When a (Particulate) Matter Strikes the City. Social Disparities and Health Costs of Air Pollution*

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Abstract

We investigate the unequal effects of air pollution on health outcomes and costs by linking daily pollutant concentration levels to information on the universe of hospitalizations in all major Italian municipalities. By exploiting daily episodes of all public transportation strikes occurred between 2013 and 2015 as an instrumental variable for pollutant concentrations, we find that higher values of particle pollution (PM_{10} and $PM_{2.5}$) induced by strikes cause a rise in urgent respiratory hospital admissions, with a larger penalty for the young, the oldest and the least educated We also estimate direct monetary costs, showing not only that air pollution increases the medical spending for a higher number of hospitalizations, but it also increases their complexity, hence their costs. In terms of total costs, we show that individuals of different ages in combination with different exposures to air pollution may face similar health costs. Our study provides large evidence of environmental inequality, suggesting that effective mitigation policies not only have to account for air pollution as a technological issue, but also as a socio-economic phenomenon with largely heterogeneous effects.

JEL: I14, I18, J45, J52, L91, Q53, R41

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1 Introduction

Air pollution represents a global and increasing concern, contributing to serious illnesses, premature deaths and productivity loss, 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 distributional impacts. Indeed, 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 hits individuals differently, public policies aimed at mitigating the impact of air pollution should incorporate such differentials in order to optimally compensate individuals for their damages.

In this paper we provide causal estimates of the differential effect of particulate matter - one of the most diffused and harmful air pollutant, on the number of hospitalizations (extensive margin) and related total costs, and on average unit costs (intensive margin), offering a large-scale analysis relative to all major Italian cities for the period 2013-2015. Indeed, hospitalizations resulting from higher air pollution concentrations might be more likely to occur and more complex to deal with. While the distinction between extensive and intensive margin is of relevant policy interest, so far the literature has limited to quantifying only the former. We fill this gap by providing an exact quantification of the hospitalization costs for pulmonary diseases caused by sudden increases of both PM_{10} and $PM_{2.5}$, exploring the effects heterogeneity through the lenses of age, educational attainment and migration status.

State-of-the-art environmental data employed in this study allow to capture a more reliable air pollution dispersion over a homogeneous and granular grid of the whole Italian territory, circumventing the non-random distribution over space and time, and the "births" and "deaths" of monitoring stations. We link these data to an administrative hospital discharge dataset including the universe of Italian daily hospital admissions and their costs in both public and private structures. Our research thus benefits from a homogeneous three-year daily pollution-hospitalizations match for all the Italian municipalities.

The endogeneity issue due to non-random pollution exposure are carefully addressed by framing the analysis in an instrumental variable (IV) approach. Precisely, we leverage episodes of public transportation (PT) strikes, which unexpectedly generate traffic congestion and increase air pollution levels on specific day-municipality combinations. PT strikes represent a unique application, as the at-risk population is potentially very large. Moreover, the universalistic nature of the Italian healthcare system offers a favorable setting for this type of analysis, as individuals face negligible barriers in accessing the healthcare.

Our results show that increases in particle pollution, instrumented by PT strikes, lead to more urgent hospital admissions. In particular, when vis-à-vis comparing exposure treatment to both PM_{10} and $PM_{2.5}$, we find much larger effects for finer particulate: one standard deviation increase in PM_{10} causes an additional 0.53 hospital admissions per 100 thousand residents, while a similar increase in $PM_{2.5}$ causes 0.88. An important finding of our study is that the penalty of air pollution exposure is particularly pronounced for the young and the least educated. Moreover, we find evidence of disparities for pollution-induced hospitalizations relative to migrants coming from low income countries. Taken together, our findings of unbalanced impacts of air pollution point to the existence of large environmental inequality as those who do not contribute the most to air pollution formation are the most affected. This suggests that not only air pollution is a technological issue, but it also constitutes a socio-economic challenge due to limited adaptive or affordable capacity of the most vulnerable population groups.

We then examine to what extent traffic-born adverse air quality affects the hospitalization costs for each disease considered. We find that one additional microgram per cubic meter of PM_{10} ($PM_{2.5}$) increases the average unit cost for asthma admissions by 133 euro (223 euro), which represents an excess expenditure of 8.1% (13.6%) relative to a standard hospitalization cost for this disease. Hence, together with a higher probability of being hospitalized, exposure to particulate matter also increases the complexity, namely the costs, of each related admission for asthma. We also find impact for higher PM_{10} concentrations on COPD costs, where a one additional microgram per cubic meter causes a rise in the admission unit costs of 45 euro, representing a 1.8% increase compared to the average total cost of 2,488 euro per admission. On the contrary, no effects are found for $PM_{2.5}$ on COPD unit costs.

Overall, considering both extensive and intensive margins, we estimate that a daily increase of one microgram/cubic meter in PM_{10} ($PM_{2.5}$) is associated with an additional 180 euro (303 euro) per 100 thousand individuals, representing 32% (49%) of the average daily expenditure on respiratory urgent admissions. In the case of PM_{10} ($PM_{2.5}$) this cost ranges between 340 euro (573 euro) for the young, and 621 euro (1,036) for the elderly patients. We summarize these results through a heat map which shows how populations with different age structures in combination with different PM exposures generate similar health costs. For instance, a modest increase of 6 microgram per cubic meter of PM_{10} among individuals aged between 15 and 24 is responsible for a similar excess expenditure as the one for 40-50 year olds in response to a 15 microgram increase.

Based on these results, we derive back-of-the-envelope calculations of total daily monetary costs relative to one standard deviation increase in PM for the 17.8 million residents of the 111 municipalities considered, which amount to 331,843 euro for PM_{10}, and 498,541 euro for $PM_{2.5}$, representing 0.37% and 0.55% of the total daily health expenditure in Italy.

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

2 Adverse effects of particulate matter

Among different types of air pollutants, most of the evidence of health effects relate to particulate matter (PM), ozone (O_3) and nitrogen dioxide (NO_2). However, due to its ability to easily penetrate into the lungs and blood streams unfiltered, 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 in particles less than 10 micrometers (μm) in aerodynamic diameter, while $PM_{2.5}$ consists of particles of even smaller diameter (less than 2.5 μm). $PM_{2.5}$ can penetrate more deeply into the lungs, where it can stimulate inflammation and produce more harmful effects compared to PM_{10}. Both PM_{10} and $PM_{2.5}$ originate from natural and anthropogenic sources, even though most particle pollution derives from fuel combustion from motor vehicles, diesel in particular (EEA, 2016).

Although air pollution represents a "public bad", it does not affect everyone to the same extent. On the contrary, the unequal distribution of the impacts of air pollution closely reflects the socio-demographic differences within the society. A pioneering study by Neidell (2004), who studied the differential impact of air pollution on child hospitalizations, has introduced the 'double jeopardy' hypothesis, according to which low SES individuals are "*not only exposed to higher levels of pollution but also are more harmed by similar amounts of pollution*" [page 1228]. Hence, 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 not only more vulnerable to air pollution, but also less responsible for air pollution 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 impacts for different ethnic groups in US, with larger effects for Whites and Hispanics (Ostro et al., 2006) and for African Americans (Apelberg et al., 2005, Bell and Dominici, 2008). A recent study of New Jersey residents found that the risk of dying early from long-term exposure to particle pollution was higher in communities with larger African-American populations (Wang et al., 2016). In Europe, the growing inflow migration from low-income countries, in particular from Africa, is increasing the share of at-risk people, as 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, policy makers need a precise calculation of these exposure differentials and compensation gap in order to effectively design policy responses able to mitigate the environmental inequalities.

Recently, a group of studies have investigated the effect of air pollution on healthcare utilization, focusing on NO_2, CO and PM. Schlenker and Walker (2015) estimate the impact of CO on hospital admissions for communities living in 12 US airport zones, showing that an additional standard deviation in the pollutant concentrations leads to a 17% increase in respiratory admissions. Based on a simple back-of-the-envelope calculation, the authors estimate a corresponding 540 thousand dollar costs for 6 million people living in the airport zones. Halliday et al. (2015) show that a one standard deviation increase in particulates from volcanic eruptions (vog), leads to a 23-36% increase in expenditures on emergency visits, though the comparability of vog and regular particulate pollution might limit the external validity of the estimated effects. More recently, Deryugina et al. (2016) demonstrate that lower $PM2.5$ concentrations experienced during the period 1999-2001 led to decrease 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. All these studies find strong adverse effects of air pollution on access to healthcare, even though the specific geographical location and subsamples of the population analyzed may represent a limit to the external validity of the results. Moreover, none of these studies provide a detailed analysis of healthcare costs due to medical treatment of different complexity, which represent a valuable evidence from a policy perspective.

3 Data

We combine administrative data on the universe of 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 relative to all the 111 province capitals cities (see Figure B1 in Appendix B). For each of the 1,095 days between 2013-2015 and 111 administrative municipalities, we consider a balanced panel consisting of 121,545 observations. This section describes the data, with additional details included in Appendix A (Table A1).[1]

[1] In January 2010 there were 8,090 Italian municipalities (corresponding to Local Administrative Units according to the European classification of territorial units), which were the building blocks of Italian provinces corresponding to the NUTS 3 level of the Eurostat classification. Each province is 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 capitali cities undergoing organizational changes: Italian provinces changed 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 in any point in time constituted an administrative city in Italy.

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 demographic data (age, gender, place of birth and residence), 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. For the same purpose, we further restrict the cases to hospitalization episodes relative to respiratory diseases based on the primary diagnosis relative to each hospitalization (codes ICD-9[2]). This choice is more stringent with respect to the analysis by Schlenker and Walker (2015), who count a patient as suffering from a sickness if either the primary or one of the secondary diagnosis code lists a respiratory illness under scrutiny. For instance, if an individual is hospitalized from a leg fracture, being at the same time an asthmatic patient, one might attribute to air pollution a hospitalization which instead might be causally related to traffic congestion.Yearly, there are roughly 9.5 million hospital admissions in 8,090 municipalities in Italy, out of which an average of 39% is of urgent nature (11.2 millions). Within the urgent hospitalizations, 31% are delivered to the residents of the 111 municipalities considered. A subset of 11.7% of hospitalizations, corresponding to 403,861 hospitalizations, is due to a primary respiratory disease diagnoses, which represent our main outcomes.

In our core analysis, we determine the count of daily admissions by considering only municipalities of residence and disregarding the municipalities where hospitalizations take place, which in 1.32% cases do not coincide for the urgent respiratory cases. While Italian residents are free to seek health-care anywhere in the Italian territory, accessing hospitals away from the municipalities of residence represents an unlike practice in urgent respiratory cases.[3] We thus aggregate the data by day-of-admission and patient municipality of residence.

In order to gauge 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 using country the classification provided by the The World Bank.[4] According to this procedure we obtain daily counts of hospitalizations for the

[2]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)

[3]For the completeness of our results, we also carry out a complementary analysis where we group patients according to the municipality of hospitalization, which delivers comparable findings.

[4]According to World Bank (2014), high income countries have a per-capita gross national income (GNI) for the previous

entire population as well as for each of the socio-economically relevant subgroup. Our final outcomes are represented by daily municipality-level admission counts expressed per 100 thousand residents. When age, education or migration specific groups are considered, the relevant resident population is adjusted to that particular group.

In quantifying 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 Groups (DRGs). DRGs classify hospital patients into homogenous groups, by assigning to each hospitalization a relative cost and a standard length of hospital stay.[5] Additionally, each DRG includes information on a supplementary cost applied to days exceeding the standard length. We thus exploit this information to construct individual hospitalization costs by assigning to each individual a cost relative to the hospitalization DRG, rescaled to account for the extra hospital stay days. We are thus 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, calculating both average unit costs and average per-capita costs. The two dimensions of the economic burden of hospitalizations, together with the frequencies of hospital admissions, allow us to quantify the extensive and intensive margins of pollution-induced hospitalizations. In summary, we consider three main outcomes: the admission count reflects the extensive margin, the average unit cost reflects the intensive margin, while per-capita admissions costs provide a measure of the total burden of air pollution.

year $> 12,746$\$, while for low-middle income countries the GNI is $\leq 12,746$\$. For further details see: https://blogs.worldbank.org/opendata/updated-income-classifications.

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

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 53,333,849 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 relative to the full sample of individual admissions considered and to 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 standard 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 pediatric age individuals. Both the overall and group-specific counts are extremely variable with standard deviations larger than the means. The number of admissions among individuals with primary education is disproportionally higher with respect to the remaining education attainment categories. Finally, the number of admissions is on average lower for migrants, although citizens of low-income countries are more frequent to undergo a hospitalization with respect to those coming from high-income countries.

An urgent respiratory admission costs, on average, 2,856 euro, and this amount varies according to the specific respiratory problem. The cost of an admission related to asthma amounts to 1,648 euro, to chronic obstructive pulmonary disease (COPD) 2,237 euro and to pneumonia 2,884 euro. In per-capita terms, hospitalization costs related to urgent respiratory problems amount to 0.06 euro/day per each resident in the 111 municipalities. To understand the magnitude of this number, one should bear in mind that the overall Italian healthcare fund amounts to an average of 5 euro per resident/day.[6]

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

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

	Mean	Std. Dev.	Min	Max
Unit cost				
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
Daily cost per resident				
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 53,333,849 individuals distributed across 111 municipalities over 1095 days.

3.2 Air pollution concentrations

Air pollution data come from the Copernicus Atmosphere Monitoring Service (CAMS) managed by ECMWF[7]. 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. Additionally, throughout the analysis, we provide in parallel results relative to particulate matter 2.5 micrometers in size or smaller ($PM_{2.5}$), which is much less frequently examined in the existing literature and, as a consequence, so far less considered in the policy debate[8].

Automobile fuel combustion creates mainly PM and CO, although to a lesser extent it also contributes to production of nitrogen oxides, and benzene. While comparable CO and NO_2 data are not available among pollutants analyzed in the dataset at hand, we additionally exploit the information on ozone (O_3), which is responsive to daily transport shock only to a narrow extent and will serve us as a placebo exercise in our IV setting. Traffic congestion results in fuel combustion with a relative tailpipe emissions of particulates, but also in the physical act of friction resulting from wheel-to-road contact exacerbated by frequent acceleration and breaking. As such, not only there are 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.

All the pollution data derive from a combination of direct observation from satellites, monitoring stations and reanalysis.[9] So far, reanalysis data have received limited attention in economic studies given the burden associated with data management and storage (among others Dell et al., 2014, Deschênes and Greenstone, 2007). In relation to air pollution, reanalysis data offer three substantial improvements over

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

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

[9] 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.

monitoring stations measures. First, as discussed in Filippini et al. (2017), 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 pollution levels other 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. Figure B2 in Appendix B plots weekly trends of PM_{10}, averaged over the period 2013-2015, from both CAMS satellite data and Italian monitoring stations data. The two sources follow a similar trend even though concentration readings from monitoring stations are higher and more variable. The higher variance is likely due to fact that monitoring stations provide readings only in the exact place where the station is placed, without accounting for air pollution dispersion in places next to the reading monitor. Given that monitoring stations are spread in a non-random order over the territory, 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 pollutants concentrations with resulting normally distributed measurement error.

Given that the concentration data are often available at a finer geographical resolution than the administrative town of individual residence, we assign each pollution grid cell to the corresponding individual's municipality following a spatial join by means of the Geographic Information System. In case of major urban centers including more than one grid cell, we assign the average of cells's centroids that fall in that area. Such a procedure guarantees a homogeneous measure of pollution over space.

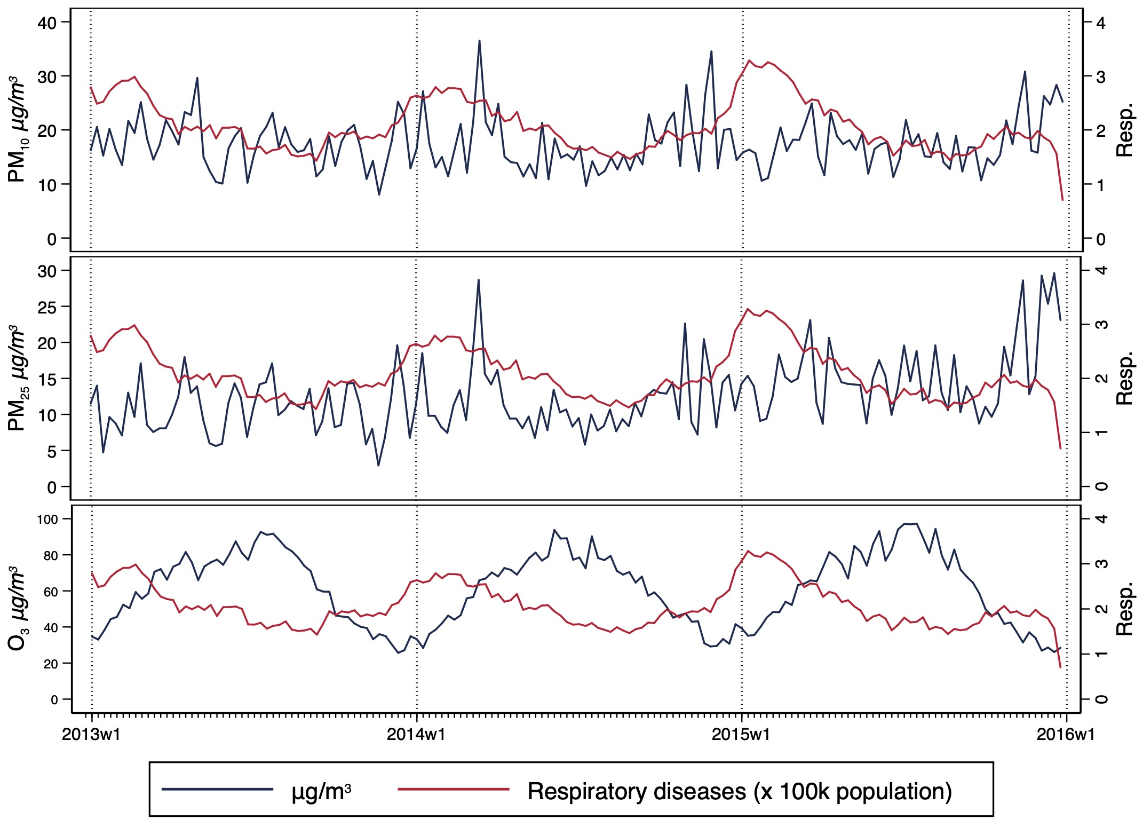
Table 3: Descriptive statistics - Air pollutants

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 particulate matter and ozone versus a moving average of weekly means of hospital urgent admission rates (Figure B3 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 winter months. Consistent with the literature, we find that O_3 exhibits only very noisy and weak unconditional associations with particle pollution (Figure B4 in Appendix B reports the correlation matrix between pollutants). This evidence comes in support for the single-pollutant setup adopted in this study, as opposed to a multi-pollutant approach, which is highly unstable 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

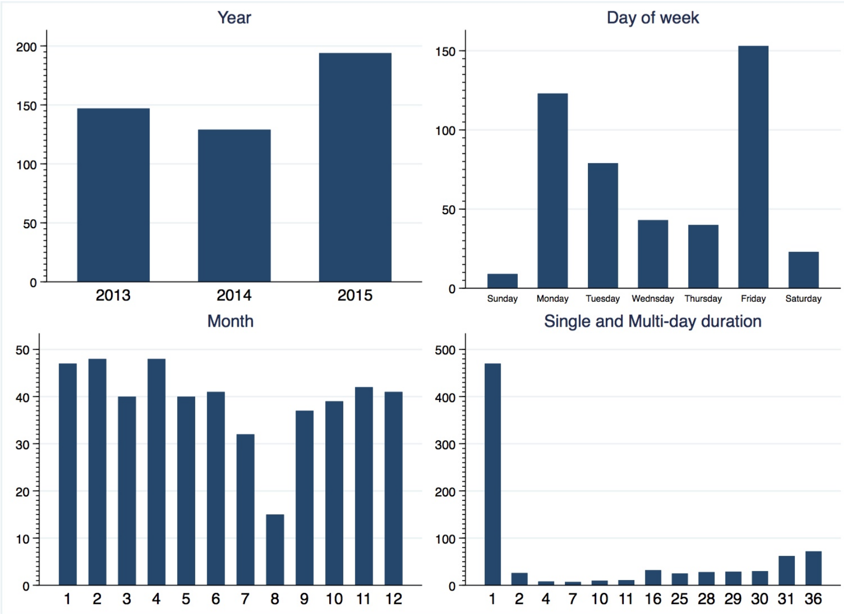
In order to carry out our IV analysis, we also merge information provided by the Italian strike commission[10] and the Ministry of Infrastructures and Transport in order to construct a public transportation (PT) strike database. We use information strikes that took place at the municipality level, excluding national and regional public transportation strikes affecting only to a narrow extent urban and residential centers. 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 administrative municipalities only, we are left with 470 single-day strike 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 week. Strikes tend to take place in all months of the year, with significant drop in 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 possibly adoption of new travel patterns. Table A2 in Appendix A shows details on all public transportation strikes across administrative towns.

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 the 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 of PT users (Adler and van Ommeren, 2016, Anderson, 2014, Bauernschuster et al., 2017, van Exel and Rietveld, 2001, among others). Consequently, with a higher rate of dependence on PT experienced in administrative municipalities, we expect a greater impact of strikes on traffic-related particulate 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 the PT serves a narrow share of population, a strike episode is unlikely to cause a sufficient variation in traffic congestion and consequent pollution.

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

Figure 2: Distribution of strikes across time.



3.4 Local population

Data of the annual local population size come from ISTAT. Table 4 shows descriptive statistics of the Italian resident population of the 111 municipalities for the 2013-2015 period. The total population of the municipalities considered for the three-year period amounts to 53,333,849 individuals.

Table 4: Descriptive statistics of the local population

	Mean	Std. Dev.	Min	Max	Total
All ages	162,199.2	311,888.5	15,176	2,872,021	53,333,849
By age					
Ages below 14	21,328.79	42,250.93	1,884	388,795	7,004,458
Ages 15 - 24	15,166.10	28,431.58	1,286	256,054	4,970,174
Ages 25 - 44	42,566.48	84,118.28	3,757	786,239	13,992,349
Ages 45 - 64	45,771.51	88,226.30	4,293	832,142	15,053,025
Ages 65 and above	37,366.34	69,706.40	3,726	620,912	12,313,843
By education levels					
% with primary edu	0.60	0.04	0.48	0.69	32,000,309
% with secondary edu	0.30	0.03	0.24	0.35	16,000,155
% with tertiary edu	0.10	0.02	0.07	0.17	5,333,385
Migrants					
All ages	32,390.44	78,769.97	642	727,126	10,786,018
Obs.=121,545; n=111; t=1095					

The numbers refer to an initial sample of 403,861 urgent respiratory hospital admissions defined in the primary diagnosis and to a population of 53,333,849 individuals distributed across 111 municipalities over 1095 days.

3.5 Weather conditions and holiday data

While 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 closely related weather variability (Deschenes and Moretti, 2009). We thus employ municipality-specific weather data from the Gridded Agro-Meteorological dataset managed by MARS-AGRI4CAST[11]. In particular, we use daily measures of temperature and sum of precipitations expressed, respectively, in Celsius degrees and mm of rain. This database contains meteorological parameters from weather stations interpolated on a 25x25 km grid.[12] 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 and trends of weather conditions are reported in Appendix A (Table A3 and Figure B5, respectively).

Furthermore, we employ data enlisting school and public holidays (both at the local and national level), in order 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, while the public holiday dates were retrieved from 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 that PM has on urgent respiratory health problems on the overall population considered 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 justification and benchmark for our quasi-experimental estimates using an IV approach. The baseline fixed-effects model including the full set of controls is as follows:

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

where H_{idwy} denotes number of respiratory urgent admissions per 100 thousand 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} or $PM_{2.5}$. 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

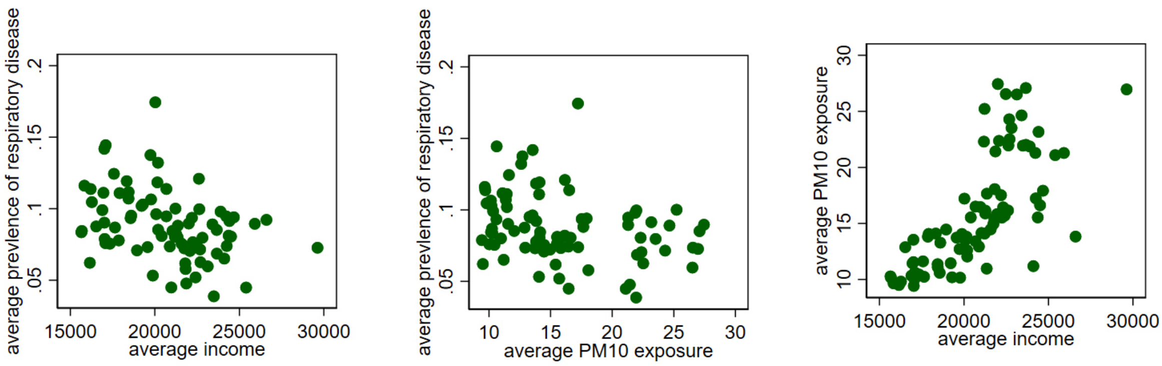
[11] http://agri4cast.jrc.ec.europa.eu/DataPortal/Index.aspx

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

during the week and seasonal effects or recurrent episodes of specific epidemics.

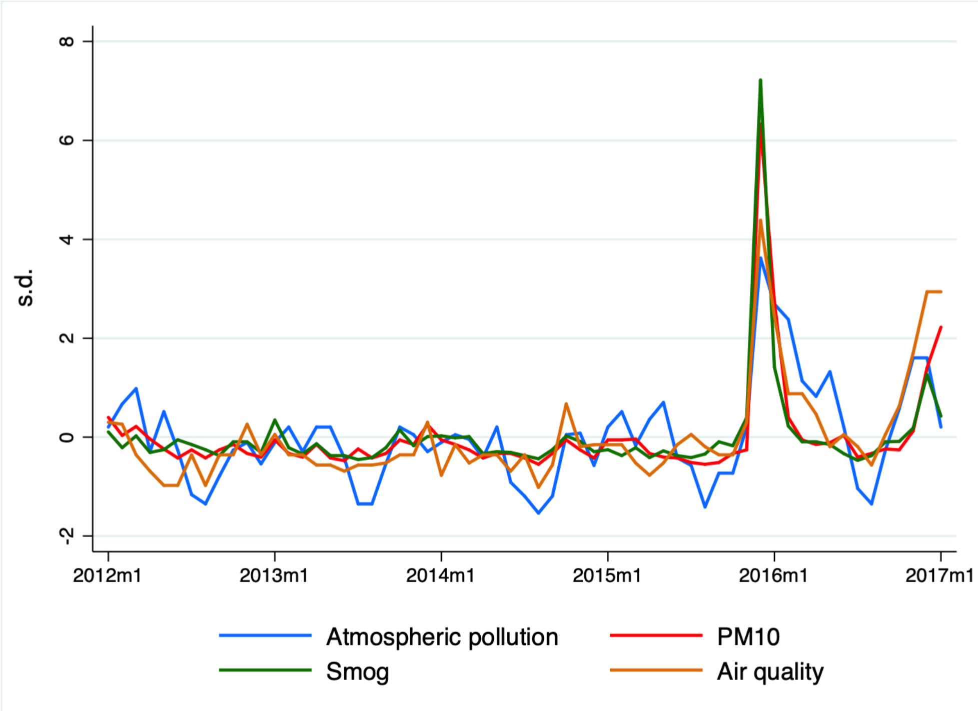
A causal interpretation of these estimates relies on the assumption that hospitalizations are not correlated with any unobserved municipal and time characteristics. In our setting, the most serious cause of concern is the non-random assignment of air pollution. If individual activity is related to air quality, there might be different sorting mechanisms, which expose people at places and periods with systematically different pollution levels. The same sorting mechanisms are likely to correlate with differences in health and socio-economic status. Indeed, better educated individuals are likely to earn more and consume more preventive healthcare, other than being more aware and cautious in dealing with air quality (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 a better health and healthcare. Evidence of these associations is provided in Figure 3, which describes unconditional correlations between average municipality income, prevalence of respiratory diseases and PM_{10} concentrations. Individuals living in municipalities with higher income are also more likely to be exposed at higher pollution levels, but at the same time are less likely to suffer from respiratory disease.

Figure 3: Unconditional 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 again from the Copernicus Atmosphere Monitoring Service (CAMS) managed by ECMWF, while 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.

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



Notes: The graph is obtained by 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 might have different impact on different groups of individuals due to their avoidance behavior. In this respect, it is worth noting that the issue of air quality in Italy has not been present in the public domain until recent times. We are able to infer this by looking at Google trends in terms of Italians' interest in air pollution, PM_{10}, smog and air quality, respectively. Figure 4 shows that interest trends before 2016, proxied by Google searches, are much flatter and negligible in size compared to trends of more recent years. To the extent Google is able to map the individual search preferences, there are no compelling reasons to consider significant avoidance pattern in the individuals' daily activities in response to air pollution levels. On the contrary, it is more plausible to assume that individuals engaged in the labour market or in a schooling track are exposed to ambient pollution on a regular basis, with limited possibility to avoid or downplay their daily obligations, especially in periods of intense economic activity. Following the same reasoning, more vulnerable groups might decide to avoid exposure in response to mild health problem they suffer during most polluted periods. In this setting, the OLS fixed-effects estimates are likely to be severely downward biased relative to the true causal effect. We thus turn to frame our analysis in a quasi experimental setting.

4.2 PT strikes as a quasi-experimental setting

To identify the causal effect of air pollution, we leverage on PT strikes as an IV to capture exogenous changes in air pollution concentrations. Several studies have analyzed the economic impact of strikes (Clark, 1996, Gunderson and Melino, 1990, Harrison and Stewart, 1989). Recently, 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. Moreover, shocks to traffic such as PT strikes, provide instruments for reducing all sources of attenuation bias due to measurement error (Goldman et al., 2011, Halliday et al., 2015, Künzli and Tager, 1997, Sheppard et al., 2012).

In Italy PT strikes hit with a relatively high frequency, which does not allow individuals to treat strikes as days off from their regular daily activities. Moreover, during strike days, a very narrow portion of PT services is guaranteed in order not to put all the activities in stand-by. During early morning and late afternoon a very limited number of PT means is active to deliver essential services, but the major portion or commuters turn to private and rental vehicles, bicycles or walking. A narrow amount of individuals commute daily outside of their municipalities, especially in the case of administrative towns, which are more common to receive inflows of workers from minor surrounding towns, rather than generate workers 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 age comprised between 30 and 45 years. We make no assumptions about commuting style of non-resident citizens, who conversely are more likely to commute outside their municipalities (27% on average in 2013). While individuals commuting to administrative municipalities are also exposed to the environmental conditions of the hosting towns and, as a consequence, likely to be hospitalized in these towns in case of urgencies, for those individuals 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.

Moreover, we do not consider hospitalizations of non-residents, while testing for mobility responses of residents on strike days. In particular, we test whether individuals living in strike municipalities are more or less likely to seek hospital admissions outside their town of residence. If traffic congestion is likely to drive the demand for healthcare away from the affected areas, the administrative towns' residents might be willing to access hospitals away from their residence area. In such case, we might face an underestimation of the treatment exposure, especially for the extensive margin of hospitalizations, since the actually treated individuals might access healthcare among areas not included in the identification strategy. However, our results show no evidence in favor of differential hospital mobility during strike days in strike towns. All these considerations suggest that our treatment IV variable is unlikely to cause any sort of endogenous mobility, since the out-of-town flows of residents are negligible and not correlated with any *ad-hoc* actions of individuals.

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} or $PM_{2.5}$ 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 P_{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 level during strike days for reasons other than strikes being in effect. All estimates are weighted by municipality population size, while standard errors are clustered at the municipality level to allow for correlation among municipalities exposed to similar levels of air pollution concentrations (Cameron and Miller, 2015).[13] To support our identification strategy, in subsection 5.6 we present an extensive set of placebo and falsification tests as well as alternative model specifications.

5 Results

5.1 OLS estimates

We begin by presenting in Table 5 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)).

[13]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.

Table 5: 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}	-0.0007	-0.001	-0.0007	-0.001
	[0.0004]	[0.0005]	[0.0004]	[0.0005]
CONTROL (holiday)		YES		YES
CONTROL (weather)			YES	YES
TIME FE	YES	YES	YES	YES
MUNICIPALITIES FE	YES	YES	YES	YES
N	121,545	121,545	121,545	121,545

$^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$
Notes: The coefficients indicate effects for 100,000 residents. 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 (atmospheric temperature and amount of precipitation). Standard errors (in parentheses) are clustered at the municipality level. Estimates are weighted by municipality population size.

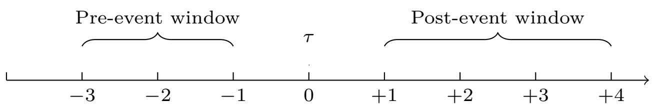
The OLS estimates show noise and no statistically significant effect of PM_{10} on hospital admissions. As explained earlier in Section 4, our baseline model suffers from severe underestimation due to different sources of bias. This evidence is largely consistent with several studies that deal with causal 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).

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[14]. We thus augment our empirical strategy presented in Equation 2 with distributed lags and leads terms 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, according to the timeline in Figure 5.

Figure 5: Timeline for the event study



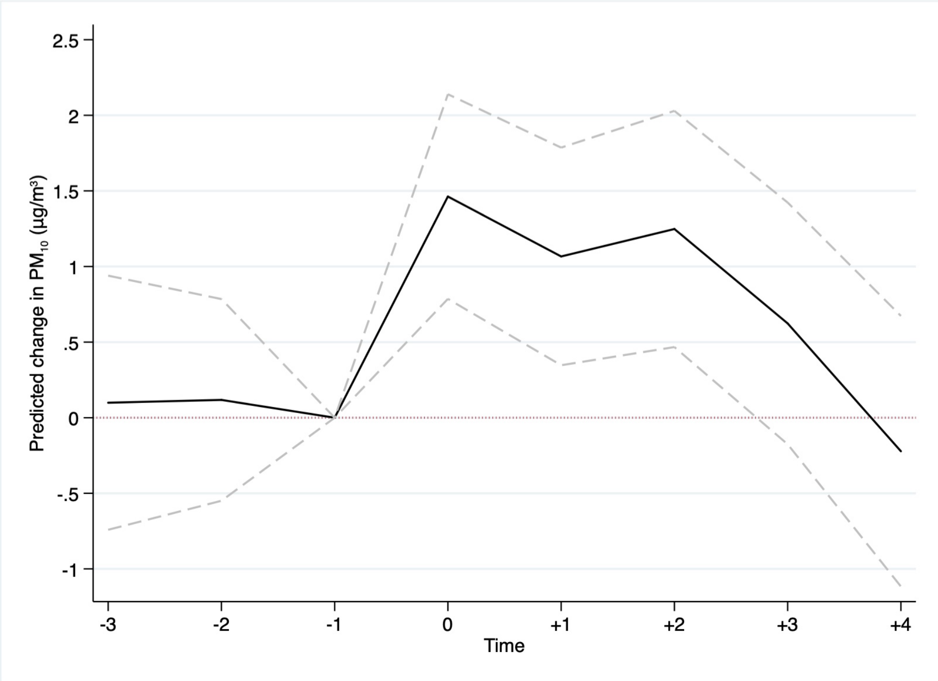
We thus frame the actual timing of each strike on this synthetic timeline, and we estimate the following reduced-form equation:

[14]For the sake of brevity, we report only the event study for PM_{10}. For $PM_{2.5}$ the results are qualitatively similar and available upon request.

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

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. We impose that $\tau_{-1} = 0$, as in the presence of fixed effects not all of the τ's are identified. Finally, ε_{idwy} is an idiosyncratic error term.

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



Notes: The figure presents marginal effect 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 effect (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.

During a PT strike day ($\tau = 0$), we observe an average increase of 1.5 $\mu g/m^3$ in PM_{10} and a persistent decline in PM_{10} in the days following the strike event. These results obtained on the sample of all municipalities where a strike event takes place (see subsection 3.3), are consistent with the first-stage results performed on the entire sample of municipalities. In our core IV specification presented in Table 6, we find that PT strikes lead to an increase in PM_{10} of 1.20 $\mu g/m^3$ (column (1)). In qualitative terms, this is is consistent 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. Our results are also robust to alternative model specifications where we control for holidays (column (3) and (4)) and weather conditions (column (2) and (4))[15]. These controls might be useful as during rainy days individuals might modify their daily activities, thus being less affected by strikes (Bauernschuster et al., 2017). It might also be the case, however, that heavier traffic congestion experienced during sunny strike days might generate higher pollution concentrations than the ones occurring during rainy strike days[16]. Finally, during holiday periods strikes are less likely to occur but pollution levels are slightly higher. In line with our expectations, when including these controls the magnitude of our first-stage coefficient estimates for PM_{10} decreases slightly. In the most demanding specification where both dummies for holidays (public and school) and weather controls (rain and temperature) are included (column (4)), the PM_{10} coefficient decreases to 1.12 $\mu g/m^3$ but still maintains full statistical significance.

Table 6: 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***	1.17***	1.12***	1.12***
	[0.30]	[0.25]	[0.30]	[0.25]
CONTROL (weather)		YES		YES
CONTROL (holiday)			YES	YES
TIME FE	YES	YES	YES	YES
MUNICIPALITIES FE	YES	YES	YES	YES
F-stat	28.821	29.123	25.239	26.497
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 (atmospheric temperature and amount of precipitation). Standard errors (in parentheses) are clustered at the municipality level. STR 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 diseases.

Table 7 reports second stage marginal effects (Panel A) and the relative semi-elasticity estimates (Panel B). Contrary to our baseline OLS model presented in 5.1, our quasi-experimental estimates point to a positive and statistically significant relationship between PM_{10} and urgent respiratory disease. Panel A (column 1) shows that one additional unit of $\mu g/m^3$ in PM_{10} causes a 0.05 increase in respiratory admissions per 100,000 residents. Hence, one standard deviation increase in PM_{10} is likely to cause a 26% increase in respiratory hospitalizations. The coefficients estimates preserve both magnitude and statistical significance also in the most demanding specification (column 4), where both dummies for

[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 through the "wash-out" effect (Ardon-Dryer et al., 2015, Guo et al., 2016).

public and school holidays as well as weather variables are included.

Our results are in line with recent evidence on causal effect of pollution on health problems (Halliday et al., 2015, Knittel et al., 2016, Schlenker and Walker, 2015, e.g.), but larger in magnitude with respect to less precise identification strategies. Among 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 pollution particulate, while 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, temperatures, concomitant air pollutants and other factors. Although less comparable, the study by Ward (2015) finds that a one standard deviation increase in PM concentrations causes a 4% increase in children hospitalization. A direct comparison of our results with other studies is difficult given that we address contemporaneous health problems, while most literature focuses on mortality, which is the most severe manifestation of health issues, at least in terms of day-to-day air pollution fluctuations.

Table 7: IV estimates of the effect of PM_{10} on respiratory disease (all patients)

	Respiratory (all patients)	Respiratory (all patients)	Respiratory (all patients)	Respiratory (all patients)
Panel A - Marginal effects:				
PM_{10}	0.0527***	0.0536***	0.0523***	0.0523***
	[0.0174]	[0.0162]	[0.0190]	[0.0172]
Panel B - Semi-elasticities:				
PM_{10}	0.0257***	0.0262***	0.0255***	0.0255***
	[0.00846]	[0.00789]	[0.00921]	[0.00836]
CONTROL (weather)		YES		YES
CONTROL (holiday)			YES	YES
TIME FE	YES	YES	YES	YES
MUNICIPALITIES FE	YES	YES	YES	YES
N	121,545	121,545	121,545	121,545

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

Notes: The coefficients indicate effects for 100,000 residents.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 (atmospheric temperature and amount of precipitation). Standard errors (in parentheses) are clustered at the municipality level. Estimates are weighted by municipality population size.

5.3 Heterogeneous effects of PM_{10} on respiratory diseases.

The results discussed so far refer to the overall population, without accounting for the fact that there are important sources of heterogeneity in how exposure to air pollution shocks affects the individual health. As discussed earlier, it is well documented that the adverse health effects of air pollution are stronger for the very young and the elderly. 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). In elderly people, co-existing chronic diseases together with a cumulative exposure to air pollution, determine increased susceptibility, increased hospitalization and risk of mortality (Janke et al., 2009, Simoni et al., 2015).

In this section we extend the analysis by testing the hypothesis that air pollution generates different impacts also for disadvantaged socio-economic groups. If a lower education and a lower income generate a weaker health endowment, any additional health shock suffered by disadvantaged individuals is likely to give rise to greater health damages (Forastiere et al., 2007b, Neidell, 2004, O'Neill et al., 2003, among others). Quantification of such differentials is important from the policy perspective, as in universalistic healthcare systems adopted by many European countries, the financial burden of air pollution damages is directly transferred to the public finance with a larger burden for healthcare costs. We thus isolate distinct portions of population, based on their age group, migration status and education attainment, evaluating if 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 5 age-specific bins, and create distinct outcome measures, i.e. the count of admissions for 100,000 residents in each age group. Table 8 presents second-stage results for five age subgroups separately following Equation 3, weighted by size of municipality population for each age group.

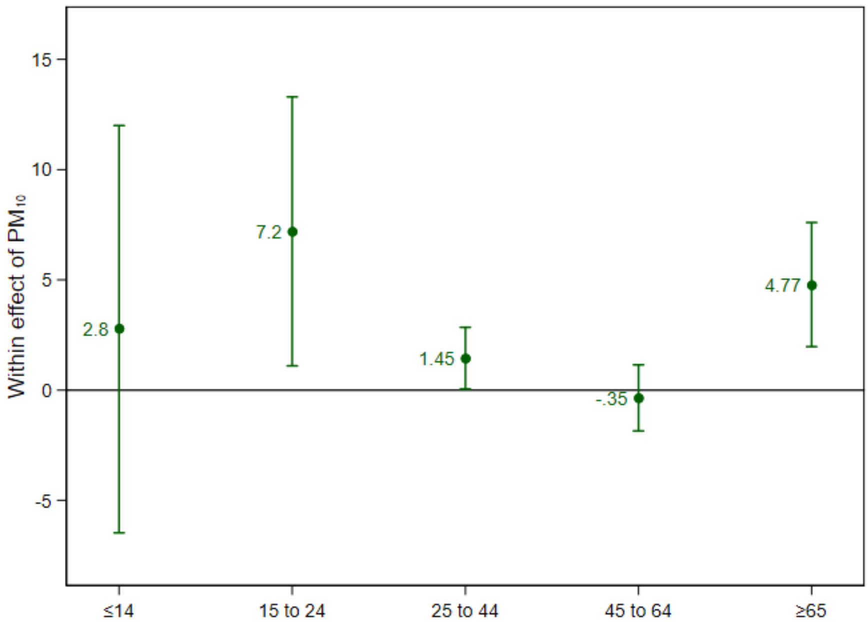
Table 8: IV estimates of the effect of PM_{10} on respiratory diseases in different age groups.

	Respiratory (1)	Respiratory (2)	Respiratory (3)	Respiratory (4)
Panel A: ages below 14				
PM_{10}	0.0416	0.0424	0.0489	0.0490
	[0.0699]	[0.0698]	[0.0744]	[0.0725]
Panel B: ages 15 - 24				
PM_{10}	0.0716*	0.0723*	0.0740	0.0729*
	[0.0415]	[0.0380]	[0.0454]	[0.0400]
Panel C: ages 25 - 44				
PM_{10}	0.0289**	0.0296**	0.0304*	0.0305**
	[0.0143]	[0.0138]	[0.0157]	[0.0147]
Panel D: ages 45 - 64				
PM_{10}	-0.00727	-0.00744	-0.0108	-0.0109
	[0.0152]	[0.0154]	[0.0162]	[0.0160]
Panel E: ages 65 and above				
PM_{10}	0.167***	0.170***	0.165***	0.165***
	[0.0496]	[0.0491]	[0.0532]	[0.0512]
CONTROL (weather)		YES		YES
CONTROL (holiday)			YES	YES
TIME FE	YES	YES	YES	YES
MUNICIPALITIES FE	YES	YES	YES	YES
N	121,545	121,545	121,545	121,545

$^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.
Notes: The coefficients indicate effects for 100,000 residents. 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 (atmospheric temperature and amount of precipitation). Standard errors (in parentheses) 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 8 accounting for the variability of the estimates due to the different number of ages that form each age group. 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 numbers indicate larger effects. We observe an increase of 0.17 admissions (statistically significant at 1%) in the number of urgent respiratory cases for the elderly (individuals aged 65 and older) for 1 $\mu g/m^3$ increase in PM_{10}. If this coefficient is scaled up to standard deviations (s.d.), the effect amounts to an additional 1.8 daily admission for one s.d. increase in PM_{10}. Interestingly, we find significant and positive effects also in young adults, with a one s.d. increase in PM_{10} being responsible for an additional 0.75 increase in 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. A possible explanation channel for the magnitude of this result is likely to be related to lifestyle patterns of the young. As earlier discussed, according to official statistics (Istat, 2013), 73.1% of Italian individuals aged between 15 and 24 engaged daily 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 particular 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 are calculated following Halliday et al. (2015): effects/(no. of ages in group)×1000. Confidence intervals are set to 95%.

While heterogeneous response to adverse health shocks have been more frequently studied in the existing literature, there are other mechanisms related to individual vulnerability that might be interesting from the policy perspective. 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). To the extent environmental aspects are potentially affected by public policy, the related health inequalities represent consequences of differences largely beyond the 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 9 point to a particularly pronounced effect of PM_{10} on urgent admissions among individuals with primary education attainment, where 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. Among individuals with tertiary education, the additional PM_{10} concentrations induced by public PT strikes are no longer responsible for any increase in urgent respiratory cases. Under the assumption that our IV estimates are no longer biased by avoidance behavior (see Section 4), the mechanisms driving these differential results are plausibly linked to an overall better health status of individuals with the highest education level, which downplays the adverse effects of daily fluctuations in PM_{10} concentrations.

Table 9: 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 educ. lev.				
PM_{10}	0.0937***	0.0946***	0.0948**	0.0938***
	[0.0357]	[0.0327]	[0.0394]	[0.0349]
Panel B: Secondary educ. lev.				
PM_{10}	0.0318**	0.0328**	0.0323**	0.0326**
	[0.0141]	[0.0142]	[0.0152]	[0.0150]
Panel C: Tertiary educ. lev.				
PM_{10}	-0.00245	-0.00255	-0.00526	-0.00527
	[0.0302]	[0.0312]	[0.0326]	[0.0330]
CONTROL (weather)		YES		YES
CONTROL (holiday)			YES	YES
TIME FE	YES	YES	YES	YES
MUNICIPALITIES FE	YES	YES	YES	YES
N	121,545	121,545	121,545	121,545

$^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.
Notes: The coefficients indicate effects for 100,000 residents. 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 (atmospheric temperature and amount of precipitation). Standard errors (in parentheses) 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 10 and point to no significant effects of PM_{10} on urgent respiratory problems when considering for foreign citizens coming from countries with middle and high income according to the World Bank classification (see Section 3). However, migrants included in these categories are substantially different in terms of socio-demographic and economic characteristics from those coming from low income countries, who often represents most marginalized individuals. We thus provide a more in-depth view focusing on the sole group of African migrants who mainly come from Morocco, Egypt, Nigeria, Senegal and Tunisia, who represent the vast majority of low income migrants in Italy. Even though only weakly statistically significant, this particular group of nationalities seems to be adversely affected by PM_{10}, with one additional s.d. of PM_{10} causing 0.30 additional admissions. When interpreting this result, it is important to underline that the average number of hospitalizations for migrants is much lower and amounts to only 1.5% of total admissions. The pollution penalization is thus disproportionally larger for migrants as if scaled up to one standard deviation, PM_{10} doubles their hospitalization rate. Nonetheless, a potential caveat of this evidence is that access barriers to healthcare utilization for a large group of migrants is limited. Due to normative regulations, full healthcare coverage in Italy is granted to foreign citizens upon registration to the national healthcare service (SSN), which is not guaranteed without a formal residency. Since these foreign citizens live often in informal rentals or under illegal subletting, they face difficulties in obtaining the residency status which provides access also to a healthcare coverage. As a result, hospital admissions of migrants that we observe in the data might represent a severe underestimation of the actual healthcare demand. Indeed, the left out unobserved healthcare needs of irregular migrants might be much more pronounced with respect to the portion of migrant population that we detect. 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 10: 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}	0.00279	0.00282	0.00312	0.00313
	[0.00978]	[0.0102]	[0.0105]	[0.0108]
Panel B: Low-middle income Countries				
PM_{10}	0.0159	0.0165	0.0156	0.0158
	[0.0178]	[0.0186]	[0.0190]	[0.0195]
Panel C: African countries				
PM_{10}	0.0261*	0.0271*	0.0274*	0.0278*
	[0.0145]	[0.0150]	[0.0154]	[0.0157]
CONTROL (weather)		YES		YES
CONTROL (holiday)			YES	YES
TIME FE	YES	YES	YES	YES
MUNICIPALITIES FE	YES	YES	YES	YES
N	121,545	121,545	121,545	121,545

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

Notes: The coefficients indicate effects for 100,000 residents.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 (atmospheric temperature and amount of precipitation). Standard errors (in parentheses) are clustered at the municipality level. Estimates are weighted by municipality population size by age group.

5.4 Results for $PM_{2.5}$

The existing literature discussing the causal link between particulate matter and health mainly focuses on PM_{10}. From the policy perspective, PM_{10} represents a more widespread measure of particle pollution, with precise indications in terms of daily/annual limits. Nevertheless, finer particulate matter such as $PM_{2.5}$ is found to be particularly harmful from the clinical perspective due to its deeper penetration into organs. Exploiting the information in our air pollution data, we benchmark the results obtained for PM_{10} with the respective estimates for $PM_{2.5}$. The main results are presented in Figure 8 and Figure 9, while we additionally show the full set of estimates for $PM_{2.5}$ in Table A4 in Appendix A.

Figure 8: IV estimates of the marginal effects of PM_{10} and $PM_{2.5}$ on respiratory diseases by age groups.

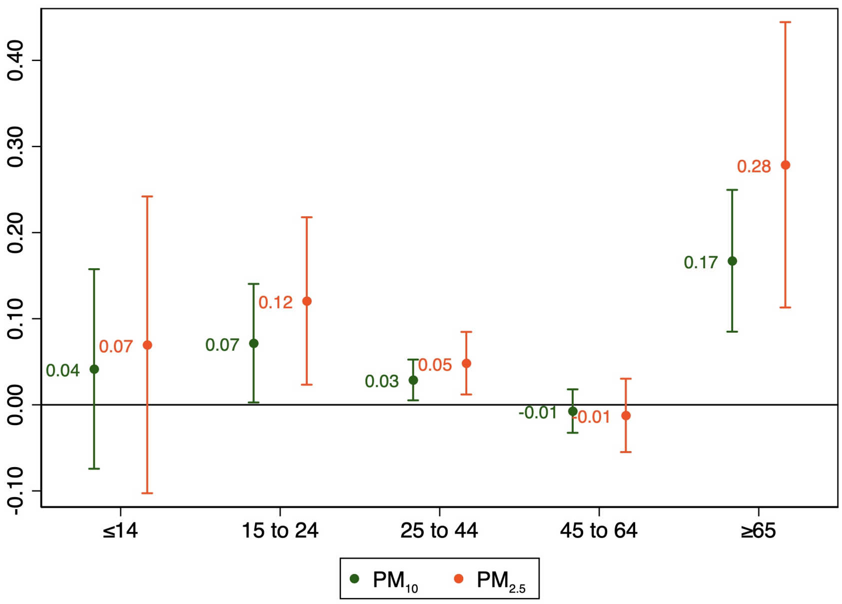
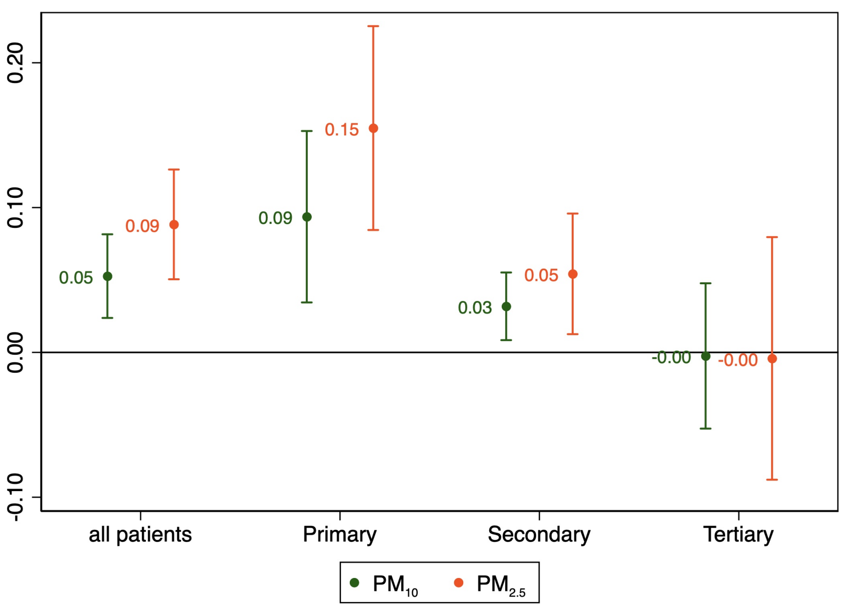


Figure 9: IV estimates of the marginal effects of PM_{10} and $PM_{2.5}$ on respiratory diseases by educational attainment.



We find that the adverse health effects of $PM_{2.5}$ are stronger with respect to the ones of PM_{10}, with one additional unit of $PM_{2.5}$ causing a raise of 0.09 respiratory urgent admissions, which amounts to 5.44% increase. This is in line with the results by Halliday et al. (2015), who consider volcanic fine particulate matter and find an increase of 7%. Again, our results are heterogeneous across age and education attainment groups, in all cases being roughly 40% higher with respect to PM_{10} effects. Moreover, even though not fully comparable, our estimated effects for the elderly are consistent with those by Deryugina et al. (2016), who find that each additional unit of $PM_{2.5}$ causes an increase in hospital admissions by 2.3 each million of population, while our calculation points to a 2.8 increase for the same age group[17].

5.5 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 have increasingly focused on their quantification. Using 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, finding that a one standard deviation increase in daily pollution leads to an additional $540 thousand per day in hospitalization costs for respiratory and heart related admissions of individuals within 10 km of one of the twelve largest airports. 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 $\mu g/m^3$ increase in daily $PM_{2.5}$ causes an increase in emergency room (ER) inpatient spending of approximately $16 thousand per million beneficiaries relative to a mean of $16.8 million. 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 standard deviation increase in particulate pollution leads to a 23-36% increase in expenditures on ER visits for pulmonary-related outcomes. These studies quantify the overall cost for the underlying populations (total costs), but none of them addresses the treatment complexity. We expand the analysis of the health consequences of pollution by measuring hospitalization complexity proxied by average unit costs, which represents an important policy parameter in order to design optimal environmental and health policies.

Table 11 shows the impact of PM_{10} and $PM_{2.5}$ separately, for four outcomes referring to average unit cost of an urgent hospital admission with the primary diagnosis related to any respiratory problem, asthma, pneumonia and COPD. While we find no statistically significant effects of PM on the complexity in the overall group of respiratory problems, in the case of hospitalization admissions for asthma and

[17] Last coefficient estimate in Figure 8 is scaled up to 1 million instead of 100,000.

COPD, one additional $\mu g/m^3$ of PM_{10} increases the relative unit cost by 133 euro, which represents 8.1% of the average unit cost of asthma episodes. The same increase in $PM_{2.5}$ raises by 13.6% the complexity of an urgent admission for asthma, corresponding to additional 223 euro. This set of results lead to conclude that exposure to PM is not only responsible for increased hospitalizations, but it also increases the complexity of asthma related admissions, with associated excess expenditures. We find no effect on the complexity of urgent admissions for pneumonia. In this respect, the clinical literature, has frequently underlined the association between long-term exposure to air pollution and pneumonia, but evidence on the contemporaneous effects is scarce (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 causing a rise of admission costs by additional 45 euro, representing a 1.8% increase relative to an average total cost of 2,488 euro per admission. We find no evidence of adverse effects of $PM_{2.5}$ on COPD unit costs. 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). Our results on the impact of PM on the admission complexity suggest that previous studies analyzing the sole amount of hospitalizations are likely to underestimated the impact of particle pollution.

Table 11: IV estimates of the effect of PM_{10} and $PM_{2.5}$ on average unit costs for hospital admissions for four distinct respiratory problems.

	Unit Cost (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]
$PM_{2.5}$	21.24	223.1*	6.506	75.05
	[24.39]	[119.5]	[46.62]	[46.33]
TIME FE	YES	YES	YES	YES
MUNICIPALITIES FE	YES	YES	YES	YES
N	121,545	121,545	121,545	121,545

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

Notes : The coefficients indicate daily expenditures (euro) x 100,000 residents.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 (atmospheric temperature and amount of precipitation). Standard errors (in parentheses) are clustered at the municipality level. Estimates are weighted by municipality population size by age group.

Table 12: IV estimates of the effect of PM_{10} and $PM_{2.5}$ 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***	184.0***	180.5***	180.8***
	[61.19]	[57.14]	[66.63]	[60.40]
Panel B - Marginal effects :				
$PM_{2.5}$	303.0***	312.4***	329.0**	335.5**
	[105.8]	[110.3]	[127.0]	[128.6]
CONTROL (weather)		YES		YES
CONTROL (holiday)			YES	YES
TIME FE	YES	YES	YES	YES
MUNICIPALITIES FE	YES	YES	YES	YES
N	121,545	121,545	121,545	121,545

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

Notes : The coefficients indicate daily expenditures (euro) x 100,000 residents.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 (atmospheric temperature and amount of precipitation). Standard errors (in parentheses) are clustered at the municipality level. Estimates are weighted by municipality population size by age group.

Finally, considering both extensive and intensive margins, we estimate the effect of particulate matter on total healthcare costs. Table 12 shows that a daily increase of one $\mu g/m^3$ in PM_{10} ($PM_{2.5}$) is associated with an additional 180 euro (303 euro) per 100,000 individuals. If scaled up to the respective s.d., these figures correspond to 32% and 49% of the average daily expenditure on respiratory urgent admissions, respectively for PM_{10} and $PM_{2.5}$. Again, in Table 12 we deliver the same set of results according to age group, showing that the cost resulting from air pollution is unequally distributed across various age groups. These results are in line with the implications concerning the extensive margin presented in Table 8. We find that a daily increase of one $\mu g/m^3$ in PM_{10} is responsible for additional 340 euro each 100,000 individuals between 15 and 24 years old. The same increase in $PM_{2.5}$ concentrations amounts to a penalty of 573 euro. The results are of a slightly weaker order of magnitude for individuals between 25 and 64 years of age, even though still statistically significant. The coefficients relative to the elderly are the largest in magnitude, with one additional $\mu g/m^3$ of PM_{10} ($PM_{2.5}$) causing an increase of 621 euro (1,036 euro) each 100,000 individuals.

Table 13: IV estimates of the effect of PM_{10} and $PM_{2.5}$ on total health costs for respiratory hospital admissions by age class.

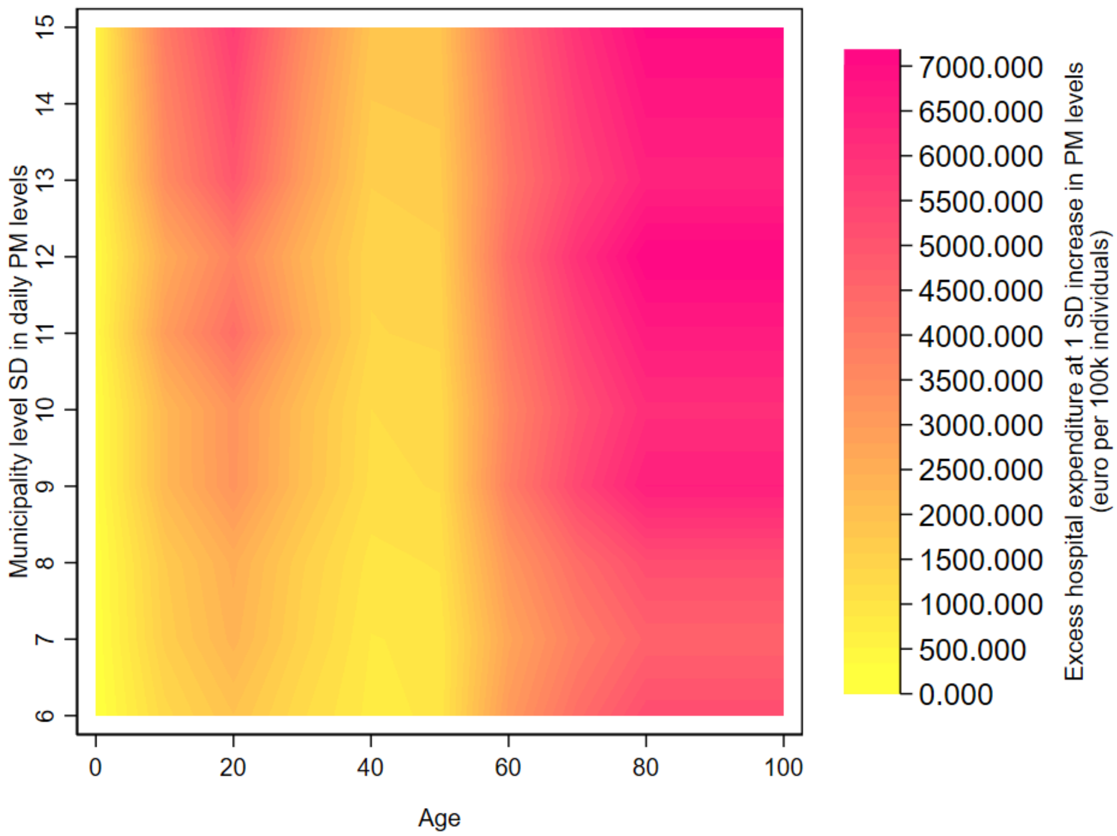
	Respiratory (0-14)	Respiratory (15-24)	Respiratory (25-44)	Respiratory (45-64)	Respiratory (65-100)
PM_{10}	73.72	339.6**	112.3*	127.6*	621.2***
	[104.2]	[149.2]	[62.48]	[76.91]	[194.9]
$PM_{2.5}$	123.4	572.7**	188.0**	216.3*	1036.0***
	[152.0]	[245.9]	[90.67]	[125.8]	[392.2]
TIME FE	YES	YES	YES	YES	YES
MUNICIPALITIES FE	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 coefficients indicate daily expenditures (euro) x 100,000 residents. 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 (atmospheric temperature and amount of precipitation). Standard errors (in parentheses) are clustered at the municipality level. Estimates are weighted by municipality population size by age group.

In order to appreciate the heterogeneity of the total costs relative to urgent respiratory hospital admissions resulting from PM_{10}, in Figure 10 we plot excess hospital expenditures relative to a one s.d. increase in PM_{10} at the municipality level. Precisely, for each municipality we obtain predictions from the age-specific model estimates (Table 13), computed at one standard deviation of PM_{10} and demographic structure as observed in 2015. We smooth out the predictions on a regular grid of each age/s.d. combination. The figure is structured as a heat map, where red tones signal higher excess expenditure levels[18]. The overall reading of the figure shows how different ages, in combination with different PM_{10} concentrations, deliver similar health costs. For instance, a modest six $\mu g/m^3$ increase in PM_{10} among individuals aged between 15 and 24 is responsible for a similar excess expenditure as the one among individuals 40-50-year-olds exposed to a 15 microgram increase. The highest cost is accumulated for young adults at pronounced increases of PM_{10}, and for the elderly. In relative terms, the extra healthcare costs of air pollution for the very young are extremely high and amount to 33% each one additional $\mu g/m^3$ increase; for the elderly the same cost differential amounts to 4% only, and is related to high average costs relative to urgent respiratory admissions in this age group.

[18]The predictions are based on semi-elasticities of total urgent respiratory hospital costs with respect to PM_{10} concentrations. We compute predictions at each municipality specific standard deviation 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 applying a moving average to the coefficient estimates. Each age/s.d. combination is then assigned to a color relative to the specific level in excess expenditure.

Figure 10: 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 costs of PM for the 17.8 million residents of the 111 municipalities considered, which amount to 332,000 euro for one s.d. increase in PM_{10}, and 499,000 for the relative increase in $PM_{2.5}$. These numbers represent, respectively, 0.37% and 0.55% of the total public health expenditure in Italy. Overall, our quantification of health cost burden still represents a lower bound of the total health costs, not accounting for the long run, cumulative effect of pollution on health. Moreover, day-to-day fluctuations in hospital admissions do not account for individuals who experience less severe health issues in relation to pollution, and limit themselves to see their primary care physician or stay home sick. Still, the amount of costs relative to hospital care is a policy relevant parameter, as health expenditures devoted to hospital admissions represent roughly 60% of the national healthcare budget in Italy and are the least cost-effective health-care service.

5.6 Robustness checks

In addition to the main set of estimates, we conduct a number of sensitivity checks to warrant the robustness of our empirical findings. We develop a number of parallel tests, where we first switch the treatment type, then the outcomes and finally, the treatment assignment. Subsequently, we alter our identification strategy by addressing multi-day strike episodes, municipality level demand for public transportation and a larger estimation sample which includes all the Italian municipalities. Moreover, in order to validate the use of pollution reanalysis data, we benchmark our analysis with estimates based on PM measures coming from monitoring stations. We also check the sensitivity of our analysis to alternative weighting schemes. In addition, we correct our findings to account for testing multiple null hypotheses simultaneously. Finally, we run our IV estimates in a Poisson regression setting. All these tests consistently point to a correct identification strategy and provide validation to our main results.

Falsification of treatment - O_3 as a placebo pollutant

An important check of our identification strategy consists in 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 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 B3). This means that, even in presence of a traffic shock, weather factors can strongly affect the formation of O_3. Second, this pollutant has a life-span of several days and, consequently, higher ozone concentrations can be found in regions distant from precursor emission sources due to the effect 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 high levels of precursors are emitted from vehicles, as in rural areas (Pires et al., 2012). Finally, O_3 levels are low during the morning, when most of the effects of strike takes places, and peaks during the afternoon. We thus estimate our baseline specification by substituting PM with O_3. The results are presented in Table A5 in Appendix C and show that the effect of strike on O_3 is not statistically significant.

Falsification of outcome - 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 A6 in Appendix C and do not provide any statistically significant results.

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 that days, we rerun our baseline model estimation. The results are presented in Table A7 in Appendix C, showing no significant effects on PM_{10} in these non-affected cities.

Multi-day strikes and adapting response

Following Bauernschuster et al. (2017), we also test the effects of strikes with a duration of more than one day across provincial county municipalities. We thus substitute our IV of one-day strikes with multi-day strike dummy variable. As shown in Table A8 in Appendix C, the first stage effect of multi-day strikes on pollution is weaker relative to the single-day strikes (0.94 instead of 1.20, both statistically significant at 1%). As anticipated, this result is in line with the hypothesis of attitudinal change in travel patterns after the first day of strike, since individuals are likely to adapt their response strategy to persistent PT stops, hence at the margin, generating less additional PM relative to 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 might 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 persisting over several days.

Estimates taking into account the per capita demand of PT

We also validate the robustness of our empirical strategy considering municipality-level per capita demand of PT. The per-capita demand is measured by the number of passengers carried by PT yearly per resident population. We construct an indicator dummy variable equal to unity for top ten municipalities in terms of their dependance on PT (DPT_{idwy}). We exploit this variable in a dual way. We first interact the strike dummy with high PT demand dummy variable ($STR_{idwy} \times DPT_{idwy}$) and estimate our model specification in the usual sample of municipalities (Table A9 in Appendix C). Second, we restrict our analysis to the 10 municipalities with the highest PT demand and within the sample we estimate the effect of PM_{10} on respiratory urgent admissions (Table A10 in Appendix C). The first stage estimates show larger magnitude in both exercises, suggesting that the effect of STR on pollution is proportional to the PT network usage. The second stage results suggest 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 exhaust. 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

In contrast to the above presented robustness check, we now offer an alternative to our baseline set of results by estimating our model specification considering the sample of all Italian municipalities, including non-administrative small towns; we do so by constructing a balanced panel dataset for all the Italian municipalities (*obs.*= 8,858,550; n=8,090, t=1,095). The resulting IV estimates, presented in table Table A11, 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 our reanalysis pollution data, we offer a benchmarking exercise where we replicate the baseline results using air pollution data from monitoring stations. As previously discussed, data from monitoring stations may suffer from spatial selection but their use still represents a standard in literature (Janke, 2014, e.g.). We collect data from the European Environmental Agency (EEA) AirBase database, which includes daily and hourly concentration measures for the main 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 includes only municipalities in which at least one station operates on a regular basis during the period of analysis. When multiple stations are present in the same municipality, we average their values. Given the granular texture of Italian municipalities, we assume that the measurement error in pollution assignment is limited and allows for a comparison with our original dataset [19]. However, the main limitation of monitoring stations is their heterogeneous distribution, which does not allow for pollutant dispersion and the consequent exposure assignment characterized by large noise. Given the data limitations, the estimates based on monitoring stations are carried out for 66 administrative municipalities only. In the baseline specification presented in Table A12 we again weight the estimates by the municipality population size[20]. Our findings, presented in Table A12, suggest that the effect of strike is larger when PM is measured by monitoring stations, which is likely to be driven by the higher variance of the readings (see Figure B2 in Appendix B). On the contrary, the second stage results are smaller in magnitude and less statistically significant than the ones 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 a serious attenuation bias.

Additional checks

Since our dependent variable is initially measured as hospital admissions counts in a given municipality and day, we also estimate an IV Poisson regression model (Cameron and Trivedi, 2013, Mullahy, 1997, Windmeijer and Santos Silva, 1997) to 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

[19] To give an order of magnitude, the average area of an Italian municipality is only 37.3 kmq, as derived from our own calculations using ISTAT data. Assuming a squared administrative shape, our pollution assignment is based on a grid with sides of about 6.1 km on average, which is much less than the one of reanalysis data (about 17x17 km).

[20] We also weight by the number of monitoring stations in each municipality. These additional results are only weakly statistically significant and available upon request.

(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 exceeds largely 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 as control variable in Equation 3 the residual from our Equation 2 (i.e. the effect of PT strikes on pollution). In contrast to 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 7.

We also test the robustness of our results by not including weights and to 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 the ones obtained using original weights.

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 to test the significance of our results, we observe that the effects of PM significantly persist. Again, this last set of evidence are available upon request.

6 Conclusions

In this study we provide a quasi-experimental investigation of the effects of acute (short-term) exposure to two different particle pollutants, PM_{10} and $PM_{2.5}$. The causal effect of PM is identified by leveraging PT strikes episodes occurring in specific city-day combinations that are able to generate traffic shocks with associated higher air pollution concentrations. Together with the effects on hospitalizations, we present exact estimates of both intensive and extensive margins of hospitalization costs. Our calculations consider hospital admission unit costs, which represent an important policy parameter for which - to our knowledge - no other estimates are available on a large scale and for different SES.

In our full sample estimates, we find that an increase in both PM_{10} and $PM_{2.5}$, induced by PT strikes, translate into a higher hospitalization rate for pulmonary diseases. In line with the clinical evidence, the effects associated with $PM_{2.5}$ are substantially larger.

Our data allow to largely explore the effects heterogeneity, testing if air pollution disproportionately affects more disadvantage individuals characterized by a lower SES. By disentangling the impacts through the lenses of ages, educational attainments and migrant status by country of origin, we find that young individuals aged 15-24 and the elderly experience similar hospitalization costs for urgent respiratory diseases for the same increase in PM_{10} or $PM_{2.5}$. Moreover, the impacts of air pollution induced by PT strikes are much lower for individuals with a higher education, with even no effects for those with tertiary education. When considering the migrant status and the country of origin, we find that air pollution affects migrants only from low-income African countries. Overall, these results show that air pollution does not affect individuals in the same way but the impacts closely reflect the socio-demographic differences within the society. This implies that policy makers should look at air pollution not only as a technological issue, but also as a socio-economic phenomenon. Effective policies aimed at reducing air pollution effects should thus account for larger compensation mechanisms for more disadvantaged individuals. In addition, the strict and reinforcing linkage between air pollution impacts and SES stresses the role of complementary policies aimed at improving the "boundary conditions" that are able to substantially reduce or amplify these effects. Among these, we explicitly examine the role of age, education and broad marginalized conditions of migrants from low-income African countries. Nonetheless, many other factors such as income and employment conditions, urban context and lifestyle have to be further explored yet, representing important research avenues.

An important part or 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 these latter tend to be more complex and expensive. For a one $\mu g/m^3$ increase in PM_{10}, we estimate a hospitalization cost approximately 8% higher than an average urgen admission cost for asthma. The estimated cost for $PM_{2.5}$ is even larger, being approximately 14% higher. These figures imply that the quantification of the healthcare burden relative to PM should take into account not only the number of hospitalizations as done in previous studies, but also their complexity.

Given that our analysis considers air pollution effects that occur within one day, we provide important information also for setting the hazard limit to $PM_{2.5}$ daily concentrations, which has not been established yet in Europe by the European Commission. Other than finding larger effects on respiratory hospitalizations, we estimate that a daily increase of one $\mu g/m^3$ of $PM_{2.5}$ is associated with a cost of 303 euro per 100,000 citizens, which is approximately 70% higher than the cost generated by the same increase in PM_{10}.

Among the several limitations of our study, two ones deserve a brief discussion. First, it is important to highlight that by employing the PT strike as an IV implicitly focuses our analysis on pollutant concentrations deriving from fuel combustion for vehicles. This may result in an underestimation of the total effect of particle pollution in urban centers where a large fraction of both PM_{10} and $PM_{2.5}$ is produced also by heating systems for houses and buildings. However, from a regulation standpoint, assessing the health effects of air pollution associated with the road transport provides also implications for policies specifically designed for this important emitting source (Bell et al., 2014, Park and Oh, 2018). Second, although our study is perhaps the first to provide causal evidence of the air pollution effects on the migrant population in Italy, these results should be interpreted with cautious. Migrants coming from African low-income countries, who currently represent a large fraction of in-flows in Italy, live often in informal rentals or under illegal subletting, facing significant barriers in accessing healthcare. Despite signaling an interesting evidence, our estimates for this population group should thus be viewed as a lower bound of the true effects.

Appendices

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A 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: Descriptive statistics for public transportation strikes (2013-2015).

	Consecutive days of strike events													
Municipality	1	2	4	7	10	11	16	25	28	29	30	31	36	Freq.
Agrigento	1	0	0	0	0	0	0	0	0	0	0	0	0	1
Alessandria	12	0	1	0	0	0	1	0	1	1	1	2	1	217
Asti	2	0	1	0	0	0	0	1	0	0	0	0	0	31
Avellino	2	0	0	0	0	0	0	0	0	0	0	0	0	2
Bari	12	0	0	0	0	0	0	0	0	0	0	0	0	12
Belluno	2	0	0	0	0	0	0	0	0	0	0	0	0	2
Benevento	3	0	0	0	0	0	0	0	0	0	0	0	0	3
Bergamo	6	0	0	0	0	0	0	0	0	0	0	0	0	6
Biella	1	0	0	0	0	0	0	0	0	0	0	0	0	1
Bologna	13	0	0	0	0	0	0	0	0	0	0	0	0	13
Bolzano	12	0	0	0	0	0	1	0	0	0	0	0	0	28
Brescia	12	0	0	0	0	0	0	0	0	0	0	0	0	12
Cagliari	16	0	0	0	0	0	0	0	0	0	0	0	0	16
Campobasso	7	0	0	0	0	0	0	0	0	0	0	0	0	7
Caserta	13	1	0	0	0	0	0	0	0	0	0	0	0	15
Catania	12	0	0	0	0	0	0	0	0	0	0	0	0	12
Catanzaro	4	0	0	0	0	0	0	0	0	0	0	0	0	4
Cesena	8	0	0	0	0	0	0	0	0	0	0	0	0	8
Chieti	6	0	0	0	0	0	0	0	0	0	0	0	0	6
Como	2	0	0	0	0	0	0	0	0	0	0	0	0	2
Cosenza	12	0	0	0	0	0	0	0	0	0	0	0	0	12
Crotone	0	3	0	0	0	0	0	0	0	0	0	0	0	6
Cuneo	5	0	0	0	0	0	0	0	0	0	0	0	0	5
Ferrara	2	0	0	0	0	0	0	0	0	0	0	0	0	2
Firenze	10	0	0	0	0	0	0	0	0	0	0	0	0	10
Foggia	5	0	0	0	0	0	0	0	0	0	0	0	0	5
Frosinone	3	0	0	0	0	0	0	0	0	0	0	0	0	3
Genova	14	4	0	0	0	0	0	0	0	0	0	0	0	22
Gorizia	3	1	0	0	0	0	0	0	0	0	0	0	0	5
Imperia	1	1	0	0	0	0	0	0	0	0	0	0	0	3
L'Aquila	1	0	0	0	0	0	0	0	0	0	0	0	0	1
La Spezia	6	0	0	0	0	0	0	0	0	0	0	0	0	6
Latina	11	0	0	0	0	0	0	0	0	0	0	0	0	11
Lecce	1	0	0	0	0	0	0	0	0	0	0	0	0	1
Lecco	1	0	0	0	0	0	0	0	0	0	0	0	0	1
Lodi	2	0	0	0	0	0	0	0	0	0	0	0	0	2
Lucca	5	0	0	0	0	0	0	0	0	0	0	0	0	5
Macerata	1	0	0	0	0	0	0	0	0	0	0	0	0	1
Mantova	2	0	0	0	0	0	0	0	0	0	0	0	0	2
Massa	1	0	0	0	0	0	0	0	0	0	0	0	0	1
Matera	1	0	0	0	0	0	0	0	0	0	0	0	0	1
Messina	2	0	0	0	0	0	0	0	0	0	0	0	0	2
Milano	14	0	0	0	0	0	0	0	0	0	0	0	0	14
Modena	7	0	0	0	0	0	0	0	0	0	0	0	0	7
Napoli	26	1	0	0	0	0	0	0	0	0	0	0	0	28
Palermo	11	0	0	0	0	0	0	0	0	0	0	0	0	11
Parma	2	0	0	0	0	0	0	0	0	0	0	0	0	2
Pavia	11	0	0	0	0	0	0	0	0	0	0	0	0	11
Pescara	6	0	0	0	0	0	0	0	0	0	0	0	0	6
Piacenza	3	0	0	0	0	0	0	0	0	0	0	0	0	3
Pisa	0	0	0	0	0	0	0	0	0	0	0	0	1	36
Pistoia	1	0	0	0	1	0	0	0	0	0	0	0	0	11
Pordenone	4	0	0	0	0	0	0	0	0	0	0	0	0	4
Potenza	9	0	0	0	0	0	0	0	0	0	0	0	0	9
Reggio di Calabria	8	0	0	0	0	0	0	0	0	0	0	0	0	8
Reggio nell'Emilia	6	0	0	0	0	0	0	0	0	0	0	0	0	6
Rieti	4	0	0	0	0	0	0	0	0	0	0	0	0	4
Rimini	4	0	0	0	0	0	0	0	0	0	0	0	0	4
Roma	65	2	0	0	0	0	0	0	0	0	0	0	0	69
Salerno	2	0	0	0	0	0	0	0	0	0	0	0	0	2
Savona	1	0	0	0	0	0	0	0	0	0	0	0	0	1
Siena	2	0	0	0	0	0	0	0	0	0	0	0	0	2
Taranto	1	0	0	0	0	0	0	0	0	0	0	0	0	1
Teramo	3	0	0	0	0	0	0	0	0	0	0	0	0	3
Torino	17	0	0	0	0	0	0	0	0	0	0	0	0	17
Trapani	1	0	0	0	0	0	0	0	0	0	0	0	0	1
Trento	6	0	0	0	0	0	0	0	0	0	0	0	0	6
Treviso	1	0	0	0	0	0	0	0	0	0	0	0	0	1
Trieste	2	0	0	0	0	0	0	0	0	0	0	0	0	2

Cond't of Table A2

	Consecutive days of strike events													
Municipality	1	2	4	7	10	11	16	25	28	29	30	31	36	Freq.
Urbino	1	0	0	0	0	0	0	0	0	0	0	0	0	1
Varese	1	0	0	0	0	0	0	0	0	0	0	0	0	1
Venezia	9	0	0	1	0	1	0	0	0	0	0	0	0	27
Verona	4	0	0	0	0	0	0	0	0	0	0	0	0	4
Vicenza	3	0	0	0	0	0	0	0	0	0	0	0	0	3
Totale	470	26	8	7	10	11	32	25	28	29	30	62	72	810

Table A3: 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)
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.

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

First stage

	Panel A	*Panel B*	*Panel C*	*Panel D*
	$PM_{2.5}$	$PM_{2.5}$	$PM_{2.5}$	$PM_{2.5}$
STRIKE	0.714*** [0.218]	0.692*** [0.217]	0.615*** [0.212]	0.604*** [0.209]
$F-stat$	15.543	15.152	11.577	11.580

Second stage

	Respiratory (all patients)	Respiratory (all patients)	Respiratory (all patients)	Respiratory (all patients)
Panel A - Marginal effects:				
$PM_{2.5}$	0.0884*** [0.0228]	0.0911*** [0.0231]	0.0953*** [0.0278]	0.0971*** [0.0271]
Panel B - Semi-elasticities:				
$PM_{2.5}$	0.0431*** [0.0111]	0.0445*** [0.0112]	0.0465*** [0.0135]	0.0474*** [0.0132]
CONTROL (weather)		YES		YES
CONTROL (holiday)			YES	YES
TIME FE	YES	YES	YES	YES
MUNICIPALITIES FE	YES	YES	YES	YES
N	121,545	121,545	121,545	121,545

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

B Figures

Figure B1: Map of the 111 Italian municipalities

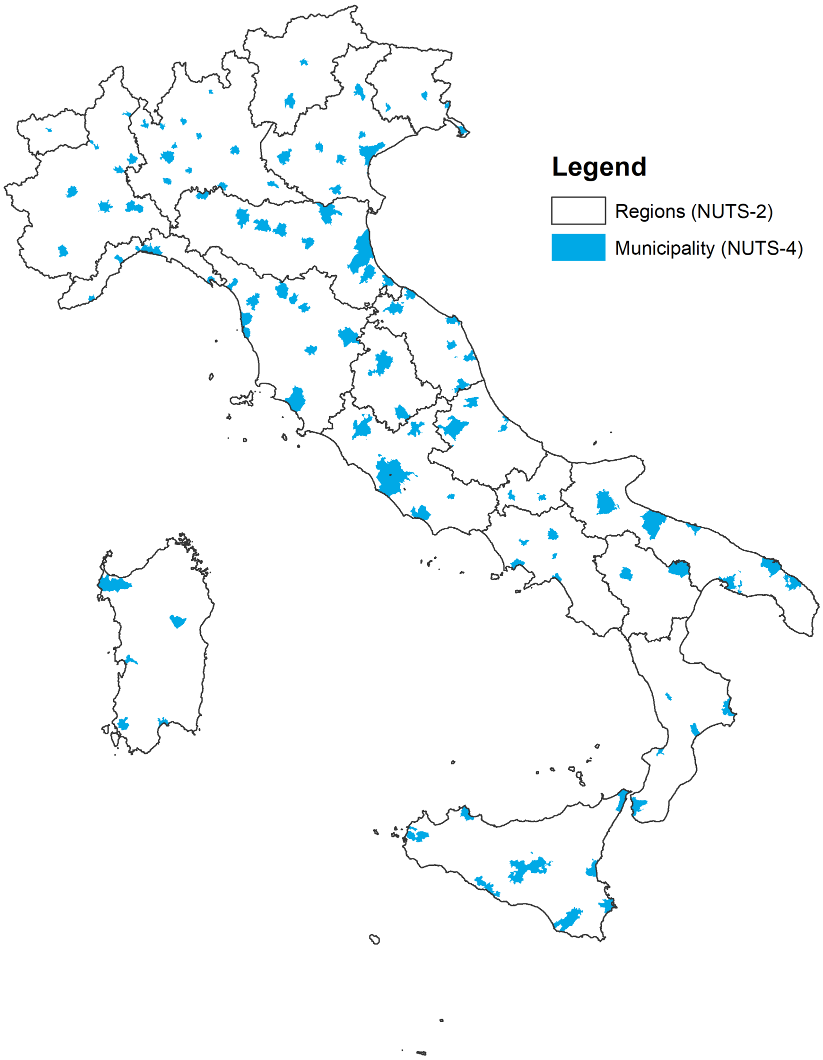


Figure B2: Weekly average values of PM_{10}

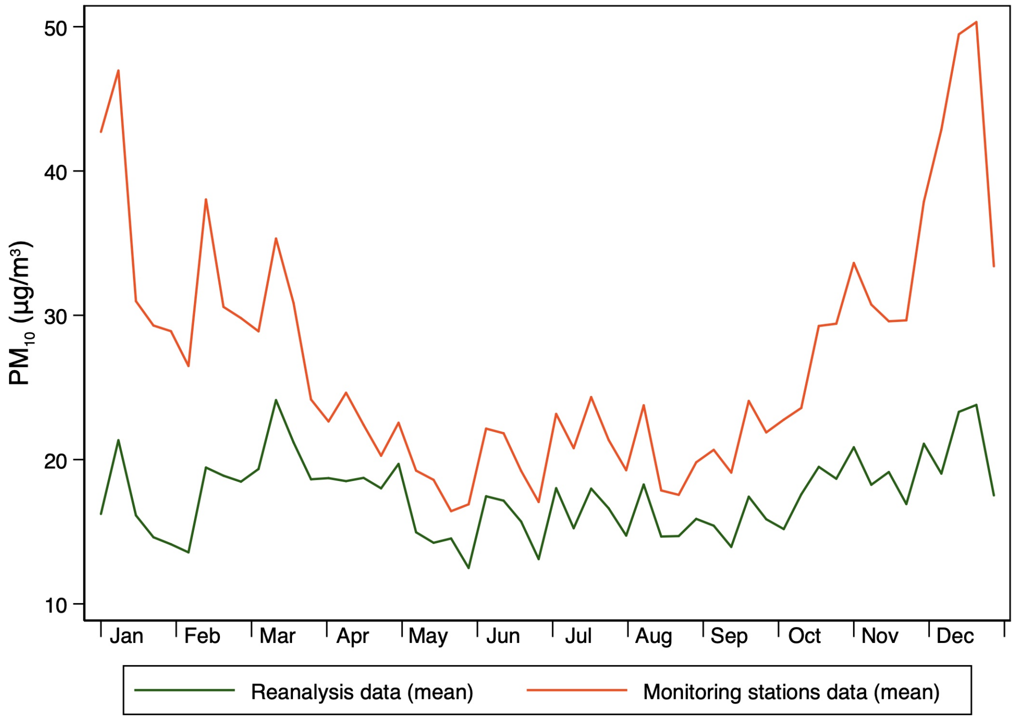


Figure B3: Weekly average concentrations of air pollutants (2013-2015)

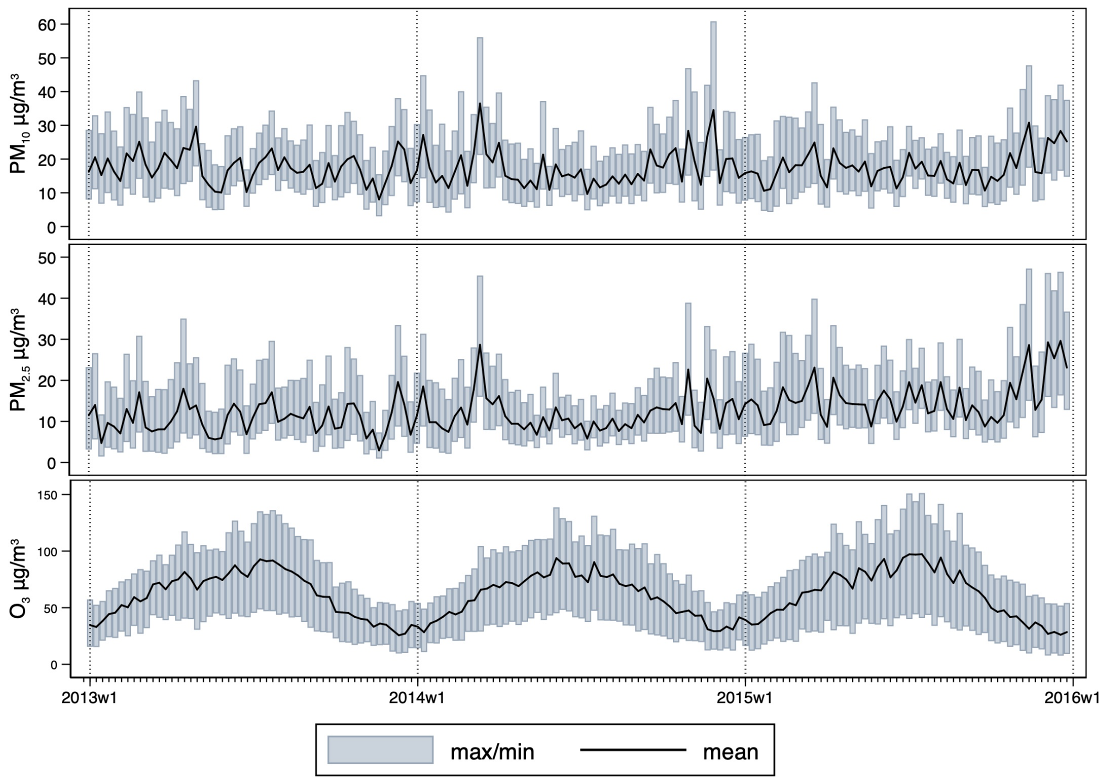


Figure B4: Scatter correlation matrix for air pollutants

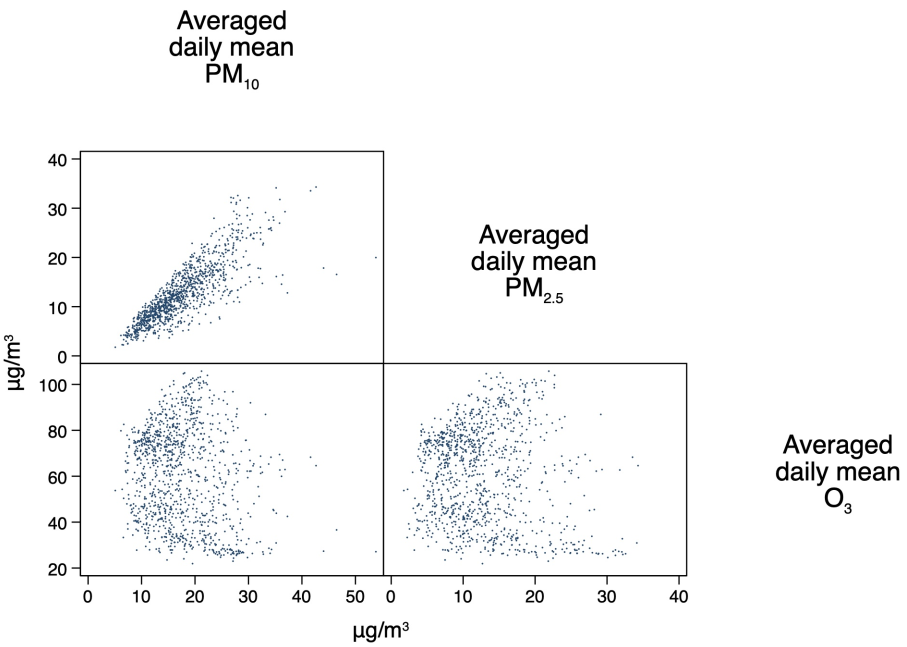
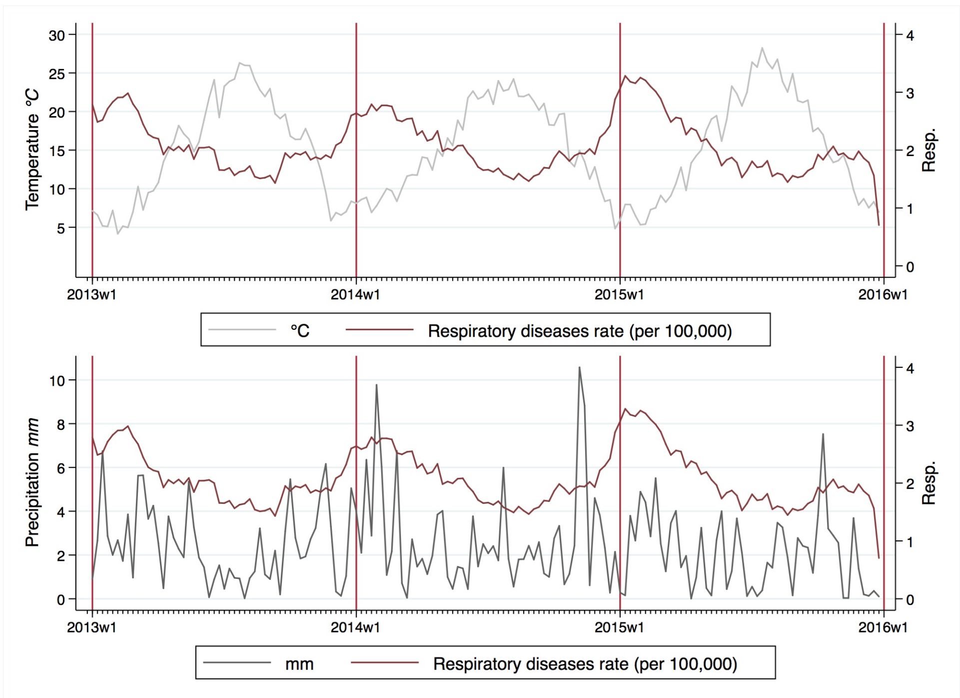


Figure B5: Trends of weekly respiratory diseases rate and weather conditions (2013-2015)



C Robustness check

C.1 Estimates using O_3 as a placebo pollutant

Table A5: 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	0.0232	0.0291	0.0831
	[0.362]	[0.399]	[0.358]	[0.395]
$F-stat$	0.005	0.008	0.012	0.109

Second stage

	Respiratory (all patients)	Respiratory (all patients)	Respiratory (all patients)	Respiratory (all patients)
Panel A - Marginal effects:				
O_3	3.457	2.719	2.014	0.705
	[68.53]	[46.78]	[24.75]	[3.347]
Panel B - Semi-elasticities:				
O_3	1.687	1.327	0.983	0.344
	[33.30]	[22.73]	[12.03]	[1.626]
CONTROL (weather)		YES		YES
CONTROL (holiday)			YES	YES
TIME FE	YES	YES	YES	YES
MUNICIPALITIES FE	YES	YES	YES	YES
N	121,545	121,545	121,545	121,545

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

Notes: All regressions control for day-of-week, week-of-year, year and municipality fixed effects. Controls include dummies for school holidays and national public holidays the following weather variables: atmospheric temperature and amount of precipitation. Standard errors (in parentheses) clustered by municipality. $STRIKE$ is the strike dummy variable equal to unity when a strike is in effect and zero otherwise. First stage F-statistic coefficients are calculated using the Cragg-Donald F-test. Estimates are weighted by size of municipality population.

C.2 Placebo diseases

Table A6: IV estimates of the effect of PM_{10} on placebo diseases.

Second stage – Nervous system diseases (ICD09 320-359)				
	Panel A	*Panel B*	*Panel C*	*Panel D*
	Respiratory (all patients)	Respiratory (all patients)	Respiratory (all patients)	Respiratory (all patients)
Panel A - Marginal effects:				
PM_{10}	-0.00360	-0.00366	-0.00652	-0.00649
	[0.0132]	[0.0135]	[0.0136]	[0.0138]
Panel B - Semi-elasticities:				
PM_{10}	0.0578	0.0589	0.0559	0.0559
	[0.0414]	[0.0399]	[0.0458]	[0.0432]
Second stage – Musculoskeletal diseases (ICD09 710-739)				
	Respiratory (all patients)	Respiratory (all patients)	Respiratory (all patients)	Respiratory (all patients)
Panel A - Marginal effects:				
PM_{10}	-0.00650	-0.00662	-0.00906*	-0.00901*
	[0.00515]	[0.00546]	[0.00505]	[0.00534]
Panel B - Semi-elasticities:				
PM_{10}	0.0591	0.0606	0.0535	0.0540
	[0.0480]	[0.0468]	[0.0527]	[0.0502]
Second stage – Endocrine systems diseases (ICD09 240-279)				
	Respiratory (all patients)	Respiratory (all patients)	Respiratory (all patients)	Respiratory (all patients)
Panel A - Marginal effects:				
PM_{10}	-0.00726	-0.00740	-0.00908	-0.00890
	[0.00894]	[0.00916]	[0.00956]	[0.00961]
Panel B - Semi-elasticities:				
PM_{10}	0.0179	0.0182	0.0142	0.0145
	[0.0297]	[0.0299]	[0.0335]	[0.0332]
CONTROL (weather)		YES		YES
CONTROL (holiday)			YES	YES
TIME FE	YES	YES	YES	YES
MUNICIPALITIES FE	YES	YES	YES	YES
N	121,545	121,545	121,545	121,545

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

Notes: The coefficients indicate effects for 100,000 residents. 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 (atmospheric temperature and amount of precipitation). Standard errors (in parentheses) are clustered at the municipality level. Estimates are weighted by municipality population size.

C.3 Placebo strike effect in non-affected cities

Table A7: IV estimates of the effect of PM_{10} on respiratory diseases in non-affectd cities.

First stage

	Panel A	*Panel B*	*Panel C*	*Panel D*
	PM_{10}	PM_{10}	PM_{10}	PM_{10}
$STRIKE$	0.0145	0.129	0.0696	0.170
	[0.538]	[0.523]	[0.529]	[0.518]
$F-stat$	0.000	0.034	0.009	0.059

Second stage

	Respiratory (all patients)	Respiratory (all patients)	Respiratory (all patients)	Respiratory (all patients)
Panel A - Marginal effects:				
PM_{10}	4.479	-0.501	-0.987	-0.401
	[165.0]	[2.073]	[7.367]	[1.276]
Panel B - Semi-elasticities:				
PM_{10}	-2.186	-0.244	-0.482	-0.196
	[80.15]	[1.007]	[3.579]	[0.620]
CONTROL (weather)		YES		YES
CONTROL (holiday)			YES	YES
TIME FE	YES	YES	YES	YES
MUNICIPALITIES FE	YES	YES	YES	YES
N	121,545	121,545	121,545	121,545

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

Notes: The coefficients indicate effects for 100,000 residents. 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 (atmospheric temperature and amount of precipitation). Standard errors (in parentheses) are clustered at the municipality level. $STRIKE$ is the strike dummy variable equal to unity when a strike is in effect and zero otherwise. First stage F-statistic coefficients are calculated using the Cragg-Donald F-test. Estimates are weighted by municipality population size.

C.4 Estimates using multi-day strikes

Table A8: 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***	0.904***	0.829***	0.827***
	[0.257]	[0.219]	[0.255]	[0.217]
$F - stat$	20.340	19.889	15.927	116.633

Second stage

	Respiratory (all patients)	Respiratory (all patients)	Respiratory (all patients)	Respiratory (all patients)
Panel A - Marginal effects:				
PM_{10}	0.0651***	0.0674***	0.0689***	0.0692***
	[0.0218]	[0.0211]	[0.0255]	[0.0235]
Panel B - Semi-elasticities:				
PM_{10}	0.0318***	0.0329***	0.0336***	0.0338***
	[0.0106]	[0.0103]	[0.0124]	[0.0114]
CONTROL (weather)		YES		YES
CONTROL (holiday)			YES	YES
TIME FE	YES	YES	YES	YES
MUNICIPALITIES FE	YES	YES	YES	YES
N	121,545	121,545	121,545	121,545

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

Notes: The coefficients indicate effects for 100,000 residents. 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 (atmospheric temperature and amount of precipitation). Standard errors (in parentheses) are clustered at the municipality level. $MULTI - DAY\ STRIKES$ is the strike dummy variable equal to unity when a strike is in effect and zero otherwise. First stage F-statistic coefficients are calculated using the Cragg-Donald F-test. Estimates are weighted by municipality population size.

C.5 Estimates taking into account the demand per capita of PT

Table A9: 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***	1.559***	1.564***	1.503***
	[0.209]	[0.214]	[0.199]	[0.207]
$F - stat$	42.259	39.890	38.292	37.117

Second stage

	Respiratory (all patients)	Respiratory (all patients)	Respiratory (all patients)	Respiratory (all patients)
Panel A - Marginal effects:				
PM_{10}	0.0453***	0.0475***	0.0448***	0.0464***
	[0.00821]	[0.00838]	[0.00914]	[0.00920]
Panel B - Semi-elasticities:				
PM_{10}	0.0221***	0.0232***	0.0219***	0.0226***
	[0.00399]	[0.00407]	[0.00444]	[0.00447]
CONTROL (weather)		YES		YES
CONTROL (holiday)			YES	YES
TIME FE	YES	YES	YES	YES
MUNICIPALITIES FE	YES	YES	YES	YES
N	121,545	121,545	121,545	121,545

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

Notes: The coefficients indicate effects for 100,000 residents. 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 (atmospheric temperature and amount of precipitation). Standard errors (in parentheses) are clustered at the municipality level. Estimates are weighted by municipality population size. First stage F-statistic coefficients are calculated using the Cragg-Donald F-test. Estimates are weighted by municipality population size.

Table A10: 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***	1.478***	1.444***	1.420***
	[0.0782]	[0.108]	[0.0736]	[0.102]
$F - stat$	8.892	8.714	8.005	8.041

Second stage

	Respiratory (all patients)	Respiratory (all patients)	Respiratory (all patients)	Respiratory (all patients)
Panel A - Marginal effects:				
PM_{10}	0.0334**	0.0343**	0.0319*	0.0323**
	[0.0126]	[0.0125]	[0.0141]	[0.0138]
Panel B - Semi-elasticities:				
PM_{10}	0.0164***	0.0169***	0.0157**	0.0159**
	[0.00585]	[0.00580]	[0.00656]	[0.00642]
CONTROL (weather)		YES		YES
CONTROL (holiday)			YES	YES
TIME FE	YES	YES	YES	YES
MUNICIPALITIES FE	YES	YES	YES	YES
N	10,950	10,950	10,950	10,950

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

Notes: The coefficients indicate effects for 100,000 residents. 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 (atmospheric temperature and amount of precipitation). Standard errors (in parentheses) are clustered at the municipality level. First stage F-statistic coefficients are calculated using the Cragg-Donald F-test. Estimates are weighted by municipality population size.

C.6 Estimates on all Italian municipalities

Table A11: 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*** [0.308]	1.161*** [0.253]	1.101*** [0.310]	1.106*** [0.255]
$F-stat$				

Second stage

	Respiratory (all patients)	Respiratory (all patients)	Respiratory (all patients)	Respiratory (all patients)
Panel A - Marginal effects:				
PM_{10}	0.0499*** [0.0151]	0.0508*** [0.0143]	0.0484*** [0.0161]	0.0482*** [0.0149]
CONTROL (weather)		YES		YES
CONTROL (holiday)			YES	YES
TIME FE	YES	YES	YES	YES
MUNICIPALITIES FE	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 coefficients indicate effects for 100,000 residents. 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 (atmospheric temperature and amount of precipitation). Standard errors (in parentheses) are clustered at the municipality level. First stage F-statistic coefficients are calculated using the Cragg-Donald F-test. Estimates are weighted by municipality population size.

C.7 Estimates using monitoring station data for pollution

Table A12: 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**	1.695**	1.605**	1.586**
	[0.763]	[0.759]	[0.742]	[0.736]
$F - stat$	18.89	18.633	16.450	16.311

Second stage

	Respiratory (all patients)	Respiratory (all patients)	Respiratory (all patients)	Respiratory (all patients)
Panel A - Marginal effects:				
PM_{10}	0.0320**	0.0324**	0.0317**	0.0321**
	[0.0124]	[0.0125]	[0.0131]	[0.0131]
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 FE	YES	YES	YES	YES
MUNICIPALITIES FE	YES	YES	YES	YES
N	72,270	72,270	72,270	72,270

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

Notes: The coefficients indicate effects for 100,000 residents. 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 (atmospheric temperature and amount of precipitation). Standard errors (in parentheses) are clustered at the municipality level. First stage F-statistic coefficients are calculated using the Cragg-Donald F-test. Estimates are weighted by municipality population size.

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