictions of our IV strategy. 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 Table A10 in Appendix A 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 to test whether PT strikes

[19]To obtain this comparison, the last coefficient estimate in Figure 9 is scaled up to 1 million instead of 100,000.

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also affect programmed hospitalizations for pollution-induced diagnosis as well as urgent ones. We thus run our baseline model specification on a sample of 132,317 day-hospital programmed admissions for respiratory disease, singled out according to the primary diagnosis records. The resulting IV estimates are reported in Table A11 in Appendix A and point to no statistically significant effects of PM_{10} on elective cases examined. Taken together, the two falsification tests on the disease type and the admission type reinforce the choice of the identification strategy adopted in this study, confirming the PT strike as the mechanism through which urgent respiratory cases are affected by air pollution.

Falsification of IV assignment - Placebo strikes in non-affected 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 model estimation. The results are presented in Table A12 in Appendix A, showing no significant effects on PM_{10} in the non-affected cities.

Multi-day strikes and adapting response

Following Bauernschuster et al. (2017), we also test the effects of PT strikes lasting longer than one day across provincial county municipalities. We thus substitute our IV of one-day strikes with multi-day strike dummy variables. As shown in Table A13 in Appendix A, the first stage effect of multi-day strikes on pollution is weaker in magnitude than single-day strikes (0.94 instead of 1.20, both statistically significant at 1%). As discussed earlier, this result is in line with the hypothesis of attitudinal change in travel patterns after the first day of a strike since individuals are likely to adapt their response strategy 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 admissions 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} is likely to generate larger adverse effects on health if it persists over several days.

Estimates taking into account the per capita demand of PT

We also validate the robustness of our empirical strategy by considering the municipality-level per capita de- mand of PT. Per capita demand is measured by the number of passengers served by PT yearly in relation to the resident population. We construct a binary indicator variable equal to unity for the top-10 municipalities in terms of their dependence on PT (DPT_{idwy}). We exploit this variable in a dual way. We first interact the strike dummy with the high PT demand dummy variable ($STR_{idwy} \times DPT_{idwy}$) and estimate our model specification in the usual sample of municipalities (Table A14 in Appendix A). Second, we restrict our analysis to the 10 municipalities with the highest PT demand and, within the

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sample, estimate the effect of PM_{10} on urgent respiratory admissions (Table A15 in Appendix A). The first stage estimates show larger magnitude in both exercises, suggesting that the effect of STR on pollution is proportional to usage of the PT network. The second stage results show that the effect of one additional $\mu g/m^3$ of PM_{10} is slightly lower for larger PT networks. The result is likely to be driven by a number of confounding factors. For instance, larger PT networks, *ceteris paribus*, are likely to be associated with lower levels of PM from vehicle exhausts. In cumulative terms, one $\mu g/m^3$ of PM_{10} is likely to generate a narrower health penalty. It is however difficult to provide a precise mechanism that explains this differential.

Estimates on all Italian municipalities

Together with the robustness check presented above, we now offer an alternative to our baseline set of results by estimating our model specification by considering all Italian municipalities, including non-administrative small towns; we do so by constructing a balanced panel dataset for all the Italian municipalities. The numbers refer to an initial sample of 1,267,367 urgent respiratory hospital admissions defined in the primary diagnosis and to 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 table Table A16, confirm the results of our preferred specification using the sample of 111 administrative municipalities.

Estimates based on pollution data from monitoring stations

In order to validate the reanalysis air pollution data employed in our study, we offer a benchmarking exercise in which we replicate the baseline results using air pollution data from monitoring stations. As previously discussed, data from monitoring stations may suffer several limitations. Nevertheless, their use constitutes a standard practice in the existing literature (Janke, 2014, e.g.). We collect data from the European Environmental Agency (EEA) AirBase database, which includes concentration measures for the traffic-related pollutants and time span considered in our analysis. We aggregate the data by municipality and day in order to obtain concentration averages that are fully consistent with our original dataset. However, our final monitoring sample is limited to municipalities in which at least one station operates on a regular basis during the period of analysis, which results in 66 cities. Given this data limitation, in order to provide a vis-à-vis comparison, we also provide results of our IV framework using reanalysis data including the same sample of 66 administrative cities where monitoring stations are present. When multiple stations are present in the same municipality, we average the relative readings. Given the granular texture of Italian municipalities, we assume that the measurement error in pollution assignment is limited and allows for comparison with our original dataset [20]. In the baseline specification

[20] To give an order of magnitude, the average area of an Italian municipality is only 37.3 km^2, as derived from our own

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presented in Table A17 weight the estimates by the size of the municipality population[21]. Our findings, presented in Table A17 and Table A18, suggest that the effect of a strike is larger when PM is measured by monitoring stations which is likely to be driven by the higher concentration values measured by monitors (see Figure B.2 in Appendix B). On the contrary, the second stage results are smaller in magnitude and less statistically significant than those from our estimates using CAMS data. This warrants the hypothesis that the measurement error in the standard approach based on monitoring stations is not negligible when assigning air pollution exposure and constitutes serious attenuation bias.

Additional checks

Since our dependent variable is initially measured as hospital admissions counts counts in a given municipality on a given day, we also estimate an IV Poisson regression model (Cameron and Trivedi, 2013, Mullahy, 1997, Windmeijer and Santos Silva, 1997) to better 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 deriving from, e.g. zeros, in the dependent variable. The excess of zeroes is detected when the number of observed zeroes largely exceeds the number of zeroes reproduced by the fitted Poisson distribution (Mouatassim and Ezzahid, 2012). For the sake of completeness, we still provide the Poisson estimates. Following Deryugina et al. (2016), we include the residual from our Equation 2 (i.e. the effect of PT strikes on pollution) as control variable in Equation 3. In contrast with the baseline model, we do not employ weights. The results, available upon request, qualitatively confirm that respiratory diseases are sensitive to PM fluctuations as presented in Table 8.

We also test the robustness of our results by not including weights and using an alternative weighting scheme which includes the number of hospitalizations at municipality level instead of municipality population size. The results, available upon request, are fully consistent with those obtained using original weights.

The PT-strike induced mobility of workers may also constitute a concern in our empirical setting. If traffic congestion is likely to drive the demand for healthcare away from the affected areas, residents in administrative towns may be willing to access hospitals outside their residence area. If this is the case, we may face an underestimation of the treatment exposure, especially for the extensive margin of hospitalizations, since the actually treated individuals may access healthcare in areas not included in the 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 variable is unlikely to cause any sort of endogenous mobility since the out-of-town flows of residents are negligible and not correlated

calculations using ISTAT data.

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

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with any *ad-hoc* actions of individuals.

Finally, since different null hypothesis 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 testing multiple null hypotheses simultaneously in our dataset (Clarke, 2016, Romano and Wolf, 2016). Under this demanding criterion for testing the significance of our results, we observe that the effects of PM persist significantly. Again, this last set of evidence is available upon request.

6 Conclusions

In this study we provide a quasi-experimental investigation of the negative health effects of acute (short-term) exposure to PM_{10}. The causal effect of air pollution is identified by leveraging PT strike episodes occurring in specific city-day combinations that are able to generate traffic shocks with associated higher air pollution concentrations. Together with the extensive margin measured by the number of hospitalizations, we also quantify the intensive margin measured hospitalizations unit costs. Unit costs reflect the complexity of admissions, and represent an important policy parameter for which - to our knowledge - no other estimates are available.

In our full-sample estimates, we find that an increase in PM_{10} induced by PT strikes, leads to a higher number of hospitalizations for urgent cases of respiratory disease. Our data allow us to explore the heterogeneity of the effect by testing if air pollution disproportionately affects individuals with lower SES. By disentangling the impact through the lens of age, educational attainment and migrant status, we find that the young aged 15-24 and the elderly exposed to the same increase in PM_{10} generate similar hospitalization costs for urgent cases of respiratory disease. Moreover, the impact of air pollution is strongest for individuals with 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 detrimental effect of air pollution for migrants from low-income African countries.

Overall, our results show that the health effects of air pollution are disproportionally distributed and the penalties reflect the socio-demographic differences. This implies that policy makers should perceive air pollution not only as a technological issue, but also as a socio-economic phenomenon. Effective policies aimed at reducing air pollution should thus account for larger compensation mechanisms for more disadvantaged individuals. In addition, 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. Of these, we explicitly examine the role of age, education and broad marginalized conditions of migrants from low-income countries. Nonetheless, other important factors such as income, employment conditions, urban context and lifestyle remain unexplored and constitute an important research avenue.

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A pivotal part of our analysis refers to the decomposition of healthcare costs in which we provide a quantification of both extensive (greater number of hospitalizations) and intensive (greater complexity of hospitalizations) margins caused by PM increases. While other studies find that pollution causes additional costs due to a higher number of hospitalizations, we also show that the latter tend to be more complex and expensive. For a one Âţg/m3 increase in PM_{10}, we estimate a hospitalization cost that is approximately 8% higher than an average urgent admission cost for asthma. These findings imply that the quantification of the healthcare burden relative to PM and potentially to other adverse impacts on health should take into account not only the number of healthcare services accessed, but also the relative complexity of the services, representing additional costs.

Our analysis also considers health consequences of $PM_{2.5}$, a finer particulate for which we find stronger effects both in terms of hospitalization number and costs. In particular, a daily increase of one $\mu g/m^3$ of $PM_{2.5}$ is associated with a cost of 303 euros per 100,000 citizens, which is approximately 70% higher than the cost generated by the same increase in PM_{10}. Since these effects occur within one day, our estimates constitute important information for setting the hazard limit to $PM_{2.5}$, which has not yet been established in Europe by the European Commission.

When interpreting the results, the limitations of our study should be taken into account. First, employing PT strikes as an IV implicitly focuses our analysis on pollutant concentrations deriving from fuel combustion from vehicles. While this effect is fully captured by our RF estimates, we are able to provide an explicit test of the underlying mechanism only for PM_{10} and $PM_{2.5}$. Within this setting, the residual effects of CO and NO2 remain unaddressed. This may result in an overestimation of the health effects of PM. However, our RF estimates of hospitalizations for respiratory diseases are only approximately 2% larger than those from the second stage using PM_{10}, suggesting that most of the health effects induced by PT strikes are driven by particle pollution.

Second, while the evidence of air pollution on the migrant population represents a novel finding, these results should be interpreted with caution. Migrants from African low-income countries, who currently represent a large fraction of migrant inflows in Italy, face important access barriers to healthcare since their irregular status precludes them from applying for public healthcare. Although suggesting that SES plays an important role in air pollution, our evidence on migrants should be seen as partial and be interpreted as a lower bound estimate of the true effect.

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References

Adler, M. W. and J. N. van Ommeren (2016). Does public transit reduce car travel externalities? quasi-natural experiments' evidence from transit strikes. *Journal of Urban Economics 92*, 106–119.

Almond, D., L. Edlund, and M. Palme (2009). Chernobyl's subclinical legacy: prenatal exposure to radioactive fallout and school outcomes in sweden. *The Quarterly journal of economics 124*(4), 1729–1772.

Anderson, M. L. (2014). Subways, strikes, and slowdowns: The impacts of public transit on traffic congestion. *American Economic Review 104*(9), 2763–96.

Apelberg, B. J., T. J. Buckley, and R. H. White (2005). Socioeconomic and racial disparities in cancer risk from air toxics in maryland. *Environmental Health Perspectives 113*(6), 693–699.

Arceo, E., R. Hanna, and P. Oliva (2016). Does the effect of pollution on infant mortality differ between developing and developed countries? evidence from mexico city. *The Economic Journal 126*(591), 257–280.

Ardon-Dryer, K., Y.-W. Huang, and D. J. Cziczo (2015). Laboratory studies of collection efficiency of sub-micrometer aerosol particles by cloud droplets on a single-droplet basis. *Atmospheric Chemistry and Physics 15*(16), 9159–9171.

ARPA (2016). Rapporto sulla qualità dell'aria della città metropolitana di milano. Technical report, ARPA Lombardia. Settore Monitoraggi Ambientali.

Basagaña, X., M. Triguero-Mas, D. Agis, N. Pérez, C. Reche, A. Alastuey, and X. Querol (2018). Effect of public transport strikes on air pollution levels in barcelona (spain). *Science of The Total Environment 610*, 1076–1082.

Bauernschuster, S., T. Hener, and H. Rainer (2017). When labor disputes bring cities to a standstill: The impact of public transit strikes on traffic, accidents, air pollution, and health. *American Economic Journal: Economic Policy 9*(1), 1–37.

Beatty, T. K. and J. P. Shimshack (2014). Air pollution and children's respiratory health: A cohort analysis. *Journal of Environmental Economics and Management 67*(1), 39–57.

Bell, M. L. and F. Dominici (2008, 02). Effect Modification by Community Characteristics on the Short-term Effects of Ozone Exposure and Mortality in 98 US Communities. *American Journal of Epidemiology 167*(8), 986–997.

Electronic copy available at: https://ssrn.com/abstract=3430573

Cameron, A. C. and D. L. Miller (2015). A practitioner's guide to cluster-robust inference. *Journal of Human Resources 50*(2), 317–372.

Cameron, A. C. and P. K. Trivedi (2013). *Regression analysis of count data*, Volume 53. Cambridge university press.

Chaloulakou, A., P. Kassomenos, G. Grivas, and N. Spyrellis (2005). Particulate matter and black smoke concentration levels in central athens, greece. *Environment international 31*(5), 651–659.

Chang, T., J. Graff Zivin, T. Gross, and M. Neidell (2016, August). Particulate pollution and the productivity of pear packers. *American Economic Journal: Economic Policy 8*(3), 141–69.

Chay, K., C. Dobkin, and M. Greenstone (2003). The clean air act of 1970 and adult mortality. *Journal of risk and uncertainty 27*(3), 279–300.

Chay, K. Y. and M. Greenstone (2005). Does air quality matter? evidence from the housing market. *Journal of Political Economy 113*(2), 376–424.

Chernozhukov, V. and C. Hansen (2008). The reduced form: A simple approach to inference with weak instruments. *Economics Letters 100*(1), 68 – 71.

Clarke, D. (2016). Rwolf: Stata module to calculate romano-wolf stepdown p-values for multiple hypothesis testing. *Statistical Software Components, Boston College Department of Economics*.

Cournane, S., D. Byrne, R. Conway, D. O'Riordan, S. Coveney, and B. Silke (2017). Effect of social deprivation on the admission rate and outcomes of adult respiratory emergency admissions. *Respiratory medicine 125*, 94–101.

Currie, J. and M. Neidell (2005). Air pollution and infant health: what can we learn from california's recent experience? *The Quarterly Journal of Economics 120*(3), 1003–1030.

Currie, J. and R. Walker (2011). Traffic congestion and infant health: Evidence from e-zpass. *American Economic Journal: Applied Economics 3*(1), 65–90.

Dell, M., B. F. Jones, and B. A. Olken (2014). What do we learn from the weather? the new climate-economy literature. *Journal of Economic Literature 52*(3), 740–98.

Deryugina, T., G. Heutel, N. H. Miller, D. Molitor, and J. Reif (2016, November). The mortality and medical costs of air pollution: Evidence from changes in wind direction. Working Paper 22796, National Bureau of Economic Research.

Deschênes, O. and M. Greenstone (2007). The economic impacts of climate change: evidence from agricultural output and random fluctuations in weather. *American Economic Review 97*(1), 354–385.

Electronic copy available at: https://ssrn.com/abstract=3430573

Deschenes, O. and E. Moretti (2009). Extreme weather events, mortality, and migration. *The Review of Economics and Statistics 91*(4), 659–681.

DeVries, R., D. Kriebel, and S. Sama (2016). Low level air pollution and exacerbation of existing copd: a case crossover analysis. *Environ Health. 15*(1).

Dominici, F., R. D. Peng, C. D. Barr, and M. L. Bell (2010). Protecting human health from air pollution: shifting from a single-pollutant to a multi-pollutant approach. *Epidemiology (Cambridge, Mass.) 21*(2), 187.

Dominici, F., L. Sheppard, and M. Clyde (2003). Health effects of air pollution: a statistical review. *International Statistical Review 71*(2), 243–276.

EEA (2016). Air quality in europe - eea report n.28/2016. Technical report, European Environment Agency.

Filippini, M., G. Masiero, and S. Steinbach (2019, Apr). The impact of ambient air pollution on hospital admissions. *The European Journal of Health Economics*.

Forastiere, F., M. Stafoggia, C. Tasco, S. Picciotto, N. Agabiti, G. Cesaroni, and C. A. Perucci (2007a). Socioeconomic status, particulate air pollution, and daily mortality: differential exposure or differential susceptibility. *American journal of industrial medicine 50*(3), 208–216.

Forastiere, F., M. Stafoggia, C. Tasco, S. Picciotto, N. Agabiti, G. Cesaroni, and C. A. Perucci (2007b). Socioeconomic status, particulate air pollution, and daily mortality: differential exposure or differential susceptibility. *American journal of industrial medicine 50*(3), 208–216.

Fowlie, M., E. Rubin, and R. Walker (2019, May). Bringing satellite-based air quality estimates down to earth. *AEA Papers and Proceedings 109*, 283–88.

GBD, 2015, Chronic, and R. D. Collaborators (2017, 09). Global, regional, and national deaths, prevalence, disability-adjusted life years, and years lived with disability for chronic obstructive pulmonary disease and asthma, 1990-2015: a systematic analysis for the global burden of disease study 2015. *The Lancet. Respiratory medicine 5*(9), 691–706.

Germani, A. R., P. Morone, and G. Testa (2014). Environmental justice and air pollution: A case study on italian provinces. *Ecological Economics 106*, 69 – 82.

Goldman, G. T., J. A. Mulholland, A. G. Russell, M. J. Strickland, M. Klein, L. A. Waller, and P. E. Tolbert (2011). Impact of exposure measurement error in air pollution epidemiology: effect of error type in time-series studies. *Environmental health 10*(1), 61.

Electronic copy available at: https://ssrn.com/abstract=3430573

Grainger, C. and A. Schreiber (2019, May). Discrimination in ambient air pollution monitoring? *AEA Papers and Proceedings 109*, 277–82.

Guo, L.-C., Y. Zhang, H. Lin, W. Zeng, T. Liu, J. Xiao, S. Rutherford, J. You, and W. Ma (2016). The washout effects of rainfall on atmospheric particulate pollution in two Chinese cities. *Environmental Pollution 215*, 195–202.

Halliday, T. J., J. Lynham, and A. de Paula (2015). Vog: Using volcanic eruptions to estimate the health costs of particulates. *The Economic Journal*.

Heissel, J., C. Persico, and D. Simon (2019, January). Does pollution drive achievement? the effect of traffic pollution on academic performance. Working Paper 25489, National Bureau of Economic Research.

Isen, A., M. Rossin-Slater, and W. R. Walker (2017). Every Breath You Take—Every Dollar You'll Make: The Long-Term Consequences of the Clean Air Act of 1970. *Journal of Political Economy 125*(3), 848–902.

Janke, K. (2014). Air pollution, avoidance behaviour and children's respiratory health: Evidence from england. *Journal of health economics 38*, 23–42.

Janke, K., C. Propper, and J. Henderson (2009). Do current levels of air pollution kill? the impact of air pollution on population mortality in england. *Health economics 18*(9), 1031–1055.

Ji, W., Y. R. Park, H. R. Kim, H.-C. Kim, and C.-M. Choi (2017). Prolonged effect of air pollution on pneumonia: a nationwide cohort study. *European Respiratory Journal 50*(6), OA467.

Knittel, C. R., D. L. Miller, and N. J. Sanders (2016). Caution, drivers! children present: Traffic, pollution, and infant health. *Review of Economics and Statistics 98*(2), 350–366.

Künzli, N. and I. B. Tager (1997). The semi-individual study in air pollution epidemiology: a valid design as compared to ecologic studies. *Environmental Health Perspectives 105*(10), 1078–1083.

Lagravinese, R., F. Moscone, E. Tosetti, and H. Lee (2014). The impact of air pollution on hospital admissions: evidence from italy. *Regional Science and Urban Economics 49*, 278–285.

Lavaine, E. (2015). An econometric analysis of atmospheric pollution, environmental disparities and mortality rates. *Environmental and Resource Economics 60*(2), 215–242.

Lavaine, E. and M. Neidell (2017). Energy production and health externalities: Evidence from oil refinery strikes in france. *Journal of the Association of Environmental and Resource Economists 4*(2), 447–477.

Electronic copy available at: https://ssrn.com/abstract=3430573

Lleras-Muney, A. (2010). The needs of the army using compulsory relocation in the military to estimate the effect of air pollutants on children's health. *Journal of Human Resources 45*(3), 549–590.

Mazzaglia, G., E. Ambrosioni, M. Alacqua, A. Filippi, E. Sessa, V. Immordino, C. Borghi, O. Brignoli, A. P. Caputi, C. Cricelli, , and L. G. Mantovan (2009). Adherence to antihy-pertensive medications and cardiovascular morbidity among newly diagnosed hypertensive patients. *Circulation 120*(6).

McCrary, J. and H. Royer (2011, February). The effect of female education on fertility and infant health: Evidence from school entry policies using exact date of birth. *American Economic Review 101*(1), 158–95.

McCubbin, D. R. and M. A. Delucchi (1999). The health costs of motor-vehicle-related air pollution. *Journal of Transport Economics and Policy*, 253–286.

Meinardi, S., P. Nissenson, B. Barletta, D. Dabdub, F. S. Rowland, and D. R. Blake (2008). Influence of the public transportation system on the air quality of a major urban center. a case study: Milan, italy. *Atmospheric Environment 42*(34), 7915–7923.

Mouatassim, Y. and E. H. Ezzahid (2012). Poisson regression and zero-inflated poisson regression: application to private health insurance data. *European actuarial journal 2*(2), 187–204.

Mudway, I. S., I. Dundas, H. E. Wood, N. Marlin, J. B. Jamaludin, S. A. Bremner, L. Cross, A. Grieve, A. Nanzer, B. M. Barratt, et al. (2018). Impact of london's low emission zone on air quality and children's respiratory health: a sequential annual cross-sectional study. *The Lancet Public Health*.

Mullahy, J. (1997). Instrumental-variable estimation of count data models: Applications to models of cigarette smoking behavior. *Review of Economics and Statistics 79*(4), 586–593.

Neidell, M. J. (2004). Air pollution, health, and socio-economic status: the effect of outdoor air quality on childhood asthma. *Journal of health economics 23*(6), 1209–1236.

O'Neill, M. S., M. Jerrett, I. Kawachi, J. I. Levy, A. J. Cohen, N. Gouveia, P. Wilkinson, T. Fletcher, L. Cifuentes, J. Schwartz, et al. (2003). Health, wealth, and air pollution: advancing theory and methods. *Environmental health perspectives 111*(16), 1861–1870.

Ostro, B., R. Broadwin, S. Green, W.-Y. Feng, and M. Lipsett (2006). Fine particulate air pollution and mortality in nine california counties: results from calfine. *Environmental health perspectives 114*(1), 29–33.

Park, E. S. and M.-S. Oh (2018). Accounting for uncertainty in source-specific exposures in the evaluation of health effects of pollution sources on daily cause-specific mortality. *Environmetrics 29*(1), 2484.

Electronic copy available at: https://ssrn.com/abstract=3430573

Pereira, B. B., E. O. de Campos, E. A. P. de Lima, M. A. S. Barrozo, and S. Morelli (2014). Biomonitoring air quality during and after a public transportation strike in the center of uberlândia, minas gerais, brazil by tradescantia micronucleus bioassay. *Environmental Science and Pollution Research 21*(5), 3680–3685.

Pires, J., M. Alvim-Ferraz, and F. Martins (2012). Surface ozone behaviour at rural sites in portugal. *Atmospheric research 104*, 164–171.

Romano, J. P. and M. Wolf (2016). Efficient computation of adjusted p-values for resampling-based stepdown multiple testing. *Statistics and Probability Letters 113*, 38 – 40.

Saitanis, C. (2003). Background ozone monitoring and phytodetection in the greater rural area of corinth—-greece. *Chemosphere 51*(9), 913–923.

Salvo, A., J. He, and N. Gouveia (2018, 04). External Effects of Diesel Trucks Circulating Inside the SÃčo Paulo Megacity.

Schlenker, W. and W. R. Walker (2015). Airports, air pollution, and contemporaneous health. *The Review of Economic Studies 83*(2), 768–809.

Schwartz, J. (2004). Air pollution and children's health. *Pediatrics 113*(Supplement 3), 1037–1043.

Sheppard, L., R. T. Burnett, A. A. Szpiro, S.-Y. Kim, M. Jerrett, C. A. Pope, and B. Brunekreef (2012). Confounding and exposure measurement error in air pollution epidemiology. *Air Quality, Atmosphere & Health 5*(2), 203–216.

Simoni, M., S. Baldacci, S. Maio, S. Cerrai, G. Sarno, and G. Viegi (2015). Adverse effects of outdoor pollution in the elderly. *Journal of thoracic disease 7*(1), 34.

Staiger, D. and J. H. Stock (1997). Instrumental variables regression with weak instruments. *Econometrica 65*(3), 557–586.

Stock, J. H. and M. Yogo (2002). Testing for weak instruments in linear iv regression.

Sun, C., M. E. Kahn, and S. Zheng (2017). Self-protection investment exacerbates air pollution exposure inequality in urban china. *Ecological economics 131*, 468–474.

van Exel, N. J. A. and P. Rietveld (2001). Public transport strikes and traveller behaviour. *Transport Policy 8*(4), 237–246.

Vandaele, K. (2011). Sustaining or abandoning "social peace"? strike development and trends in europe since the 1990s. *Working Paper Brussels: ETUI 5*.

Electronic copy available at: https://ssrn.com/abstract=3430573

Wang, Y., I. Kloog, B. A. Coull, A. Kosheleva, A. Zanobetti, and J. D. Schwartz (2016). Estimating causal effects of long-term pm2. 5 exposure on mortality in new jersey. *Environmental health perspectives 124*(8), 1182–1188.

Ward, C. J. (2015). "it's an ill wind: The effect of fine particulate air pollution on respiratory hospitalizations. *Canadian Journal of Economics, Canadian Economics Association*, 1694–1732.

WHO (2006). Air quality guidelines for particulate matter, ozone, nitrogen dioxide and sulfur dioxide, global update 2005. *World Health Organization.*

WHO (2013). Review of evidence on health aspects of air pollution - REVIHAAP project. Technical report, WHO. Copenhagen, Denmark.

Windmeijer, F. A. and J. M. Santos Silva (1997). Endogeneity in count data models: an application to demand for health care. *Journal of applied econometrics 12*(3), 281–294.

Winkelmann, R. (2008). *Econometric analysis of count data.* Springer Science & Business Media.

Zivin, J. G. and M. Neidell (2018). Air pollution's hidden impacts. *Science 359*(6371), 39–40.

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Appendices

A List of tables

Table A1: Data sources

Variable	Source
Hospital urgent admissions	Hospital Discharge Data (SDO) - Italian Ministry of Health
Air pollution data	Copernicus Atmosphere Monitoring Service (CAMS)
Weather data	MARS-AGRI4CAST - JRC
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 A2: IV estimates of the effect of PM_{10} on average unit costs for hospital admissions for four distinct respiratory problems (second stage).

	Unit Cost (1)	Unit Cost (2)	Unit Cost (3)	Unit Cost (4)
Panel A - All respiratory:				
PM_{10}	12.7	14.6	12.3	13.8
	[12.8]	[14.0]	[13.5]	[14.4]
Panel B - Asthma:				
PM_{10}	133.0*	151.7	143.1*	158.3
	[75.0]	[93.3]	[81.2]	[97.5]
Panel C - Pneumonia:				
PM_{10}	3.9	4.5	2.9	3.3
	[27.2]	[30.7]	[29.4]	[32.2]
Panel D - COPD:				
PM_{10}	44.7*	50.9**	47.2*	52.1**
	[22.8]	[24.8]	[24.8]	[26.1]
CONTROL (holiday)		YES		YES
CONTROL (weather)			YES	YES
TIME FEs	YES	YES	YES	YES
MUNICIPALITY FEs	YES	YES	YES	YES

$^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$

Notes: The numbers refer to an initial sample of 403,861 urgent respiratory hospital admissions defined in the primary diagnosis and to a population of 54,012,341 individuals distributed across 111 municipalities over 1095 days. All regressions include day-of-week, week-of-year, year and municipality fixed effects. Additional controls include dummies for school holidays and public holidays as well as weather controls (5-degree bins for atmospheric temperature, amount of precipitation and wind speed). Standard errors (in parentheses) are clustered at the municipality level. Estimates are weighted by municipality population size.

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Table A3: IV estimates of the effect of PM_{10} on total health costs for respiratory hospital admissions by age groups (second stage).

	Total Costs (1)	Total Costs (2)	Total Costs (3)	Total Costs (4)
Panel A: ages below 14				
PM_{10}	70.9	81.7	81.4	91.3
	[104.3]	[123.0]	[111.5]	[127.0]
Panel B: ages 15 - 24				
PM_{10}	338.6**	391.1**	356.4**	397.4*
	[148.7]	[195.2]	[166.8]	[205.0]
Panel C: ages 25 - 44				
PM_{10}	111.7*	128.0	117.5*	130.8
	[62.3]	[79.0]	[68.0]	[82.5]
Panel D: ages 45 - 64				
PM_{10}	126.0	143.0	123.2	135.5
	[76.5]	[92.9]	[81.8]	[95.0]
Panel E: ages 65 and above				
PM_{10}	608.6***	695.1***	609.5***	677.7***
	[193.4]	[232.6]	[207.6]	[241.1]
CONTROL (holiday)		YES		YES
CONTROL (weather)			YES	YES
TIME FEs	YES	YES	YES	YES
MUNICIPALITY FEs	YES	YES	YES	YES

$^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$

Notes: The numbers refer to an initial sample of 403,861 urgent respiratory hospital admissions defined in the primary diagnosis and to a population of 54,012,341 individuals distributed across 111 municipalities over 1095 days. All regressions include day-of-week, week-of-year, year and municipality fixed effects. Additional controls include dummies for school holidays and public holidays as well as weather controls (5-degree bins for atmospheric temperature, amount of precipitation and wind speed). Standard errors (in parentheses) are clustered at the municipality level. Estimates are weighted by municipality population size.

Table A4: IV estimates of the effect of $PM_{2.5}$ on respiratory diseases admissions

First stage

	Panel A $PM_{2.5}$	*Panel B* $PM_{2.5}$	*Panel C* $PM_{2.5}$	*Panel D* $PM_{2.5}$
STRIKE	0.714***	0.574***	0.615***	0.502***
	[0.218]	[0.202]	[0.212]	[0.198]
$F - stat$	15.543	11.82	11.577	9.053

Second stage

	Respiratory (all patients)	Respiratory (all patients)	Respiratory (all patients)	Respiratory (all patients)
Panel A - Marginal effects:				
$PM_{2.5}$	0.088***	0.110***	0.095***	0.117***
	[0.023]	[0.034]	[0.028]	[0.041]
Panel B - Semi-elasticities:				
$PM_{2.5}$	0.043***	0.053***	0.047***	0.057***
	[0.011]	[0.017]	[0.013]	[0.020]
CONTROL (weather)		YES		YES
CONTROL (holiday)			YES	YES
TIME FEs	YES	YES	YES	YES
MUNICIPALITY FEs	YES	YES	YES	YES
N	121,545	121,545	121,545	121,545

$^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$

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Table A5: IV estimates of the effect of $PM_{2.5}$ on respiratory diseases in different age groups (second stage).

	Respiratory (1)	Respiratory (2)	Respiratory (3)	Respiratory (4)
Panel A: ages below 14				
$PM_{2.5}$	0.070	0.087	0.089	0.110
	[0.104]	[0.131]	[0.118]	[0.147]
Panel B: ages 15 - 24				
$PM_{2.5}$	0.121**	0.153*	0.136*	0.171
	[0.059]	[0.090]	[0.073]	[0.110]
Panel C: ages 25 - 44				
$PM_{2.5}$	0.048**	0.060*	0.055**	0.068*
	[0.022]	[0.031]	[0.027]	[0.037]
Panel D: ages 45 - 64				
$PM_{2.5}$	-0.012	-0.015	-0.020	-0.024
	[0.026]	[0.032]	[0.030]	[0.037]
Panel E: ages 65 and above				
$PM_{2.5}$	0.279***	0.346***	0.297**	0.365**
	[0.100]	[0.128]	[0.116]	[0.149]
CONTROL (holiday)		YES		YES
CONTROL (weather)			YES	YES
TIME FEs	YES	YES	YES	YES
MUNICIPALITY FEs	YES	YES	YES	YES

$^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$

Notes: The numbers refer to an initial sample of 403,861 urgent respiratory hospital admissions defined in the primary diagnosis and to a population of 54,012,341 individuals distributed across 111 municipalities over 1095 days. All regressions include day-of-week, week-of-year, year and municipality fixed effects. Additional controls include dummies for school holidays and public holidays as well as weather controls (5-degree bins for atmospheric temperature, amount of precipitation and wind speed). Standard errors (in parentheses) are clustered at the municipality level. Estimates are weighted by municipality population size.

Table A6: IV estimates of the effect of $PM_{2.5}$ on respiratory disease by educational attainment (second stage).

	Respiratory (1)	Respiratory (2)	Respiratory (3)	Respiratory (4)
Panel A: Primary ed. lev.				
$PM_{2.5}$	0.155***	0.196***	0.171***	0.213**
	[0.042]	[0.065]	[0.054]	[0.082]
Panel B: Secondary ed. lev.				
$PM_{2.5}$	0.054**	0.067*	0.060**	0.072*
	[0.025]	[0.034]	[0.029]	[0.040]
Panel C: Tertiary ed. lev.				
$PM_{2.5}$	-0.004	-0.005	-0.010	-0.011
	[0.050]	[0.060]	[0.058]	[0.069]
CONTROL (weather)		YES		YES
CONTROL (holiday)			YES	YES
TIME FEs	YES	YES	YES	YES
MUNICIPALITY FEs	YES	YES	YES	YES
N	121,545	121,545	121,545	121,545

$^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1.$

Notes: The numbers refer to an initial sample of 403,861 urgent respiratory hospital admissions defined in the primary diagnosis and to a population of 54,012,341 individuals distributed across 111 municipalities over 1095 days. All regressions include day-of-week, week-of-year, year and municipality fixed effects. Additional controls include dummies for school holidays and public holidays as well as weather controls (5-degree bins for atmospheric temperature, amount of precipitation and wind speed) are clustered at the municipality level. Estimates are weighted by municipality population size by age group.

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Table A7: IV estimates of the effect of $PM_{2.5}$ on total health costs for respiratory hospital admissions (second stage).

	Costs (1)	Costs (2)	Costs (3)	Costs (4)
Panel A: all patients				
$PM_{2.5}$	303.011***	376.411**	329.014**	403.342**
	[105.797]	[144.826]	[127.010]	[172.390]
Panel B: ages below 14				
$PM_{2.5}$	118.692	149.039	148.140	183.899
	[152.943]	[195.801]	[175.080]	[221.707]
Panel C: ages 15 - 24				
$PM_{2.5}$	570.578**	726.988*	656.146**	822.700*
	[244.617]	[368.801]	[314.791]	[465.906]
Panel D: ages 25 - 44				
$PM_{2.5}$	186.890**	233.540*	213.340*	263.080*
	[90.179]	[131.033]	[109.637]	[157.536]
Panel E: ages 45 - 64				
$PM_{2.5}$	213.444*	262.985	226.701	274.784
	[124.890]	[167.470]	[146.227]	[192.742]
Panel F: ages 65 and above				
$PM_{2.5}$	1014.313**	1262.015**	1100.604**	1354.163**
	[387.499]	[490.081]	[451.308]	[570.377]
CONTROL (weather)		YES		YES
CONTROL (holiday)			YES	YES
TIME FEs	YES	YES	YES	YES
MUNICIPALITY FEs	YES	YES	YES	YES
N	121,545	121,545	121,545	121,545

$^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.
Notes: The numbers refer to an initial sample of 403,861 urgent respiratory hospital admissions defined in the primary diagnosis and to a population of 54,012,341 individuals distributed across 111 municipalities over 1095 days. All regressions include day-of-week, week-of-year, year and municipality fixed effects. Additional controls include dummies for school holidays and public holidays as well as weather controls (5-degree bins for atmospheric temperature, amount of precipitation and wind speed) are clustered at the municipality level. Estimates are weighted by municipality population size by age group.

Table A8: IV estimates of the effect of $PM_{2.5}$ on average unit costs for hospital admissions for four distinct respiratory problems (second stage).

	Unit Costs (1)	Unit Costs (2)	Unit Costs (3)	Unit Costs (4)
Panel A: all respiratory				
$PM_{2.5}$	21.240	26.638	22.383	27.739
	[24.380]	[29.172]	[27.905]	[32.792]
Panel B: Asthma				
$PM_{2.5}$	223.138*	277.390*	260.804*	319.402
	[119.486]	[167.077]	[142.856]	[199.414]
Panel C: Pneumonia				
$PM_{2.5}$	6.506	8.209	5.244	6.600
	[46.619]	[57.086]	[54.370]	[65.739]
Panel D: COPD				
$PM_{2.5}$	75.051	93.013*	86.051	105.009
	[46.334]	[54.415]	[55.641]	[64.404]
CONTROL (weather)		YES		YES
CONTROL (holiday)			YES	YES
TIME FEs	YES	YES	YES	YES
MUNICIPALITY FEs	YES	YES	YES	YES
N	121,545	121,545	121,545	121,545

$^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.
Notes: The numbers refer to an initial sample of 403,861 urgent respiratory hospital admissions defined in the primary diagnosis and to a population of 54,012,341 individuals distributed across 111 municipalities over 1095 days. All regressions include day-of-week, week-of-year, year and municipality fixed effects. Additional controls include dummies for school holidays and public holidays as well as weather controls (5-degree bins for atmospheric temperature, amount of precipitation and wind speed) are clustered at the municipality level. Estimates are weighted by municipality population size by age group.

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Table A9: IV estimates of the effect of O_3 on respiratory diseases admissions (placebo pollutant).

First stage

	Panel A	*Panel B*	*Panel C*	*Panel D*
	O_3	O_3	O_3	O_3
$STRIKE$	0.0183	0.041	0.0291	0.092
	[0.362]	[0.435]	[0.358]	[0.430]
$F-stat$	0.005	0.027	0.012	0.138

Second stage

	Respiratory (all patients)	Respiratory (all patients)	Respiratory (all patients)	Respiratory (all patients)
Panel A - Marginal effects:				
O_3	3.457	1.542	2.014	0.637
	[68.533]	[16.441]	[24.752]	[2.974]
Panel B - Semi-elasticities:				
O_3	1.687	0.753	0.983	0.311
	[33.295]	[7.988]	[12.025]	[1.445]
CONTROL (weather)		YES		YES
CONTROL (holiday)			YES	YES
TIME FEs	YES	YES	YES	YES
MUNICIPALITY FEs	YES	YES	YES	YES
N	121,545	121,545	121,545	121,545

$^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$

Notes: The numbers refer to an initial sample of 403,861 urgent respiratory hospital admissions defined in the primary diagnosis and to a population of 54,012,341 individuals distributed across 111 municipalities over 1095 days. All regressions include day-of-week, week-of-year, year and municipality fixed effects. Additional controls include dummies for school holidays and public holidays as well as weather controls (5-degree bins for atmospheric temperature, amount of precipitation and wind speed). Standard errors (in parentheses) are clustered at the municipality level. Estimates are weighted by municipality population size.

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Table A10: IV estimates of the effect of PM_{10} on placebo diseases.

Second stage – Nervous system diseases (ICD09 320-359)

	Panel A (all patients)	*Panel B* (all patients)	*Panel C* (all patients)	*Panel D* (all patients)
Panel A - Marginal effects:				
PM_{10}	-0.004 [0.013]	-0.004 [0.015]	-0.007 [0.014]	-0.007 [0.015]
Panel B - Semi-elasticities:				
PM_{10}	-0.007 [0.027]	-0.008 [0.030]	-0.013 [0.028]	-0.015 [0.030]

Second stage – Musculoskeletal diseases (ICD09 710-739)

	(all patients)	(all patients)	(all patients)	(all patients)
Panel A - Marginal effects:				
PM_{10}	-0.007 [0.005]	-0.007 [0.006]	-0.009 [0.005]	-0.010 [0.006]
Panel B - Semi-elasticities:				
PM_{10}	-0.030 [0.024]	-0.034 [0.026]	-0.042 [0.023]	-0.046 [0.025]

Second stage – Endocrine systems diseases (ICD09 240-279)

	(all patients)	(all patients)	(all patients)	(all patients)
Panel A - Marginal effects:				
PM_{10}	-0.007 [0.009]	-0.008 [0.010]	-0.009 [0.010]	-0.010 [0.010]
Panel B - Semi-elasticities:				
PM_{10}	-0.018 [0.023]	-0.021 [0.025]	-0.023 [0.024]	-0.025 [0.026]
CONTROL (weather)		YES		YES
CONTROL (holiday)			YES	YES
TIME FEs	YES	YES	YES	YES
MUNICIPALITY FEs	YES	YES	YES	YES
N	121,545	121,545	121,545	121,545

$^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$

Notes: The numbers refer to an initial sample of 403,861 urgent respiratory hospital admissions defined in the primary diagnosis and to a population of 54,012,341 individuals distributed across 111 municipalities over 1095 days. All regressions include day-of-week, week-of-year, year and municipality fixed effects. Additional controls include dummies for school holidays and public holidays as well as weather controls (5-degree bins for atmospheric temperature, amount of precipitation and wind speed). Standard errors (in parentheses) are clustered at the municipality level. Estimates are weighted by municipality population size.

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Table A11: IV estimates of the effect of PM_{10} on programmed hospitalization admissions for respiratory diseases.

Second stage

	Respiratory (all patients)	Respiratory (all patients)	Respiratory (all patients)	Respiratory (all patients)
Panel A - Marginal effects:				
PM_{10}	-0.0196	-0.0240	-0.0284	-0.0331
	[0.0181]	[0.0210]	[0.0187]	[0.0207]
Panel B - Semi-elasticities:				
PM_{10}	-0.108	-0.132	-0.156	-0.182
	[0.0990]	[0.115]	[0.102]	[0.113]
CONTROL (weather)		YES		YES
CONTROL (holiday)			YES	YES
TIME FEs	YES	YES	YES	YES
MUNICIPALITY FEs	YES	YES	YES	YES
N	121,545	121,545	121,545	121,545

$^{***}p < 0.01,^{**} p < 0.05,^{*} p < 0.1$

Notes: The numbers refer to an initial sample of 132,317 programmed respiratory hospital admissions defined in the primary diagnosis and to a population of 54,012,341 individuals distributed across 111 municipalities over 1095 days. All regressions include day-of-week, week-of-year, year and municipality fixed effects. Additional controls include dummies for school holidays and public holidays as well as weather controls (5-degree bins for atmospheric temperature, amount of precipitation and wind speed). Standard errors (in parentheses) are clustered at the municipality level. Estimates are weighted by municipality population size.

Table A12: IV estimates of the effect of PM_{10} on respiratory diseases in non-affected cities.

First stage

	Panel A	*Panel B*	*Panel C*	*Panel D*
	PM_{10}	PM_{10}	PM_{10}	PM_{10}
$FAKESTRIKE$	0.389	0.167	0.413	0.179
	[0.648]	[0.667]	[0.655]	[0.671]
$F-stat$	0.278	0.058	0.313	0.067

Second stage

	Respiratory (all patients)	Respiratory (all patients)	Respiratory (all patients)	Respiratory (all patients)
Panel A - Marginal effects:				
PM_{10}	-0.0101	-0.0251	-0.00463	-0.0126
	[0.221]	[0.533]	[0.205]	[0.478]
Panel B - Semi-elasticities:				
PM_{10}	-0.00495	-0.0123	-0.00226	-0.00615
	[0.107]	[0.259]	[0.0995]	[0.232]
CONTROL (weather)		YES		YES
CONTROL (holiday)			YES	YES
TIME FEs	YES	YES	YES	YES
MUNICIPALITY FEs	YES	YES	YES	YES
N	121,545	121,545	121,545	121,545

$^{***}p < 0.01,^{**} p < 0.05,^{*} p < 0.1$

Notes: The numbers refer to an initial sample of 403,861 urgent respiratory hospital admissions defined in the primary diagnosis and to a population of 54,012,341 individuals distributed across 111 municipalities over 1095 days. All regressions include day-of-week, week-of-year, year and municipality fixed effects. Additional controls include dummies for school holidays and public holidays as well as weather controls (5-degree bins for atmospheric temperature, amount of precipitation and wind speed). Standard errors (in parentheses) are clustered at the municipality level. Estimates are weighted by municipality population size.

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Table A13: IV estimates of the effect of PM_{10} on respiratory diseases considering multi-day strike.

First stage

	Panel A	*Panel B*	*Panel C*	*Panel D*
	PM_{10}	PM_{10}	PM_{10}	PM_{10}
MULTI-DAY STRIKES	0.937***	0.766***	0.829***	0.712***
	[0.257]	[0.262]	[0.255]	[0.259]
$F - stat$	20.340	15.373	15.927	13.263

Second stage

	Respiratory (all patients)	Respiratory (all patients)	Respiratory (all patients)	Respiratory (all patients)
Panel A - Marginal effects:				
PM_{10}	0.0651***	0.0796**	0.0689***	0.0804**
	[0.0218]	[0.0326]	[0.0255]	[0.0353]
Panel B - Semi-elasticities:				
PM_{10}	0.0318***	0.0388**	0.0336***	0.0392**
	[0.0106]	[0.0159]	[0.0124]	[0.0172]
CONTROL (weather)		YES		YES
CONTROL (holiday)			YES	YES
TIME FEs	YES	YES	YES	YES
MUNICIPALITY FEs	YES	YES	YES	YES
N	121,545	121,545	121,545	121,545

$^{***}p < 0.01,^{**} p < 0.05,^{*} p < 0.1$

Notes: The numbers refer to an initial sample of 403,861 urgent respiratory hospital admissions defined in the primary diagnosis and to a population of 54,012,341 individuals distributed across 111 municipalities over 1095 days. All regressions include day-of-week, week-of-year, year and municipality fixed effects. Additional controls include dummies for school holidays and public holidays as well as weather controls (5-degree bins for atmospheric temperature, amount of precipitation and wind speed). Standard errors (in parentheses) are clustered at the municipality level. Estimates are weighted by municipality population size.

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Table A14: First Stage estimates of the effect of strike on PM_{10} taking into account the demand per capita of PT (DTP)

First stage

	Panel A	*Panel B*	*Panel C*	*Panel D*
	PM_{10}	PM_{10}	PM_{10}	PM_{10}
$STRIKE \times DPT$ 1.644***	1.522***	1.564***	1.483***	
	[0.209]	[0.164]	[0.199]	[0.162]
$F-stat$	42.259	40.955	38.292	38.882

Second stage

	Respiratory (all patients)	Respiratory (all patients)	Respiratory (all patients)	Respiratory (all patients)
Panel A - Marginal effects:				
PM_{10}	0.0453***	0.0488***	0.0448***	0.0472***
	[0.00821]	[0.0103]	[0.00914]	[0.0110]
Panel B - Semi-elasticities:				
PM_{10}	0.0221***	0.0238***	0.0219***	0.0230***
	[0.00399]	[0.00502]	[0.00444]	[0.00536]
CONTROL (weather)		YES		YES
CONTROL (holiday)			YES	YES
TIME FEs	YES	YES	YES	YES
MUNICIPALITY FEs	YES	YES	YES	YES
N	121,545	121,545	121,545	121,545

$^{***}p < 0.01,^{**} p < 0.05,^{*} p < 0.1$

Notes: The numbers refer to an initial sample of 403,861 urgent respiratory hospital admissions defined in the primary diagnosis and to a population of 54,012,341 individuals distributed across 111 municipalities over 1095 days. All regressions include day-of-week, week-of-year, year and municipality fixed effects. Additional controls include dummies for school holidays and public holidays as well as weather controls (5-degree bins for atmospheric temperature, amount of precipitation and wind speed). Standard errors (in parentheses) are clustered at the municipality level. Estimates are weighted by municipality population size.

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Table A15: IV estimates of the effect of PM_{10} taking into account the demand per capita of PT (DTP) on a sample of 10 cities with high DPT.

First stage

	Panel A	*Panel B*	*Panel C*	*Panel D*
	PM_{10}	PM_{10}	PM_{10}	PM_{10}
$STRIKE$	1.523***	1.433***	1.444***	1.386***
	[0.0782]	[0.0813]	[0.0736]	[0.0841]
$F-stat$	8.892	9.276	8.005	8.669

Second stage

	Respiratory (all patients)	Respiratory (all patients)	Respiratory (all patients)	Respiratory (all patients)
Panel A - Marginal effects:				
PM_{10}	0.0334**	0.0354**	0.0319*	0.0330*
	[0.0126]	[0.0141]	[0.0141]	[0.0153]
Panel B - Semi-elasticities:				
PM_{10}	0.0164***	0.0174***	0.0157**	0.0162**
	[0.00585]	[0.00656]	[0.00656]	[0.00709]
CONTROL (weather)		YES		YES
CONTROL (holiday)			YES	YES
TIME FEs	YES	YES	YES	YES
MUNICIPALITY FEs	YES	YES	YES	YES
N	10,950	10,950	10,950	10,950

$^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$

Notes: The numbers refer to an initial sample of 157,098 urgent respiratory hospital admissions defined in the primary diagnosis and to a population of 21,154,612 individuals distributed across 10 municipalities over 1095 days. All regressions include day-of-week, week-of-year, year and municipality fixed effects. Additional controls include dummies for school holidays and public holidays as well as weather controls (5-degree bins for atmospheric temperature, amount of precipitation and wind speed). Standard errors (in parentheses) are clustered at the municipality level. Estimates are weighted by municipality population size.

Table A16: IV estimates of the effect of PM_{10} on all Italian municipalities.

First stage

	Panel A	*Panel B*	*Panel C*	*Panel D*
	PM_{10}	PM_{10}	PM_{10}	PM_{10}
$STRIKE$	1.181***	0.866***	1.101***	0.826***
	[0.308]	[0.300]	[0.310]	[0.301]

Second stage

	Respiratory (all patients)	Respiratory (all patients)	Respiratory (all patients)	Respiratory (all patients)
Panel A - Marginal effects:				
PM_{10}	0.0499***	0.0679***	0.0484***	0.0644**
	[0.0151]	[0.0253]	[0.0161]	[0.0257]
CONTROL (weather)		YES		YES
CONTROL (holiday)			YES	YES
TIME FEs	YES	YES	YES	YES
MUNICIPALITY FEs	YES	YES	YES	YES
N	8,858,550	8,858,550	8,858,550	8,858,550

$^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$

Notes: The numbers refer to an initial sample of 1,267,367 urgent respiratory hospital admissions defined in the primary diagnosis and to a population of 54,012,341 individuals distributed across 8,090 municipalities over 1095 days. All regressions include day-of-week, week-of-year, year and municipality fixed effects. Additional controls include dummies for school holidays and public holidays as well as weather controls (5-degree bins for atmospheric temperature, amount of precipitation and wind speed). Standard errors (in parentheses) are clustered at the municipality level. Estimates are weighted by municipality population size.

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Table A17: IV estimates of the effect of PM_{10} on respiratory diseases using air pollution data from monitoring stations.

First stage

	Panel A	*Panel B*	*Panel C*	*Panel D*
	PM_{10}	PM_{10}	PM_{10}	PM_{10}
$STRIKE$	1.721**	1.524**	1.605**	1.447*
	[0.763]	[0.766]	[0.742]	[0.749]
$F-stat$	18.89	19.563	16.450	18.063

Second stage

	Respiratory (all patients)	Respiratory (all patients)	Respiratory (all patients)	Respiratory (all patients)
Panel A - Marginal effects:				
PM_{10}	0.0320**	0.0359**	0.0317**	0.0350**
	[0.0124]	[0.0161]	[0.0131]	[0.0164]
Panel B - Semi-elasticities:				
PM_{10}	0.0155***	0.0157***	0.0153**	0.0155**
	[0.00595]	[0.00601]	[0.00627]	[0.00628]
CONTROL (holiday)		YES		YES
CONTROL (weather)			YES	YES
TIME FEs	YES	YES	YES	YES
MUNICIPALITY FEs	YES	YES	YES	YES
N	72,270	72,270	72,270	72,270

$^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$

Notes: The numbers refer to an initial sample of 316,109 urgent respiratory hospital admissions defined in the primary diagnosis and to a population of 41,852,702 individuals distributed across 66 municipalities over 1095 days. All regressions include day-of-week, week-of-year, year and municipality fixed effects. Additional controls include dummies for school holidays and public holidays as well as weather controls (5-degree bins for atmospheric temperature, amount of precipitation and wind speed). Standard errors (in parentheses) are clustered at the municipality level. Estimates are weighted by municipality population size.

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Table A18: IV estimates of the effect of PM_{10} on respiratory diseases using air pollution reanalysis data on the same sample of the estimates using monitorin station data.

First stage

	Panel A	*Panel B*	*Panel C*	*Panel D*
	PM_{10}	PM_{10}	PM_{10}	PM_{10}
$STRIKE$	1.185***	1.039**	1.101***	0.998***
	[0.301]	[0.338]	[0.309]	[0.339]
$F-stat$	21.881	19.563	18.866	18.063

Second stage

	Respiratory (all patients)	Respiratory (all patients)	Respiratory (all patients)	Respiratory (all patients)
Panel A - Marginal effects:				
PM_{10}	0.046***	0.053**	0.046***	0.051**
	[0.015]	[0.021]	[0.017]	[0.022]
Panel B - Semi-elasticities:				
PM_{10}	0.022***	0.025**	0.022***	0.025**
	[0.007]	[0.010]	[0.008]	[0.010]
CONTROL (holiday)		YES		YES
CONTROL (weather)			YES	YES
TIME FEs	YES	YES	YES	YES
MUNICIPALITY FEs	YES	YES	YES	YES
N	72,270	72,270	72,270	72,270

$^{***}p < 0.01,^{**} p < 0.05,^{*} p < 0.1$

Notes: The numbers refer to an initial sample of 316,109 urgent respiratory hospital admissions defined in the primary diagnosis and to a population of 41,852,702 individuals distributed across 66 municipalities over 1095 days. All regressions include day-of-week, week-of-year, year and municipality fixed effects. Additional controls include dummies for school holidays and public holidays as well as weather controls (5-degree bins for atmospheric temperature, amount of precipitation and wind speed). Standard errors (in parentheses) are clustered at the municipality level. Estimates are weighted by municipality population size.

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B List of figures

Figure B.1: Map of the 111 Italian municipalities

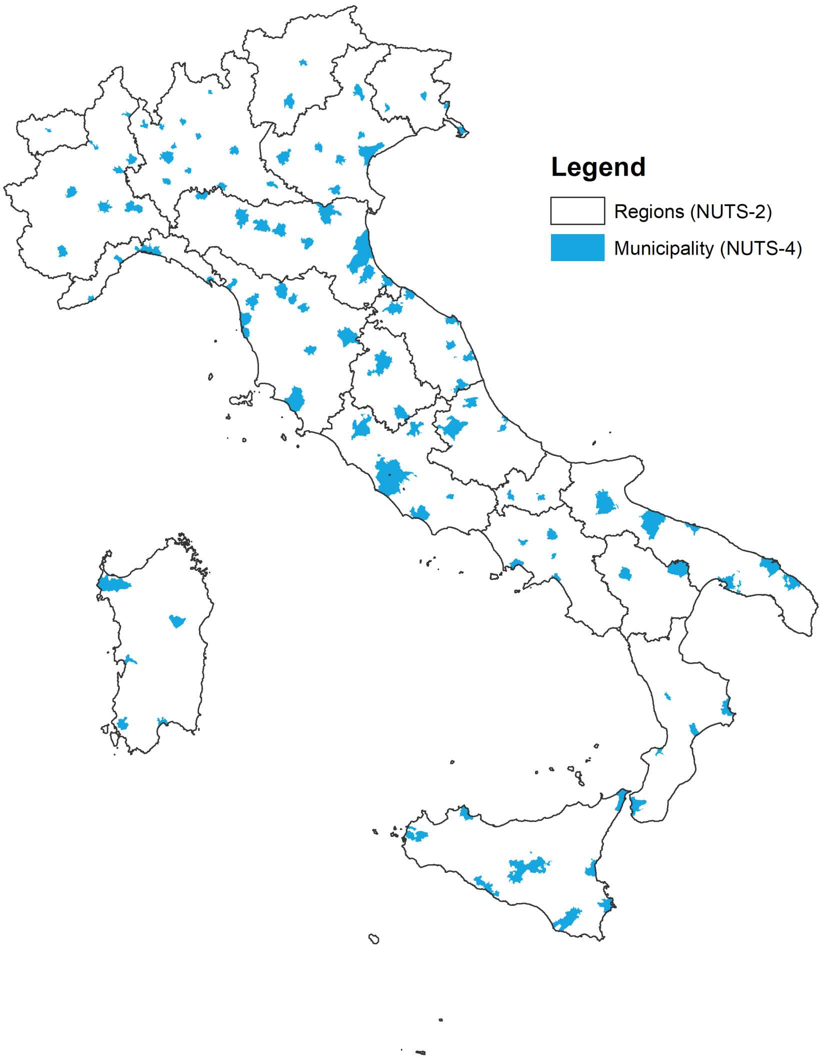

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Figure B.2: Weekly average values of PM_{10}

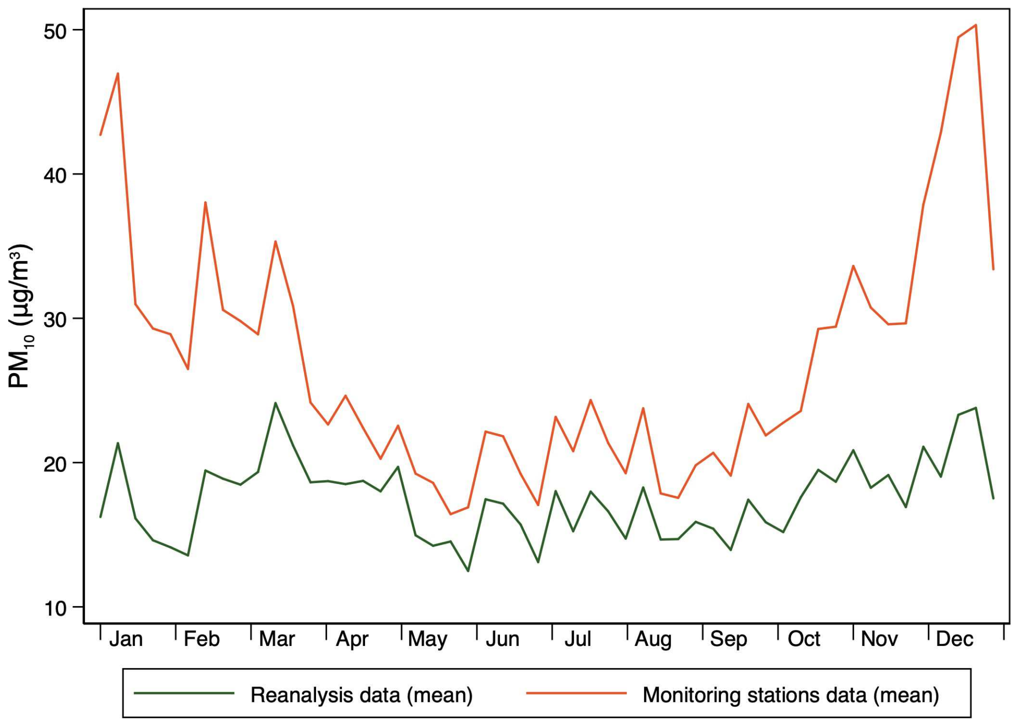

Figure B.3: Weekly average concentrations of air pollutants (2013-2015)

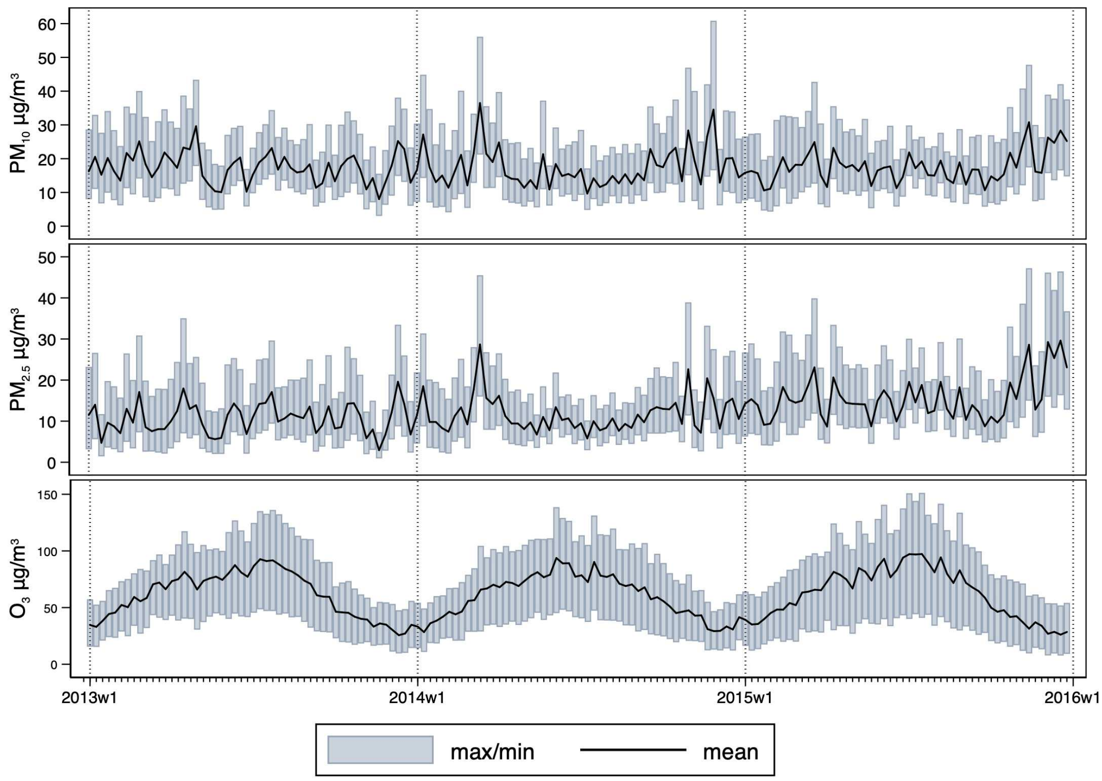

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Figure B.4: Scatter correlation matrix for air pollutants

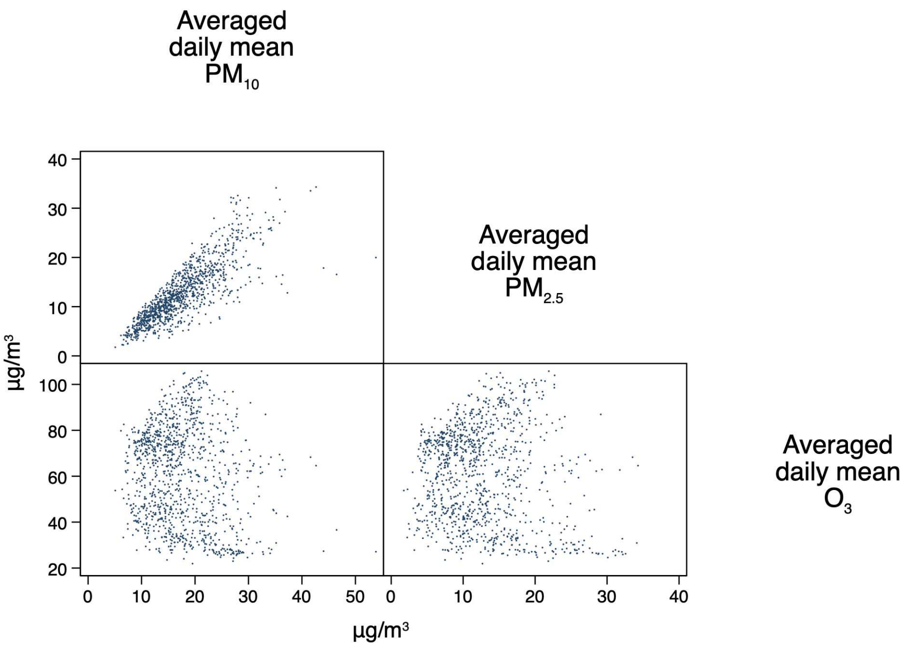

Figure B.5: Trends of weekly respiratory diseases rate and weather conditions (2013-2015)

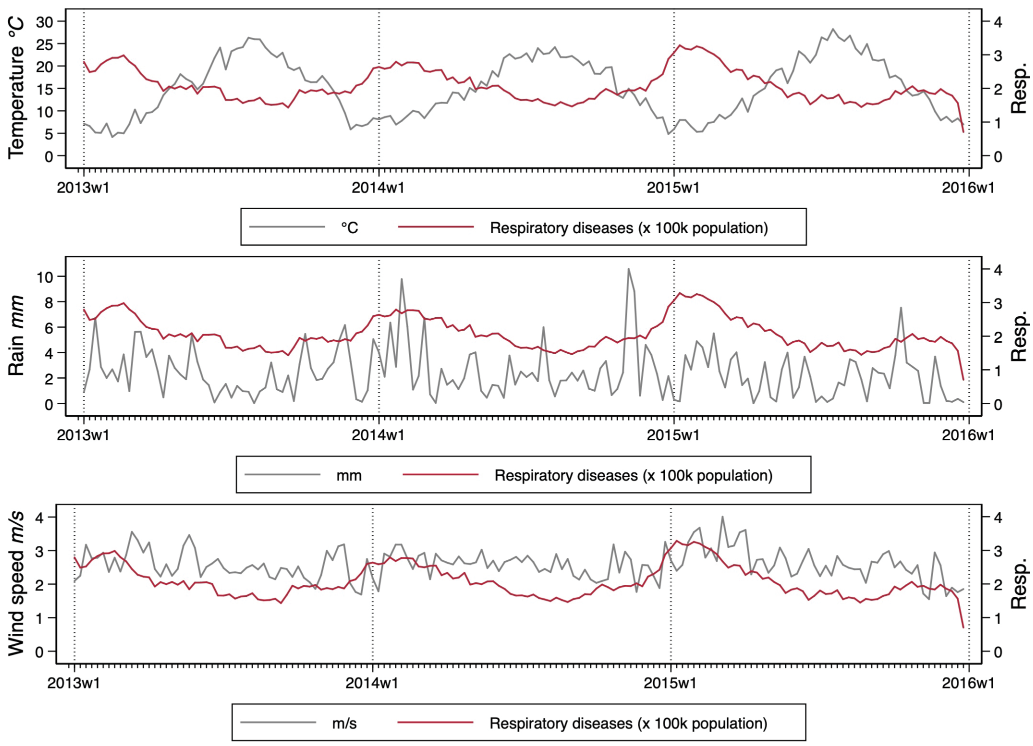

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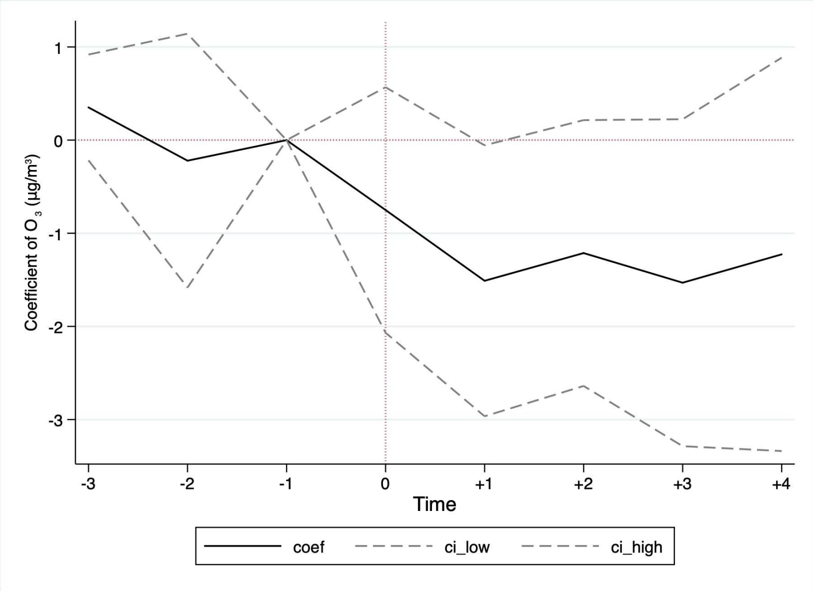
Figure B.6: The effects of PT strikes on O_3 in an event study framework



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