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Abstract*

This paper uses high-frequency data on fine particulate matter air pollution (PM 2.5) to study the effects of high pollution on health outcomes in Mexico City. We combine hourly monitoring station data on air pollution and weather conditions with a rich dataset of 10 million health episodes between 2003 and 2019, including deaths, hospitalizations, and urgent care visits. We disaggregate daily mean concentrations of PM 2.5 using the daily share of hours with PM 2.5 concentration above each WHO threshold to uncover a positive non-linear and convex relationship between hourly air pollution concentrations and same-day respiratory health outcomes of all severities. Specifically, a 1% increase in the share of hours with PM 2.5 concentrations above the highest WHO interim threshold (IT1) increases the number of respiratory deaths, hospitalizations, and urgent care visits per 1 million inhabitants by 0.001, 0.0008, and 0.024, respectively. We find that hours above IT1 have effects on respiratory health outcomes that are 20 to 30 times greater than those of additional hours above the air quality guideline, the most restrictive (i.e. lowest) WHO threshold. Furthermore, one additional hour a day with PM 2.5 above IT1 has the same effects on respiratory health outcomes as does increasing the daily average concentration of PM 2.5 in Mexico City by 41 $\mu g/m^3$. We find that the effects of PM 2.5 on respiratory mortality and morbidity are distributed differently across ages and that the effect of PM 2.5 on respiratory deaths is driven by individuals with lower educational attainment.

JEL codes: I10, Q53
Keywords: Air Quality, Health, Health Care, Public Health, Mexico

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1 Introduction

More than 4.2 million lives are lost to ambient air pollution each year, positioning air pollution as the largest environmental threat to human health (World Health Organization, 2021). Low- and middle-income countries bear a disproportionate burden of air pollution (Mannucci and Franchini, 2017). Mortality rates due to air pollution in these countries are 70% higher than in high-income countries (World Health Organization, 2016).

Many cities in low- and middle-income countries control air pollution in part through environmental policies that aim to reduce pollutant emissions during acute air pollution periods. These policies impose additional temporary restrictions on pollutant emissions with the objective of reducing ambient concentrations of air pollutants in the short term. The additional restrictions are often triggered by high daily average concentrations of air pollutants. For instance, in Mexico City, environmental contingencies (*contingencias ambientales*) are declared based on the 24-hour moving average of coarse or fine particulate matter or the hourly concentration of ozone.[1] Similarly, Santiago, Chile, has based temporary driving restrictions and physical activity recommendations on forecasts of the 24-hour averages of particulate matter (Rivera, 2021). While these policies could reduce concentrations of air pollution, they could have significant economic costs. For instance, Mexico City's Chamber of Commerce estimates that "Hoy No Circula", the city's program to limit the circulation of cars during high air pollution episodes, costs on average $12 million dollars per day, with small business owners spending an additional $22 to $50 dollars per day in transportation when they cannot use their vehicles (Cacelín, 2016).

Basing these policies on the daily mean concentration of pollutants may not be the optimal approach. If there are non-linear effects of air pollution on health or other outcomes (Hoffmann and Rud, 2024), the same daily mean concentration could have very different consequences depending on the pattern of underlying hourly concentrations. Since many metropolises experience days with short-lived spikes in pollution and low levels of pollution during the remainder of the day, better targeting of policies to improve air pollution concentrations may deliver greater health improvements at lower economic cost.

[1] https://data.consejeria.cdmx.gob.mx/portal_old/uploads/gacetas/25a1ef7295458ade0faad3daebb31f05.pdf

Disaggregating these daily effects to understand how the short-term health impacts of hourly exposure to low and high air pollution concentrations differ could inform the design of better environmental policies.

We use measures of air pollution that capture daily variation in peaks to study the impact of fine particulate matter on same-day mortality and morbidity in Mexico City. We assemble a comprehensive dataset that combines hourly air pollution and weather data from 26 ground monitoring stations across Mexico City with the universe of deaths, hospitalizations at public hospitals, and urgent care visits at public facilities over the period 2002 to 2019. To investigate non-linear impacts on health outcomes, we code the daily share of hours with PM 2.5 concentration above the WHO air quality guideline (AQG) and four progressively restrictive interim targets, IT1–IT4.[2] To overcome potential endogeneity and measurement error of air pollution, we use an instrumental variables strategy in which we instrument for the share of hours above each WHO threshold with thermal inversions duration and the daily maximum wind speed.[3] We document a positive non-linear and convex relationship between hourly concentrations of fine particulate matter and respiratory health outcomes for all levels of severity. In contrast, we find a non-linear and convex relationship between hourly fine particulate matter and total (all cause) deaths but not for hospitalizations or urgent care visits.

Mexico City is an ideal context to study the non-linear relationship between air pollution and health. Similar to many other large cities in low- and middle-income countries, it experiences both high concentrations of pollution and high variability in the concentration of pollution across and within days. Between 2003 and 2019, there were only two days when none of the monitoring stations in the metropolitan area registered any hourly PM 2.5 concentrations above the WHO air quality guideline.[4] Inhabitants of Mexico City are exposed to fine particulate matter concentrations that surpass at least three different WHO recommendation thresholds during 54% of days.

[2]The interim targets are successive thresholds from IT1, the least ambitious in terms of pollution reduction, to IT4. These targets can serve as goals along the way to achieving the air quality guideline.

[3]Thermal inversions are a meteorological phenomenon in which the usual temperature gradient in the atmospheric layers is reversed, resulting in a layer of warmer air above a layer of cooler air near the earth's surface.

[4]These two days reached a maximum PM 2.5 hourly concentration of 14 $\mu g/m^3$, 1 $\mu g/m^3$ short of the WHO's AQG recommendation threshold.

We focus on fine particulate matter (PM 2.5) air pollution because it drives most of the episodes of poor air quality in Mexico City and is documented to have a wide range of severe health impacts. Of the six air pollutants included in the Mexico City Air Quality Index, PM 2.5 is responsible for 91% of the peaks in this index during our sample period. The fine size of PM 2.5 allows these particles to penetrate the lungs and the bloodstream and to travel from there to other organs, causing stronger and wider-ranging health impacts than do other pollutants (Bell et al., 2004; Pope III and Dockery, 2006). Furthermore, ambient fine particulate matter can readily permeate buildings, making it difficult to avoid exposure (Tracy and Layton, 1995; Vette et al., 2001; Pope III and Dockery, 2006; California Air Resource Board, 2021).

Focusing on daily mean concentration of PM 2.5, we find that, on average, a 1 $\mu g/m^3$ increase in the daily mean concentration increases the number of respiratory deaths, hospitalizations, and urgent care visits per 1 million inhabitants by 0.00013, 0.00009, and 0.0024, respectively. Focusing on the share of hours with PM 2.5 above successive WHO thresholds, we find a positive non-linear and convex relationship between PM 2.5 concentrations and respiratory deaths, hospitalizations, and urgent care visits, implying that PM 2.5 concentrations have similar respiratory mortality and morbidity impacts. Focusing on the highest peaks in PM 2.5 concentrations, we find that a 1% increase in the share of hours above the least ambitious WHO threshold (IT1) can increase the number of respiratory deaths, hospitalizations, and urgent care visits per 1 million inhabitants by up to 0.001, 0.0008, and 0.024, respectively. This non-linearity implies that the effect of one additional hour a day of PM 2.5 above IT1 can be up to 30 times more harmful than one additional hour above the air quality guideline. Comparing the effect of these peaks to the effect of the daily average concentration highlights how harmful these peaks of air pollution are. One additional hour above IT1 has the same respiratory health effects as increasing the daily average PM 2.5 concentration by approximately 41 $\mu g/m^3$. The findings illustrate that disaggregating daily average PM 2.5 concentrations is important because days with the same daily average PM 2.5 concentrations will have very different health impacts depending on the underlying hourly concentrations of PM 2.5.

We find evidence of positive non-linear and convex relationships between hourly fine particulate matter and cardiovascular and total (all cause) deaths but not for hospitalizations or urgent care visits.

We explore heterogeneity in the effect of PM 2.5 on respiratory mortality and morbidity. We find no evidence of differential health effects of PM 2.5 for the respiratory outcomes of men and women. Fine particulate matter appears to cause more respiratory deaths among individuals without health insurance compared to those with public health insurance, but we do not find differences between these two groups for respiratory hospitalizations and urgent care visits. Looking across age groups reveals that, although PM 2.5 affects respiratory morbidity and mortality similarly, the burden of mortality and morbidity differs across the age distribution. PM 2.5 increases respiratory deaths mostly among individuals aged 65 or higher, while respiratory hospitalizations increase the most for patients 17 years old and younger. Additionally, respiratory urgent care visits increase the most among individuals aged between 2 and 49. Finally, we find evidence that PM 2.5 mostly causes respiratory deaths among individuals with 12 or less years of education and has barely any effect on respiratory deaths among individuals that attended higher education institutions. Since individuals with 13 or more years of education are likely to have a higher income, these findings suggest that individuals with lower socioeconomic status bear a greater burden of air pollution.

These findings have important policy implications. First, policies that focus on reducing peaks in pollutant concentrations should be a priority for policymakers, since the returns in terms of health outcomes are substantial. In contrast, further efforts to reduce air pollution when pollutant concentrations are not as severe (but still above what the WHO recommends) might deliver relatively small health benefits at larger economic cost. Second, programs that limit economic and human activity during episodes of high air pollution should be based on hourly measurements of air pollution concentrations instead of on 24-hour moving averages, triggering health alerts and restrictions on pollutant emissions (of both particulate matter and precursor gases) based on current or forecast hourly concentrations of pollutants. The duration of these programs should also be re-thought. Targeting restrictions only to hours with peaks of pollution could maximize the health benefits of pollution reductions while minimizing the economic costs. While it is important that these policies are designed and implemented to avoid temporal substitution of peaks in air pollution concentrations, our non-linear effects indicate that flattening peaks in air pollution concentrations by spreading out pollutant emissions could deliver substantial health benefits with the same or even higher

daily mean concentrations. Finally, our instrumental variables suggest that peaks in air pollution concentrations could also be reduced by temporally substituting pollutant emissions to times with more favorable weather conditions.

Our paper contributes to a large literature that documents the negative effects of air pollution, and particulate matter in particular, on health outcomes. Medical studies show that there are both short-term and long-term effects of particulate matter air pollution on health outcomes (Lin et al., 2002; Tertre et al., 2002; Anderson et al., 2011; Cesaroni et al., 2014; Crouse et al., 2015). Within the economics literature, studies document that exposure to particulate matter increases mortality in the short term (He et al., 2016), particularly among the elderly Deryugina et al. (2019) and among infants (Knittel et al., 2016), and in the long term (Ebenstein et al., 2015), especially among the elderly (Gong et al., 2023).[5] Several studies in this literature document that particulate matter increases daily hospital visits due to respiratory diseases (Dardati et al., 2024; Kim, 2021), with the largest effects for children under age 5 and adults over age 65 (Dardati et al., 2024).[6]

We make three contributions to this literature. First, while most studies of the short-term health effects of air pollution focus on a single level of severity (such as emergency room visits) for a limited set of health conditions (such as asthma or other respiratory conditions), our comprehensive health data allows us to study health outcomes at multiple severity levels (deaths, hospitalizations, and urgent care visits) for all causes in one context. The impacts of air pollution range far wider than respiratory conditions (Sager, 2019) and may also include indirect health impacts through congestion at health care facilities (Guidetti et al., 2024). Furthermore, air pollution may impact mortality and morbidity differently, and these relationships may differ across health conditions. This comprehensive perspective improves our understanding of how air pollution affects health care expenditures.

Second, the high temporal frequency of our air pollution data allows us to extend this literature by exploring within-day variation in air pollution. In particular, we exploit the hourly frequency of our air pollution data to document strong non-linearity in the effects of particulate matter on

[5] Anderson (2020) document that longer-term exposure to air pollution increases mortality among the elderly in the United States.

[6] Other studies document that other air pollutants increase daily hospitalizations for respiratory diseases in the United States (Schlenker and Walker, 2016; Moretti and Neidell, 2011; Neidell, 2009).

deaths, hospitalizations, and urgent care visits. Consistent with Heft-Neal et al. (2023)'s finding that emergency department visits due to conditions closely linked to air pollution consistently increase with wildfire smoke concentrations in California, we find that mortality (deaths) and morbidity (hospitalizations and urgent care visits) due to cardiovascular and respiratory illnesses increase non-linearly with particulate matter concentrations. While Heft-Neal et al. (2023) find that total emergency department visits increase at low and moderate smoke concentrations then decrease at high smoke concentrations, we find that morbidity (hospitalizations and urgent care visits) due to most other causes is not affected by particulate matter concentrations. However, we find that total mortality and mortality attributed to conditions seemingly unrelated to short-term particulate matter exposure, such as cancer, nutritional diseases, and digestive diseases, increase non-linearly with particulate matter concentrations.

Third, we document that economic inequality plays a role in health inequalities, suggesting one mechanism through which health and economic inequalities are linked. We find that the impacts of air pollution on mortality are driven by individuals with lower educational attainment. Our results are consistent with other studies documenting the stronger health effects of air pollution on health and cognition for households or individuals with a lower socioeconomic status (Jans et al., 2018; Zhang et al., 2018b). Jans et al. (2018) document that PM 2.5 increases health care visits due to respiratory illness in Swedish children and that the increase is larger in magnitude for children in low-income households. We provide new evidence from a high-inequality context and extend these results beyond children.

Together, our results contribute to the literature that debates whether and why the marginal damages of particulate matter are higher in low-income countries than in high-income countries. Arceo et al. (2016) find similar effects of PM 10 on infant mortality in the United States and in Mexico. Colmer et al. (2021) study the effect of particulate matter on birth weight and neonatal mortality in Hong Kong, which is a context with both high income and high pollution. They interpret their findings as suggesting that the marginal damages from pollution on mortality are high in lower-income countries because they have lower income, not because they have higher pollution concentrations. We contribute to this literature by holding the context, including health infrastructure, constant and leveraging variation in socioeconomics at the individual level. The non-linearity in the effect of particulate matter on mortality and the

greater magnitude of effect of particulate matter on mortality for lower-education individuals suggests that both income and pollution concentrations affect the marginal health damages of particulate matter.

2 Context

Air pollution is a persistent environmental problem in Mexico City. The Metropolitan Area of the Valley of Mexico contains over 21 million residents and is located in a high-altitude valley surrounded by mountains and volcanoes (Chaussard et al., 2021). Residents are concerned about local air quality. In a 2019 survey of households in lower-income neighborhoods of Mexico City, nearly 95% of 1,869 respondents reported that air pollution was a "problem" or a "big problem" in Mexico City (Hanna et al., 2021).[7]

We focus on fine particulate matter (PM 2.5) air pollution. Unlike other commonly regulated pollutants, particulate matter is not a single pollutant, but a mixture of many types of particles of different shapes, sizes, and chemical compositions. For regulatory purposes, particulate matter is monitored and regulated according to the size of particles. Fine particulate matter is composed of particles with a diameter of less than 2.5 μm (PM 2.5) and is therefore a subset of coarse particulate matter (PM 10).

Fine particulate matter is one of the most widely monitored and studied air pollutants for two principal reasons. First, fine particulates have stronger and a broader range of health impacts than do most other air pollutants, including coarser particulate matter. Fine particulate matter can penetrate into the lungs and the bloodstream, allowing it to travel to other organs (Bell et al., 2004; Pope III and Dockery, 2006). Second, ambient PM 2.5 more readily permeates buildings than ambient PM 10 can and does not break down indoors, making it difficult to avoid exposure (Tracy and Layton, 1995; Vette et al., 2001; Pope III and Dockery, 2006; California Air Resource Board, 2021).[8]

The principal sources of particulate matter in the metropolitan area of Mexico City are

[7]The (translated) survey question is: "In general, do you think air pollution is a problem in Mexico City?" and the response categories are "No, it is not a problem", "It is a problem to some extent", "It is a problem", and "It is a very big problem".

[8]https://ww2.arb.ca.gov/resources/inhalable-particulate-matter-and-health

emissions from gasoline- and diesel-powered vehicles, re-suspension of particles from paved and unpaved roads, construction, residential combustion (such as liquefied petroleum gas), and industrial processes, particularly in the chemicals, minerals, cement, and power sectors (Mugica et al., 2009; Molina et al., 2010; Espinosa et al., 2014). In addition to emissions, ambient concentrations of particulate matter in the metropolitan area are affected by exogenous factors including wildfires, wind speed and direction, air temperature, humidity, precipitation, thermal inversions, and vegetation (Beckett et al., 2000; Hien et al., 2002; Secretaria del Medio Ambiente, 2005; Janhäll, 2015).

3 Data

We combine data from several sources to create a dataset of deaths, hospital admissions, urgent care visits, air pollution concentrations, and weather data for the metropolitan area of Mexico City.

3.1 Air Pollution Data

We collect data on hourly air pollution concentrations recorded by 69 ground monitoring stations from RAMA (Automatic Atmospheric Monitoring Network), a network of stations administered by Mexico City's Secretary of the Environment (SEDEMA) that records pollutant concentrations across Mexico City's metropolitan area. Between 2003 and 2019, 26 stations in the network reported data on PM 2.5. We create hourly air pollution series for each locality and municipality using inverse-distance weighting of all monitoring stations within a 20 km radius of the centroid of the geographic unit. This results in a dataset of hourly pollutant concentrations for 696 different localities (and 49 municipalities) over 18 years.

To match the hourly pollution data with daily health outcomes, we classify pollutant concentrations according to the WHO global air quality guidelines (2021) for short-term exposure to PM 2.5, which group pollutant concentrations into six categories according to the threat they pose to human health. We code daily air pollution variables as the daily share of hours above each of the five thresholds in the WHO air quality guidelines for short-term

exposure to PM 2.5 (World Health Organization, 2021) (see Table 1). The air quality guideline (AQG) is set at daily PM 2.5 concentration of 15 $\mu g/m^3$. The WHO also set four interim targets (IT1–IT4) for 24-hour concentrations of fine particulate matter. These interim targets are intended to be used in high-pollution areas to progressively reduce air pollution. The IT1 PM 2.5 concentration represents a 4% higher short-term mortality risk than the AQG based on multi-center studies and meta-analysis (World Health Organization, 2021). In between PM 2.5 IT1 and PM 2.5 AQG are interim targets 2, 3, and 4.

Table 1: WHO recommended short-term targets for PM 2.5

Recommendation	$\mathbf{PM_{2.5}}$ $(\boldsymbol{\mu g/m^3})$
Interim target 1	75
Interim target 2	50
Interim target 3	37.5
Interim target 4	25
Air quality guideline	15

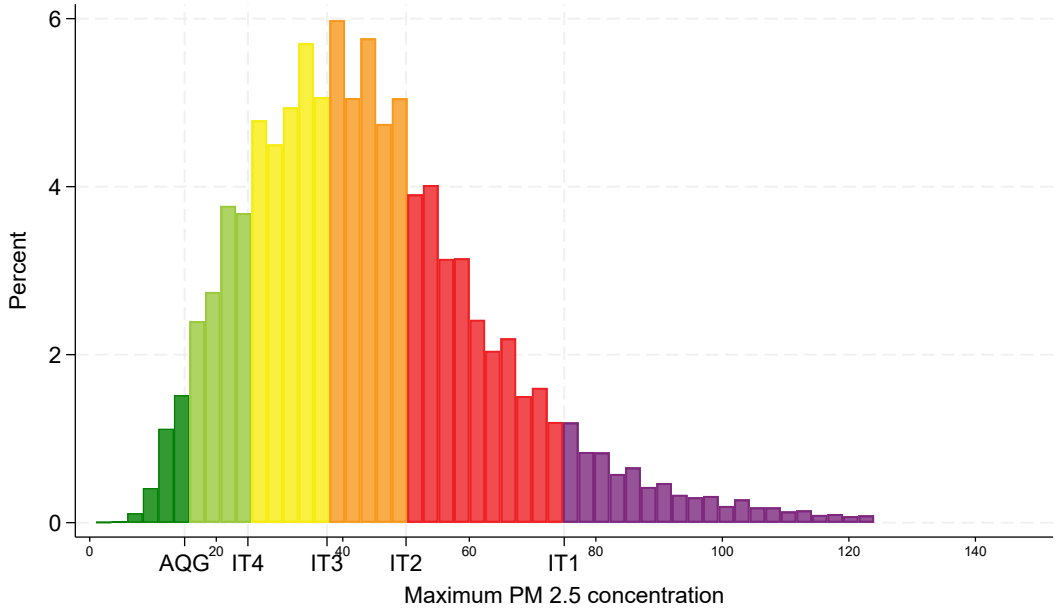
During our study period between 2003 and 2019, across all localities and days in our sample, pollution in Mexico City and surrounding localities was high and variable. Figure 1 shows the distribution of the highest hourly PM 2.5 reading per locality-day, relative to the WHO's air quality guideline and four interim targets for 24-hour concentrations of particulate matter. The distribution has wide support with the majority of locality-days experiencing at least one hour above the air quality guideline. Only 2.53% of locality-days in our sample present no hours above the air quality guideline, while 8.05% of them have at least 1 hour above the highest interim target, IT1.

We exploit this variation in PM 2.5 concentrations across locality-days to estimate the non-linear effects of PM 2.5 and the impact of consecutive high-pollution days. Our measures of daily air pollution leverage our high-frequency air pollution data to capture daily peaks in air pollution, which is key to uncovering the non-linear effects of air pollution on health outcomes.

3.2 Weather Data

We complement our air pollution data with weather variables at the hourly level from REDMET (Meteorology and Solar Radiation Network), another network belonging to

Figure 1: Distribution of maximum daily-locality PM 2.5



Note: The figure displays the distribution of the daily maximum PM 2.5 hourly-location readings for 2003–2019 and the World Health Organization's air quality guidelines (AQG) and interim targets (IT1–IT4).

SEDEMA, from 2003 to 2019. We collect data on temperature, wind speed, and wind direction at the monitoring station level, spatially aggregating to localities/municipalities using the same procedure described in Subsection 3.1. In addition, we use CHIRPS (Climate Hazards Group InfraRed Precipitation with Station Data) daily gridded precipitation data to create average levels of rainfall at the municipality level. CHIRPS incorporates 0.05-degree resolution satellite imagery with station data to create a gridded rainfall daily time series.

We combine this with data on thermal inversions. Thermal inversions are a weather phenomenon that happens when a layer of warm air traps cooler air below it, reversing the usual pattern where air gets colder as you go higher. Thermal inversions on their own are harmless to human health, but the layer of hot air trapping cool air also traps pollutants near the ground. Due to its geography, Mexico City experiences frequent thermal inversions in the winter. Thermal inversions occur on around 40% of days in December, January, and February.

We obtained daily data on thermal inversions from SEDEMA's Meteorological Unit. Twice a day at 12:00 and 00:00 UTC, which correspond to 6:00 AM and 6:00 PM in local time, they measure temperatures at different altitude levels using an aerostatic balloon. These measurements can be used to identify thermal inversions as deviations from the expected temperature patterns. We have data only on the time of rupture of each thermal inversion, so we use these data to identify days when thermal inversions occur and their duration. To calculate the duration, we assume a start time of 21:00 and calculate the duration as the time from the assumed start until the rupture. Our results are robust to changes in the assumed start time.

3.3 Health Data

We use data on health outcomes at three levels of severity. We obtained data on the universe of deaths from 2003 to 2019 from the Institute of Statistics and Geography (INEGI). This dataset contains information about the locality of residence of deceased individuals, the reason of death according to International Statistical Classification of Diseases and Related Health Problems codes (ICD-10), and demographic information, including age, sex, educational attainment, and type of health insurance.

We obtain data on public hospital admissions from 2010 to 2019 from the Automated Subsystem of Hospital Discharges (Subsistema Automatizado de Egresos Hospitalarios) provided by the Secretary of Health. This dataset contains admission-level data for public hospitals run by the Secretary of Health. It provides information related to individuals' hospitalization (e.g., diagnoses, date of admission, date of discharge, procedures, etc.). Health conditions are coded using the ICD-10 codes. The data also contains basic demographic information about patients, including locality of residence, age, sex, indigenous heritage, and type of health insurance.

Next, we compiled registries of visits to public urgent care facilities in the Mexico City metropolitan area between 2012 and 2019 from the Secretary of Health. This dataset contains information about the reason for each urgent care visit according to ICD-10 codes, municipality of residence of the patient, age, sex, and type of insurance.

For all of these outcomes, we count the number of daily occurrences for each type of disease at

each locality/municipality and express them as totals per 1 million inhabitants in the Mexico City metropolitan area. We compute total population estimates based on data from the 2000, 2005, 2010, and 2020 censuses at the municipality level, interpolating these four censuses to get yearly population figures, and then adding up the population across municipalities.

Table 2: Descriptive statistics for health outcomes

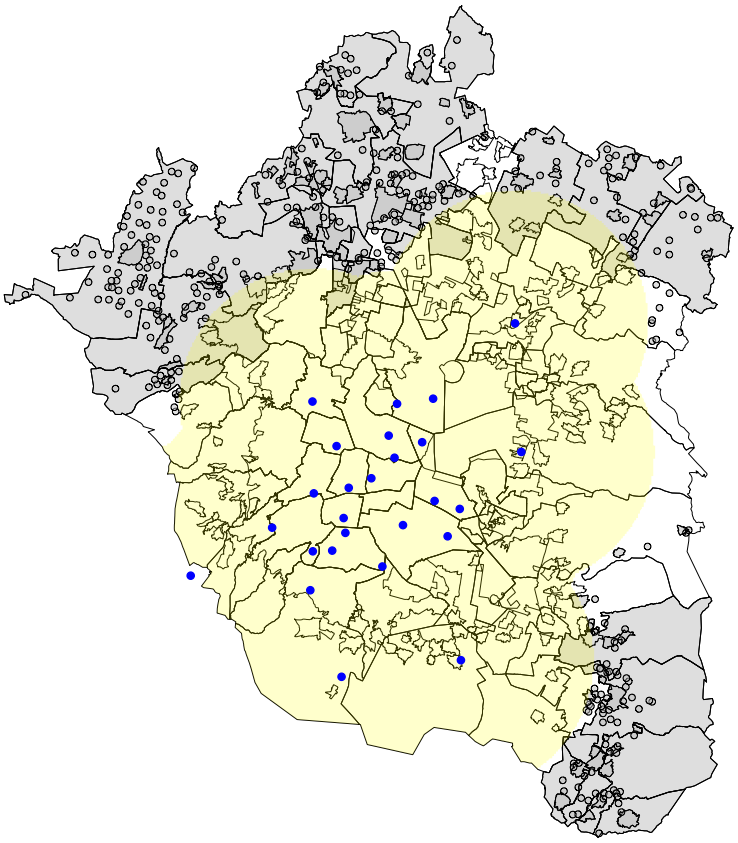
	Deaths	**Hospitalizations**	**Urgent care visits**
Observations	1,550,718	2,023,331	6,896,832
Number of localities/municipalities of residence	357	537	48
Respiratory cause	9.4	6.0	14.3
Age	64.6	38.1	29.1
Female	47.5	51.8	57.7
Type of insurance:			
No insurance	25.97	42.55	66.72
Private workers' insurance	45.97	0.26	0.13
Public workers' insurance	13.28	0.32	0.11
Social security	10.04	56.58	33.00
Years of education:			
1 to 6 years	0.5		
7 to 12 years	0.3		
More than 12 years	0.1		

Note: Deaths and hospitalizations are geocoded at the locality of residence level, but urgent care visits are geocoded at the municipality of residence level. The localities for deaths and hospitalization are contained by 58 and 59 different municipalities, respectively.

In Table 2, we present descriptive statistics for our health outcomes data. We have 1,550,718 death registries, 2,033,331 hospitalization registries, and 6,886,832 urgent care visit registries. During the time periods for which we have data, deceased individuals resided in 357 different localities and hospitalized individuals resided in 537 different localities. The data on urgent care visits does not contain the locality in which the patient resided, reporting only their municipality of residence. We have urgent care registries pertaining to patients who resided in 48 different municipalities. The share of registries attributed to respiratory causes according to ICD-10 codes is between 6% and 14%, depending on the outcome. Individuals' average age at death is 64.6 years old, and hospitalized and urgent care patients are between 30 and 40 years old on average. Females comprise between 47% and 57% of our sample, depending on the outcome. There is substantial variation in the type of health insurance individuals have. Around 58% of the deceased people in our deaths dataset had private or public worker's insurance, 10% had social security, and around 26% had no insurance. The hospitalizations and urgent care visits datasets almost exclusively contain uninsured individuals and

individuals with social security. In the hospitalizations dataset, approximately 43% of the registries correspond to patients without insurance and the remaining 57% correspond to patients with social security. In the urgent care visits dataset, around two-thirds of the patients have no insurance, with the remaining one-third of patients having social security. Finally, around 50% of deceased individual had less than primary education completed, 26% had at least some secondary education, and only 10% had post-secondary education.

Figure 2: Sample localities, municipalities, and monitoring stations



To combine our health outcomes with our air pollution and weather variables, we adopt the following procedure: for each health dataset, we first identify all locality (or municipality) and year combinations where we observe at least one health episode of any kind and where we have air pollution and weather data. For all of these locality-years, we include every day in our sample. We then add the total counts of health episodes per disease type, defining the counts as 0 when we do not observe anything for a particular locality-day.[9] This means that for each

[9]If for a given year and locality we sometimes observe health outcomes, that means that there were health registries for that locality year. Every time we do not observe health outcomes, it means that no events of that

of our health outcomes we have a balanced panel at the locality-day level.[10]

We match the air pollution and weather data with deaths, hospitalizations, and urgent care visits data by locality of residence for deaths and hospitalizations, and by municipality for urgent care visits.[11] Figure 2 shows the geographical reach of the data we use for our analysis. The figure shows all localities and municipalities in the Metropolitan Area of the Valley of Mexico. There are a total of 1,983 localities and 76 municipalities in this area. Blue dots represent the 26 stations that report PM 2.5, and the yellow circles represent 20-kilometer radii around each station. Grey areas represent localities and municipalities that ever report deaths, hospitalizations, or urgent care visits[12] but that are outside of the coverage area of our monitoring stations. Out of 1,983 localities, we have death or hospitalization records for 1,154 of them. Out of these, we have air pollution data for 765 localities. Out of the 76 municipalities, there are urgent care visit records for 75, and we have data for 52 of them. Appendix Figures A1, A2, and A3 show the geographic reach of the air pollution data with the deaths dataset, hospitalizations dataset, and urgent care visits dataset separately.

To explore the relationship between respiratory health outcomes, the occurrence of extreme concentrations of PM 2.5, and the weather variables affecting PM 2.5 concentrations, in Figure 3 we plot the average number of respiratory deaths, hospitalizations, and urgent care visits per month, together with the average number of hours of PM 2.5 above IT1 per month, the average number of thermal inversions per month, and the average daily maximum wind speed per month. If we look at health outcomes in the first column of Figure 3, we can see that respiratory deaths, hospitalizations, and urgent care visits usually peak during the winter months, then gradually decrease until they reach their minimum during the summer, then slowly start increasing again. At the same time, the second column shows a very similar pattern for PM 2.5: the number of hours of PM 2.5 above IT1 is at its highest during the winter months (December and January), but during the summer, there are almost no hours above IT1. We can see that thermal inversions

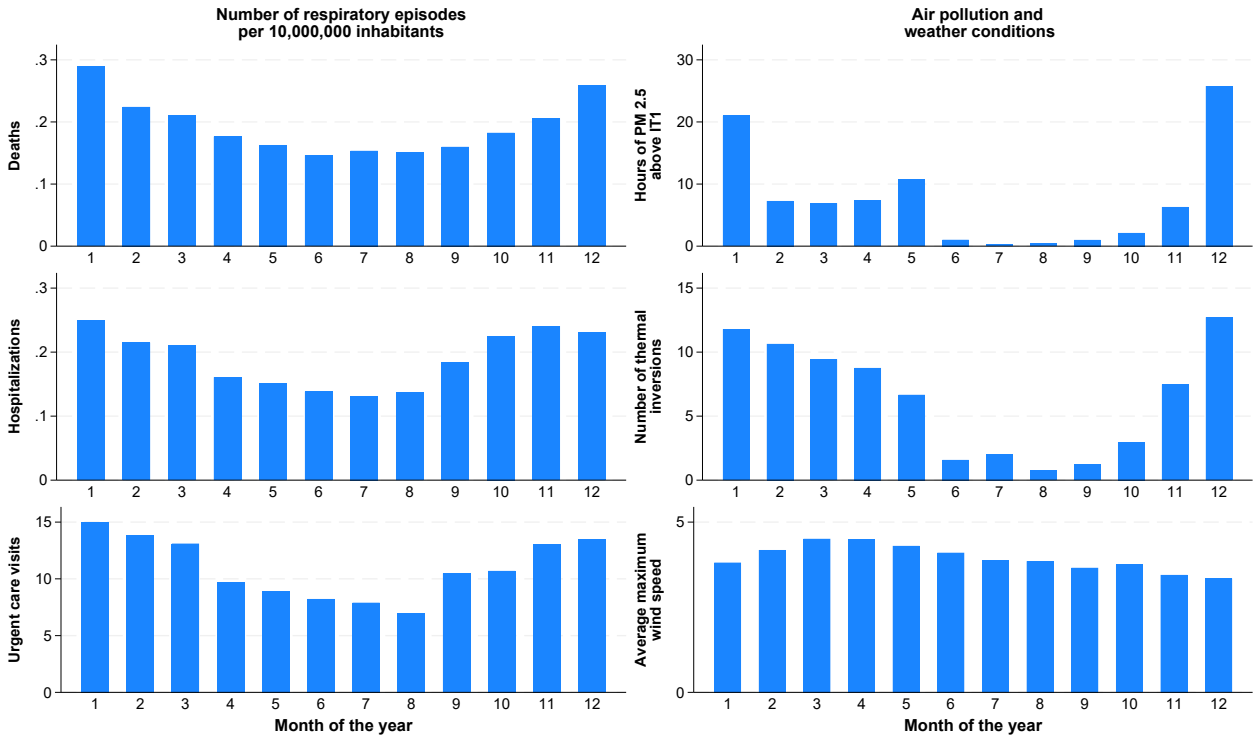
kind happened in that locality-day, not that we have missing data.

[10]The panel is actually not fully balanced, since we have localities that do not report data for our full time period and we have some locality-days with missing air pollution or weather data.

[11]For robustness, we also create a dataset in which we match the air pollution and weather data with the deaths, hospitalizations, and urgent care visits data by locality of occurrence for deaths and locality of the hospital or care facility for hospitalizations and urgent care visits.

[12]For urban localities, we have data on the shape of each locality. But for rural localities, we only have data on their centroids, so they are represented by dots.

Figure 3: Monthly respiratory episodes, PM 2.5, and instruments



yet again follow the same seasonal pattern, while the maximum wind speed is slightly higher in March and April, but it is generally constant across months.

Figure 3 motivates our empirical strategy: respiratory health episodes are correlated with the number of hours of PM 2.5 above IT1, and at the same time, thermal inversions are correlated with PM 2.5 levels.

4 Empirical Strategy

Our objective is to identify the short-term causal effect of PM 2.5 on physical health outcomes. There may be unobserved time-invariant determinants of both local air pollution and health outcomes; for instance, higher-income households may reside in areas with lower air pollution and spend more on preventative health care, leading to less health care utilization for acute health conditions. Or there may be time-varying factors that affect people's health that occur simultaneously with air pollution, such as waves of respiratory illness contagion. To address

these concerns, our empirical specifications include a comprehensive set of fixed effects.

4.1 Benchmark: Ordinary Least Squares

As a benchmark, we estimate the following panel regression using ordinary least squares:

$$Y_{lm,tc} = \beta PM2.5_{lm,tc} + \gamma X_{lm,tc} + \eta_{m,tc} + \alpha_{m,c} + \epsilon_{lm,t} \tag{1}$$

where the outcome $Y_{lm,tc}$ is the count of deaths, hospitalizations, or urgent care visits per 1 million inhabitants in locality l of municipality m on day t of calendar year c. $PM2.5_{lm,tc}$ is the share of the number of hours in which fine particulate matter exceeded the WHO's AQG, IT4, IT3, IT2, or IT1 thresholds in locality l of municipality m on day t of year c. $X_{lm,tc}$ is a vector of time-varying weather controls that consists of daily minimum temperature, precipitation, and precipitation squared. $\eta_{m,tc}$ is a set of municipality daily time trends that controls for any unobserved patterns in health over time within a municipality. $\alpha_{m,c}$ is a set of municipality-by-year fixed effects to control for time-invariant unobserved determinants of health that are common to a municipality in each year. We cluster standard errors at the locality level for deaths and hospitalizations and at the municipality level for urgent care visits, which are the levels at which our measures of air pollution vary (Abadie et al., 2022).

4.2 Main Specification: Instrumental Variables Strategy

To address potential endogeneity in air pollution concentrations, our main specification uses an instrumental variables approach in which we instrument PM 2.5 concentrations with two exogenous weather variables, thermal inversions and wind speed, that affect pollutant concentrations but do not affect health outcomes. This instrumental variable approach also overcomes the potential measurement error in our air pollution variables. Since we do not observe the actual concentrations of PM 2.5 in a locality, we approximate PM 2.5 concentrations with a weighted average of PM 2.5 concentrations measured at nearby monitoring stations. Furthermore, although our measures of PM 2.5 do not vary spatially across a locality, PM 2.5 concentrations likely do vary spatially across a locality.

We instrument our daily measures of PM 2.5 (i.e., the daily share of the number of hours above

each WHO threshold) with the maximum daily wind speed and thermal inversion duration.[13] Both of these weather variables are common instruments for air pollution concentrations in the literature because they affect pollutant concentrations (satisfying the relevance condition) but do not affect human health (satisfying the exclusion restriction) (Aguilar-Gomez, 2025; Arceo et al., 2016; Chen et al., 2018; Fu et al., 2021; Jans et al., 2018). Both low wind speed and thermal inversions have been shown to increase air pollutant concentrations in Mexico City (Molina et al., 2009) and other cities (Xu et al., 2020; Zhang et al., 2018a).

We estimate the following system of equations using two-stage least squares (2SLS):

$$PM2.5_{lm,tc} = \delta Z_{lm,tc} + \theta X_{lm,tc} + \eta_{m,tc} + \alpha_{m,c} + \epsilon_{lm,t} \tag{2}$$

$$Y_{lm,tc} = \beta \hat{PM2.5}_{lm,t} + \gamma X_{lm,tc} + \eta_{m,tc} + \alpha_{m,c} + \epsilon_{lm,t} \tag{3}$$

where $Z_{lm,tc}$ is a vector of instrumental variables for locality l in municipality m for day t during calendar year c, and all other variables are defined as in Equation (1). Vector $Z_{lm,tc}$ consists of two components: thermal inversion duration, defined as the duration (in hours) of the thermal inversion occurring in the Metropolitan Area of the Valley of Mexico during day t and year c, and the maximum daily wind speed at locality l in municipality m for day t and year c, expressed in meters per second.

Given that we cluster our standard errors, we need a weak instruments test that is robust to heteroskedasticity. Therefore, we implement the test in Olea and Pflueger (2013). Specifically, to test the null hypothesis of weak instruments in two-stage least squares, we compute the effective F statistic of the first-stage regression, a scaled version of the first-stage F statistic adjusted to reflect the potential bias in two-stage least squares, and compare it to 5% confidence level critical values for a relative bias of 5%. We reject the null hypothesis when our effective F statistic is bigger than the critical value, meaning that there is a probability of at least 95% that the bias in our estimator is smaller than 5% of the bias of an OLS estimator.

[13] During days without thermal inversion, the instrument is 0.

5 Results

In this section, we discuss our results, showing OLS estimates for Equation (1) and 2SLS estimates for Equations (2) and (3). In Subsection 5.1, we discuss the first stages. In Subsection 5.2, we show our main results for respiratory health outcomes, and in Subsection 5.3, we show how PM 2.5 affects cardiovascular and all-cause health outcomes. Then, we analyze the heterogeneity in the estimated effects of fine particulate matter on respiratory health outcomes by splitting the sample based on demographic characteristics in Subsection 5.4. Finally, in Subsection 5.5, we demonstrate that our estimates are robust to alternative specifications and matching health outcomes to PM 2.5 concentrations.

5.1 First Stages

In Table 3, we report the first stages from estimating Equations (2) and (3). To produce results that are comparable to those in the literature, we show the effects of our instruments on the average daily concentration of PM 2.5 in column 1. In columns 3 through 7, we show how the duration of thermal inversions and the maximum daily wind speed influence the share of the number of hours in which PM 2.5 is above each WHO short-term threshold. For all specifications, the results are consistent with intuition and the economics and scientific literature. The duration of thermal inversions increases the average daily concentration of PM 2.5 and the share of hours above each WHO criteria for PM 2.5. In contrast, the maximum wind speed decreases the average daily concentration of PM 2.5 and the share of hours above each WHO threshold. The effective F statistics are larger than our weak instrument 5% bias critical values, so we can reject the null hypothesis of weak instruments for all of our specifications.

The differences between the coefficients for consecutive WHO thresholds provides additional information about how the distribution of the share of hours in each category changes with one additional hour of thermal inversion or with an increase in the maximum wind speed of 1 m/s. For instance, consider the effect of thermal inversion duration in our deaths dataset. One additional hour of thermal inversion increases the share of hours above IT2 by 0.3% and the share of hours above IT1 by 0.06%. This implies that the share of hours between IT2

and IT1 increases by 0.24% while the share of hours above IT1 increases by 0.06%. Similarly, an additional hour of thermal inversion increases the share of hours above IT4 by 1.1% and the share of hours above AQG by 0.91%, which implies that the share of the number of hours between AQG and IT4 decreased by 0.19%.

Comparing the magnitudes of the effects of thermal inversion duration and maximum wind speed suggests that maximum wind speed has a much larger effect on the daily distribution of PM 2.5 than does thermal inversion duration. However, the standard deviation of thermal inversion duration is around 4 hours, while the standard deviation of maximum wind speed is around 1 m/s. We can compare the effects of the instruments by considering a one standard deviation increase in both of our instruments. The magnitude of the effect of thermal inversion duration is between 58 and 112% of the effect of maximum wind speed for the deaths sample, between 46 and 94% in the hospitalizations sample, and between 39 and 53% in the urgent care visits sample. The only specification in which the effect of thermal inversions is larger than the effect of maximum wind speed is the share of hours above IT1 in the deaths dataset.

Table 3: First stages

Variable	**Daily PM 2.5**	**AQG**	**IT4**	**IT3**	**IT2**	**IT1**
Deaths:						
Thermal inv. Duration	0.387561***	0.914745***	1.104073***	0.637320***	0.306472***	0.063647***
	(0.011968)	(0.021634)	(0.029058)	(0.021838)	(0.013938)	(0.005138)
Max wind speed	-1.971331***	-5.629641***	-5.841985***	-2.946964***	-1.227449***	-0.204370***
	(0.081978)	(0.210512)	(0.250948)	(0.143602)	(0.065528)	(0.013325)
Observations	958,202	958,202	958,202	958,202	958,202	958,202
Effective F statistic	671.6	843.7	677.5	517.6	391.4	171.8
5% Critical Value	29.1	30.2	29.8	27.2	22.9	23.4
Hospitalizations:						
Thermal inv. Duration	0.331790***	0.840126***	0.941034***	0.511696***	0.254384***	0.057709***
	(0.009598)	(0.017823)	(0.024745)	(0.017989)	(0.010580)	(0.002797)
Max wind speed	-2.308471***	-6.967477***	-6.944852***	-3.227130***	-1.287053***	-0.231686***
	(0.053038)	(0.143453)	(0.164197)	(0.093900)	(0.045218)	(0.010341)
Observations	827,889	827,889	827,889	827,889	827,889	827,889
Effective F statistic	1587.3	2260.6	1639.8	1004.2	677.2	446.6
5% Critical Value	19.4	27.2	23.0	15.9	7.5	9.2
Urgent care visits:						
Thermal inv. Duration	0.285627***	0.777316***	0.847355***	0.437553***	0.196625***	0.038168***
	(0.023378)	(0.042350)	(0.063732)	(0.045056)	(0.026389)	(0.005743)
Max wind speed	-2.737505***	-8.127619***	-8.536638***	-3.898369***	-1.537130***	-0.292573***
	(0.155100)	(0.424327)	(0.504056)	(0.270646)	(0.127536)	(0.026227)
Observations	123,837	123,837	123,837	123,837	123,837	123,837
Effective F statistic	259.0	357.7	258.0	166.2	103.6	84.9
5% Critical Value	21.5	28.9	24.0	17.3	11.5	15.0

Notes: Fixed effects at the municipality level, with municipality time trends and municipality × year indicators. Standard errors clustered at the locality/municipality level.

5.2 Results for Respiratory Health Outcomes

In Figure 4, we present our main findings. We show the estimated effect of the daily share of hours above each WHO threshold on the number of same-day deaths (first row), hospitalizations (second row), and urgent care visits (third row) due to respiratory illness per 1 million inhabitants. The column on the left-hand side presents the OLS estimates from Equation (1), and the column on the right-hand side presents the 2SLS estimates from Equations (2) and (3).

Our OLS estimates do not consistently illustrate a non-linear effect of PM 2.5 concentrations on respiratory health outcomes across all levels of severity. In particular, the OLS estimates demonstrate a non-linear effect of PM 2.5 concentrations on deaths due to respiratory illnesses but do not demonstrate non-linear effects for hospitalizations or urgent care visits due to respiratory illnesses. In addition, for respiratory deaths, the magnitude of the effect of increasing the daily concentration of PM 2.5 by 1 $\mu g/m^3$ is similar to the magnitude of the effect of the share of hours above IT1, while we observe that the daily concentration of PM 2.5 has larger effects than those of the share of hours above every PM 2.5 WHO threshold for respiratory hospitalizations and urgent care visits.

On the other hand, our IV estimates demonstrate a clear non-linear convex effect of the share of hours with PM 2.5 above WHO thresholds for all severities of health outcomes. As expected, the magnitude of the effect of fine particulate matter on respiratory health outcomes decreases with the severity of health outcomes, since more severe outcomes occur less frequently, but the fact that we find the same positive non-linear effect of PM 2.5 concentrations on deaths, hospitalizations, and urgent care visits due to respiratory conditions implies that PM 2.5 concentrations have similar respiratory mortality and morbidity impacts.

Table 4 presents the coefficients from Figure 4. According to our OLS estimates, on average, a 1 $\mu g/m^3$ increase in the daily average concentration of PM 2.5 increases the number of respiratory deaths, hospitalizations, and urgent care visits per 1 million inhabitants by 0.00004, 0.00002, and 0.00074, respectively. The effects of the share of hours above each WHO threshold on the number of respiratory deaths per 1 million inhabitants are positive and range from 0.00001 to

0.00004, with the effects increasing in PM 2.5 concentration thresholds. For hospitalizations, the effects range between -0.000019 and 0.000012, with a non-statistically significant effect for IT2 and a negative effect for IT1. One possible explanation for this negative coefficient is that concentrations of PM 2.5 above IT1 are associated with a lower number of total hospitalizations (as discussed later in Figure 6), with respiratory hospitalizations decreasing less than all-cause hospitalizations. So, in this case, respiratory hospitalizations decrease, but they decrease by a lesser amount than total hospitalizations. Finally, we observe the same patterns for urgent care visits as for hospitalizations. The effects of increasing the share of hours above each WHO threshold by 1% on respiratory urgent care visits per 1 million inhabitants range from -0.00033 to 0.00042, with non-statistically significant effects for IT2 and IT1.

Next, we turn to the IV estimates. A 1 $\mu g/m^3$ increase in the daily concentration of fine particulate matter, on average, increases the number of respiratory deaths, hospitalizations, and urgent care visits per 1 million inhabitants by 0.00013, 0.00009, and 0.0024, respectively. A 1% increase in the share of hours above a certain WHO threshold increases the number of respiratory deaths, hospitalizations, and urgent care visits per 1 million inhabitants by up to 0.001, 0.0008, and 0.024, respectively. Here, we observe a non-linear convex relationship between hourly PM 2.5 concentrations and respiratory health outcomes. The effects of increasing the share of hours above AQG and IT4 are not statistically different. But the IT3 coefficients are roughly twice the magnitude of the IT4 coefficients, and the IT2 coefficients are around 2.5 times the magnitude of the IT3 coefficients. Finally, the IT1 coefficients are more than 4 times larger in magnitude than the IT2 coefficients. Comparing the effects of an increase in the share of hours above IT1 and AQG, the effects of the share of hours above IT1 are between 20 and 30 times greater in magnitude than the effects of the share of hours above AQG. This non-linear relationship suggests that the effects of PM 2.5 concentrations on respiratory health outcomes grow exponentially.

Furthermore, the magnitude of the effects for IT1 are much larger than the magnitude of the effects for the daily average concentration. Our IT1 effects reflect the effect of increasing the share of hours above PM 2.5 by 1%. Since 1 hour represents approximately 4.1% of the 24 hours of the day, we can multiply our coefficients by 4.1 to compute effects of an additional hour of PM 2.5 concentrations above IT1. Since our IT1 coefficients are roughly 10 times our

daily concentration coefficients, we can see that one additional hour per day with PM 2.5 concentrations above IT1 has the same effect as increasing the daily average PM 2.5 concentration by approximately 41 $\mu g/m^3$. To put this number in perspective, in our sample, the mean of the daily concentration of PM 2.5 is around 23 $\mu g/m^3$, its standard deviation is 11 $\mu g/m^3$, its interquartile range is 13 $\mu g/m^3$, and its 95th percentile is 42 $\mu g/m^3$. This illustrates that a massive increase in daily average PM 2.5 is required to obtain a health effect of a similar magnitude to that of an additional hour above IT1. This comparison highlights the non-linearity in health damages due to fine particulate matter and implies that the daily mean concentration of PM 2.5 masks important temporal variation. The health benefits of reducing peaks in fine particulate matter far exceed those that would be expected based on the impact of the same reduction in peaks on the daily mean PM 2.5 concentration. This implies that policies focused on reducing peaks in fine particulate matter will deliver the largest health benefits.

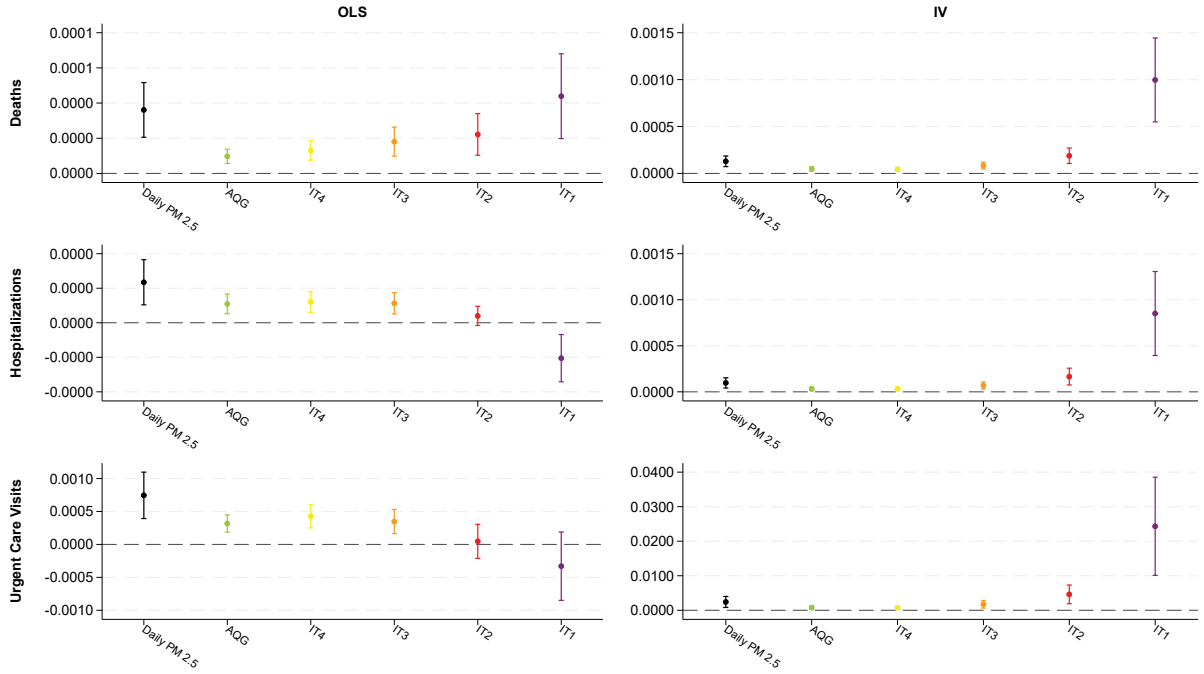
Our specification with the share of hours above AQG captures the combined effect of hours in each bin created by WHO thresholds, for instance, between AQG and IT4, between IT4 and IT3, all the way up to hours above IT1. In our sample of urgent care visits, on an average day 70.4% of hourly PM 2.5 concentrations are above AQG. Multiplying this share by its respective coefficient implies that hours above AQG increase respiratory urgent care visits by $0.0008 * 70.4 = 0.056$ per 1 million inhabitants. In the same sample of urgent care visits, the daily average concentration of PM 2.5 is around 23 $\mu g/m^3$ on an average day. Multiplying this number by the IV coefficient associated with daily average PM 2.5 implies that a daily concentration of 23 $\mu g/m^3$ increases respiratory urgent care visits by $0.0024 * 23 = 0.055$ per 1 million inhabitants. Both calculations imply nearly the same effect of PM 2.5 on urgent care visits, which shows that our non-linear specification both captures the same effect as daily PM 2.5 concentrations when it pools all WHO categories together and decomposes the effect of the daily average concentration into different impacts for different categories of PM 2.5 concentrations.

Table 4: Effects of PM 2.5 levels on respiratory health outcomes

Variable	Daily PM 2.5	AQG	IT4	IT3	IT2	IT1
Deaths:						
OLS coefficient	0.000036***	0.000010***	0.000013***	0.000018***	0.000022***	0.000044***
	(0.000008)	(0.000002)	(0.000003)	(0.000004)	(0.000006)	(0.000012)
IV coefficient	0.000129***	0.000047***	0.000044***	0.000084***	0.000189***	0.000997***
	(0.000029)	(0.000011)	(0.000010)	(0.000018)	(0.000042)	(0.000228)
Observations	958,202	958,202	958,202	958,202	958,202	958,202
Mean of outcome	0.01	0.01	0.01	0.01	0.01	0.01
Hospitalizations:						
OLS coefficient	0.000023***	0.000011***	0.000012***	0.000011***	0.000004	-0.000021***
	(0.000007)	(0.000003)	(0.000003)	(0.000003)	(0.000003)	(0.000007)
IV coefficient	0.000097***	0.000032***	0.000032***	0.000069***	0.000166***	0.000851***
	(0.000028)	(0.000010)	(0.000009)	(0.000020)	(0.000046)	(0.000232)
Observations	827,889	827,889	827,889	827,889	827,889	827,889
Mean of outcome	0.01	0.01	0.01	0.01	0.01	0.01
Urgent care visits:						
OLS coefficient	0.000745***	0.000317***	0.000427***	0.000347***	0.000047	-0.000330
	(0.000175)	(0.000065)	(0.000087)	(0.000091)	(0.000128)	(0.000258)
IV coefficient	0.002416***	0.000786***	0.000760***	0.001742***	0.004604***	0.024321***
	(0.000793)	(0.000274)	(0.000256)	(0.000543)	(0.001348)	(0.007064)
Observations	123,837	123,837	123,837	123,837	123,837	123,837
Mean of outcome	0.37	0.37	0.37	0.37	0.37	0.37

Notes: Fixed effects at the municipality level, with municipality time trends and municipality × year indicators. Standard errors clustered at the locality/municipality level.

Figure 4: Effects of PM 2.5 levels on respiratory health outcomes



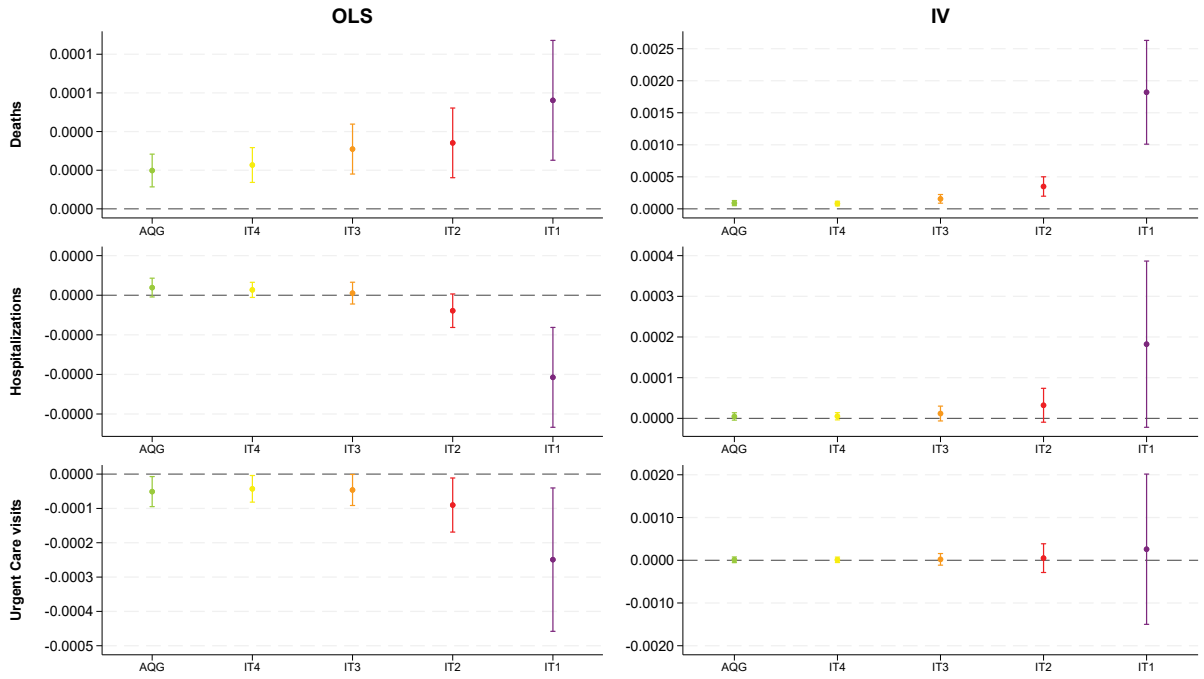
5.3 Results for Other Health Outcomes

In Figures 5 and 6, we explore the effects of fine particulate matter on cardiovascular and all-cause health outcomes. Figure 5 illustrates that hours above WHO PM 2.5 thresholds increase cardiovascular deaths, but there are no significant effects on hospitalizations or urgent care visits due to cardiovascular conditions. The coefficients for hospitalizations show the same pattern of increasing effects across WHO thresholds as for deaths, but the effects are not statistically significant. Cardiovascular events represent 26% of our sample for deaths, but only between 2 and 3% for hospitalizations and urgent care visits, so we may lack power to identify pollution effects on hospitalizations and urgent care visits. This lack of power to detect effects of PM 2.5 on cardiovascular hospitalizations and especially urgent care visits may be at least partially due to the fact that cardiovascular conditions that may be triggered or exacerbated by peaks in air pollution, such as heart failure or stroke, tend to be severe. In contrast, peaks of air pollution might trigger asthma episodes or other non-lethal respiratory ailments, and some of them may lead to deaths, especially among groups at higher risk. Consistent with the severity of cardiovascular conditions, the effect of a 1% increase in the share of hours above IT1 on

cardiovascular deaths is larger in magnitude than the effect on respiratory deaths.

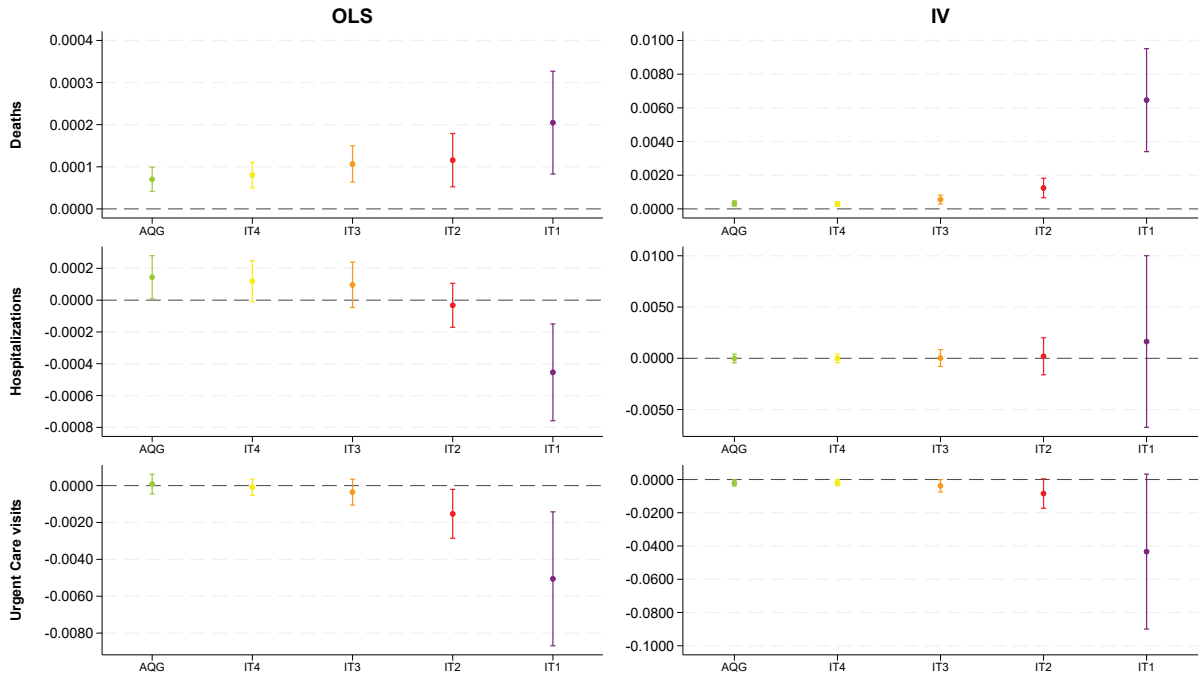
In Figure 6, we report the effects of the share of hours above PM 2.5 thresholds on all-cause health outcomes. We find statistically significant effects on total deaths per 1 million inhabitants, but not on total hospitalizations or total urgent care visits per 1 million inhabitants. The shares of respiratory diseases for deaths, hospitalizations, and urgent care visits are 9%, 3%, and 12%, respectively, and together, respiratory and cardiovascular causes represent 35%, 5%, and 15% of total deaths, hospitalizations, and urgent care visits. PM 2.5 concentrations have a non-linear effect on deaths due to both respiratory and cardiovascular causes, and together they represent 35% of total deaths. Therefore, we see the same positive and non-linear effect of PM 2.5 concentrations on all-cause deaths. But for hospitalizations and urgent care visits, the shares due to respiratory causes are likely not large enough to have their effects show in the totals.

Figure 5: Effects of PM 2.5 levels on cardiovascular health outcomes



Notes: Coefficients in grey have weak instruments. Shares of circulatory diseases are 26%, 2%, and 3%.

Figure 6: Effects of PM 2.5 levels on health outcomes (all causes)



Notes: Coefficients in grey have weak instruments. Shares of total diseases are 100%, 100%, and 100%.

5.4 Heterogeneous Results

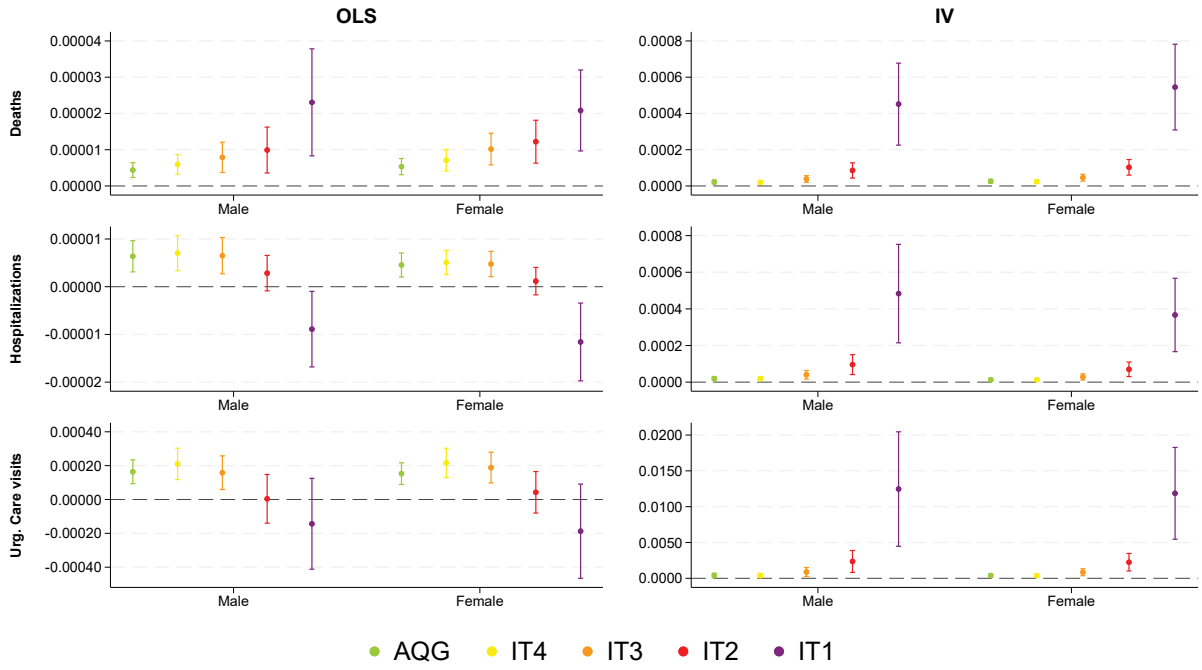
In this section, we explore potential heterogeneity in our main results on respiratory outcomes across several demographic variables. For each locality (or municipality for urgent care visits), we identify all years in which we observe at least one health event and create balanced panels at the locality-day level that include all days in these years. We define the count of health episodes as 0 for all locality-days and subgroups for which we do not observe any health episodes.[14] Then, we re-estimate Equations (1), (2), and (3) in these balanced panels for each of the values of our variable of interest.

In Figure 7, we explore potential differences in the health effects of PM 2.5 by gender. The non-linear pattern of effects holds for both groups, and these effects are not statistically different. These effects are smaller in magnitude than the effects in the whole sample, which is expected given how we built the datasets, Specifically, for each locality-day, we have one count for

[14]This avoids excluding locality-days in which no health events were observed in a subgroup, which is an issue that would arise by simply splitting the sample. For instance, consider a locality-day in which three respiratory deaths occurred and all of the deceased individuals were men. In this case, splitting the sample by gender would cause this locality-day to be missing for the sample of women, instead of correctly capturing that the count of respiratory deaths among women on this locality-day was 0.

respiratory outcomes of men and another count for those of women, whereas in our original dataset we have only one count that sums respiratory outcomes for both men and women. Because of this, our counts of outcomes are lower in our separate regressions for men and women, leading to lower magnitudes of effects, and the effects for men and women sum to the overall effects. For instance, a 1% increase in the share of hours above IT1 will lead to increases in respiratory urgent care visits per 1 million inhabitants of 0.0117 for men and of 0.0123 for women. These two coefficients sum to 0.0241, which is exactly the effect that we observe for the overall population in Table 4.

Figure 7: Effects of PM 2.5 levels on respiratory health outcomes by gender

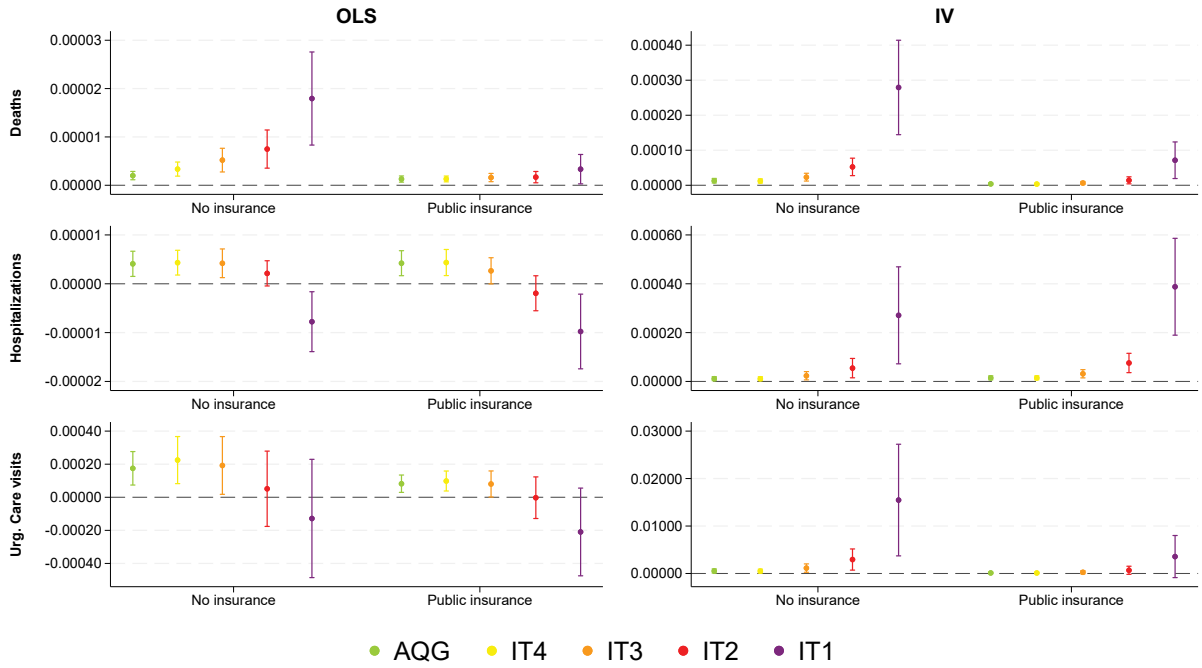


Notes: Coefficients from regressions in separate samples split by gender, each with only one endogenous variable. Coefficients in grey have weak instruments.

In Figure 8, we explore how fine particulate matter affects respiratory outcomes for individuals with different health insurance status. Because our data for hospitalizations and urgent care visits is limited to the public system, we do not observe these outcomes for individuals with workers' insurance who typically rely on the private system. Therefore, we estimate effects for people without health insurance and for people that participate in the public health insurance program. For hospitalizations and urgent care visits, we do not observe a statistically significant difference between individuals without insurance and those with the public insurance. For deaths, while the non-linear pattern of effects of PM 2.5 on respiratory deaths is the same

among individuals without insurance and those with public insurance, the magnitudes are greater among individuals without health insurance.

Figure 8: Effects of PM 2.5 levels on respiratory health outcomes by type of health insurance



Notes: Coefficients from regressions in separate samples split by type of insurance, each with only one endogenous variable. Coefficients in grey have weak instruments.

Next, in Figures 9, 10, and 11, we explore how fine particulate matter affects respiratory deaths, hospitalizations, and urgent care visits for different age groups. For each severity of health outcome, the effects display the same positive non-linear pattern within each age group. In Figure 9, we see that a 1% increase in the share of hours above IT1 leads to an increase in respiratory deaths among children less than 2 years old by 0.00008 per 1 million inhabitants. We observe no statistically significant effects for individuals aged 2 to 17, marginally significant effects for those aged 18 to 34, and a pattern in which the magnitude of the effects increase with age for individuals older than 35 years. Specifically, a 1% increase in the share of hours above IT1 leads to an increase in respiratory deaths per 1 million inhabitants of 0.00012 for individuals aged 50 to 64, 0.00033 for those aged 65 to 80, and 0.00036 for individuals aged 81 to 100. The effect of the share of hours above IT1 on the general population is approximately 0.001 (see Table 4). Around 8% of this total effect can be attributed to respiratory deaths among individuals aged 0 to 2, 8% to those aged 50 to 64, 33% to individuals aged 65 to 80, and 35% to those aged 81 to 100.

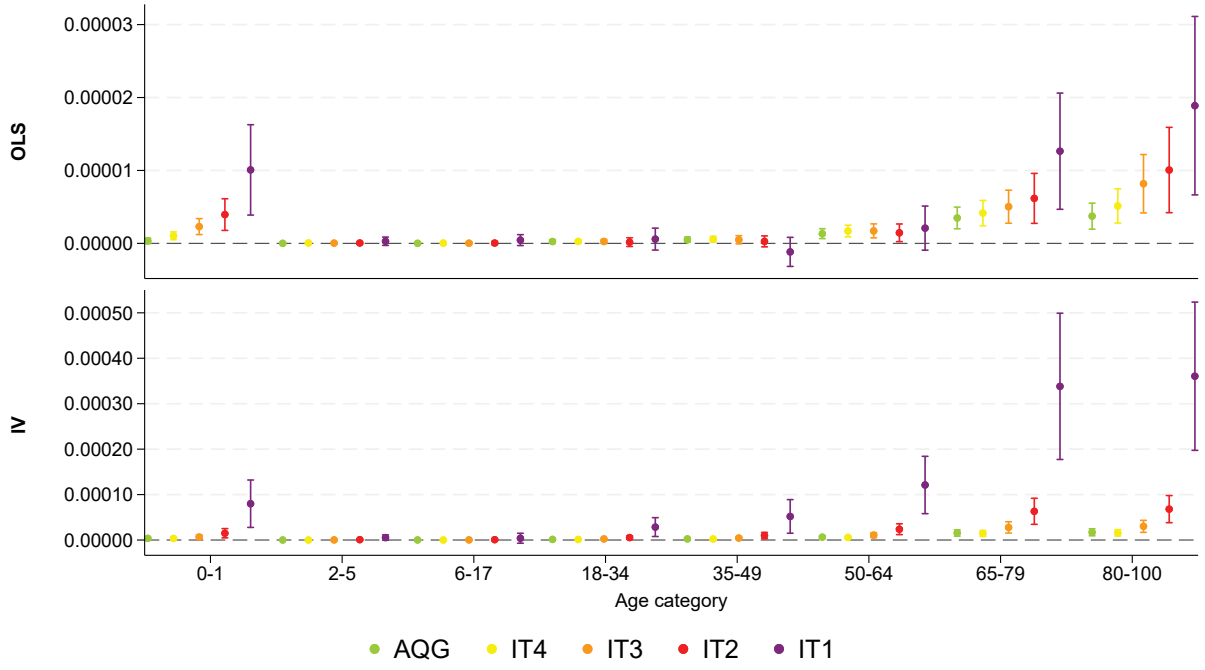
In contrast, Figure 10 shows that PM 2.5 concentrations affect respiratory hospitalization primarily among individuals aged 0 to 17 with very small or non-statistically significant effects for patients older than 17 years. The total effect of a 1% increase in the share of hours above IT1 is 0.0008 respiratory hospitalizations per 1 million inhabitants. We can attribute 19%, 29%, and 27% of these hospitalizations to individuals aged 0 to 1, 2 to 5, and 6 to 17, respectively. Figure 11 displays the results for urgent care visits for different age groups. In terms of magnitude, the largest effects are among individuals less than 2 years old, but they are not statistically significant. The next largest effects are among individuals in age groups 2 to 5 and 6 to 17, and then for age groups 18 to 34 and 35 to 49. Out of the total effect of PM 2.5 above IT1 on respiratory urgent care visits, approximately 20% can be attributed to individuals aged 2 to 5, 18% to those aged 6 to 17, 12% to patients aged 18 to 34, and 11% to those aged 35 to 49.

While the impact of PM 2.5 on respiratory mortality and morbidity are both positive and non-linear (see Figure 4), Figures 9, 10, and 11 illustrate that mortality and morbidity burdens are distributed differently across age groups with less mortality but more hospitalizations and urgent care visits occurring among school-aged children and younger adults than among babies and the elderly.

Finally, we explore heterogeneity across levels of educational attainment since education is highly correlated with income levels. The death registries report the highest educational level that a deceased individual attained. In Figure 12, we display results for different groups by educational attainment. The effects are largest for individuals with primary education (6 or less years), followed by the effects for those with high school education (7 to 12 years) and those without any education. The effects for individuals with tertiary education are significantly smaller than those for individuals with primary education, but we cannot reject that the effects for individuals with primary education is the same as for those with high school education.

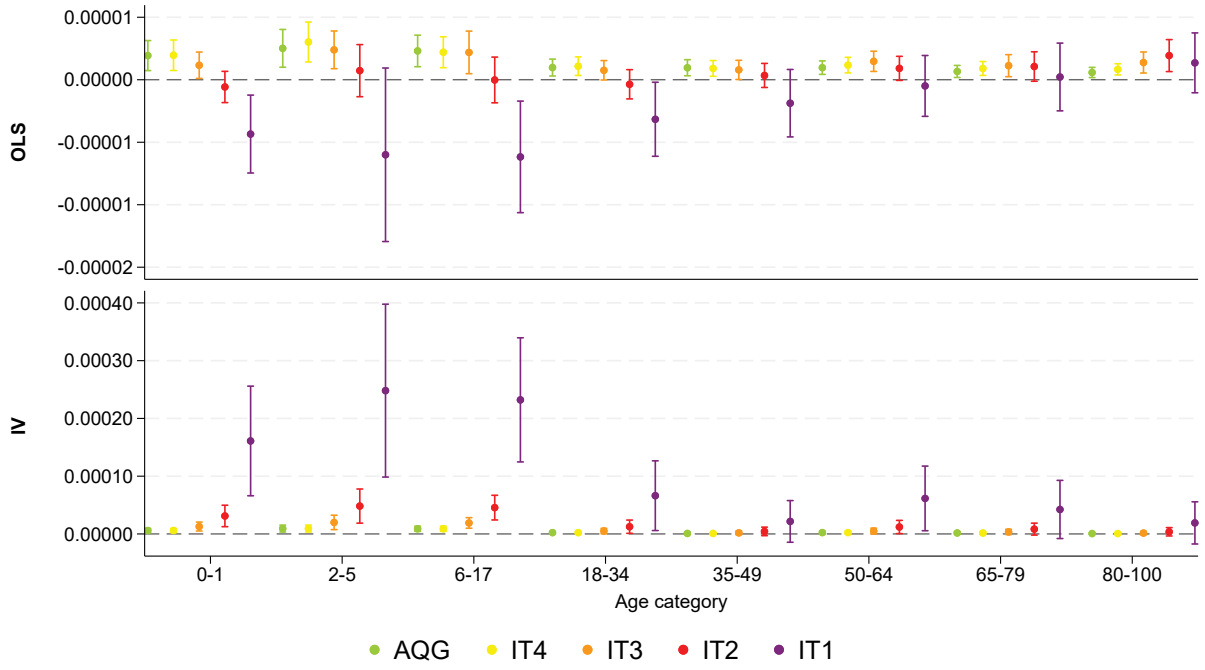
These categories of educational attainment contain substantial age heterogeneity. For instance, the deaths of both an 80-year-old who dropped out of primary school as a child and an 8-year-old who died while in primary school are categorized as achieving 6 years or less of education. In addition, educational groups could conflate educational attainment and age if educational attainment is generally increasing over cohorts. Appendix Figure A4 shows the frequencies for

Figure 9: Effects of PM 2.5 levels on respiratory deaths by age groups



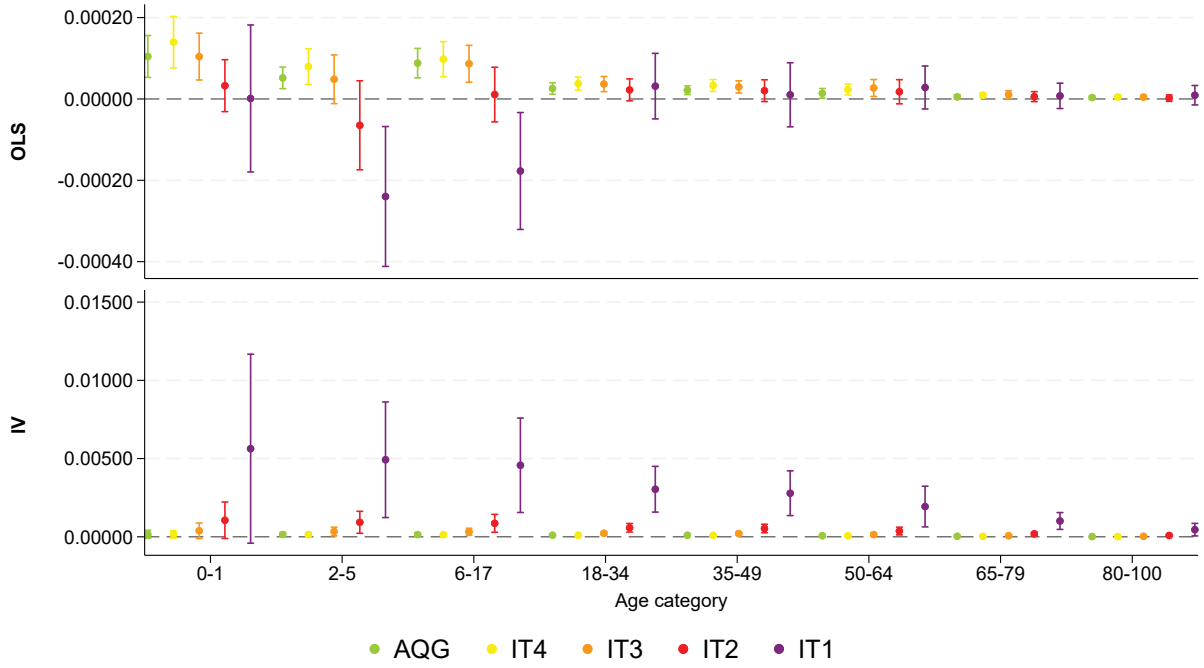
Notes: Coefficients from regressions in separate samples split by age groups, each with only one endogenous variable. Coefficients in grey have weak instruments.

Figure 10: Effects of PM 2.5 levels on respiratory hospitalizations by age groups



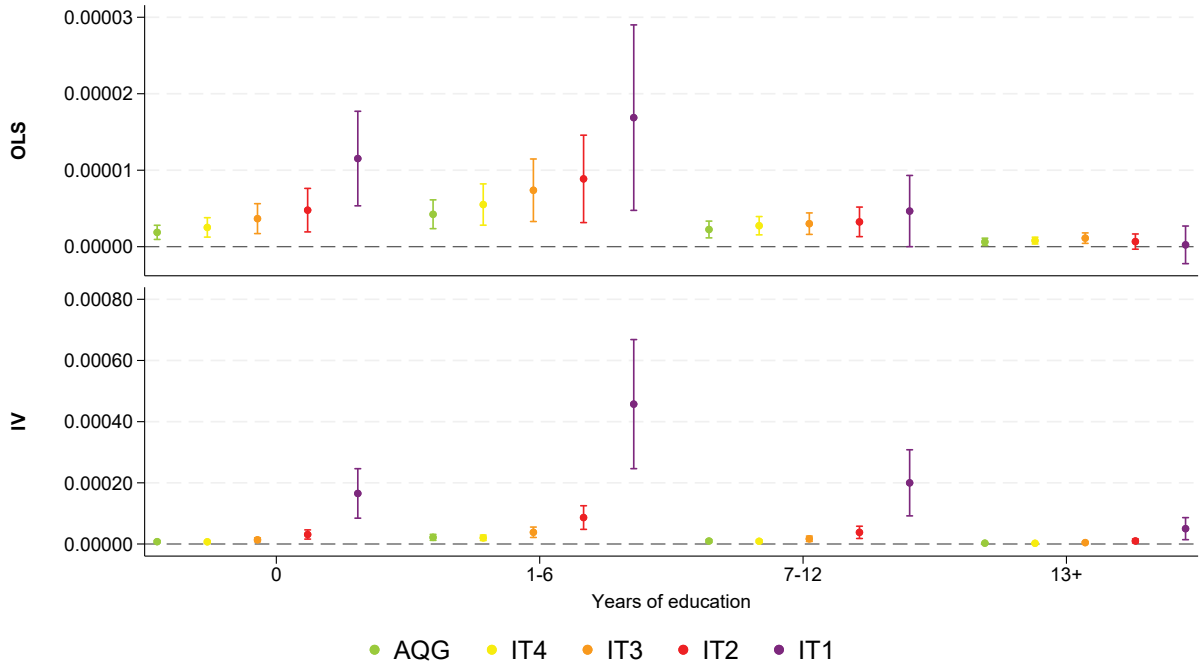
Notes: Coefficients from regressions in separate samples split by age groups, each with only one endogenous variable. Coefficients in grey have weak instruments.

Figure 11: Effects of PM 2.5 levels on respiratory urgent care visits by age groups



Notes: Coefficients from regressions in separate samples split by age groups, each with only one endogenous variable. Coefficients in grey have weak instruments.

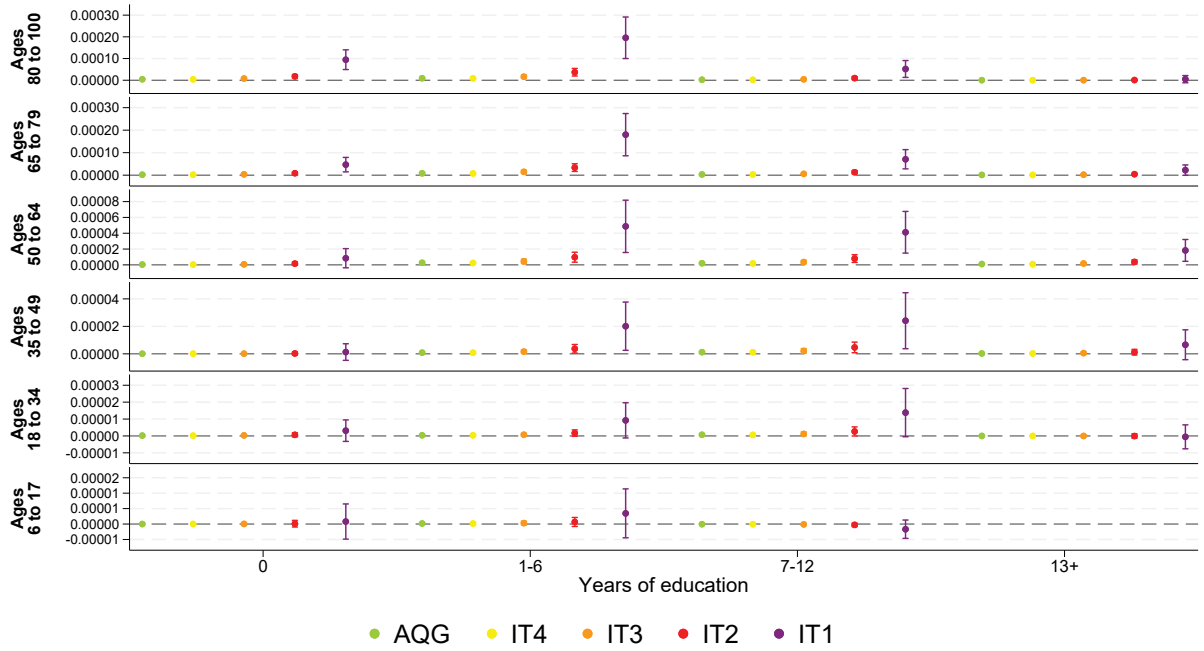
Figure 12: Effects of PM 2.5 levels on respiratory deaths by educational level



Notes: Coefficients from regressions in separate samples split by education levels, each with only 1 endogenous variable. Coefficients in grey have weak instruments.

each age and educational group, demonstrating that there are more individuals in the older age groups and that most individuals with up to 6 years of education were aged 65 or more. Therefore, in Figure 13, we decompose the effects of fine particulate matter on respiratory deaths by age and education groups. Figure 13 shows that age plays an important role in the results in Figure 12. Focusing on the share of hours above IT1, among individuals with no education significant positive effects begin at ages above 65 years old, and significant effects for individuals with primary school education begin for those aged 50 or more. For individuals with 13 or more years of schooling, across all age groups, only those aged 50 to 64 show a positive and significant effect, and this effect is relatively small in magnitude. Holding the age group constant, we can focus on the role of educational attainment. Among school-aged children, educational attainment does not play a role, which is likely because this group is still completing their education. Among older adults, those aged 65 to 79 and 80 to 100, we find that the magnitude of the effect of the share of hours above IT1 is largest among those with a primary education. Overall, it appears that the overall effects by educational attainment are primarily driven by older individuals and that the results are consistent with individuals of lower socioeconomic status bearing a greater health burden of air pollution.

Figure 13: Effects of PM 2.5 levels on respiratory deaths by educational-level and age groups



Notes: Coefficients from instrumental variables regressions in separate samples split by education levels and age groups, each with only 1 endogenous variable. Coefficients in grey have weak instruments.

5.5 Robustness

To demonstrate the robustness of our main results, we match fine particulate matter data to health outcomes by locality of occurrence for deaths and locality of health care facility for hospitalizations and urgent care visits, consider the effects of coarse particulate matter, and estimate alternative specifications. First, we change the location at which we measure the pollution associated with each health event. For deaths and hospitalizations, instead of coding fine particulate matter concentrations in the locality of residence, we code them in the locality of occurrence and locality of hospitalization, respectively. For urgent care visits, instead of coding fine particulate matter in the municipality of residence, we code it in the locality of the urgent care facility. For deaths, the number of localities in our dataset changes from 357 to 311. For hospitalizations, the number of localities in our dataset decreases from 537 to 36, and for urgent care visits, the number of geographic units in our dataset changes from 48 municipalities to 36 localities. The reduction in the number of localities is small for deaths, but our geographic reach is greatly diminished for hospitalizations and urgent care visits. Similarly, our sample sizes decrease from approximately 966,000 to 836,000 observations for deaths and from 858,000 to 110,000 observations for hospitalizations. In contrast, our sample size increases from 123,000 to 130,000 observations for urgent care visits because, even though there are fewer geographic units, there are two additional years of data in which the records contain information on the locality of the facility but not on the municipality of residence.

We report our first and second stages with these alternative sample definitions in Tables 5 and 6. If we compare Tables 3 and 5, the coefficients for both of our instruments are very similar, but our effective F statistics decrease, especially for hospitalizations and urgent care visits, though the decrease is not enough to induce weak instrument concerns. Comparing the results in Tables 4 and 6, the IV coefficients for respiratory deaths are similar in magnitude, but for respiratory hospitalizations and urgent care visits, the effects are greater in magnitude with this alternative location of measurement of PM 2.5. Despite these differences in magnitudes, the IV coefficients for the share of hours above IT1 are still roughly 10 times the coefficients for daily average PM 2.5 in Table 6, consistent with our previous result that one additional hour per day above IT1 has the same impact as increasing the average daily concentration of PM 2.5 by 41 $\mu g/m^3$.

Table 5: First stages, alternative geocoding level

Variable	**Daily PM 2.5**	**AQG**	**IT4**	**IT3**	**IT2**	**IT1**
Deaths:						
Thermal inv. Duration	0.39123***	0.92566***	1.12064***	0.64421***	0.30618***	0.06224***
	(0.01247)	(0.02266)	(0.03019)	(0.02285)	(0.01460)	(0.00533)
Max wind speed	-1.97968***	-5.65293***	-5.87936***	-2.96895***	-1.23233***	-0.20351***
	(0.08780)	(0.22516)	(0.26910)	(0.15376)	(0.07016)	(0.01438)
Observations	832,574	832,574	832,574	832,574	832,574	832,574
Effective F statistic	602.2	752.5	608.0	466.0	349.4	151.3
5% Critical Value	29.5	30.5	30.2	27.5	23.1	23.1
Hospitalizations:						
Thermal inv. Duration	0.32513***	0.84857***	0.97610***	0.50531***	0.23488***	0.04844***
	(0.02313)	(0.04180)	(0.06028)	(0.04452)	(0.02691)	(0.00699)
Max wind speed	-2.80397***	-8.44046***	-8.87813***	-4.02012***	-1.54444***	-0.27392***
	(0.17019)	(0.48267)	(0.55834)	(0.29877)	(0.13799)	(0.02939)
Observations	110,313	110,313	110,313	110,313	110,313	110,313
Effective F statistic	245.3	314.2	249.5	160.9	101.5	64.7
5% Critical Value	25.5	30.2	27.6	22.5	13.5	10.0
Urgent care visits:						
Thermal inv. Duration	0.35139***	0.89199***	1.08542***	0.57544***	0.25679***	0.04580***
	(0.02531)	(0.04093)	(0.06374)	(0.04999)	(0.03218)	(0.00937)
Max wind speed	-2.73985***	-8.12493***	-8.67398***	-4.08242***	-1.57487***	-0.24674***
	(0.17934)	(0.50767)	(0.60712)	(0.31247)	(0.13114)	(0.02636)
Observations	130,838	130,838	130,838	130,838	130,838	130,838
Effective F statistic	217.4	279.2	217.2	154.5	97.3	40.5
5% Critical Value	27.8	31.2	29.7	25.7	19.0	20.7

Notes: Fixed effects at the municipality level, with municipality time trends and municipality × year indicators. Standard errors clustered at the locality/municipality level.

Table 6: Effects of PM 2.5 levels on respiratory health outcomes, alternative geocoding level

Variable	**Daily PM 2.5**	**AQG**	**IT4**	**IT3**	**IT2**	**IT1**
Deaths:						
OLS coefficient	0.00004***	0.00001***	0.00002***	0.00002***	0.00003***	0.00006***
	(0.00001)	(0.00000)	(0.00000)	(0.00000)	(0.00001)	(0.00001)
IV coefficient	0.00014***	0.00005***	0.00005***	0.00009***	0.00021***	0.00113***
	(0.00003)	(0.00001)	(0.00001)	(0.00002)	(0.00005)	(0.00026)
Observations	832,574	832,574	832,574	832,574	832,574	832,574
Number of localities	311	311	311	311	311	311
Mean of outcome	0.01	0.01	0.01	0.01	0.01	0.01
Hospitalizations:						
OLS coefficient	0.00011***	0.00005***	0.00007***	0.00006***	0.00001	-0.00023***
	(0.00004)	(0.00001)	(0.00002)	(0.00002)	(0.00002)	(0.00008)
IV coefficient	0.00060***	0.00019***	0.00019***	0.00042***	0.00112***	0.00629***
	(0.00016)	(0.00005)	(0.00005)	(0.00011)	(0.00030)	(0.00176)
Observations	110,313	110,313	110,313	110,313	110,313	110,313
Number of localities	36	36	36	36	36	36
Mean of outcome	0.07	0.07	0.07	0.07	0.07	0.07
Urgent care visits:						
OLS coefficient	0.00202***	0.00083***	0.00103***	0.00079***	0.00038	-0.00038
	(0.00045)	(0.00016)	(0.00019)	(0.00021)	(0.00026)	(0.00054)
IV coefficient	0.00780***	0.00256***	0.00245***	0.00528***	0.01374***	0.08689***
	(0.00152)	(0.00052)	(0.00047)	(0.00099)	(0.00262)	(0.01900)
Observations	130,838	130,838	130,838	130,838	130,838	130,838
Number of localities	36	36	36	36	36	36
Mean of outcome	0.79	0.79	0.79	0.79	0.79	0.79

Notes: Fixed effects at the municipality level, with municipality time trends and municipality × year indicators. Standard errors clustered at the locality/municipality level.

Second, we consider the effect of coarse particulate matter concentrations, PM 10, on respiratory health outcomes. We categorize PM 10 according to the WHO recommendations for coarse particulate matter described in Appendix Table A1. Figure 14 and Table 7 display the same non-linear pattern of coefficients as PM 2.5. In particular, a 1% increase in the share of hours in which PM 10 concentrations exceed IT1 increases the number of respiratory deaths, hospitalizations, and urgent care visits per 1 million inhabitants by 0.0011, 0.0062, and 0.086, respectively. The magnitudes of the IT1 coefficients are between 4.8 and 8.5 times the magnitudes of daily average PM 10 coefficients, which implies that one additional hour per day with PM 10 above IT1 is equivalent to increasing the average daily concentration of PM 10 by 20 to 35 $\mu g/m^3$. In our sample, the mean of the daily concentration of PM 10 is around 43 $\mu g/m^3$, and its standard deviation is approximately 22 $\mu g/m^3$, so the effect of one additional hour of PM 10 above IT1 is roughly equivalent to the effect of one additional hour of PM 2.5 above IT1 in terms of daily concentration effects.

However, comparing the results in Tables 4 and 7, we see that the effects of PM 10 are smaller than those of PM 2.5. Increasing the share of hours with PM 2.5 above IT1 by 1% has between 1.2 and 5.6 times the magnitude of the effect of increasing the share of hours with PM 10 above IT1 by 1%. This is consistent with studies in the medical and epidemiological literature that find that fine particulate matter has stronger health effects than coarse particulate matter does (see Section 2).

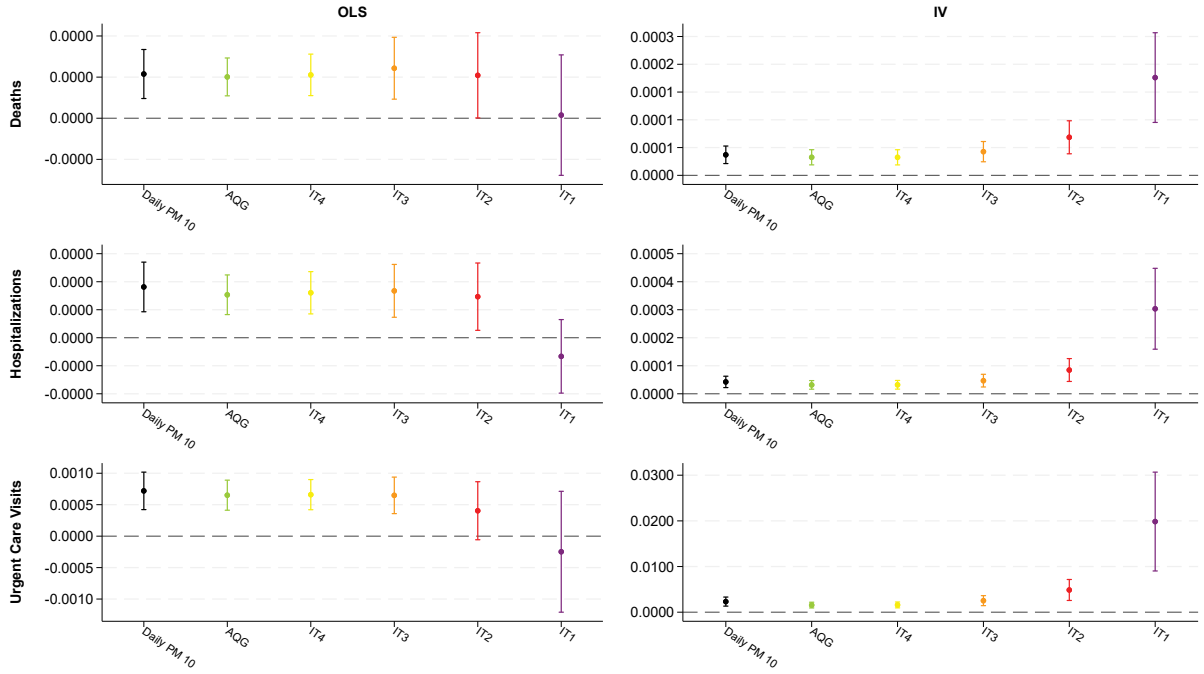
Third, in Figure 15, we demonstrate that our main results are robust to alternative fixed effects specifications. The first column shows our main results from estimating Equations (2) and (3) for reference. The second column includes only geographic-level fixed effects, and columns 3 and 4 include only municipality time trends or municipality $\times$ year interactions. For respiratory deaths and hospitalizations, our effects remain consistent across fixed effects specifications. For respiratory urgent care visits, only columns 1 and 4 produce statistically significant effects across all PM 2.5 categories. This demonstrates that municipality-level fixed effects and municipality-specific time trends are not enough on their own to well identify PM 2.5 effects on respiratory urgent care visits and that municipality-year specific indicators are playing an important role in controlling for local yearly patterns in urgent care visits.

Table 7: Effects of PM 10 levels on respiratory health outcomes

Variable	**Daily PM 10**	**AQG**	**IT4**	**IT3**	**IT2**	**IT1**
Deaths:						
OLS coefficient	0.000011***	0.000010***	0.000011***	0.000012***	0.000010**	0.000001
	(0.000003)	(0.000002)	(0.000003)	(0.000004)	(0.000005)	(0.000007)
IV coefficient	0.000037***	0.000032***	0.000032***	0.000043***	0.000069***	0.000176***
	(0.000008)	(0.000007)	(0.000007)	(0.000009)	(0.000015)	(0.000041)
Observations	1,470,442	1,470,442	1,470,442	1,470,442	1,470,442	1,470,442
Mean of outcome	0.00	0.00	0.00	0.00	0.00	0.00
Effective F statistic	1264.2	1878.8	1751.3	1105.3	629.0	339.5
5% Critical Value	14.6	15.0	11.5	17.3	25.1	29.8
Hospitalizations:						
OLS coefficient	0.000018***	0.000015***	0.000016***	0.000017***	0.000015**	-0.000007
	(0.000005)	(0.000004)	(0.000004)	(0.000005)	(0.000006)	(0.000007)
IV coefficient	0.000042***	0.000032***	0.000032***	0.000047***	0.000085***	0.000303***
	(0.000010)	(0.000008)	(0.000008)	(0.000012)	(0.000021)	(0.000074)
Observations	1,317,259	1,317,259	1,317,259	1,317,259	1,317,259	1,317,259
Mean of outcome	0.00	0.00	0.00	0.00	0.00	0.00
Effective F statistic	1559.1	1961.6	1796.4	1154.8	750.0	425.2
5% Critical Value	12.5	11.2	8.7	15.3	23.2	28.9
Urgent care visits:						
OLS coefficient	0.000720***	0.000651***	0.000659***	0.000649***	0.000404*	-0.000248
	(0.000149)	(0.000119)	(0.000120)	(0.000145)	(0.000230)	(0.000480)
IV coefficient	0.002323***	0.001558***	0.001591***	0.002530***	0.004868***	0.019852***
	(0.000495)	(0.000314)	(0.000321)	(0.000547)	(0.001149)	(0.005407)
Observations	172,867	172,867	172,867	172,867	172,867	172,867
Mean of outcome	0.31	0.31	0.31	0.31	0.31	0.31
Effective F statistic	183.4	208.1	196.0	136.5	81.5	42.2
5% Critical Value	12.0	20.3	17.3	16.1	25.9	32.3

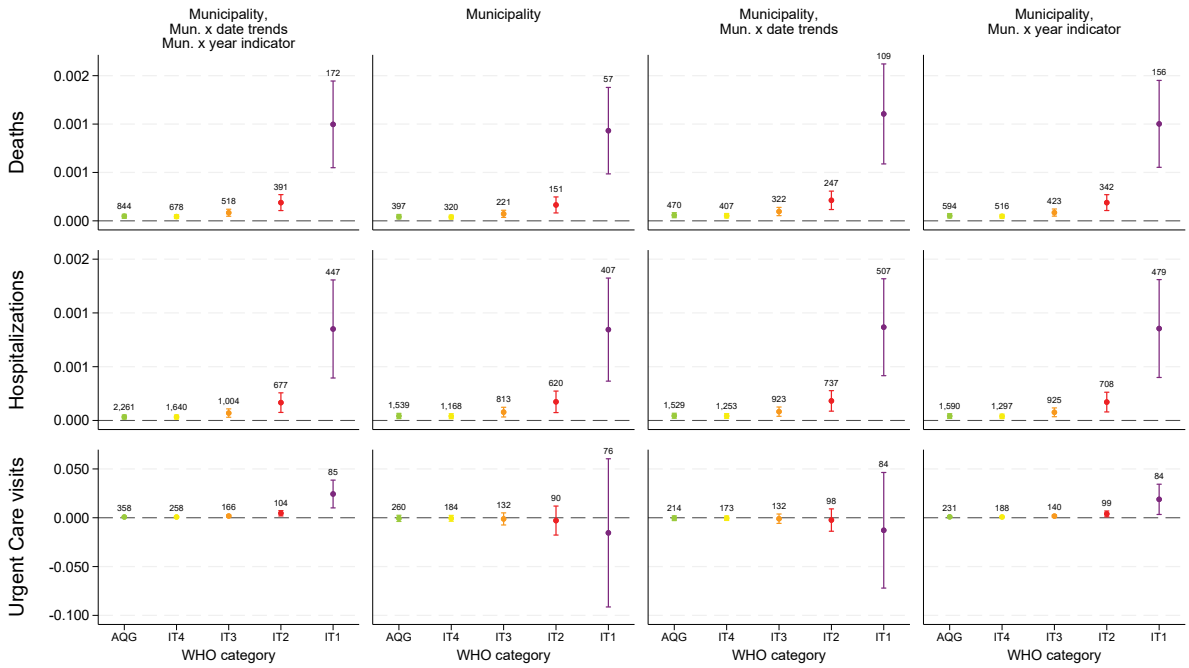
Notes: Fixed effects at the municipality level, with municipality time trends and municipality × year indicators. Standard errors clustered at the locality/municipality level.

Figure 14: Effects of PM 10 levels on respiratory health outcomes



Note: Coefficients in grey have weak instruments.

Figure 15: Effects of PM 2.5 on respiratory health outcomes with different fixed effects



Notes: Number above coefficients denote effective F statistic. Coefficients in grey have weak instruments.

6 Conclusion

In this paper, we document a positive non-linear and convex relationship between hourly fine particulate matter concentrations and respiratory deaths, hospitalizations, and urgent care visits per 1 million inhabitants. One additional hour a day of PM 2.5 concentrations above the WHO's interim target 1 can be up to 30 times more harmful than one additional hour above the WHO air quality guideline. One additional hour above the IT1 threshold has the same respiratory health consequences as increasing the daily average PM 2.5 concentration by approximately 41 $\mu g/m^3$, which is equivalent to a day with a mean concentration of PM 2.5 of 0 $\mu g/m^3$ moving to the 95th percentile of the distribution of daily PM 2.5 in Mexico City.

We find evidence of a non-linear and convex relationship between hourly fine particulate matter concentrations and cardiovascular and total (all cause) deaths, but no evidence that hourly PM 2.5 concentrations affect cardiovascular and total hospitalizations or urgent care visits. We do not observe significant differences in effects across genders. Respiratory deaths are driven by older people, respiratory hospitalizations are more common among younger people, and respiratory urgent care visits are driven by teenagers and young adults, illustrating that the mortality and morbidity burdens of PM 2.5 are distributed differently across ages. We find no effects of PM 2.5 on respiratory deaths among highly educated individuals, which suggests that lower socioeconomic groups bear a greater share of the health consequences of fine particulate matter.

These findings have important policy implications. First, policies that focus on reducing peaks in pollutant concentrations should be a priority for policymakers since the returns in terms of health outcomes are substantial. In contrast, further efforts to reduce air pollution when pollutant concentrations are not as severe (but still above what the WHO recommends) might deliver relatively small health benefits at larger economic cost. Second, programs that limit economic and human activity during episodes of high air pollution should be based on hourly measurements of air pollution concentrations instead of 24-hour moving averages, triggering health alerts and restrictions on pollutant emissions based on current hourly concentrations of pollutants or hourly forecasts of pollution concentrations. The duration of these programs should also be re-thought. Targeting them only to hours with peaks of

pollution could maximize the health benefits of pollution reductions while minimizing the economic costs of these restrictions. While it is important that these policies are designed and implemented to avoid temporal substitution of peaks in air pollution concentrations, our non-linear effects indicate that flattening peaks in air pollution concentrations by spreading out pollutant emissions could deliver substantial health benefits with the same or even higher daily mean concentrations. Finally, our instrumental variables suggest that peaks in air pollution concentrations could also be reduced by temporally substituting pollutant emissions to times with more favorable weather conditions.

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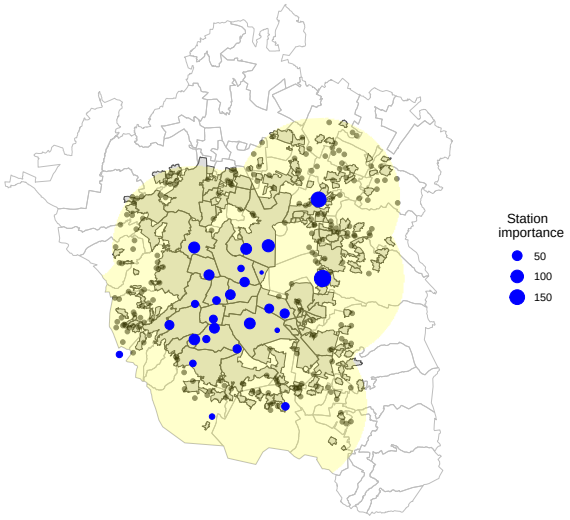
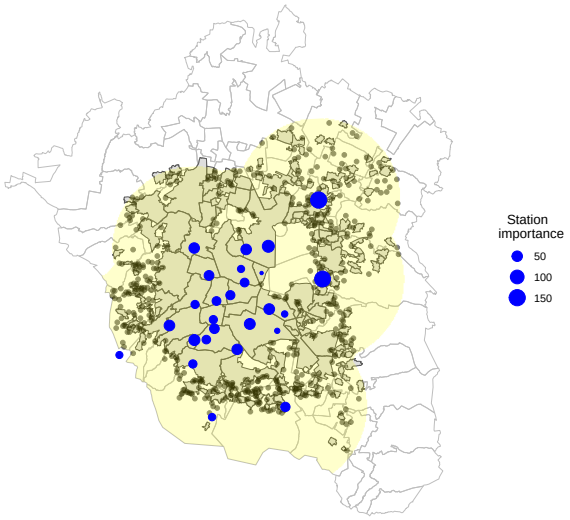
Figure A1: Monitoring Stations and Sample Localities: Deaths Data



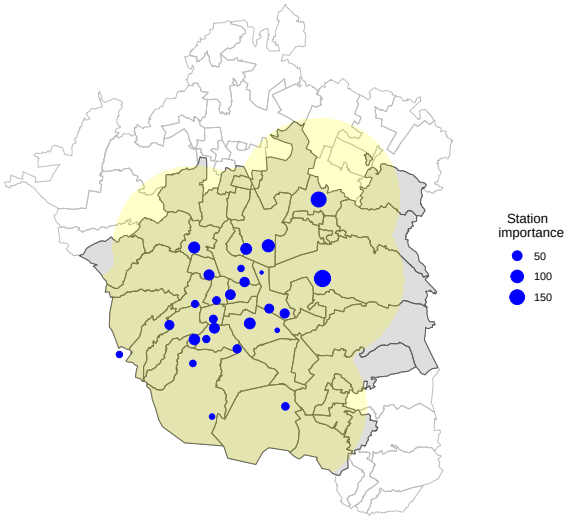
Notes: Grey areas represent the 357 included localities. Yellow areas represent 20 km buffers around the 26 monitoring stations used in the analysis. Blue dots represent the location of these stations, with their size representing their importance, meaning how many times they are used to produce locality-level PM 2.5 concentrations.

Figure A2: Monitoring Stations and Sample Localities: Hospitalizations Data



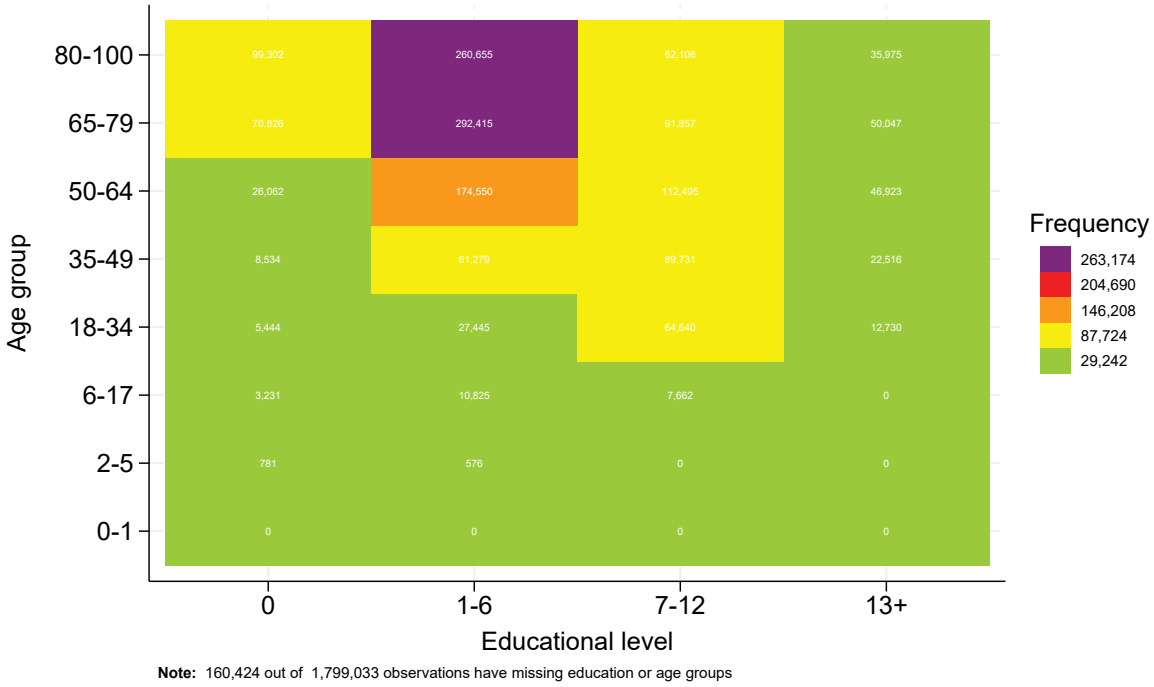
Notes: Grey areas represent the 537 localities included in the sample. Yellow areas represent 20 km buffers around the 26 monitoring stations used in the analysis. Blue dots represent the location of these stations, with their size representing their importance, meaning how many times they are used to produce locality-level PM 2.5 concentrations.

Figure A3: Monitoring Stations and Sample Localities: Urgent Care Visits Data



Notes: Grey areas represent the 48 municipalities included in the sample. Yellow areas represent 20 km buffers around the 26 monitoring stations used in the analysis. Blue dots represent the location of these stations, with their size representing their importance, meaning how many times they are used to produce locality-level PM 2.5 concentrations.

Figure A4: Frequencies for age and educational-level groups



Note: 160,424 out of 1,799,033 observations have missing education or age groups

Table A1: WHO recommended short-term targets for PM 10

Recommendation	$\mathbf{PM_{10}}(\boldsymbol{\mu g/m^3})$
Interim target 1	150
Interim target 2	100
Interim target 3	75
Interim target 4	50
Air quality guideline	45