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Health Shocks under Hospital Capacity Constraint: Evidence from Air Pollution in Sao Paulo, Brazil
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ABSTRACT

How responsive to health shocks are healthcare systems in the developing world? Developing countries are known to have both lower levels of hospital infrastructure and serious health shocks driven by air pollution. These shocks are transitory and may be marginal relative to other health demands, so healthcare systems might be able to manage them. On the other hand, with limited capacity hospitals may not be able to respond rapidly, possibly exacerbating health damages from pollution. In this study, we examine the consequences of health shocks induced by air pollution in a megacity in the developing world: Sao Paulo, Brazil. Using daily data on pediatric hospitalizations from 2015-2017, an instrumental variable approach based on wind speed, and a plausibly exogenous measure of hospital capacity constraints, we show that such transitory health shocks can disrupt healthcare services due to limited capacity, including for conditions seemingly unrelated to air pollution. Also, we cannot rule out severe deterioration of health outcomes.

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1 Introduction

How responsive to health shocks are healthcare systems in developing countries? It is well-known that the developing world has much lower levels of hospital infrastructure. According to the World Development Indicators, the number of hospital beds per 1,000 population in high-income countries is 5.3, whereas in developing countries it is only 2.3. At the same time, health shocks driven by environmental insults like air pollution are common around the world, particularly in developing countries. Pollution shocks are transitory and may be marginal relative to other health demands in the developing world, so it is possible that healthcare systems can manage these changes quite easily. On the other hand, with limited capacity, hospitals may not be able to respond quickly, possibly exacerbating health damage from pollution.

In this study, we examine the healthcare system responses to daily air pollution shocks in the megalopolis of Sao Paulo, Brazil, which is among the ten largest metropolitan areas in the world. Among large cities, Sao Paulo is as polluted as Singapore and Barcelona, much less polluted than Delhi and Beijing, but more polluted than London and Madrid.[1] We focus on the effects of short-term exposure to PM10 – particulate matter 10 micrometers or less in diameter – on pediatric hospitalizations.[2] Usually, air pollution studies implicitly assume that the current pollution concentration measures each individual's contemporaneous and lifetime exposure. Nevertheless, the lifetime exposure to pollution might be unknown. The shorter exposure period and more limited geographic mobility of children make it easier to determine the effects of pollution on them compared to adults (Currie et al., 2014).[3]

Although this study focuses on air pollution, Figure 1 shows that the pattern and the order of magnitude of the hospitalization swings are relatively similar across pollution shocks and heatwaves – another common environmental insult around the world. Heatwaves will become even more frequent and more severe with climate change (IPCC, 2022). In the figure, the swings are all calculated relative to the previous day without the shock, which we call day zero. That is, the swings on days 1 through 5 are all relative to day zero. For instance, the swing in day 5 for air pollution above the WHO guidelines means that on the fifth consecutive day of high pollution, hospitalizations increase 2.3 p.p. on average. Similarly, for heatwaves,

[1]See Appendix Table A1 for comparisons. We look at recent PM data, but our setting is similar to developed nations decades ago, and likely China and India in the future (Hanlon and Tian, 2015; Clay et al., 2016).

[2]There is a preponderance of evidence that air pollution is harmful to health, particularly for children (e.g., Chay and Greenstone, 2003; Currie and Neidell, 2005; Currie and Walker, 2011; Currie et al., 2015; Knittel et al., 2016; Schlenker and Walker, 2016; Deschenes et al., 2017; Severnini, 2017; Deryugina et al., 2019; Alexander and Schwandt, 2022). Short-term exposure has been associated with increased respiratory illness and duration of symptoms, exacerbation of asthma, and decline in lung function, among other outcomes (e.g., Pope et al., 1995).

[3]Our analysis focuses on children aged 1-5 years. Despite similar patterns, results are noisier for other age groups. For adults, we present estimates for the elderly, another group of the population sensitive to pollution.

the swing on day 5 means that hospitalizations on the fifth consecutive day of temperature 5°C above the historical average for a district is 2.4 p.p. larger than on day zero. Based on this comparison, the responses we estimate for the healthcare system in the context of pollution shocks might serve as good approximations for potential responses of the system to other environmental insults driven by climate change, such as heatwaves.

In our empirical analysis, we consider the impacts of air pollution shocks on hospitalizations for respiratory illnesses and conditions seemingly unrelated to pollution separately. Exposure to air pollution has a detrimental impact on people's health, leading to an increased *demand* for healthcare services, particularly for respiratory illnesses. This increased demand can strain healthcare facilities, reducing the *supply* of resources to treat other illnesses. Hence, in strained hospitals, treatment for illnesses seemingly unrelated to pollution might also be indirectly affected. Within each category, hospitalizations are classified as emergent or elective by the hospitals when reporting data to the Brazilian Ministry of Health.

Our identification strategy addresses two key challenges related to pollution exposure and hospital capacity constraints. Regarding pollution, to address omitted variable bias from confounding factors such as unobserved economic activity and attenuation bias from measurement error (Chay and Greenstone, 2003; Currie et al., 2014; Dominici et al., 2014), we use an instrumental variable approach. We exploit an instrument capable of dealing with non-stationary sources of pollution:[4] wind speed. This approach builds on insights from Liu and Salvo (2018) and He et al. (2019), which instrument particulate matter with atmospheric ventilation shocks. The idea is that wind speed dissipates particle pollution, reducing PM10 concentration, but does not have first-order direct impacts on health outcomes.

As for hospital capacity constraints, we aim to assess the effects of *ex-ante* constraints on the pollution-hospitalization relationship for respiratory and other illnesses. The idea is to evaluate the potential for the unavailability of healthcare infrastructure to generate the crowd-out effect of air pollution on hospitalizations for causes seemingly unrelated to pollution. We construct plausibly exogenous "district-level occupancy rates" of pediatric beds by leveraging (i) the rich administrative matched patient-hospital data, (ii) the considerable weekly cycle in hospital admission and air pollution, and (iii) the extent of the estimated delayed effects of pollution on pediatric hospitalization. Such a variable reflects present-day constraints but is not determined by contemporaneous conditions. In our empirical approach, that variable is represented by an indicator of the district-level occupancy rate of seven days ago above 85%, a

[4]The main sources of pollution in Sao Paulo are vehicle emissions, similar to urban areas in the United States (e.g., Currie and Walker, 2011; Marcus, 2017; Anderson, 2020; He et al., 2019; Alexander and Schwandt, 2022).

threshold highlighted by the Brazilian Ministry of Health as the maximum hospital utilization that would not adversely affect health outcomes (Ministério da Saúde, 2011).

When it comes to data, the Environmental Protection Agency of the State of Sao Paulo (CETESB) tracks pollutants and meteorological variables hourly, using several monitors across the Sao Paulo Metropolitan Area (SPMA).[5] The health data are collected and organized by the Brazilian Hospital Data System (SIHSUS), which allows us to observe daily hospitalizations for respiratory illnesses and other causes by zip code of residence. Our estimation includes virtually all districts in the SPMA – there are 157 districts in our sample. We link these districts to the two nearest CETESB monitors, and calculate hospitalization rates per one million children for each day due to respiratory and non-respiratory illnesses as dependent variables.

Three key findings emerge from our analysis. First, the direct effect of exposure to PM10 on pediatric hospitalization for respiratory illnesses is both statistically and economically significant. It represents a non-trivial demand shock for the SPMA health care system and seems to be driven by acute respiratory infections such as pneumonia and chronic respiratory diseases such as asthma. However, hospitalizations increase only in hospitals that are relatively unconstrained. A $10\mu g/m^3$ increase in PM10 concentration leads to 2.5 additional hospital admissions per million children aged 1 to 5 years in unconstrained hospitals, or about 5.6% of the sample mean for hospitalization rates for all respiratory illnesses. Hospitals with ex-ante capacity over 85% are unable to admit more patients, which leads to patient displacement, even for emergencies. These effects increase monotonically with the size of the pollution shocks.

Second, to face the increased demand due to respiratory illnesses, strained hospitals displace even patients with illnesses seemingly unrelated to air pollution. In days with a $10\mu g/m^3$ higher PM10 concentration, hospitals with occupancy rates above 85% in the baseline reduce admissions for non-respiratory conditions by about 3.6 per million children aged 1 to 5 years, or about 5.1% of the sample mean for hospitalization rates for all non-respiratory illnesses. Most of this reduction, however, is among elective procedures related to genitourinary and skin and connective conditions (e.g., phimosis surgeries).

Third, because strained hospitals are displacing not only elective hospitalizations for non-respiratory illnesses, but also emergent hospitalizations for respiratory illnesses, there seems to be nontrivial impacts on health outcomes. In fact, using unconditional quantile regression methods proposed by Firpo et al. (2009), we conduct a distributional analysis with three commonly used health outcomes: mortality and readmission within 30 days, and ICU admission. The evidence indicates a relative deterioration of these health outcomes related to respiratory

[5] This is the same data used by Salvo and Geiger (2014), Salvo and Wang (2017), and He et al. (2019).

conditions in the upper part of the distribution of those outcomes. Thus, we cannot rule out impacts on public health of air pollution shocks under hospital capacity constraints.

These findings are robust to various specifications and variable definitions, including the timing and threshold of occupancy rates, alternative assumptions regarding the exclusion restriction (Conley et al., 2012; Nevo and Rosen, 2012), and the inclusion of interactions between PM and socio-economic variables such as income and rural/urban status. The Stable Unit Treatment Values Assumption (SUTVA) seems to hold in our setting as well, as there is only limited evidence of spillover effects into neighboring areas. Also, we document heterogeneity in the effects of public versus philanthropic hospitals and for different age groups.

Our analysis illustrates how the healthcare system handles a sudden health shock in a developing country. In our setting, the shocks are driven by air pollution, but we argue that climatic shocks such as heatwaves may have comparable strength and may happen even more frequently around the world. We provide evidence indicating not only patient displacement but also deterioration of health outcomes. Multilateral organizations such as the World Bank have pointed out several challenges faced by the Brazilian healthcare system. They have stated that "several surveys show high levels of dissatisfaction with public health services ... The most commonly reported problems are delays in access or treatment and a lack of doctors" (Gragnolati et al., 2013, p.9-10). Our findings not only corroborate the survey evidence but also highlight potential challenges that the healthcare system may experience in the coming decades because of climate change.

This study makes two main contributions to the literature. First, it contributes to the emerging literature on how healthcare infrastructure may interact with environmental insults to affect public health. Prior research has pointed out that access to primary care, vaccination, and emergency healthcare services may mitigate the impacts of air pollution and high temperatures on health outcomes (Mullins and White, 2020; Cheung et al., 2020; Colmer et al., 2021; Clay et al., 2022; Graff-Zivin et al., 2023). Our study contributes by examining both the consumption and production of healthcare during negative health shocks driven by environmental insults. It highlights that air pollution can affect health not only directly, but also indirectly via supply-side constraints. Climate change is poised to increase both the frequency of heatwaves (IPCC, 2022) and pollution shocks due to wildfires and increased formation of local pollutants (Jacob and Winner, 2009; Bento et al., 2023). Because air pollution and heatwaves appear to create health shocks of similar strength, our findings could serve as guidance for policymakers looking to improve healthcare emergency preparedness in face of current and future challenges.

Second, it provides a unique look at how developing countries cope with limited health-care capacity, especially during negative health shocks. Most of the previous work has examined how the health care system adjusts to demand surges or supply constraints in the developed world.[6] Notable exceptions are Adhvaryu and Nyshadham (2015), Godlonton and Okeke (2016), and Manang and Yamauchi (2020), but they have looked at changes in access to health care facilities in *low-income* countries. To the best of our knowledge, there is no study examining impacts of healthcare constraints in a *middle-income* country. Developing nations usually face an array of unmet healthcare needs to start with, so any further shocks could overwhelm the system. Even in Sao Paulo, a relatively modern megalopolis, public hospitals cannot manage the increased demand arising from pollution shocks without imposing non-trivial costs to society. Given the ubiquity of high levels of air pollution and limited healthcare infrastructure in the developing world, more research is needed in other contexts.

Our study also adds to the literature documenting the health impacts of air pollution in developing countries, where pollution levels are usually higher but the willingness to pay to reduce pollution is usually lower due to relatively lower income levels (Jayachandran, 2009; Arceo et al., 2016; Cesur et al., 2017; Barwick et al., 2018; Rangel and Vogl, 2019). In particular, our PM estimated effects complement those reported by He et al. (2019) regarding the effects of NOx from diesel exhaust on hospitalizations for respiratory illnesses in Sao Paulo.

This paper is organized as follows: Section 2 introduces background information on air pollution in the SPMA, health care in Brazil, and the medical and epidemiological effects of pollutants on human health. Section 3 presents the data sources and some descriptive statistics. Section 4 explains the empirical strategy. Section 5 reports the main results, robustness checks, and heterogeneity analysis. Lastly, Section 6 provides some concluding remarks.

[6] Previous studies have examined the impacts of longer-term changes in supply or demand for health care – such as openings or closures of hospitals and clinics and influxes of immigrants – and have found mixed results. From the supply side, constrained healthcare capacity has been shown to lead to treatment delays and worsened health outcomes, but mostly for time-sensitive conditions (e.g., Buchmueller et al., 2006; Jacobson and Royer, 2011; Avdic, 2016; Lu and Slusky, 2016; Alexander et al., 2019; Carroll, 2019; Gujral and Basu, 2019; Kleiner, 2019; Simonsen et al., 2021; Zhang, 2022). Healthcare demand shocks such as the ones driven by immigration have also been found to affect health care services, but primarily in areas with low baseline levels of healthcare infrastructure (Giuntella et al., 2018; Aygün et al., 2021).

2 Background

2.1 Air pollution in Sao Paulo

The Sao Paulo Metropolitan Area (SPMA) is the largest metropolitan area in Brazil, with over 21 million people, representing approximately 10% of the Brazilian population.[7] It is among the 10 largest metropolitan areas in the world and consists of 39 municipalities, where the country's largest industrial zone is located. In Brazil, Sao Paulo is popularly known for its traffic congestion, high building density, and poor air quality.

The two main sources of air emissions in the SPMA are automobiles and manufacturing (Braga et al., 2001). While vehicle emissions are predominant in Sao Paulo city, industrial emissions dominate in the other municipalities of the metropolitan area. According to the Environmental Protection Agency of the State of Sao Paulo (CETESB), more than 7 million vehicles – automobiles, trucks, buses, and motorcycles – circulated in the region in 2015 (CETESB, 2016). Although the Sao Paulo vehicle fleet is not old (8.9 years, on average), CETESB draws attention to their contribution to local air pollution, especially particulate matter and ambient ozone, which usually reach unhealthy values in the SPMA.

CETESB is in charge of measuring the levels of pollutants in the air. It has been monitoring some pollutants since 1972, but only for a few monitors. Consistent measurement of pollutants started in 1981, but only after 2008 the monitoring network became denser. Notwithstanding, most of the monitors are still located in the SPMA.[8]

2.2 The Brazilian healthcare system

In Brazil, public and private healthcare systems coexist. The public system, called the Unified Healthcare System (*Sistema Único de Saúde* – SUS), was established by the 1988 federal constitution to provide universal preventive and curative care to the overall population (Paim et al., 2011).[9] The private system can be complementary or supplementary to the public system. If a patient shows up to a private hospital in a severe condition, the hospital has to treat and stabilize them, even if they are not insured. Private hospitals can also allocate at least 60% of their hospital beds to SUS and, in return, obtain exemption from federal taxes. These are the philanthropic hospitals. SUS reimburses private and philanthropic hospitals by procedure,

[7] Sao Paulo is the largest city in Brazil, with a population of over 12 million. Despite the distinction between the SPMA and Sao Paulo city, we will use the terms interchangeably.

[8] Details on pollution policy in Brazil can be found in Appendix A.1.

[9] Appendix A.2 discusses details on SUS infrastructure and performance in Brazil.

usually at standard fees below market prices, but they may agree to a higher negotiated price.[10] As supplementary, some private hospitals and clinics only provide services covered by health insurance plans or out-of-pocket expenses.

Appendix Figure A1 displays hospital beds per 1,000 population by bed type for the four largest metropolitan areas in Brazil. The smaller the share of beds in public hospitals, the larger the share of beds in philanthropic hospitals, suggesting that their relationship is more complementary than supplementary. In all four locations, the share of beds in private hospitals is in the range of a quarter to over a third. In the SPMA, we observe that the total number of beds per 1,000 population is below three, which is comparable to the average in the United States.

2.3 Air pollution and human health

The medical and economic literatures have documented the impacts of particulate matter, especially the finer ones, on health outcomes (e.g., Pope, 1989, 2000; Brauer, 2000; Braga et al., 2001; Chay and Greenstone, 2003; Currie and Neidell, 2005; Currie and Walker, 2011; Dominici et al., 2014; Schlenker and Walker, 2016; Deschenes et al., 2017; Deryugina et al., 2019; Alexander and Schwandt, 2022). These particles can easily penetrate the tissues of the body, and increase blood coagulation, which can cause heart attack and lung problems (Brauer, 2000; Braga et al., 2001).

Air pollution does not affect all individuals equally. Children and the elderly are more likely to suffer from poor air quality because they have a more fragile immunological system. Other vulnerable groups include people with chronic diseases, such as asthma, who may have more acute episodes (Gouveia and Fletcher, 2000; Braga et al., 2001). For children, both short- and long-term outcomes can be affected by pollution (Currie et al., 2014; Isen et al., 2017).

3 Data

3.1 Data description

We use administrative data on hospital admissions from the Brazilian Hospital Data System (SIHSUS).[11] We observe all publicly funded or reimbursed hospital admissions by individuals'

[10]The SUS reimbursement is similar to Medicare in the United States in that it is prospective, paying a preset amount for given procedures or diagnoses. Reimbursement is based on average hospital costs, thus not designed to cover the medical expenses of any given patient.

[11]SIHSUS is one of the several data systems of the Ministry of Health – named DATASUS – that provide data on health outcomes in Brazil.

zip code of residence from January 2015 to December 2017. In 2016, 87% of total hospital admissions in Brazil were funded by the public system. This percentage is lower in Southern states where private markets are more prevalent.[12] SIHSUS crucially collects data on the date of admission, cause, and length of hospital stay – according to the International Classification of Diseases, Tenth Revision (ICD-10). We also use novel data that allow us to track all admissions for the same patient over our study period.[13] Using the patient identifier, we compute the probability of ICU admission, and mortality and readmission within 30 days, which are standard measures of hospital/healthcare quality (Doyle et al., 2019).

We classify hospitalizations using the broad ICD-10 categories and group them based on similarities or due to the small number of observations in some categories. To identify elective and emergent illnesses, we use the Brazilian Ministry of Health classification of hospitalizations according to their urgency status and need for emergency department care. By their definition, "[e]lective hospitalization is necessary for treating a non-urgent patient or when there is no immediate risk of life or intense suffering. Elective hospitalization can occur on a date scheduled in advance since it does not compromise the effectiveness of the treatment."

We restrict our sample to hospitalizations of children aged 1 to 5 years. We focus the analysis on individuals living in the SPMA due to the availability of environmental data. CETESB collects hourly air pollution and weather variables using 30 monitors throughout the SPMA. We also use two additional monitors located in neighboring municipalities. Not every pollutant is measured by every monitor. Our pollution variable is particulate matter with less than 10 micrometers of diameter (PM10, in $\mu g/m^3$) because it is regularly collected by most of the monitors (25 monitors in the SPMA). PM10 levels are high in the SPMA and highly correlated with PM2.5, as it contains PM2.5. Because there were only 14 PM2.5 monitors in 2017, we run the analysis only with PM10 data. The weather variables we use are relative humidity (in percentage), temperature (in degrees Celsius), and wind speed (in m/s).[14]

The daily pollution and weather variables are the average of the day.[15] We spatially inter-

[12]Machado et al. (2016) shows that, in Sao Paulo state from 2008-10, 22.1% of the hospitalizations were private, 25.4% were public, and 52.5% were mixed (public or private financed). Back-of-the-envelop calculations using Machado et al. (2016)'s numbers approximate public hospitalizations by about 60.3% of all hospital admissions.

[13]Data obtained via the Access to Information Act in Brazil (Act 12,527/2011).

[14]Other meteorological variables collected are wind direction and air pressure. Later on, we perform robustness checks using wind direction variables as well.

[15]We exclude all days with less than twelve hours of data. We fill the missing hourly data by weighting the first hour before and after by 1-$\frac{|h_i - h_m|}{h_a - h_b}$, $i = a, b$, where h_a is the hour after, h_b is the hour before, and h_m is the hour missing data. For example, if we have no information for 3PM and 4PM, but we have for 2PM and 5PM, we impute the value for 3PM by weighting the data for 2PM by $\frac{2}{3}$ and 5PM by $\frac{1}{3}$. On the same way, we weight 2PM by $\frac{1}{3}$ and 5PM by $\frac{2}{3}$ to fill the values of 4PM. For the missing days, we follow the same weighted scheme, but replace hours with days.

polate meteorological variables to get complete weather information for all monitors that measure PM10, by using an inverse distance criterion.[16] Due to evidence on the non-randomness of monitor siting, we do not spatially interpolate pollution data (Muller and Ruud, 2018). Because pollution monitoring is intermittent like the United States (see for example, Zou, 2021), our panel is unbalanced.

Lastly, we match individuals' zip code of residence from the health data with the corresponding district in the SPMA. Daily hospital admissions are expressed as hospitalization rates per one million children. Because we need population data to compute hospitalization rates, and the most reasonable level of geographic disaggregation available to us is at the district level, our unit of analysis is a district.[17] The environmental data assigned to a district comprise of the weighted average of pollution and meteorological variables from the two nearest monitors – we use the inverse distance between the district and the monitor as the weight. The distance between monitors and districts is never greater than 50 kilometers and is lower than 10 kilometers for more than 50% of the districts. Figure 2 displays the location of the monitors.

To calculate the occupancy rate of hospitals in the SPMA, we combine SIHSUS data with administrative data on hospital beds from the National Registry of Health Establishments (CNES). We restrict our data to pediatric beds as children are the population of interest. To compute the number of beds occupied, we use the length of stay of individuals between 28 days and 14 years old admitted to the pediatric department between 2015 and 2017. We exclude newborn infants (younger than 28 days) as they go to neonatal beds.

We construct a data-driven network of hospitals and districts to attribute hospital occupancy rates to districts. We leverage the observed patterns of origin-destination of residents to hospitals from the past. The network is given by the shares of children between 1 and 5 years who live in district i and are treated in hospital j over our baseline period January 2010 to December 2014. Recall that our study period is 2015-2017. It is important to note that, to define the hospital catchment area, we analyze past hospital admissions of children aged 1 to 5 to determine which hospitals their caregivers typically choose for healthcare services. However, when creating the occupancy variable (representing children's hospital capacity), we consider

[16] Previous studies have used inverse distance for similar purposes (Neidell, 2004; Schlenker and Walker, 2016).

[17] Population data from the 2010 Census are also available at the census tract level, which is more disaggregated than districts. However, the matching of zip codes and census tracts is quite imprecise, given that both are small geographic units and the matching is carried out using the centroid of each unit. Technically, the centroid of a zip code might match the census tract, but most of its area may be in another tract or vice-versa. Moreover, the precision of the analysis and the construction of the network would be in jeopardy had we used census tract rather than district as our unit of analysis, given how sparsely the admissions would be distributed among census tracts.

all hospital admissions from the age of 28 days to 14 years (the age range that use pediatric beds), as we need a measure of the actual occupancy of these hospitals. We create a different network for every quarter of the year, separately for weekdays vs. weekend. Mathematically, for each pair of district – denoted by i – and hospital – denoted by j – at a given quarter and weekday/weekend – denoted by $\tilde{t}$ – the network is defined by the set of shares

$$w_{ij\tilde{t}} = \frac{\sum_{t \in \tilde{t}} \sum_{c \in i} \mathbb{1}[\text{child c from i in hospital j in day t}]}{\sum_j \sum_{t \in \tilde{t}} \sum_{c \in i} \mathbb{1}[\text{child c from i in hospital j in day t}]},$$

where $\mathbb{1}[\text{child c from i in hospital j in day t}]$ indicates whether a child c from a given district i is being treated in hospital j at time t. Note that child c may have been admitted days before day t. Because the network is created *before* our period of analysis, it indicates how likely it is for a child from district i to receive care in hospital j. Moreover, by considering the child's admission every day she spends in the hospital, we allow the relationship between a district and a hospital to be stronger if a given hospital treats more complex or risky illnesses that require longer treatment. Lastly, note that the sum of $w_{ij\tilde{t}}$ is equal to 1 for every combination of district, quarter, and weekday vs. weekend.

To calculate the occupancy rate at the district level, we compute the weighted sum of the occupancy rate at the hospital level, using $w_{ij\tilde{t}}$ as weights, i.e,

$$\text{occupancy rate}_{it} = \sum_j w_{ij\tilde{t}} \times \text{occupancy rate}_{jt},$$

such that t represents days within the period 2015-2017, and again $\tilde{t}$ represents combinations of quarter and weekday vs. weekend. Consequently, any pair of ij on all $t \in \tilde{t}$ receives the same network weight. This approach gives us the *implicit* daily hospital occupancy rate that residents from district i are exposed to according to the baseline network.

Our analysis contains a network of 157 districts linked to 203 hospitals. Out of the 164 districts in the SPMA, three had no child admission and four did not have admission in all quarters and weekdays/weekends in our baseline period (2010-2014). Thus, we have excluded these seven districts because we could not infer their network.[18]

[18]Regarding hospitals, the original database contains 267 healthcare facilities with children aged 1 to 5 admitted in our baseline period (2010-2014). Out of those, 57 had no pediatric admission and beds in our main period of analysis (2015-2017), and 7 had no pediatric beds even though we observe pediatric admissions. We exclude such hospitals from our analysis.

3.2 Descriptive statistics

Figure 3 displays the daily mean and maximum level of PM10 by monitor. The small numbers above the red dashed line represent the number of days between 2015 and 2017 with daily maximum concentration above the current World Health Organization (WHO) short-term guideline, which is $45\mu g/m^3$. All monitors have measured many days of PM levels above the WHO recommendation.

Monitors location and average district hospitalization rates for respiratory illness by quartile can be seen in Appendix Figure A2. The darker the district, the larger the average hospitalization rate. The map does not directly imply any relationship between hospitalizations and pollution. However, Appendix Figures A2 and A3 together suggest a correlation between expressways/highways and admissions, which is consistent with the main sources of pollutants in SPMA being vehicles.

Table 1 reports the hospitalization rate and the share of emergent admissions for the five most common causes of respiratory illnesses and for conditions seemingly unrelated to pollution.[19] Pneumonia is the most prevalent disease among acute respiratory infections (66.4% of all illnesses in this category), with an average district-day admission rate of 21 per million children. Asthma is the most prevalent illness among chronic lower respiratory illnesses (5.66 admissions per million children). According to the Ministry of Health classification, most acute and chronic respiratory diseases are emergent. In contrast, about 95% of the hospitalizations for other respiratory illnesses are elective. The most prevalent causes in this category are chronic diseases of the tonsils and adenoids.

Among illnesses seemingly unrelated to pollution, Table 1 shows that the most common are phimosis, a genitourinary condition (average district-day admission rate of 9.11 per million children), and umbilical hernia, classified as other non-respiratory (5.73 admissions per million children). The table also shows that hospitalizations for genitourinary and other non-respiratory illnesses are usually less emergent than for skin and connective conditions.

4 Empirical Strategy

Our main econometric specification describes a model to assess the effect of particle pollution on pediatric hospitalization, as well as the effect of *ex-ante* hospital capacity constraints on

[19] Appendix Table A2 reports the share of readmission, death, and emergency status for the most prevalent respiratory and non-respiratory illnesses. The probability of readmission and death seems to be positively correlated with the level of emergency of the illness.

the PM-hospitalization relationship. The estimating equation is:

$$\mathrm{Hosp}_{it} = \delta_1 \mathrm{PM}_{it} + \delta_2(\mathrm{PM}_{it} \times 1[\mathrm{HCap}]_{it}) + \delta_3 1[\mathrm{HCap}]_{it} + X_{it}\phi + \alpha_i + \alpha_t + \varepsilon_{it}, \quad (1)$$

where i denotes districts, and t calendar dates from 2015 to 2017. Hosp mainly represents the hospital admissions rate for children aged 1 to 5 years, and PM is the level of PM10. $1[\mathrm{HCap}]_{it}$ is the baseline measure of hospital capacity constraints. It is an indicator for whether the implicit district-level occupancy rate lagged by a week is above 85%, a threshold highlighted by the Brazilian Ministry of Health as the maximum hospital utilization that would not adversely affect health outcomes (Ministério da Saúde, 2011).[20] X represents time-varying controls, including a quadratic function of temperature, humidity, and their interaction. α_i represents district fixed effects, α_t represents time fixed effects that correct for the potential weekly cycle in admissions and aggregate shocks (day-of-week, month-of-year, and year fixed effects), and ε represents idiosyncratic terms. Importantly, district fixed effects control for time-invariant characteristics of districts, such as overall socioeconomic status, topography, and other geographical features of the area. In this sense, we explore variation within districts to estimate air pollution effects on pediatric hospitalizations.[21]

To credibly identify the causal effects of exposure to air pollution on pediatric hospitalization, we instrument PM with contemporaneous and lagged wind speed, to account for potential lingering wind effects on air pollution. This approach builds on insights from Liu and Salvo (2018) and He et al. (2019), which instrument particle pollution with atmospheric ventilation shocks. Similarly, to identify the interaction effect between PM and our baseline measure of hospital capacity constraints, we instrument that interaction with the interaction between contemporaneous and lagged wind speed and the baseline measure of hospital capacity constraints. The instruments should address two potential endogeneity issues. The first is the omitted variable bias from unobserved confounding factors such as the state of the economy. The second is the potential attenuation bias from measurement error. Air pollution is not measured exactly where individuals live, but rather approximated by measurements in the closest available monitors. As usual, the wind speed instruments must satisfy the relevance

[20] The Ministry of Health recommends an occupancy rate below 85% for hospital beds (we have not found any guidelines for children's beds in general). Moreover, according to the Brazilian Health Authority that regulates the private sector (ANS) an occupancy rate above 85% is associated with a decrease in safety and quality of care (ANS, 2012). In fact, using simulations of queuing theory, McManus et al. (2004) show that when ICU occupancy exceeds 80-85% (children beds), patient refusal increases, even when they need intensive care in the emergency room.

[21] Appendix Figure A4 displays the residualized PM10 regarding fixed effects for location and time separately, and location and time together. There seems to be still variation at the cross-sectional level, but the main source of variation is temporal.

condition and the exclusion restriction.

Regarding the relevance condition, wind speed appears a well-suited instrument for particle pollution in our context. In megalopolises like Sao Paulo, variation in pollution exposure at the individual level may depend less on where the wind is blowing from, but more on how strong the wind is blowing and potentially dispersing emissions. Indeed, the main sources of pollution in large urban centers are typically *non-stationary* (vehicle emissions), therefore ubiquitous across the metropolitan area.[22] Hence, differently from locations with important *stationary* sources of pollution, wind direction might matter less than wind speed. Notwithstanding, we present results from alternative analysis adding wind direction. The estimates end up being noisier despite still relatively precisely estimated.

As for the exclusion restriction, wind speed should affect pediatric hospitalization only through its effect on air pollution. It might be, however, that wind speed affects economic behavior and health through other channels. For example, some heat indices depend not only on temperature and humidity but also on wind speed, such as apparent temperature, the temperature equivalent perceived by humans. Because heat can impact health directly, this would be a threat to our identification strategy. We control for temperature and humidity in our analysis. Furthermore, we have found only one study that provides suggestive evidence of an impact of a proxy for apparent temperature on health (Cai et al., 2018), and it is focused on chronic obstructive pulmonary disease (COPD) among the elderly. Also, the only two other studies that show some relationship between wind speed and health outcomes are merely correlational (Ferrari et al., 2012; Hervás et al., 2015), and only the latter is focused on children's outcomes.[23] In any case, we conduct bounding exercises for potentially small violations of the exclusion restriction following methodologies developed by Conley et al. (2012) – instruments are only plausibly exogenous – and Nevo and Rosen (2012) – imperfect instruments.

As for health outcomes, we use primarily hospitalization rates per million children aged 1 to 5 years. We first estimate the direct effects of air pollution on hospitalization due to respiratory illnesses. Then, to assess the potential for hospital admissions driven by air pollution to crowd out hospitalizations for causes unrelated to pollution, we also consider all other illnesses. The potential indirect effects on conditions seemingly unrelated to pollution might broaden the health costs associated with air pollution.

[22]Many roads in the SPMA can be heavily congested in peak times (see Appendix Figure A3).

[23]During the pandemic, several studies highlighted the relationship between wind speed and COVID-19, but eventually air pollution emerged as the underlying force behind those findings (see review by Han et al., 2022). Therefore, the direct impacts of wind speed on health status documented during the pandemic can be recast as the results of reduced-form analyses.

Figure 4 illustrates the channels through which air pollution shocks may affect the *demand* of healthcare services for respiratory illnesses and the *supply* of healthcare services for illnesses seemingly unrelated to pollution. Exposure to air pollution has a detrimental impact on people's health, leading to an increased *demand* for healthcare services, particularly for respiratory illnesses. In Panel (a) of this figure, this is represented by the rightward shift in the demand curve, which moves the equilibrium from point A to point B. Thus, air pollution shocks can disrupt and strain healthcare facilities, potentially reaching capacity and compromising the quality of care. These disruptions in the healthcare system, which may affect the *supply* of resources to treat other illnesses, can therefore impact the health of individuals not directly exposed to air pollution events. In Panel (b) of the figure, this is represented by the leftward shift in the supply curve, which moves the equilibrium from point C to point D.[24]

Now we are able to more fully interpret the main coefficients on interest in Equation (1). The coefficient δ_1 associated with PM should be interpreted as the impact of PM on admissions in hospitals with low baseline occupancy rates. This PM coefficient reflects both the biological impact of air pollution on the human body as well as all defensive investments made by individuals to protect themselves from pollution, such as wearing masks, avoiding outdoor activities, installing indoor air purifiers, and taking medications (see discussions by Ebenstein et al., 2017; Deschenes et al., 2017; Liu and Salvo, 2018).

The coefficient δ_2 associated with the interaction between PM and the baseline indicator for capacity constraints reflects the differential impact on admissions in overcrowded hospitals (when the baseline occupancy rate exceeds 85%). For example, if pollution-related hospitalizations displace hospital admissions for non-respiratory causes under baseline capacity constraints, then δ_2 will be negative. Given that we do not anticipate displacement when constraints are not binding, the PM coefficient δ_1 for non-respiratory hospitalizations should be close to zero. This is, in fact, a straightforward way to test our research design regarding capacity constraints.

Notice that the empirically inferred network explained in the data section is crucial for the construction of this plausibly exogenous indicator for capacity constraints. Again, we identify *de facto* hospital catchment areas in the baseline and add a more nuanced dimension to the

[24]Notice that the same figure could be used to understand the impacts of air pollution shocks on emergent and elective treatment, even within respiratory illnesses. The increase in demand for emergent care would be represented by a rightward shift in the demand curve in Panel (a) of the figure, resulting in a shift from equilibrium point A to point B. Then, the disruptions in the healthcare system caused by the increase in air pollution may affect the supply of healthcare services for elective treatments, considerably less urgent. In Panel (b) of the figure, this impact would be represented by a leftward shift in the supply curve, shifting the equilibrium from point C to point D. Likewise, the figure could help provide insights into spillover effects across districts: from areas directly exposed to pollution shocks to those that are not.

data to learn about the effect of the *ex-ante* measure of capacity constraints on outcomes. Indeed, because we can detect the effects of PM10 shocks up to five days in the future, we take advantage of the *predetermined* network and hospital utilization data lagged by a week to generate implicit district-level occupancy rates. The week lag in hospital utilization data and the within-week cycle in hospital admission and pollution concentration, evident in Figures 5 and 6, give rise to a quasi-experimental measure of hospital capacity constraint.[25] It reflects present-day constraints but is not determined by contemporaneous conditions, as displayed in Figure 7, Panels (a) and (b).

One concern with our measure of capacity constraints is that healthcare systems might be designed for the current needs of the populations they serve (Doyle, 2011; Doyle et al., 2015), and perhaps with pollution damages in mind. If that is the case, the coefficient of the interaction between PM and capacity constraints might not be reasonably thought of as a *causal* moderator – how healthcare capacity constraints may affect marginal damages from pollution. The concern is that, instead, we may be estimating an *effect* moderator, where the interaction term captures healthcare capacity and any other factors that could be correlated with the healthcare system that also moderate the pollution-hospitalization relationship.

Our empirical approach addresses such a concern in several ways. *First*, we include district fixed effects in our estimating equations to control for long-term capital and labor investment in healthcare capacity that may reflect the needs of the populations they serve, as well as the long-term patterns of air pollution. Pollution shocks, on the other hand, are transitory and arguably marginal relative to other health demands in our developing country context. In fact, Figure 7 shows that our baseline measure of healthcare capacity constraints is positively correlated to the contemporaneous measure (Panel b), but crucially not correlated to contemporaneous pollution (Panel a). *Second*, we use only hospitalizations that happen in public hospitals or that are reimbursed by the universal health care system; hence, this is not a system that aims for profit maximization like most hospitals in the United States.

Third, our analysis is focused on the metropolitan area of Sao Paulo, where the planning and operations of the healthcare system are aimed at serving the urban center as a whole, not a particular district. Incidentally, a study carried out by the Public Archive of the State of Sao Paulo has revealed that the historical build-up of hospitals in the metropolitan area over time was related to a variety of reasons likely unrelated to air pollution – e.g., religious philanthropy, medical schools, historical immigration, and epidemics.[26] *Fourth*, our analysis is

[25]Notice that Panel (b) of Figure 5 reflects the pattern of past occupancy rates, which appears to be correlated to the contemporaneous measures presented in Panel (a). It helps to justify our measure of capacity constraints.

[26]See study here: www.arquivoestado.sp.gov.br/exposicao_saude_publica_sp/linha_tempo#1947titulo.

focused on children, which are served by a well-defined and segmented part of the healthcare system. Pediatric wards provide *multidisciplinary* pediatric care, different from departments serving adult populations which may specialize in certain areas according to the characteristics of the local population (Casimir, 2019).

Lastly, we add interactions of socio-economic variables – monthly average district income and rural share above the median – with the pollution shock in our main analysis as a robustness check. Reassuringly, this turns out not changing the broad patterns of our main findings, suggesting that although our measure of healthcare capacity constraints is not experimental, what we might be capturing are *causal* moderators rather than *effect* moderators.[27]

5 Results

In this section, we present the main estimates of how the health care system in SPMA responds to transitory air pollution shocks, and how this response differs depending on system capacity. We report impacts on hospitalizations for respiratory illnesses and for conditions seemingly unrelated to pollution, separately.

We use data on virtually every district of the SPMA (157 districts), observed daily over the period 2015-2017. All regressions are weighted by district population aged 1 to 5, and all estimated coefficients are reported along with standard errors two-way clustered at the district and calendar date levels.

5.1 Responses of the healthcare system to pollution shocks

We use an instrumental variable approach based on wind speed to estimate causal effects of air pollution on pediatric hospitalizations depending on system capacity. Recall that the *ex-ante* indicator of daily "district-level occupancy rates" of pediatric beds a week before admission is our plausibly exogenous measure of hospital capacity constraints. This is the *implicit* daily hospital occupancy rate that residents from a particular district are exposed to according to the patterns of origin-destination of residents to hospitals inferred at baseline.

Table 2 reports first-stage results. First stage regressions examine whether wind speed is correlated with PM10, holding other variables constant. In Columns (1) and (2), PM10 and PM10 interacted with our measure of capacity constraint, respectively, are regressed on the four instrumental variables – contemporaneous and lagged wind speed and the interaction

[27] This is not surprising in light of Appendix Figure A5, which displays the temporal variation in our measure of hospital capacity constraints and revels nontrivial idiosyncratic variation.

between them and our measure of capacity constraint – as well as fixed effects and the other control variables described in the empirical strategy section.

As expected, the estimated coefficients of wind speed on the same day and the day before are both negative and statistically significant. Because wind disperses pollution, the stronger the wind blows, the more particulate matter is taken away, and the cleaner the air. Not surprisingly, however, wind speed on the day before admission has a lower impact on the contemporaneous levels of air pollution when compared to its impact on the same day. Notice that this pattern is the same in both columns – the instruments with the interaction explain variation in levels of PM, and the interacted instruments explain variation in the interaction of PM and our measure of capacity constraint. The F-statistic of the joint significance of instruments is 66.66 in Column (1) and 46.69 in Column (2), indicating relatively strong instruments.[28]

Our main results indicate that an increase in PM10 levels creates a non-trivial demand shock in Sao Paulo. In Table 3, the coefficient on PM_t measures the effect of pollution on districts with corresponding baseline hospital capacity below 85% and the coefficient on $PM_t * 1[occup_{t-7} > 0.85]$ measures the differential effect between districts with corresponding baseline capacity above and below the 85% threshold. Because each unit of PM10 represents $10\mu g/m^3$, all marginal effects should be interpreted as arising from a variation of $10\mu g/m^3$ in PM10 levels. The Kleibergen-Paap rk Wald F-statistics of the joint significance of all four instruments is 67.06, again indicating relatively strong instruments.

Panel A shows that when PM10 levels increase by $10\mu g/m^3$, there is an increase of 2.51 hospitalizations for respiratory illnesses per million children aged 1 to 5 in relatively unconstrained settings. The estimated effect represents a 5.6% increase relative to the mean. This would represent an increase in demand along the upward-sloping portion of the supply curve in Panel (a) of Figure 4. This finding is driven by acute respiratory infections such as pneumonia and chronic respiratory diseases such as asthma. On the other hand, we cannot rule out a net zero impact in capacity-constrained settings. The net effect is the sum of the estimated coefficients on PM and its interaction with baseline hospital constraint. The estimated negative interaction effect for capacity-constrained hospitals indicates that demand may have reached the inelastic portion of the supply curve in Panel (a) of Figure 4, potentially leading to patient displacement. In other words, constrained hospitals are unable to admit more patients during pollution episodes.[29]

[28]In the robustness checks, we also include wind direction variables as instruments. Results are discussed later, but estimates based only on wind speed instruments are robust to the inclusion of wind direction variables.

[29]Interestingly, Appendix Figure A6 reveals that this pattern of results can be seen even descriptively. The figure plots the relationship between district-level occupancy rate and admission rates for respiratory illnesses

The increased demand due to respiratory illnesses also displaces admissions for illnesses seemingly unrelated to air pollution, but only in hospitals closer to full capacity. Panel B reports a drop of 3.61 hospital admissions for all non-respiratory illnesses per million children aged 1 to 5, which represents a nontrivial 5.1% reduction from the mean. Intuitively, when hospitals get close to full capacity, possibly due to a surge in hospitalizations for respiratory illnesses, the supply curve in Panel (b) of Figure 4 shifts leftward, and there is displacement of treatment for other illnesses seemingly unrelated to pollution. That is why the estimated coefficient of the interaction between pollution and our measure of capacity constraints is negative. This result is mainly due to genitourinary and skin and connective-related conditions.[30] Reassuringly, we do not find any direct effect of PM on admission for illnesses seemingly unrelated to air pollution in districts served by relatively unconstrained hospitals as we do not expect a crowd-out when the constraints are not binding.

We also examine the responses to pollution shocks of different magnitudes. As shown in Figure 8, the impacts of air pollution on pediatric hospitalizations for respiratory illnesses and the displacement of treatment for non-respiratory conditions happen for levels of PM10 far below the 24-hour air quality guideline level recommended by the World Health Organization (WHO), which is $45 \mu g/m^3$. The effects start to increase at about $40 \mu g/m^3$, and at $50 \mu g/m^3$ they become roughly double the effects estimated with the $25 \mu g/m^3$ threshold. To put these findings into perspective, during the 2023 Canadian wildfires affecting air quality in the U.S. Midwest and Northeast, PM10 levels surpassed $300 \mu g/m^3$. In fact, climate change is poised to increase not only the frequency of heatwaves but also pollution shocks due to wildfires and increased formation of local pollutants (Jacob and Winner, 2009; Bento et al., 2023).[31]

To meet the increased demand caused by poor air quality, strained hospitals reduce hospitalizations not only for elective non-respiratory conditions, but also for emergent respiratory illnesses, as indicated by Table 4. Using the classification of hospitalizations as emergent or elective, reported by the hospitals themselves to the Brazilian Ministry of Health, we estimate the PM effects on emergent and elective admissions due to all respiratory and all non-respiratory illnesses. In the table, each column reports coefficients from a different regression, depending on the level of emergency and type of disease.

and for illnesses seemingly unrelated to air pollution. That relationship is positive up to the occupancy rate of 85%, which represents the maximum hospital utilization that would not adversely affect health outcomes, as recommended by the Brazilian authorities. After that threshold, the relationship turns negative, indicating supply-side constraints.

[30] Appendix Table A3 shows results disaggregated by ICD-10 for illnesses seemingly unrelated to air pollution.

[31] Regarding hospital utilization, we have shown in the next subsection (Appendix Tables A10 and A11) that the displacement effects appear even for occupancy rates starting at 80%.

While unconstrained hospitals admit more patients for emergent respiratory conditions during pollution episodes, capacity-constrained hospitals displace even these emergent cases. In fact, we cannot rule out a zero effect on constrained settings. That is, we cannot rule out that the sum of the PM coefficient and the coefficient on the interaction between PM and lagged high occupancy rates is zero. In addition, when PM10 levels increase by $10\mu g/m^3$, constrained hospitals decrease 3.15 admissions for elective non-respiratory conditions per million children aged 1 to 5, a 9.5% reduction from the mean. These results indicate that hospitals cope with strained capacity by rescheduling elective care among non-respiratory illnesses on more polluted days. If we were to consider the returns to hospitalizations vis-à-vis the costs, the displacement of elective procedures suggests that the avoided hospitalizations for non-respiratory conditions among the hospitals close to full capacity might be marginal ones.

To sum up, the health shocks triggered by highly-polluted days in the Sao Paulo Metropolitan Area seem to considerably affect the operations of the healthcare system. While healthcare infrastructure is relatively fixed in the short run, air pollution drives demand up due to hospitalizations for respiratory illnesses. Hospitals appear to absorb some of the excess demand induced by air pollution, but admissions for emergent respiratory illnesses and other illnesses, especially elective, may be rescheduled or transferred to less strained hospitals (approximately 9.5% of emergent respiratory admissions, and 9.5% of elective non-respiratory admissions).[32]

We then investigate whether pollution shocks, when combined with hospital capacity constraints, contribute to the deterioration of health outcomes. We leverage novel individual-level data linked across multiple hospitalizations, and examine the impact of pollution and capacity constraints on three key measures of healthcare complications commonly used in the United States: mortality and readmission within thirty days, and admission to the intensive care unit (ICU) (Doyle et al., 2019). We explore the effects on the mean and at different points of the outcome distribution.[33] For the distributional analysis, we employ unconditional quantile regression methods proposed by Firpo et al. (2009) to assess how pollution and hospital capacity constraints affect different parts of the distribution of each outcome variable. As pointed out by Bitler et al. (2006), effects on the mean might hide important heterogeneity across different points of the distribution.

Firpo et al. (2009) show that the average derivative of a regression of the recentered influence function (RIF) of an outcome variable concerning an explanatory variable corresponds to the marginal effect of a small location shift in the distribution of the covariate on the un-

[32]This is related to the situation during the coronavirus pandemic, as discussed anecdotally by the New York Times: www.nytimes.com/2020/04/20/health/treatment-delays-coronavirus.html.

[33]See Appendix Tables A4 and A5 for first and second stage results on the mean. The IV estimates are noisy.

conditional quantile of the outcome variable, holding other factors constant. In our setting, the coefficients for each RIF-quantile can be interpreted as the effect of PM and the interaction between PM and hospital capacity constraints on the q^{th} quantile of the unconditional distribution of the outcome. We generate 10 RIF statistics, each corresponding to one of the deciles, ranging from the tenth to the ninetieth percentiles of each outcome's distribution. We then replace the dependent variable in our main estimating equation with one of these RIF-quantile statistics.

Figure 9 displays the results. Each panel presents 10 distinct regression estimates for every coefficient of interest, with the dependent variable replaced by the RIF counterpart for each decile of the outcome variable. The figure provides a visual summary of the effect of PM and the interaction of PM and the indicator for high occupancy rates on different quantiles of the unconditional distribution of each outcome. Given that each observation represents a hospitalization and each outcome is binary, conditional on the hospitalization, we first run a probit model for each outcome to obtain estimated probability of ICU admission, mortality, and readmission. The probit estimation includes covariates such as gender, racial group dummies, broad ICD-10 categories dummies, and an emergency hospitalization dummy.

The evidence from the left panels in Figure 9 suggests that health outcomes related to respiratory conditions deteriorate relatively more in the upper part of the distribution of the probability of ICU admission, as well as in the probability of mortality and readmission within 30 days.[34] The estimates indicate that the largest differential effects of PM under high occupancy rates occur above the median of each outcome's distribution, particularly for the probability of ICU admission. The higher probability of ICU admission above the median might reflect poor care as a result of strained capacity. On the other hand, the lower probability of ICU admission below the median might indicate displacement of those patients with less urgent needs. In any case, we cannot rule out nontrivial impacts of pollution shocks under hospital capacity constraints on adverse health outcomes.

In the right panels of the figure, despite the clear pattern indicating the displacement of ICU beds for non-respiratory illnesses, there appears to be no corresponding relative increase in the probability of mortality within 30 days in the upper part of the distribution. Recall that our estimates in Table 4 suggest displacement of elective care for non-respiratory conditions in response to PM shocks under high occupancy rates. Thus, healthcare professionals specialized in the treatment of these illnesses such as pediatric surgeons, pediatric urologists, pediatric

[34] Imbens (2021) emphasizes that when "decision makers are faced with deciding whether to implement a new policy or not, confidence intervals are a more useful way of communicating uncertainty..." (p.159).

cardiologists, among other specialists, might have fewer patients to attend to, which could explain the differentially lower effects on mortality at the top of the distribution. The reduced mortality among more medically vulnerable infants might alter the composition of surviving infants, potentially leading to a relative increase in the probability of readmission within 30 days among the upper deciles of the distribution.[35]

In conclusion, with regard to the potential health consequences of hospital capacity constraints, our analysis reveals that we need to consider effects across different parts of the distribution of health outcomes. Because the evidence suggests a relative deterioration of health outcomes related to respiratory conditions in the upper part of the distribution of those outcomes, we cannot rule out nontrivial impacts of pollution shocks under hospital capacity constraints. While the healthcare system appears to accommodate the increased demand caused by pollution, operating the system under pressure seems detrimental to public health.

5.2 Robustness Checks

Threats to the exclusion restriction: We conduct bounding exercises for minor exclusion restriction violations, such as wind speed's potential effects on economic behavior and health outcomes through other channels than pollution. Appendix Table A6 shows the results for respiratory illnesses using the methodologies developed by Conley et al. (2012) – instruments are only plausibly exogenous (Panel B) – and Nevo and Rosen (2012) – imperfect instruments (Panel C). Comparing to the baseline specification in Panel A for PM_t (Column 1) and $PM_t * 1[occup_{t-7} > 0.85]$ (Column 2), we find that the main results are robust to such potentially negligible violations. In fact, the intervals created by the Conley et al. bounds contain our main estimates, and the Nevo and Rosen bounds are within the 95% confidence interval of our main estimates.

Geographical spillovers: We examine the impact of air pollution on healthcare services not only in directly exposed districts but also in neighboring areas. The districts that experience pollution shocks face increased strain on their hospital capacity due to higher patient demand for healthcare services for respiratory illnesses. Consequently, the services for illnesses seemingly unrelated to pollution may be negatively affected. The neighboring districts, while not directly exposed, might also experience increased strain and decreased care services due to the outflow of patients from exposed districts. Although we find suggestive evidence of

[35]It is noteworthy that this distributional analysis is only feasible with individual-level data. Our main hospitalization analysis relies on time-varying district-level hospitalization rates to estimate the effects of interest.

neighboring spillover effects, Appendix Table A7 shows that they do not appear to be of first-order importance. The table reports estimates from a specification adding a triple interaction on district PM, district high occupancy rate, and neighboring low occupancy rates. Neighboring low occupancy is defined as an indicator for at least 75% of the neighboring districts having an occupancy rate below 0.85. Our goal is to consider a situation where most of the neighboring districts have available capacity, which would be conducive to finding spillover effects. If there is displacement of hospitalizations to neighboring districts, then the coefficient of the triple interaction will be positive. While all but one of these coefficients are positive, only the one for hospitalizations for skin and connective illnesses is statistically significant. The point estimate is, however, less than half of the negative coefficient of the double interaction between district PM and district high occupancy rate. Taken altogether, the evidence seems to support the Stable Unit Treatment Values Assumption (SUTVA) in our setting.

Alternative specifications: Our main specification controls for humidity due to its high correlation to precipitation and its more direct relationship with health. To address the concern that humidity may not capture all factors related to precipitation, Appendix Table A8, Panel A, adds precipitation as a control as well (Column 1), and the results are robust to its inclusion. Column (2) of the same panel also includes month-by-year fixed effects instead of year and month fixed effects separately, as in our main specification. Column (3) replaces year, month, and day-of-week fixed effects, as in our main specification, with day of admission fixed effects. We do not observe significant changes in the pattern of our estimates in these last two columns, but they are noisier. Because these less parsimonious specifications explain too much of our identifying variation, we prefer our baseline specification.

Alternative instruments: As mentioned earlier, we also carry out a robustness check leveraging plausibly exogenous variation from sudden changes in wind direction. Following Deryugina et al. (2019), we add three quadrants of wind direction as instruments in the first stage. Appendix Table A8, Panel B, shows that our second stage results are robust to this less parsimonious specification. The Kleibergen-Paap rk Wald F-statistic of the joint significance of instruments is reduced from 67.06, as in our main specification in Table 3, to 35.56 (Column 4, Panel B) when we include the wind direction quadrants. The same joint statistic is reduced to 9.96 when wind direction quadrants are the only instruments (Column 5, Panel B). Column (6) adds interactions of wind direction quadrants with four quadrants of the metropolitan area. The Kleibergen-Paap rk Wald F-statistic is still much smaller than in our main specification. These results indicate that wind speed is a stronger instrument in our setting; therefore, we use only wind speed in our primary specification. Indeed, because the main source of air pollution in the metropolitan area of Sao Paulo is non-stationary (vehicle emissions) and ubiquitous across the area, the direction should be less important than the speed that the wind blows. Emissions only get dispersed when the wind blows strongly locally.

Alternative lags of occupancy rate: Appendix Table A9 reports estimates from similar specifications as in Panel A of Table 3 but considering different lags for high occupancy rate. In our main analysis, occupancy rate is lagged by a week. In Appendix Table A9, we replace it with the contemporaneous measure of occupancy rate (Panel A), as well as lags 6 to 8 (Panels B to D). All capacity measures used in this table are strongly correlated, indicating that they are intrinsically related to each other but not perfectly correlated.[36] The results are qualitatively the same among different timing of occupancy rates for respiratory illnesses.

Alternative definitions of strained hospitals: Appendix Tables A10 and A11 report estimates from similar specifications as in Table 3, but considering a threshold for high occupancy rate of 80% (Panel A), 85% (Panel B), and 90% (Panel C) for respiratory and other illnesses, respectively. Recall that in our main analysis, we consider high occupancy rate as above 85%, following the guidelines of the Brazilian Health Authority. The higher the occupancy rate, the greater the potential for rescheduling, cancellations, and/or transfers of hospital admissions for respiratory and other illnesses from strained hospitals to less crowded ones. The results are even larger for illnesses seemingly unrelated to air pollution (Appendix Table A11).

Inclusion of socio-economic interactions: Appendix Table A12 adds interactions of socio-economic variables – indicator variables of average district income and rural share from the 2010 Census above the median – with the pollution shock in our main analysis. The idea is to distinguish between causal moderators, where the interaction term can be interpreted as causally capturing health care capacity constraints, and effect moderators, where the interaction term captures capacity constraints and any other factors that could be correlated with the healthcare system that also moderate the pollution-hospitalization relationship. Reassuringly, our main findings are robust to the inclusion of those additional interactions, suggesting that the interaction effect we estimate between PM and capacity constraints might be reasonably thought of as a causal moderator.

Air pollution dissipation: We also examine the lagged effect of air pollution on pediatric hospital admissions. For simplicity, we add six lags of PM10 in a more parsimonious second

[36]Figure 7 shows that our baseline measure of healthcare capacity constraints is positively correlated to the contemporaneous measure (Panel b). Moreover, Appendix Figure A5 plots the variation in our lagged measure of hospital capacity constraints. As we can see, the temporal variation is nontrivial and might even be the main force behind our estimates.

stage equation without interactions with capacity constraints.[37] The results reported in Appendix Table A13 may reflect an interesting pattern of biological and/or behavioral responses, which we are unable to disentangle: some pathologies might take time to manifest and parents might react with delay. One may assume that the exact day of admission vary with parental concerns about a child's health. Parents may take a child to the hospital as soon as the first symptoms appear or delay it for a few days – no more than 5, if we take our estimates at face value – if they believe it would not be a serious problem. Importantly, the evidence shows that lagged PM effects by and large do not change the magnitude of the contemporaneous effect. Furthermore, the significant effects only up to five days suggest that our baseline measure of capacity constraint – occupancy rate of the week before hospital admission – should not be related to our estimated pollution effects.

5.3 Heterogeneity Analysis

Other age groups: We investigate the effects of PM on hospitalization for respiratory illnesses for other age groups (Appendix Table A14). For children younger than one year (Panel A), although the broad pattern of results is similar to our main findings for children from 1 to 5 years old (Panel B), the estimates are larger and noisier. Infants are known to be more sensitive to pollution, but there are many competing health risks among newborns. For children from 6 to 14 years old (Panel C), the estimates are also imprecisely estimated but smaller in magnitudes. A complication in the estimation for this group is the extra noise in the measures of pollution exposure – part at or around home, part in the school. We have also examined the effects of pollution and capacity constraints on hospitalization among the elderly, another group vulnerable to pollution. Because Deryugina et al. (2019) show that the health effects are larger for the oldest individuals, we focus on outcomes for people 75+ years old. Building on Deryugina et al. (2019), we look at 3-day hospitalization rates. This aggregation accounts for short-term displacements: if a hospitalization happens one to two days earlier due to higher pollution exposure, it does not impact the 3-day measurement.[38] As reported in Appendix Table A15, we find that elderly hospitalization increased with pollution due to cancer, injury and external causes, and for other illnesses. These effects are concentrated among hospitals with capacity relatively unconstrained. The estimates for cancer are consistent with Deryugina et al. (2019), who also find higher pollution-driven cancer mortality among the elderly. The estimates for

[37]The first stage now includes contemporaneous wind speed (WS_t), as well as seven lags: WS_{t-1}, ..., WS_{t-7}.

[38]In Appendix Table A16 we show that the pattern of results for pediatric hospitalization remains the same with 3-day hospitalization rates.

injury and external causes are consistent with evidence from Bedi et al. (2021), Carneiro et al. (2021), La Nauze and Severnini (2021) and Bishop et al. (2023) on the impacts of exposure to particle pollution on adult cognition, and from Sager (2019) on the effects of increased air pollution on the number of road traffic accidents. The results for all other illnesses are consistent with short-term exposure to pollution leading to health deterioration in elderly individuals who are already medically vulnerable.

Public versus philanthropic hospitals: We also run our primary specifications separately for public and publicly-reimbursed philanthropic hospitals.[39] Results are reported in Appendix Table A17 for respiratory illnesses. Panel A shows the estimates considering only admissions to public hospitals, while Panel B reports the same estimates for philanthropic hospitals. Our findings are driven by the response of public hospitals. In other words, public hospitals may be dealing with all of the additional demand due to air pollution for emergent conditions. It is important to acknowledge that although increasingly strained, public health services in Sao Paulo are still a reference for the whole country. For completeness, approximately 62% of all pediatric hospital beds in the SPMA are publicly funded. About 54% of all pediatric beds are in public hospitals, but about 21% of pediatric beds in private/philanthropic hospitals are also publicly funded (Ministério da Saúde, 2015).

6 Concluding Remarks

Developing countries are known to have lower levels of healthcare infrastructure and higher levels of air pollution than the developed world. On top of many other demands for healthcare services, pollution may create additional nontrivial transitory health shocks because it usually affects the health of vulnerable population groups, such as children, in the short term. Using rich daily pediatric hospitalization data for Sao Paulo, we find that pollution creates transitory health shocks that generate excess hospital demand. Hospitals linked to the areas hit by the pollution shocks seem to have absorbed most of the increased demand, except those that were capacity-constrained in the baseline. In the latter case, they were not able to accommodate additional admissions even for emergent respiratory conditions. Hospitals that were capacity-constrained in the baseline turned away patients with illnesses seemingly unrelated to pollution for elective procedures, suggesting that they shifted attention to sicker

[39] The public healthcare system owns hospitals but also uses hospital beds in philanthropic health centers. The government only pays for those beds if they are used. A private hospital must allocate at least 60% of its beds for public use to be considered philanthropic and obtain exemptions from federal taxes. For completeness, public and private hospitals/health centers were classified according to National Classification Commission – CONCLA.

patients. More importantly, health outcomes appear to have deteriorated in the metropolitan area. We find suggestive evidence that hospital readmissions, admissions to ICU, and mortality increased. Although the healthcare system seems to have accommodated some of the increased demand caused by pollution, operating the system under pressure turned out to be detrimental to public health.

Regarding policy implications, because our estimates are identified from short-term pollution shocks, our findings should have more relevance for short-term planning and operations. For starters, managers of healthcare systems could use weather and pollution forecasts a few days in advance to allocate hospital beds and personnel (e.g., physicians, paramedics, and nurses) accordingly. It is also possible to preemptively reschedule non-urgent procedures to avoid crowded hospitals on those days (and reduce non-urgent patients' costs) and transfer simpler procedures to outpatient settings such as ambulatories and clinics. In addition, public health officials could alert or mandate schools to avoid outdoor activities on hot and/or polluted days, and more broadly, firms whose workers are exposed to heat and/or pollution to reschedule or reshuffle activities within the working day.

From the perspective of local environmental agencies, the weather and pollution forecasts could be leveraged to design programs aimed at providing information and changing behavior to avoid undesirable outcomes. For example, air quality and flood alerts could incentivize parents to avoid sending their children to school on those days and, more broadly, individuals to work from home and reschedule errands. In the extreme, such agencies could mandate that polluting activities be shut down temporarily or reshuffled within those days.

Naturally, coordination across local government agencies – particularly environmental and public health agencies – could improve societal outcomes. Also, a cost-benefit analysis of several potential policies – e.g., allocation of hospital beds and personnel, alerts, and mandates – could help those agencies prioritize some strategies.

Because hospitals were strained, but healthcare infrastructure in Sao Paulo is still much better than in other developing countries such as India, research in other contexts is warranted. Also, the fact that hospital capacity constraint is binding primarily for the public system has implications for the overall design and evaluation of healthcare systems worldwide.

One limitation of our analysis is that we do not observe data for out-of-pocket and insured hospitalizations. As a consequence, the wealthier portion of the population may not be represented in our findings. Despite this limitation, the impact of air pollution on the low-income population is key for policymaking.

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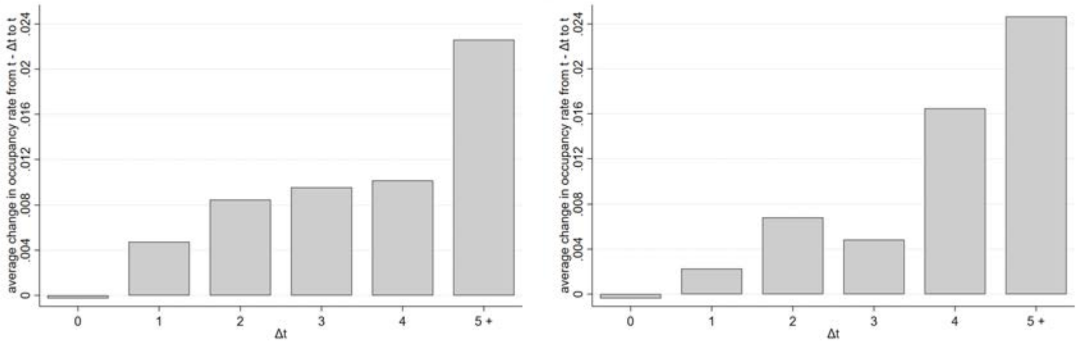
Figures

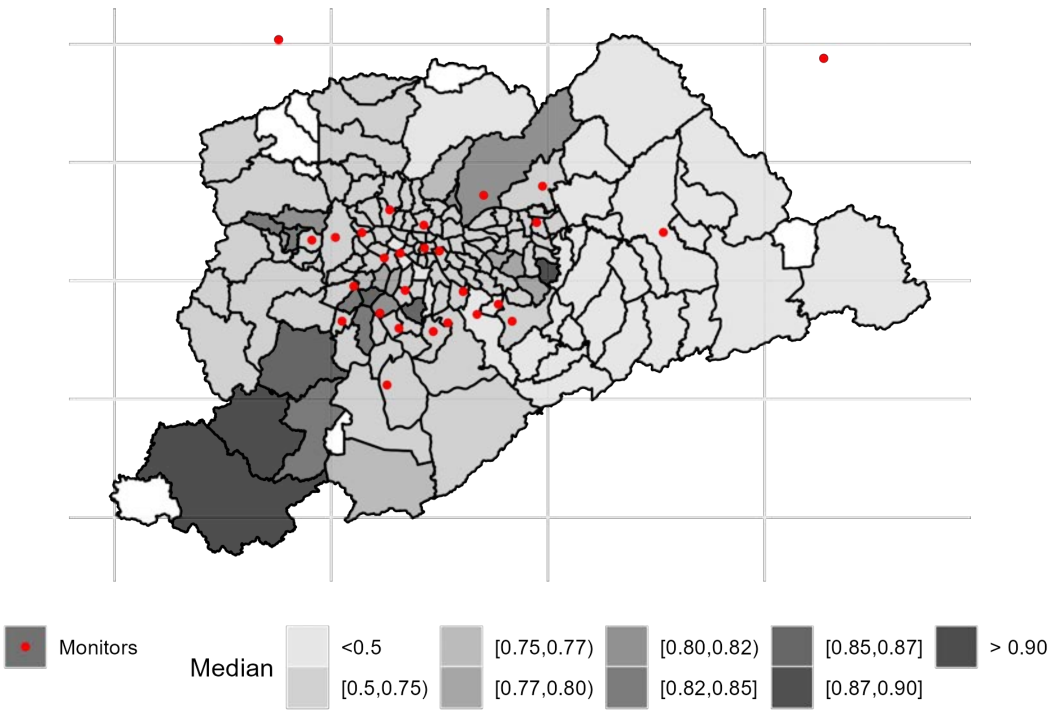
Figure 1: Change in hospitalization associated with high air pollution and heatwaves in the Sao Paulo Metropolitan Area



(a) PM10 $> 45 \mu g/m^3$ (b) Heatwaves

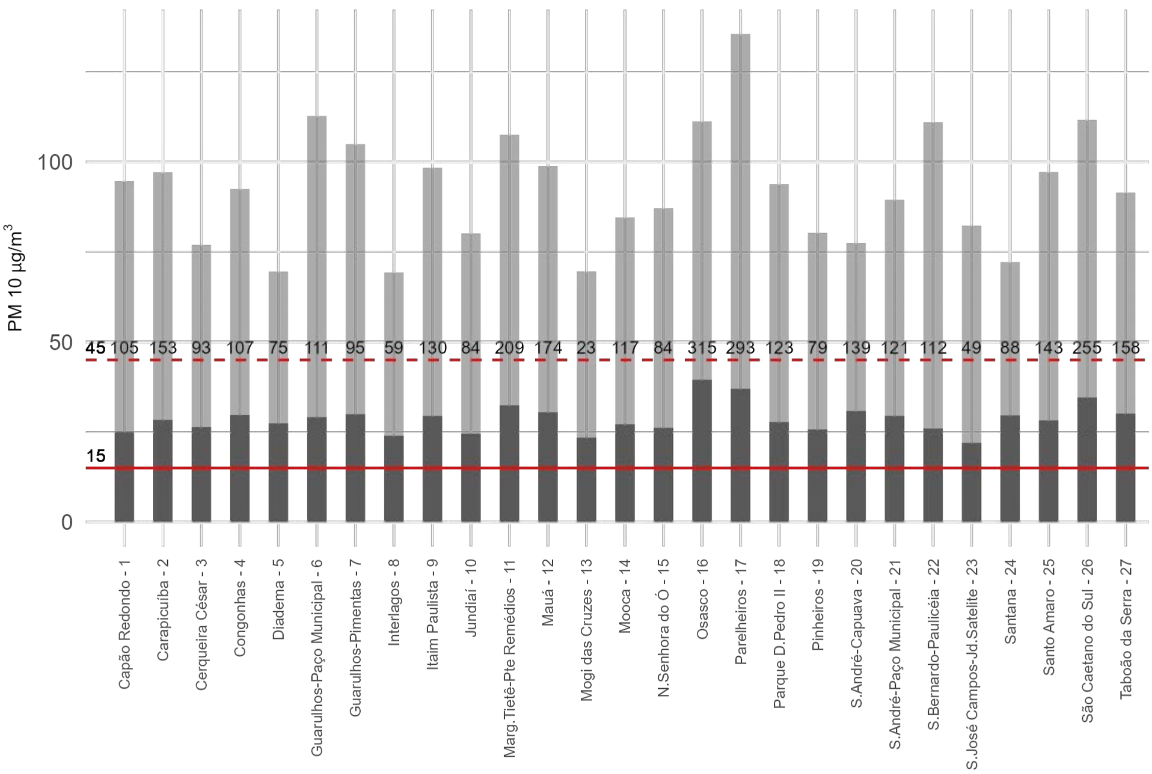
Notes: This figure shows the average change in occupancy rate from $t - \Delta t$ to t in the Sao Paulo Metropolitan Area related to pollution shocks (number of days with air pollution above the WHO guidelines) and temperature shocks (heatwaves). The hospitalization swings are all calculated relative to the previous day without the shock, which we call day zero. That is, the swings on days 1 through 5 are all relative to day zero.

Figure 2: Median occupancy rate by district in the Sao Paulo Metropolitan Area



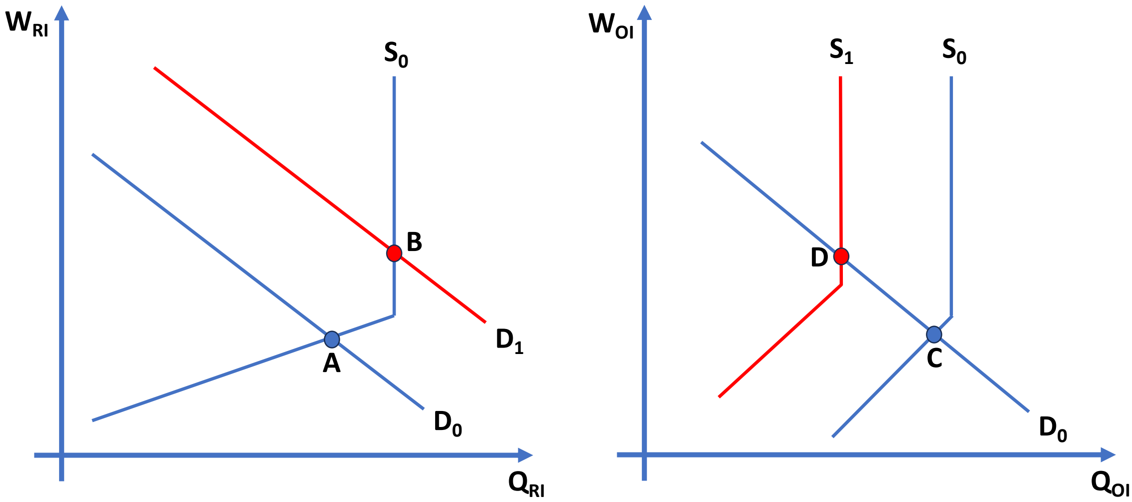
Notes: This figure displays the median occupancy rate by district of the Sao Paulo Metropolitan Area. Red dots highlight the location of pollution monitors. The occupancy rate is our *ex-ante* measure of hospital capacity constraints. It is the *implicit* daily hospital occupancy rate that residents from a particular district are exposed to according to the *de facto* hospital catchment areas we have identified in the baseline via the empirically-inferred network of hospitals and districts, and hospital utilization data.

Figure 3: Average and maximum PM10 level, and number of days above WHO guidelines



Notes: This figure displays the average PM10 concentration (dark gray) and maximum daily averages (light gray) for each pollution monitor in the Sao Paulo Metropolitan Area. The red horizontal lines indicate the values recommended by the WHO's guidelines: the dashed line represents the daily maximum for PM10 (maximum for short-term exposure), and the solid line the maximum annual average (maximum for long-term exposure). The numbers above the dashed line indicate the total number of days above the maximum recommended by the WHO by monitor from 2015-2017.

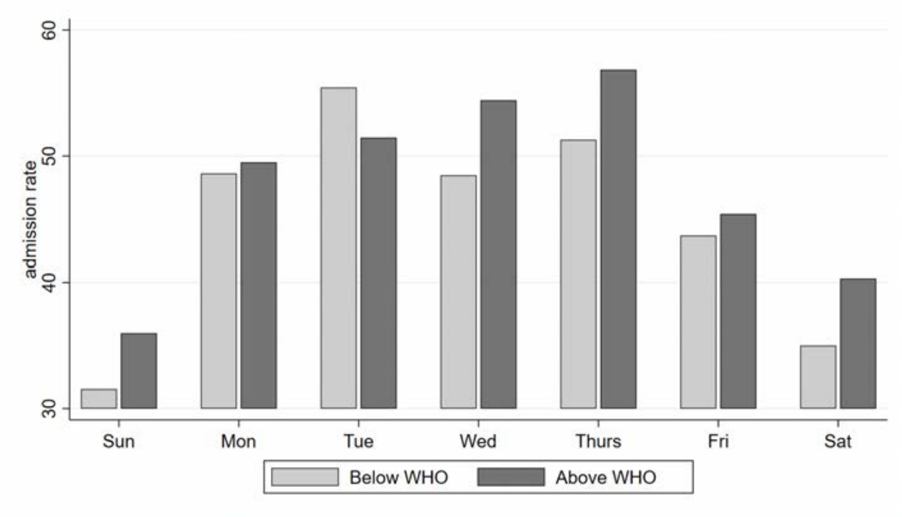
Figure 4: Impacts of Air Pollution on Healthcare Demand and Supply



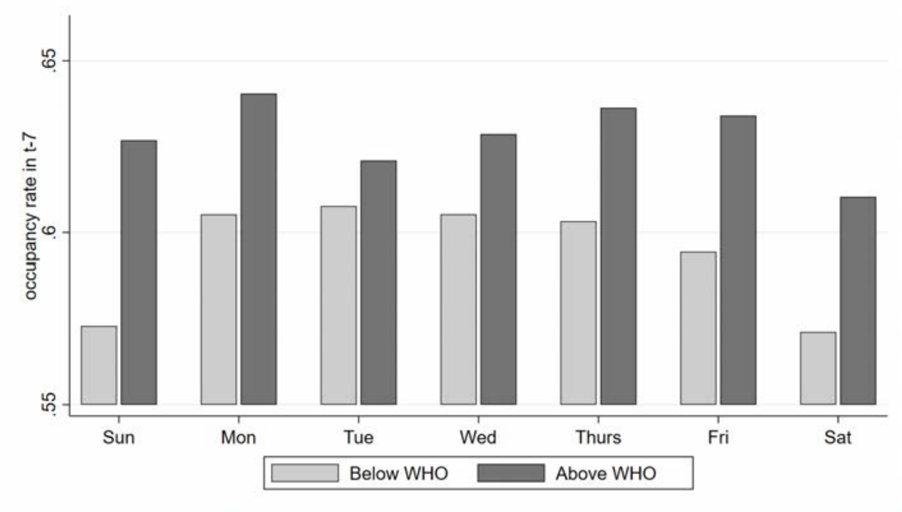
(a) Respiratory Illnesses (b) Other Illnesses

Notes: This figure illustrates the impacts of air pollution on the demand and supply of healthcare for respiratory illnesses (RI) and other illnesses (OI) seemingly unrelated to pollution. The demand curve is downward sloping, and the supply curve is upward sloping up to the point of maximum capacity when it becomes vertical. One can think of supply as a composite of hospital beds, materials, and possibly hospital personnel such as physicians and nurses: it can accommodate patients until it reaches full capacity. Notice that the y-axis has waiting times (W) as the "price." Because there is universal health coverage in Brazil, increased demand or decreased supply implies longer waiting times to receive treatment. In Panel (a), when a pollution shock hits, the demand for healthcare, associated with respiratory illnesses, shifts rightward, potentially reaching the inelastic part of the healthcare supply curve. The equilibrium goes from point A to point B. On the other hand, the increased demand for treatment for respiratory illnesses decreases the supply of resources to treat other illnesses seemingly unrelated to pollution. In Panel (b), the supply curve shifts leftward. The equilibrium goes from point C to point D, similarly reaching the inelastic part of the healthcare supply curve.

Figure 5: Patterns of hospital admissions for respiratory illnesses by day of the week and pollution levels



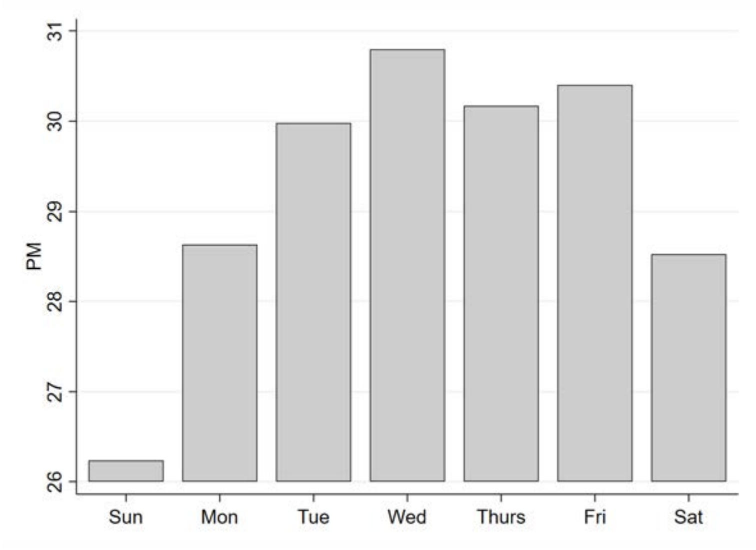
(a) Average admission rate



(b) Average occupancy rate in t-7

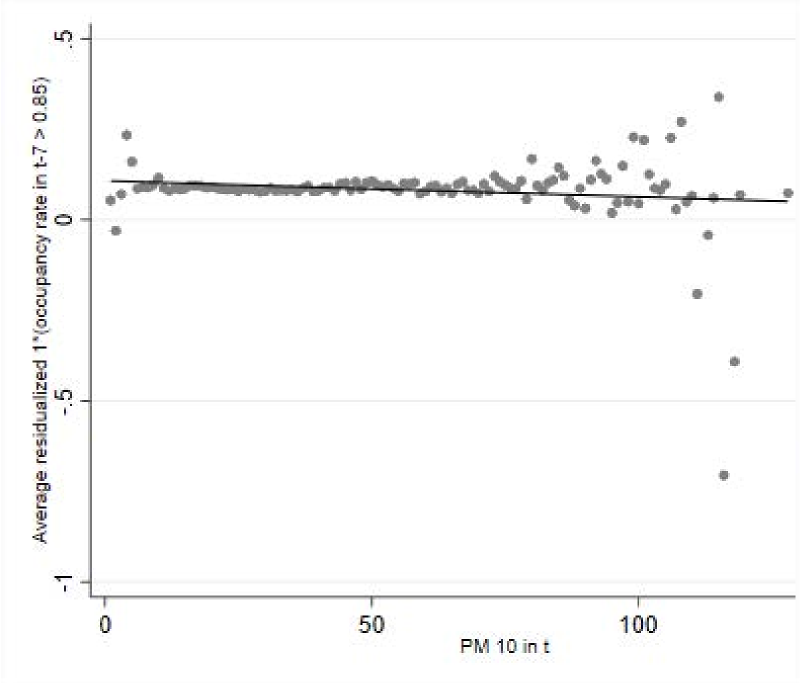
Notes: This figure displays patterns of hospital admissions by day of the week and pollution levels in the Sao Paulo Metropolitan Area. Panel (a) shows the average admission rate per one million children aged 1-5 years for respiratory illnesses by day of the week and pollution level (below or above WHO guidelines of 45 $\mu g/m^3$). Panel (b) shows the average occupancy rate by day of the week, lagged by a week, and pollution level (below or above WHO guidelines of 45 $\mu g/m^3$). The occupancy rate is our *ex-ante* measure of hospital capacity constraints. It is the *implicit* daily hospital occupancy rate that residents from a particular district are exposed to according to the *de facto* hospital catchment areas we have identified in the baseline via the empirically-inferred network of hospitals and districts, and hospital utilization data lagged by a week.

Figure 6: Average PM10 level by day of the week

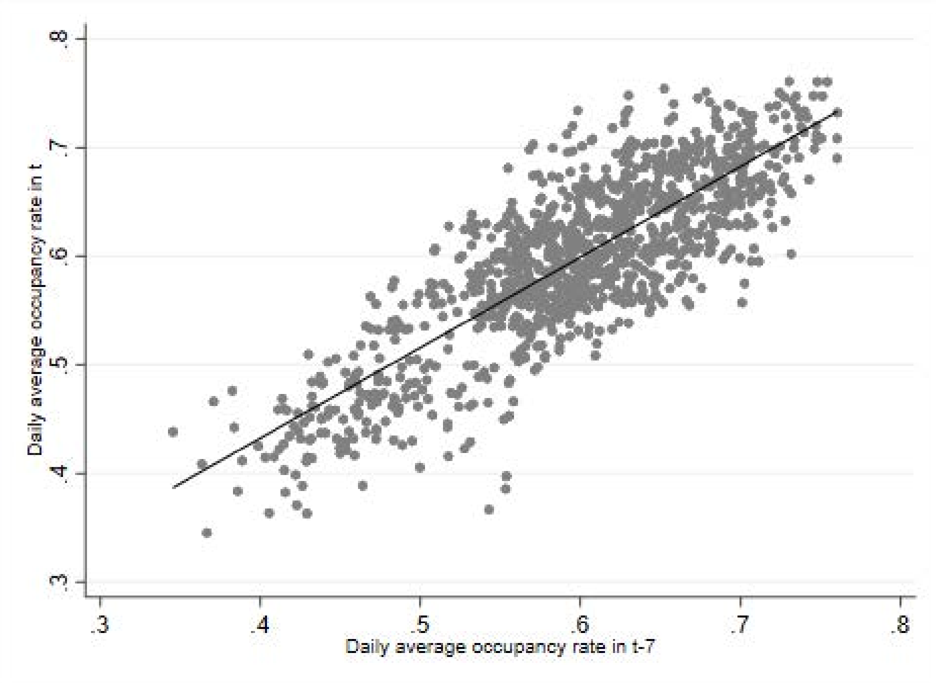


Notes: This figure shows the average PM10 level (in $\mu g/m^3$) from January 2015 to December 2017 by day of the week across the Sao Paulo Metropolitan Area.

Figure 7: Relationship between our measure of hospital capacity constraints and: (a) *contemporaneous* pollution, and (b) *contemporaneous* hospital capacity constraints



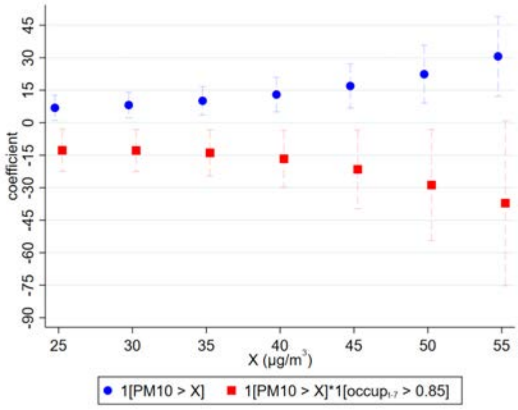
(a) $1 * (\mathrm{occup}_{t-7} > 0.85)$ versus PM_t



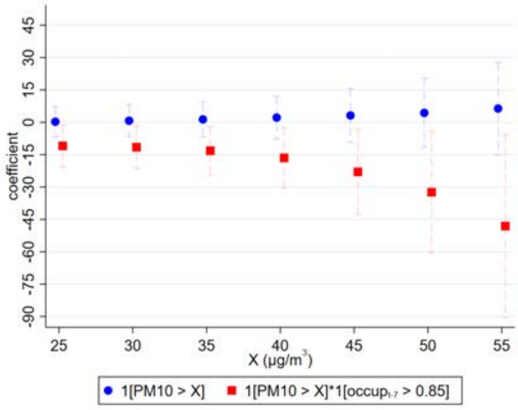
(b) Occupancy rate in t versus (t-7)

Notes: This figure displays the relationship between high occupancy rate $1[\mathrm{occup}_{t-7} > 0.85]$ and PM10 ($\mu g/m^3$), and occupancy rate in t and t-7. Panel (a) shows the average $1 * (\mathrm{occup}_{t-7} > 0.85)$ by PM10 level after controlling for fixed effects of the district, month, year, and day of the week. Panel (b) shows the scatterplot of the daily average occupancy rate in t and t-7. The occupancy rate above 85% is our *ex-ante* measure of hospital capacity constraints. It is the *implicit* daily hospital occupancy rate that residents from a particular district are exposed to according to the *de facto* hospital catchment areas we have identified in the baseline via the empirically-inferred network of hospitals and districts, and hospital utilization data lagged by a week.

Figure 8: Impacts of PM above various thresholds on children's hospitalization by occupancy rate – Respiratory illnesses and illnesses seemingly unrelated to air pollution



(a) All respiratory

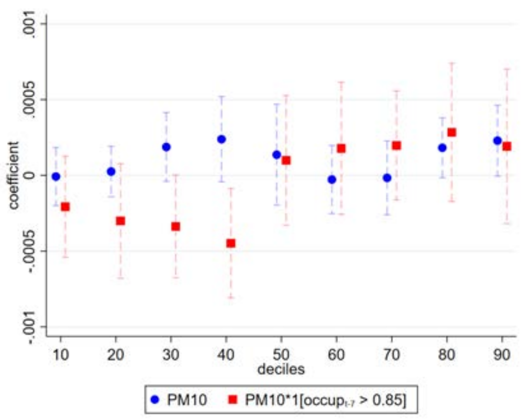


(b) All non-respiratory

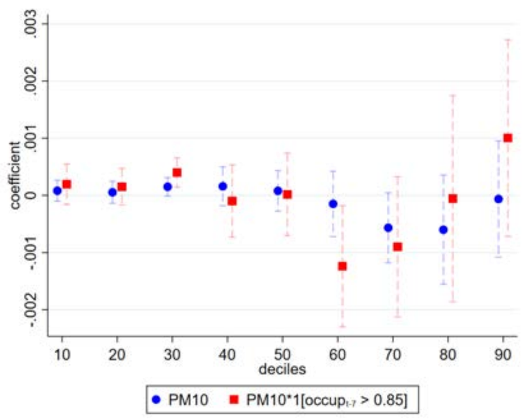
Notes: This figure displays the IV estimated impacts of PM being above various thresholds on hospitalization rates for children between 1 and 5 years old. Panel (a) shows the results for respiratory illnesses, and Panel (b) presents the results for illnesses seemingly unrelated to air pollution (non-respiratory). $\mathbb{1}[\text{occup}_{t-7} > 0.85]$ is our *ex-ante* measure of hospital capacity constraints. The 90% confidence intervals around the estimates are based on standard errors two-way clustered by district and calendar date.

Figure 9: PM impacts on children's health outcomes by occupancy rate – Respiratory illnesses and illnesses seemingly unrelated to air pollution

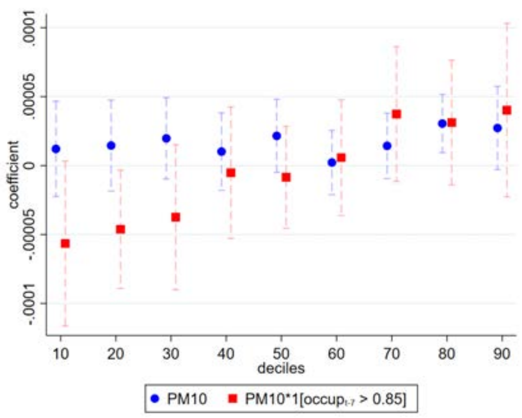
(a) ICU - Respiratory



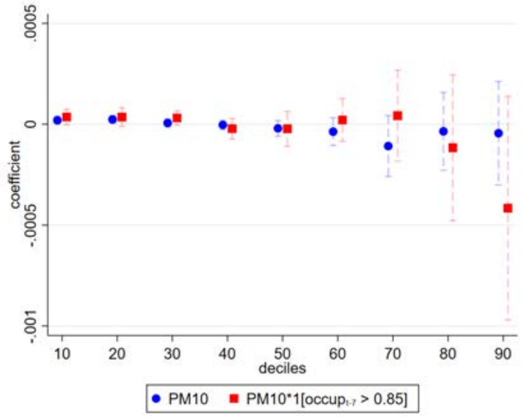
(b) ICU - Non-respiratory



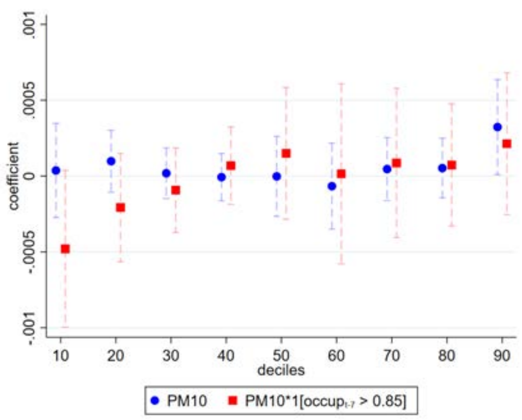
(c) Death within 30 days - Respiratory



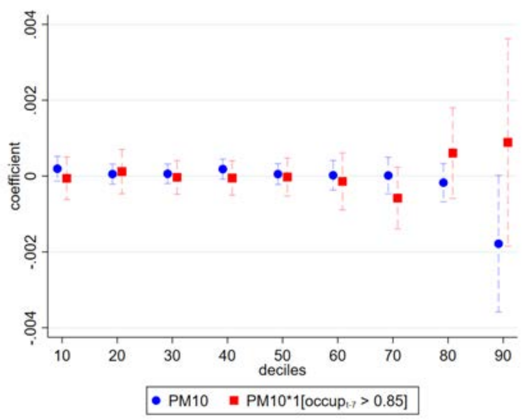
(d) Death within 30 days - Non-respiratory



(e) Readmission - Respiratory



(f) Readmission - Non-respiratory



Notes: This figure displays the IV estimated PM10 impacts on the probability of admission to the intensive care unit (ICU), and death and readmission within 30 days for children between 1 and 5 years old. The left panels show the results for respiratory illnesses, and the right panels display the results for illnesses seemingly unrelated to air pollution (non-respiratory). We plot the marginal effects for PM10 and its interaction with our measure of high hospital capacity at different points of the distribution (deciles) of each outcome variable. We use the unconditional quantile regression methods proposed by Firpo et al. (2009) to estimate these distributional effects. The 90% confidence intervals around the estimates are based on standard errors two-way clustered by district and calendar date.

Tables

Table 1: Mean admission rate and share of emergent admissions by most prevalent causes of hospitalization in Sao Paulo

	Admission rate	Share of emergent
Acute respiratory infections	**31.76**	**0.98**
Pneumonia, organism unspecified	21.10	0.99
Bacterial pneumonia, not elsewhere classified	3.68	0.99
Acute bronchiolitis	3.67	0.98
Acute upper respiratory infections of multiple and unspecified sites	0.90	0.88
Acute tonsillitis	0.76	0.99
Chronic lower respiratory diseases	**7.11**	**0.96**
Asthma	5.66	0.96
Bronchitis, not specified as acute or chronic	0.72	0.97
Status asthmaticus	0.30	0.94
Unspecified chronic bronchitis	0.23	0.96
Other chronic obstructive pulmonary disease	0.09	0.88
Other respiratory	**6.08**	**0.24**
Chronic diseases of tonsils and adenoids	4.55	0.05
Respiratory failure, not elsewhere classified	0.68	0.88
Other respiratory disorders	0.17	0.81
Peritonsillar abscess	0.13	0.96
Postprocedural respiratory disorders, not elsewhere classified	0.10	0.35
Genitourinary	**13.70**	**0.28**
Redundant prepuce, phimosis and paraphimosis	9.11	0.05
Other disorders of urinary system	2.40	0.96
Hydrocele and spermatocele	0.49	0.07
Nephrotic syndrome	0.44	0.76
Obstructive and reflux uropathy	0.12	0.40
Skin and connective	**6.03**	**0.79**
Cellulitis	2.19	0.98
Other disorders of skin and subcutaneous tissue, not elsewhere classified	0.79	0.32
Urticaria	0.60	0.99
Cutaneous abscess, furuncle and carbuncle	0.49	0.95
Follicular cysts of skin and subcutaneous tissue	0.25	0.09
Other non-respiratory	**50.45**	**0.56**
Umbilical hernia	5.73	0.07
Other gastroenteritis and colitis of infectious and unspecified origin	3.49	0.98
Inguinal hernia	2.84	0.10
Epilepsy	2.11	0.88
Undescended testicle	1.60	0.07

Notes: This table shows the five most common causes of hospitalization within each of our main categories of analysis. Causes of hospitalization are classified based on the three-digit ICD-10. “Admission rate” has the average admission rate per 1 million children between 1 and 5 years across districts in Sao Paulo Metropolitan Area in days along 2015-2017, and “% Share of Emergent” denotes the share of admissions among children aged 1 to 5 years with illness classified as emergent by health care professionals in Sao Paulo Metropolitan Area over the period 2015-2017.

Table 2: Impacts of wind speed and its interaction with high occupancy rate on PM 10 - First stage

	PM_t (1)	$PM_t * 1[occup_{t-7} > 0.85]$ (2)
ws_t	-0.70^{***}	0.01
	(0.051)	(0.008)
ws_{t-1}	-0.20^{***}	0.00
	(0.049)	(0.008)
$ws_t * 1[occup_{t-7} > 0.85]$	-0.04	-0.85^{***}
	(0.045)	(0.097)
$ws_{t-1} * 1[occup_{t-7} > 0.85]$	-0.04	-0.29^{***}
	(0.045)	(0.099)
Dep. var. mean	2.95	0.27
F-statistic	66.66	46.69
Number of districts	157	157
Number of days	1088	1088
Observations	170078	170078

Notes: This table reports the first stage of our main results. Each column represents the first stage results for one of the endogenous variables, PM_t and $PM_t * 1[occup_{t-7} > 0.85]$, respectively. $1[occup_{t-7} > 0.85]$ is our *ex-ante* measure of hospital capacity constraints. The units of analysis are districts of the Sao Paulo Metropolitan Area, observed daily over the period 2015-2017. We include district, day-of-week, month-of-year, and year fixed effects. We also add temperature and humidity in quadratic form as controls. Standard errors in parentheses are two-way clustered by district and calendar date. *** p<0.01, ** p<0.05, * p<0.1.

Table 3: PM impacts on children's hospitalization by occupancy rate – Respiratory illnesses and illnesses seemingly unrelated to air pollution

Panel A: Respiratory illnesses	All respiratory	Acute respiratory infections	Chronic lower respiratory diseases	Others respiratory
	(1)	(2)	(3)	(4)
PM_t	2.51**	2.04**	0.57*	−0.10
	(1.010)	(0.815)	(0.320)	(0.260)
$PM_t * 1[occup_{t-7} > 0.85]$	−3.88**	−3.91**	0.11	−0.07
	(1.813)	(1.681)	(0.634)	(0.529)
Dep. var. mean	44.95	31.76	7.11	6.08
Panel B: Illnesses seemingly unrelated to air pollution	All non-respiratory	Genitourinary	Skin and connective	Others non-respiratory
	(5)	(6)	(7)	(8)
PM_t	0.30	−0.05	0.17	0.18
	(1.280)	(0.454)	(0.223)	(0.948)
$PM_t * 1[occup_{t-7} > 0.85]$	−3.61*	−1.87***	−0.88**	−0.87
	(1.860)	(0.705)	(0.425)	(1.645)
Dep. var. mean	70.17	13.70	6.03	50.45
Kleibergen-Paap rk Wald F-statistic	67.06	67.06	67.06	67.06
F-stat: PM_t	66.66	66.66	66.66	66.66
F-stat: $PM_t * 1[occup_{t-7} > 0.85]$	46.69	46.69	46.69	46.69
Number of districts	157	157	157	157
Number of days	1088	1088	1088	1088
Observations	170078	170078	170078	170078

Notes: This table reports the IV estimated PM10 impacts on hospitalization rates for children between 1 and 5 years old. The hospitalization rate is measured as the number of hospital admissions per one million children. Panel A shows the results for the number of hospital admissions per one million children for respiratory illnesses, and Panel B shows the results for illnesses seemingly unrelated to pollution. $1[occup_{t-7} > 0.85]$ is our *ex-ante* measure of hospital capacity constraints. Each column in each panel reports coefficients from a different regression, with hospitalizations classified based on ICD-10 categories. The units of analysis are districts of the Sao Paulo Metropolitan Area, observed daily from 2015-2017. We include district, day-of-week, month-of-year, and year fixed effects. We also add temperature and humidity in quadratic form as controls. Standard errors in parentheses are two-way clustered by district and calendar date. The PM effects on constrained locations are -1.37 (1.811) for all respiratory, and -3.31 (2.071) for all non-respiratory. *** p<0.01, ** p<0.05, * p<0.1.

Table 4: PM impacts on children's hospitalization by occupancy rate and emergency level – Respiratory illnesses and illnesses seemingly unrelated to air pollution

	All respiratory		All non-respiratory	
	Emergent (1)	Elective (2)	Emergent (3)	Elective (4)
PM_t	2.67***	−0.16	−0.11	0.41
	(0.947)	(0.247)	(0.721)	(0.819)
$PM_t * 1[occup_{t-7} > 0.85]$	−3.76**	−0.11	−0.46	−3.15***
	(1.672)	(0.456)	(1.395)	(1.138)
Dep. var. mean	39.43	5.52	37.01	33.16
Kleibergen-Paap rk Wald F-statistic	67.06	67.06	67.06	67.06
F-stat: PM_t	66.66	66.66	66.66	66.66
F-stat: $PM_t * 1[occup_{t-7} > 0.85]$	46.69	46.69	46.69	46.69
Number of districts	157	157	157	157
Number of days	1088	1088	1088	1088
Observations	170078	170078	170078	170078

Notes: This table reports the IV estimated PM10 impacts on hospitalization rates for children between 1 and 5 years old. Columns (1) and (2) show the results for the number of hospital admissions per one million children for respiratory illnesses, and Columns (3) and (4) show the results for illnesses seemingly unrelated to pollution. $1[occup_{t-7} > 0.85]$ is our *ex-ante* measure of hospital capacity constraints. Each column reports coefficients from a different regression, with hospitalizations classified based on ICD-10 categories and emergency (emergent or elective) levels based on the Brazilian Ministry of Health's classification. The units of analysis are districts of the Sao Paulo Metropolitan Area, observed daily over the period 2015-2017. We include district, day-of-week, month-of-year, and year fixed effects. We also add temperature and humidity in quadratic form as controls. Standard errors in parentheses are two-way clustered by district and calendar date. *** p<0.01, ** p<0.05, * p<0.1.

Online Appendix

A. Further Background Information

A.1. Pollution Policy in Brazil

In an effort to control vehicle emissions, the National Environmental Council (CONAMA) established emission standards and programs in 1986. Partly because of the success of these programs, carbon monoxide is no longer considered a serious concern in the SPMA. Another reason may be the agreement reached by the government and automakers in 1992 to produce only vehicles with emissions-reducing devices, such as electronic fuel injection and catalytic converters (Jacobi et al., 1997). Today, the state of Sao Paulo has the Plan for Reduction of Emissions from Stationary Sources (PREFE), created in 2014 to map emissions by subregions of the state. The city of Sao Paulo has also implemented the Vehicle Pollution Control Plan (PCPV) since 2011. Both programs aim at maintaining emission levels within the CONAMA requirements. Meanwhile, the Environmental Protection Agency of the State of Sao Paulo (CETESB) has been in charge of measuring the levels of pollutants in the air, leading an expansion in measurements throughout the state. Most of the monitors, however, are located in the SPMA.

A.2. SUS: The Brazilian healthcare public system

Facing the challenge of providing good-quality health care to the entire population, SUS has performed well in vaccination, and high-cost services and complex procedures such as hemodialysis and transplants, which are also used by private insured people according to Paim et al. (2011). SUS also manages the national HIV/AIDS prevention and control program, and the Popular Pharmacy Program (*Programa Farmácia Popular*), which provides subsidized medicines to treat the most common health conditions or remediate exposure to pollution (i.e., asthma medication).

Another SUS effort was the establishment of the Family Health Program (*Programa Saúde da Família* – PSF), with the purpose of providing primary health care through regular visits to households in order to reduce hospital demand, which has resulted in reduction of child mortality, complications from chronic diseases, and hospitalizations that could be treated with ambulatory care (Macinko and Harris, 2015).[40]

Usually, the SUS system consists not only of hospitals, but also community health clinics called Basic Health Units (*Unidade Básica de Saúde* – UBS), and Emergency Care Units (*Unidade de Pronto Atendimento* – UPA), where regular appointments and emergencies of medium-high complexity are handled, respectively. In the city of Sao Paulo, the system also includes Ambulatory Medical Assistance (*Assistência Médica Ambulatorial* – AMA), and Specialty Medical Ambulatory (*Ambulatório Médico de Especialidades* – AME) to meet the demand for outpatient procedures of medium complexity, and avoid overwhelming hospitals with cases in which the patient's life is not at risk. There are no AMA and AME out of the city of Sao Paulo. The Prefecture of Sao Paulo claims that public facilities, especially the Basic Health Units, are better distributed throughout the city than the private ones, although hospitals are concentrated in the center of the city (IVP, 2011).

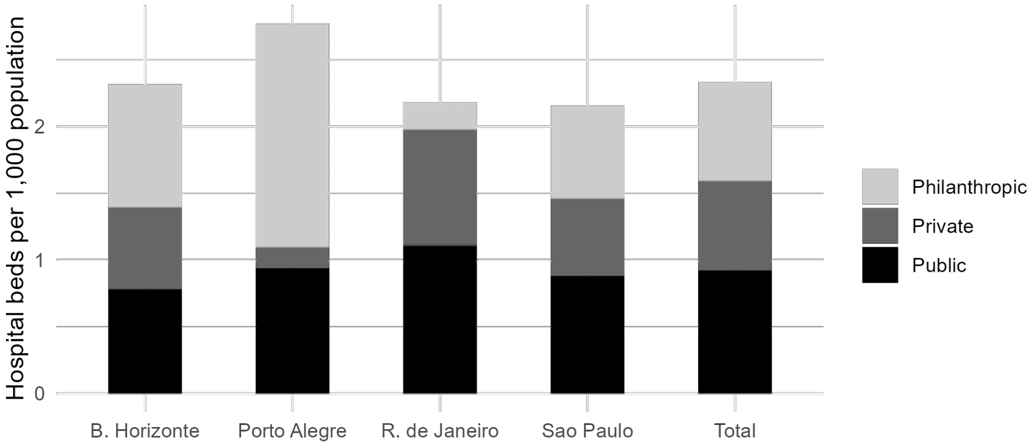
Appendix Figure A1, the SPMA has slightly fewer hospital beds per 1,000 population than the other large metropolitan areas. Thus, the available healthcare infrastructure may not be

[40] SUS also manages other programs such as the More Physicians Program (*Programa Mais Médicos*), the Psychosocial Care Network (*Rede de Atenção Psicossocial*), and the Emergency Care Service (*Serviço de Atendimento Móvel de Urgência – SAMU*).

sufficient to meet Sao Paulo demands for healthcare assistance. It is possible, however, that the reduced number of beds may reflect improvements in the provision of primary care services, which may either reduce the demand for healthcare assistance in general or the demand for high complex services.

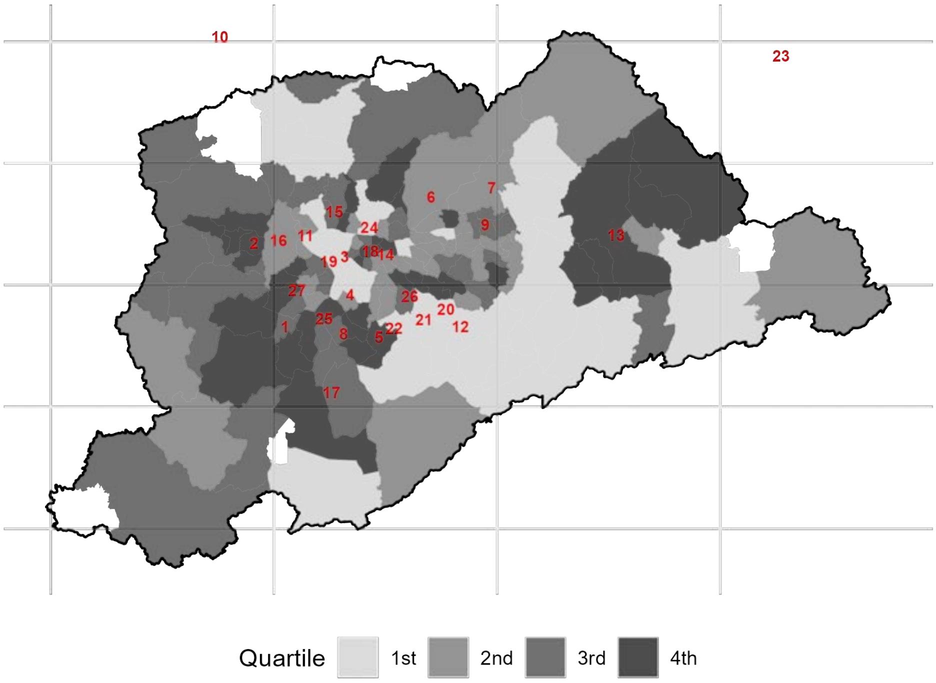
Appendix Figures

Figure A1: Hospital beds per 1,000 population by bed type and MSA in Brazil



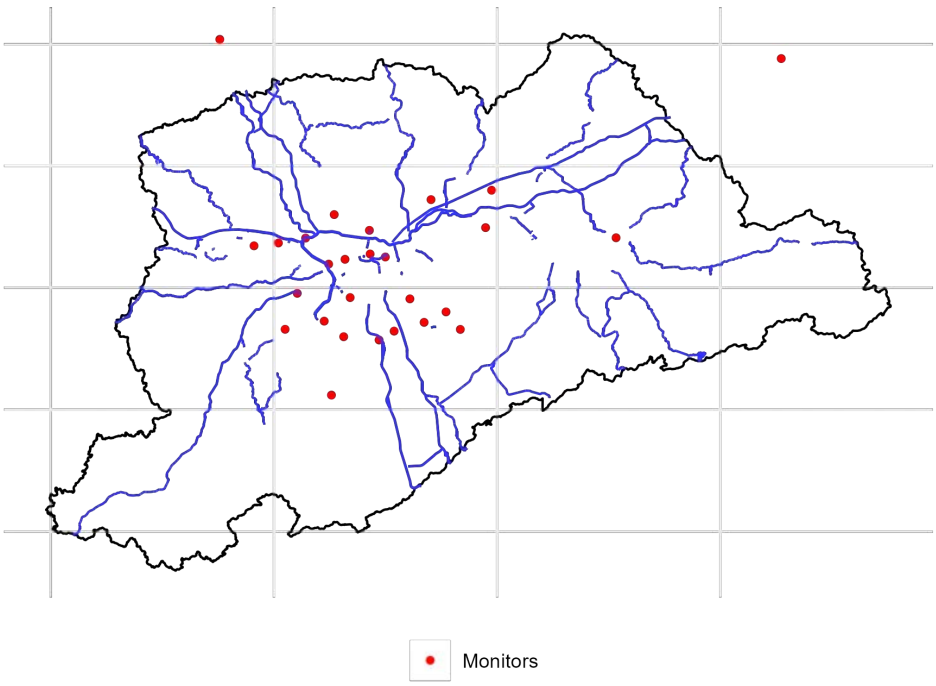
Notes: This figure displays the number of hospital beds per 1,000 population for the four largest metropolitan areas in Brazil. The hospital beds are classified into public, purely private, and philanthropic. *Source*: DATASUS.

Figure A2: Pediatric hospitalization rate and pollution monitors in Sao Paulo



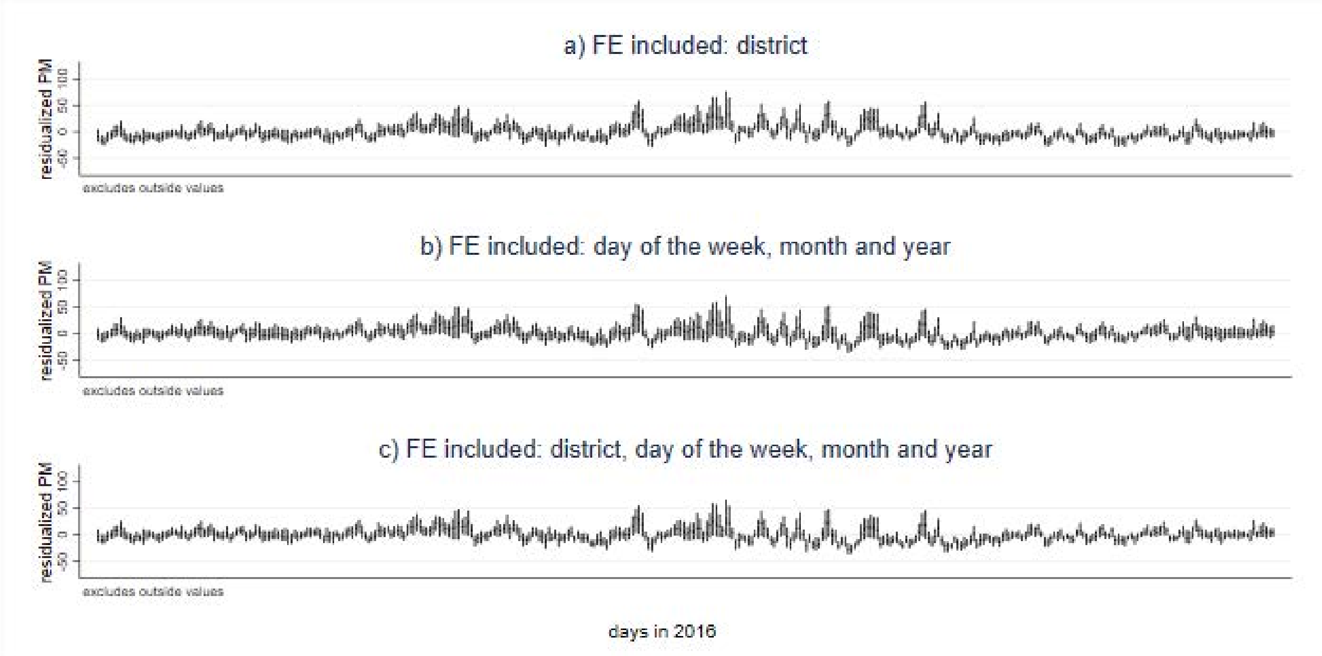
Notes: This map displays a representation of average pediatric hospitalization rates from 2015-2017 by quartile in the Sao Paulo Metropolitan Area (SPMA). Hospitalization rate is measured as the number of hospital admissions per one million children 1-5 years old. The red numbers correspond to the pollution monitors enumerated in Figure 3.

Figure A3: Expressways and highways in Sao Paulo



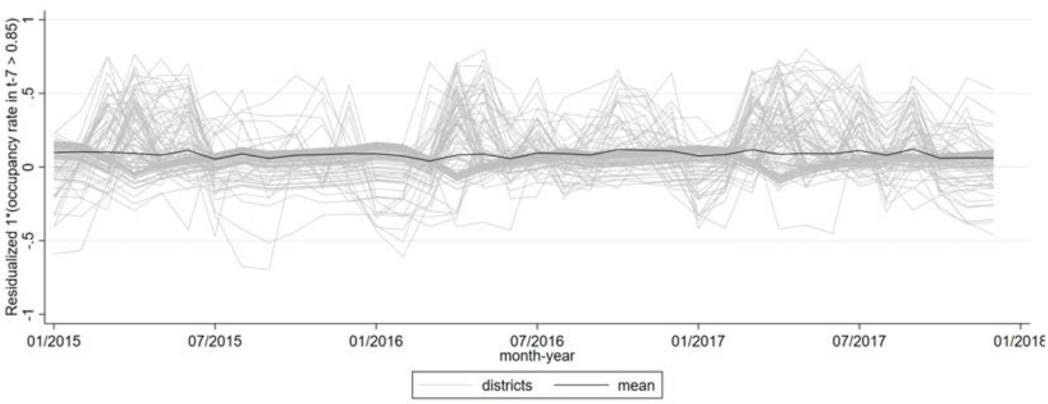
Notes: This map displays expressways and highways (blue lines) together with pollution monitors (red dots) in the Sao Paulo Metropolitan Area.

Figure A4: Residualized PM on different sets of fixed effects by districts in 2016.



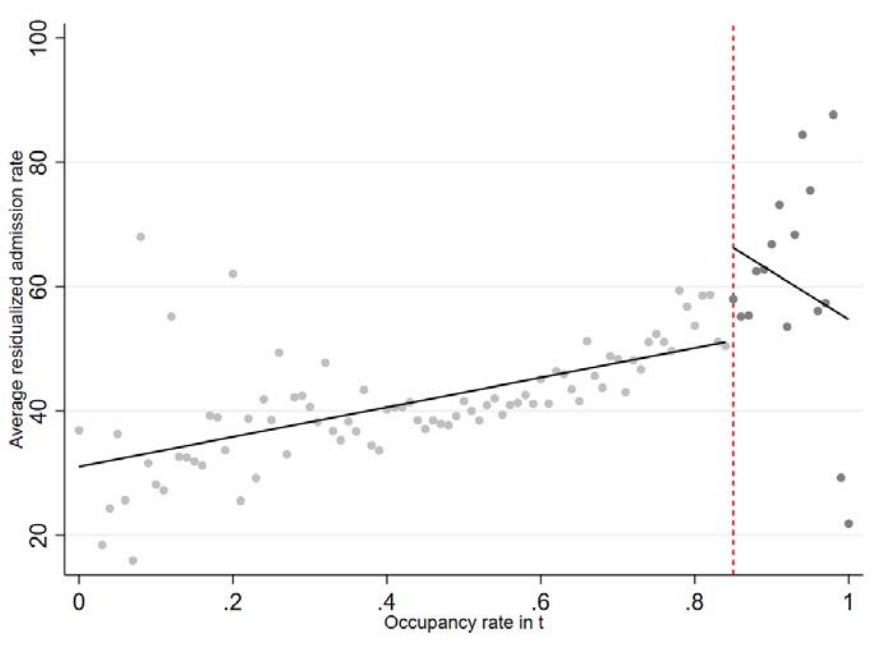
Notes: This figure displays the variation in PM10 after controlling for different sets of fixed effects in days in 2016 in Sao Paulo Metropolitan Area. Each bar corresponds to the range of residualized PM 10 of the districts on a given day. Figure (a) controls only for district fixed effects. Figure (b) controls for the day of the week, month, and year fixed effects. Figure (c) controls for the district, day of the week, month, and year fixed effect.

Figure A5: Average residualized high occupancy rate in t-7 by month and district

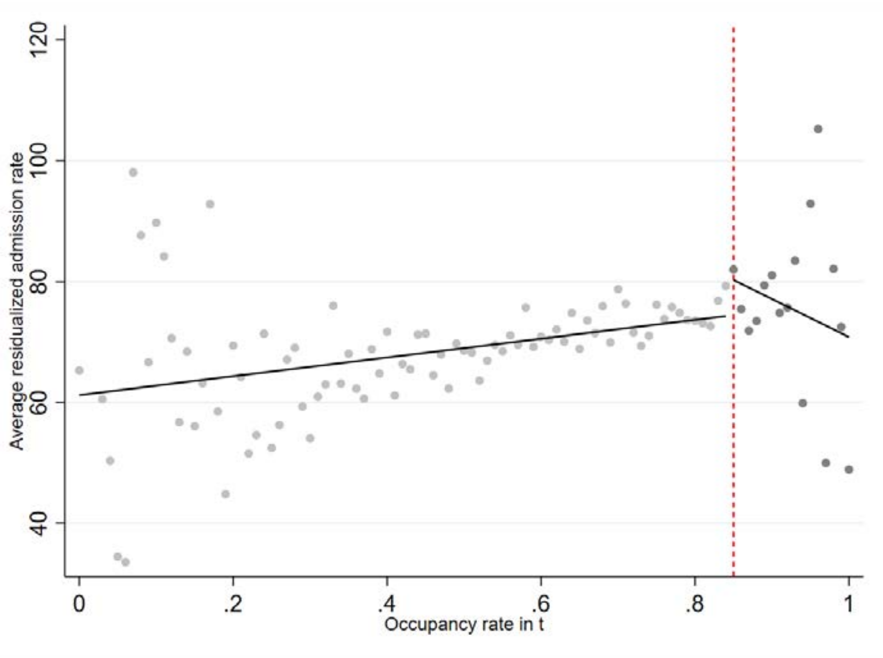


Notes: This figure displays the monthly average of the indicator variable of occupancy rate in t-7 greater than 85% after controlling for district, day of the week, month, and year fixed effects. Each light gray line corresponds to a different district. The black line corresponds to the average across districts.

Figure A6: Relationship between district-level occupancy rate and admission rates for respiratory illnesses and for illnesses seemingly unrelated to air pollution



(a) Respiratory



(b) Non-respiratory

Notes: This figure displays the relationship between admission rates and district-level occupancy rates measured at the admission day. The vertical dashed line represents the occupancy rate of 85%, which represents the maximum hospital utilization that would not adversely affect health outcomes, as recommended by the Brazilian authorities. Panel (a) shows the average admission rate for respiratory illnesses for different occupancy levels after controlling for fixed effects of the district, month, year, and day of the week, as in our main econometric specification. Analogously, Panel (b) shows the scatter-plot of the average admission rate for illnesses seemingly unrelated to air pollution for different occupancy levels after controlling for the same set of fixed effects.

Appendix Tables

Table A1: Average PM10 and PM2.5 concentration in large cities around the world

Country	City	Year	PM
Panel A: PM10 ($\mu g/m^3$)			
India	Delhi	2019	198.8
India	Mumbai	2019	125.3
Peru	Lima	2018	73.9
Chile	Santiago	2019	72.2
Philippines	Manila	2018	62.0
South Africa	Johannesburg	2019	57.2
Thailand	Bangkok	2019	43.1
Mexico	Mexico City	2018	42.5
South Korea	Seoul	2019	42.0
Turkey	Istanbul	2019	39.7
Brazil	Sao Paulo	2019	29.0
Singapore	Singapore	2018	29.0
Spain	Barcelona	2019	26.8
Argentina	Buenos Aires	2019	25.5
France	Paris	2019	24.8
United States	Los Angeles	2019	21.6
United Kingdom	London	2019	20.5
United States	Chicago	2019	18.9
Spain	Madrid	2019	17.3
Panel B: PM2.5 ($\mu g/m^3$)			
India	Delhi	2019	105.0
Indonesia	Jakarta	2019	46.4
India	Mumbai	2019	40.0
China	Shanghai	2018	37.7
South Africa	Johannesburg	2019	37.3
China	Beijing	2019	37.0
Peru	Lima	2019	30.1
Chile	Santiago	2019	25.4
South Korea	Seoul	2019	25.0
Thailand	Bangkok	2019	23.1
Mexico	Mexico City	2018	22.7
Turkey	Istanbul	2019	21.9
Spain	Barcelona	2019	17.8
Brazil	Sao Paulo	2019	16.7
France	Paris	2019	15.5
Singapore	Singapore	2018	15.0
Japan	Tokyo	2018	12.9
United Kingdom	London	2019	11.4
United States	Chicago	2018	10.7
Spain	Madrid	2019	9.9
United States	Los Angeles	2019	9.0

Notes: This figure displays the annual average of PM10 and PM2.5 (in $\mu g/m^3$) for selected large cities worldwide. New York and Los Angeles refer to the metropolitan area. *Source*: World Health Organization – August, 2022.

Table A2: Mean emergency level, readmission rate, and death rate by most prevalent causes of hospitalization in São Paulo

	Total	% of emergent	% in ICU	% of readmission	% of death within 30 days
All respiratory illnesses	**61553**	**87.47**	**3.97**	**4.97**	**0.33**
Pneumonia, organism unspecified	28923	98.79	3.90	5.11	0.35
Asthma	7819	96.38	2.69	4.22	0.09
Chronic diseases of tonsils and adenoids	6474	4.68	0.28	1.71	0.00
Acute bronchiolitis	5042	98.16	1.75	5.19	0.19
Bacterial pneumonia, not elsewhere classified	4846	98.70	4.42	6.11	0.37
Acute upper respiratory infections of multiple and unspecified sites	1261	87.95	1.27	6.81	0.08
Acute tonsillitis	1055	98.86	0.57	3.16	0.00
Bronchitis, not specified as acute or chronic	971	97.43	2.06	3.45	0.11
Acute laryngitis and tracheitis	946	94.93	4.55	6.54	0.34
Respiratory failure, not elsewhere classified	833	87.76	46.39	17.68	6.02
All non-respiratory illnesses	**96417**	**51.84**	**4.15**	**6.91**	**0.52**
Redundant prepuce, phimosis and paraphimosis	12964	4.96	0.01	2.40	0.00
Umbilical hernia	8156	6.51	0.07	3.02	0.00
Other gastroenteritis and colitis of infectious and unspecified origin	4865	97.45	0.99	4.71	0.09
Inguinal hernia	4042	10.07	0.17	2.79	0.00
Other disorders of urinary system	3303	95.94	0.58	5.10	0.10
Cellulitis	3040	97.50	0.39	2.49	0.00
Epilepsy	2877	87.49	10.08	9.98	0.57
Undescended testicle	2278	6.80	0.00	2.64	0.04
Intracranial injury	1952	96.11	8.36	2.20	0.73
Lymphoid leukaemia	1736	52.36	1.90	63.96	1.93

Notes: This table reports the ten most prevalent conditions by cause of admission (respiratory illnesses or illnesses seemingly unrelated to air pollution). The columns represent the count, percentage of emergent admissions, percentage of admissions to ICU, percentage of admissions that resulted in a readmission within 30 days, and percentage of death within 30 days. Illnesses are classified based on the three-digit ICD-10. The data contain all children 1 to 5 admissions in Sao Paulo Metropolitan Area over the period 2015-2017.

Table A3: PM impacts on children's hospitalization by occupancy rate – Illnesses seemingly unrelated to air pollution

	Digestive and nutritional (1)	Genitourinary (2)	Injury, external, and others (3)	Infectious (4)	Pregnancy, congenital, and perinatal (5)	Skin and connective (6)	Circulatory, eye, ear, and blood (7)	Cancer (8)	Nervous and mental (9)
PM_t	0.64	−0.05	−0.21	−0.16	−0.10	0.17	0.33	0.03	−0.35*
	(0.477)	(0.454)	(0.345)	(0.290)	(0.229)	(0.223)	(0.202)	(0.246)	(0.184)
$PM_t * 1[occup_{t-7} > 0.85]$	−1.08	−1.87***	0.35	0.04	0.61	−0.88**	−0.31	0.15	−0.62*
	(0.861)	(0.705)	(0.811)	(0.471)	(0.445)	(0.425)	(0.407)	(0.362)	(0.350)
Dep. var. mean	14.44	13.70	9.22	8.17	6.33	6.03	4.64	4.02	3.63
Kleibergen-Paap rk Wald F-statistic	67.06	67.06	67.06	67.06	67.06	67.06	67.06	67.06	67.06
F-stat: PM_t	66.66	66.66	66.66	66.66	66.66	66.66	66.66	66.66	66.66
F-stat: $PM_t * 1[occup_{t-7} > 0.85]$	46.69	46.69	46.69	46.69	46.69	46.69	46.69	46.69	46.69
Number of districts	157	157	157	157	157	157	157	157	157
Number of days	1088	1088	1088	1088	1088	1088	1088	1088	1088
Observations	170078	170078	170078	170078	170078	170078	170078	170078	170078

Notes: This table reports the IV estimated PM10 impacts on hospitalization for children between 1 and 5 years old per one million children for illnesses seemingly unrelated to pollution. $1[occup_{t-7} > 0.85]$ is our *ex-ante* measure of hospital capacity constraints. Each column in each panel reports coefficients from a different regression, with hospitalizations classified based on ICD-10 categories. The units of analysis are districts of the Sao Paulo Metropolitan Area, observed daily over the period 2015-2017. We include district, day-of-week, month-of-year, and year fixed effects. We also add temperature and humidity in quadratic form as controls. Standard errors in parentheses are two-way clustered by district and calendar date. *** p<0.01, ** p<0.05, * p<0.1.

Table A4: Impacts of wind speed and its interaction with high occupancy rate on PM10 - First stage, individual-level

	All respiratory		All non-respiratory	
	PM_t	$PM_t * 1[occup_{t-7} > 0.85]$	PM_t	$PM_t * 1[occup_{t-7} > 0.85]$
	(1)	(2)	(3)	(4)
Panel A: ICU admission				
ws_t	-0.69^{***}	-0.00	-0.71^{***}	0.01
	(0.054)	(0.012)	(0.056)	(0.012)
ws_{t-1}	-0.25^{***}	0.01	-0.21^{***}	0.01
	(0.052)	(0.013)	(0.053)	(0.012)
$ws_t * 1[occup_{t-7} > 0.85]$	-0.06	-0.85^{***}	0.01	-0.83^{***}
	(0.048)	(0.107)	(0.051)	(0.114)
$ws_{t-1} * 1[occup_{t-7} > 0.85]$	0.01	-0.30^{***}	-0.06	-0.31^{**}
	(0.058)	(0.112)	(0.046)	(0.118)
Dep. var. mean	3.02	0.40	3.00	0.32
F-statistic	60.59	52.71	56.34	45.60
Number of districts	157	157	157	157
Number of days	1088	1088	1088	1088
Observations	61524	61524	96387	96387
Panel B: Death within 30 days				
ws_t	-0.70^{***}	-0.00	-0.71^{***}	0.01
	(0.054)	(0.012)	(0.056)	(0.012)
ws_{t-1}	-0.25^{***}	0.01	-0.21^{***}	0.01
	(0.052)	(0.013)	(0.053)	(0.012)
$ws_t * 1[occup_{t-7} > 0.85]$	-0.06	-0.85^{***}	0.01	-0.80^{***}
	(0.048)	(0.107)	(0.052)	(0.116)
$ws_{t-1} * 1[occup_{t-7} > 0.85]$	0.01	-0.30^{***}	-0.06	-0.33^{***}
	(0.059)	(0.112)	(0.046)	(0.119)
Dep. var. mean	3.02	0.40	3.00	0.32
F-statistic	60.99	53.45	55.95	41.80
Number of districts	157	157	157	157
Number of days	1088	1088	1088	1088
Observations	58469	58469	88764	88764
Panel C: Readmission within 30 days				
ws_t	-0.70^{***}	-0.00	-0.71^{***}	0.01
	(0.054)	(0.012)	(0.056)	(0.012)
ws_{t-1}	-0.25^{***}	0.01	-0.21^{***}	0.01
	(0.052)	(0.013)	(0.053)	(0.012)
$ws_t * 1[occup_{t-7} > 0.85]$	-0.06	-0.85^{***}	0.01	-0.80^{***}
	(0.048)	(0.107)	(0.051)	(0.116)
$ws_{t-1} * 1[occup_{t-7} > 0.85]$	0.01	-0.30^{***}	-0.06	-0.32^{***}
	(0.059)	(0.112)	(0.046)	(0.118)
Dep. var. mean	3.02	0.40	3.00	0.32
F-statistic	61.00	53.71	56.18	41.73
Number of districts	157	157	157	157
Number of days	1088	1088	1088	1088
Observations	58327	58327	88403	88403

Notes: This table reports the first stage for the results at the individual level. The first two columns show the results for all admissions for respiratory illnesses and the last two for all non-respiratory illnesses. Within cause of admission, each column represents the first stage results for one of the endogenous variables, PM_t and $PM_t * 1[occup_{t-7} > 0.85]$, respectively. Panel A reports the first stage results for the sample used to estimate the probability of being admitted to the ICU. Panel B reports the first stage results for the sample used to estimate the probability of death within 30 days, and Panel C reports the first stage results for the sample used to estimate the probability of readmission within 30 days. The units of analysis are districts of the Sao Paulo Metropolitan Area, observed daily over the period 2015-2017. We include hospital, age, race, gender, ICD-10, district, day-of-week, month-of-year, and year fixed effects. We also add temperature and humidity in quadratic form as controls. Standard errors in parentheses are two-way clustered by district and calendar date. *** p<0.01, ** p<0.05, * p<0.1.

Table A5: PM impacts on children's health outcomes by occupancy rate and emergency level – Respiratory illnesses and illnesses seemingly unrelated to air pollution

	All respiratory			All non-respiratory		
	All (1)	Emergent (2)	Elective (3)	All (4)	Emergent (5)	Elective (6)
Panel A: ICU admission						
PM_t	−0.0016	−0.0017	−0.0013	−0.0003	−0.0027	0.0009
	(0.0026)	(0.0027)	(0.0051)	(0.0019)	(0.0032)	(0.0021)
$PM_t * 1[occup_{t-7} > 0.85]$	−0.0045	−0.0042	0.0073	0.0034	0.0058	−0.0002
	(0.0035)	(0.0036)	(0.0075)	(0.0034)	(0.0063)	(0.0034)
Dep. var. mean	0.0397	0.0417	0.0252	0.0415	0.0511	0.0311
Kleibergen-Paap rk Wald F-statistic	60.37	58.18	48.61	59.37	41.75	51.79
F-stat: PM_t	60.59	59.20	52.32	56.34	55.12	53.20
F-stat: $PM_t * 1[occup_{t-7} > 0.85]$	52.71	53.10	23.11	45.60	41.71	38.68
Number of districts	157	156	153	157	157	157
Number of days	1088	1088	1011	1088	1088	1088
Observations	61524	53806	7697	96387	49949	46420
Panel B: Death within 30 days						
PM_t	0.0001	−0.0001	0.0009	−0.0008	−0.0014	−0.0002
	(0.0007)	(0.0008)	(0.0017)	(0.0009)	(0.0016)	(0.0006)
$PM_t * 1[occup_{t-7} > 0.85]$	−0.0013	−0.0014	−0.0005	0.0012	0.0019	0.0005
	(0.0010)	(0.0010)	(0.0012)	(0.0015)	(0.0030)	(0.0008)
Dep. var. mean	0.0033	0.0035	0.0013	0.0052	0.0080	0.0022
Kleibergen-Paap rk Wald F-statistic	60.59	58.38	47.11	58.89	37.00	50.87
F-stat: PM_t	60.99	59.71	50.52	55.95	54.45	52.12
F-stat: $PM_t * 1[occup_{t-7} > 0.85]$	53.45	53.86	22.38	41.80	37.47	35.08
Number of districts	157	156	152	157	157	157
Number of days	1088	1088	1002	1088	1088	1088
Observations	58469	51038	7411	88764	46063	42683
Panel C: Readmission within 30 days						
PM_t	−0.0009	−0.0031	0.0130*	−0.0001	−0.0012	−0.0000
	(0.0031)	(0.0032)	(0.0075)	(0.0029)	(0.0040)	(0.0034)
$PM_t * 1[occup_{t-7} > 0.85]$	0.0029	0.0054	−0.0141	−0.0053	−0.0002	−0.0090*
	(0.0031)	(0.0037)	(0.0099)	(0.0033)	(0.0059)	(0.0049)
Dep. var. mean	0.0497	0.0510	0.0408	0.0691	0.0736	0.0643
Kleibergen-Paap rk Wald F-statistic	60.56	58.30	47.10	59.27	37.70	51.11
F-stat: PM_t	61.00	59.70	50.52	56.18	54.68	52.25
F-stat: $PM_t * 1[occup_{t-7} > 0.85]$	53.71	54.11	22.38	41.73	37.59	34.96
Number of districts	157	156	152	157	157	157
Number of days	1088	1088	1002	1088	1088	1088
Observations	58327	50900	7407	88403	45768	42617

Notes: This table reports the IV estimated PM10 impacts on the probability of being admitted to the ICU, death within 30 days and readmission within 30 days for children between 1 and 5 years old. Panel A shows the results for the probability of being admitted to the ICU, and Panels B and C show the results for the probability of death and readmission within 30 days, respectively. All measures from Panels A to C are conditional on having been admitted. Columns (1)-(3) show the results for respiratory illnesses, and Columns (4)-(6) show the results for illnesses seemingly unrelated to pollution. $1[occup_{t-7} > 0.85]$ is our *ex-ante* measure of hospital capacity constraints. Each column reports coefficients from a different regression, with hospitalizations classified based on ICD-10 categories and emergency (emergent or elective) levels based on the Brazilian Ministry of Health's classification. The units of analysis are districts of the Sao Paulo Metropolitan Area, observed daily over the period 2015-2017. We include hospital, age, race, gender, ICD-10, district, day-of-week, month-of-year, and year fixed effects. We also add temperature and humidity in quadratic form as controls. Standard errors in parentheses are two-way clustered by district and calendar date. *** p<0.01, ** p<0.05, * p<0.1.

Table A6: PM impacts on children's hospitalization allowing for slightly endogenous instruments – Respiratory illnesses

	PM_t (1)	$PM_t *$ $1[occup_{t-7} > 0.85]$ (2)
Panel A: Main specification		
PM_t	2.51**	−3.88**
	(1.010)	(1.813)
Hansen's J statistic	3.949	
Hansen's J p-value	0.139	
Kleibergen-Paap rk Wald F-statistic	67.06	
Panel B: Conley et al. (2012)		
Violation	Bounds	
[-0.3;0]	[0.76;3.67]	[-6.79;-1.42]
[-0.2;0]	[0.96;3.67]	[-6.63;-1.44]
[-0.1;0]	[1.15;3.67]	[-6.46;-1.45]
[0;0.1]	[1.35;3.87]	[-6.31;-1.29]
[0;0.2]	[1.35;4.07]	[-6.32;-1.13]
[0;0.3]	[1.35;4.26]	[-6.33;-0.96]
Panel C: Nevo and Rosen (2012)		
Assumption	Bounds	
Positive correlation	[0.74;4.52]	[-0.64;-0.46]
Negative correlation	[1.19;1.77]	[-3.39;-0.08]

Notes: This table reports bounds for the main results allowing for potential correlation between the instruments and the error term. The dependent variable is the admission rate per 1 million children aged 1 to 5 for respiratory illnesses. Column (1) and (2) reports the results for PM_t and $PM_t * 1[occup_{t-7} > 0.85]$, respectively. Panel A replicates the main results. Panel B uses Conley et al. (2012) and allows for potential direct correlation between the instruments and the dependent variable, violating IV assumptions. We allow for a positive and negative violations of various magnitudes. We define the violations such that all instruments have the same maximum and minimum correlation with the dependent variable. Panel C follows Nevo and Rosen (2012) and allows for positive and negative correlation between the instruments and the unobserved error term. To define bounds for both endogenous variables, we consider one endogenous at a time, holding the other as exogenous and using only the relevant instruments: wind speed for PM and its interactions with high occupancy when the endogenous is PM interacted with high occupancy. The units of analysis are districts of the Sao Paulo Metropolitan Area, observed daily over the period 2015-2017. We include district, day-of-week, month-of-year, and year fixed effects. We also add temperature and humidity in quadratic form as controls. Standard errors in parentheses are two-way clustered by district and calendar date. *** p<0.01, ** p<0.05, * p<0.1.

Table A7: PM impacts on children's hospitalization by own and neighboring occupancy rate – Respiratory illnesses and illnesses seemingly unrelated to air pollution

Panel A: Respiratory illnesses	All respiratory	Acute respiratory infections	Chronic lower respiratory diseases	Others respiratory
	(1)	(2)	(3)	(4)
PM_t	2.50**	2.04**	0.57*	−0.10
	(1.009)	(0.815)	(0.319)	(0.260)
$\mathrm{PM}_t * 1[\mathrm{occup}_{t-7} > 0.85]$	−4.02**	−3.96**	0.03	−0.09
	(1.750)	(1.599)	(0.655)	(0.532)
$\mathrm{PM}_t * 1[\mathrm{occup}_{t-7} > 0.85] * 1[\text{p75 occup nb}_{t-7} < 0.85]$	0.57	0.22	0.29	0.06
	(0.917)	(0.768)	(0.284)	(0.158)
Dep. var. mean	44.95	31.76	7.11	6.08
Panel B: Illnesses seemingly unrelated to air pollution	All non-respiratory	Genitourinary	Skin and connective	Others non-respiratory
	(5)	(6)	(7)	(8)
PM_t	0.29	−0.05	0.16	0.18
	(1.280)	(0.454)	(0.223)	(0.949)
$\mathrm{PM}_t * 1[\mathrm{occup}_{t-7} > 0.85]$	−3.77*	−1.83***	−0.98**	−0.96
	(1.983)	(0.695)	(0.441)	(1.798)
$\mathrm{PM}_t * 1[\mathrm{occup}_{t-7} > 0.85] * 1[\text{p75 occup nb}_{t-7} < 0.85]$	0.56	−0.13	0.41***	0.28
	(1.175)	(0.331)	(0.153)	(0.996)
Dep. var. mean	70.17	13.70	6.03	50.45
Kleibergen-Paap rk Wald F-statistic	46.03	46.03	46.03	46.03
F-stat: PM_t	48.18	48.18	48.18	48.18
F-stat: $\mathrm{PM}_t * 1[\mathrm{occup}_{t-7} > 0.85]$	32.89	32.89	32.89	32.89
F-stat: $\mathrm{PM}_t * 1[\mathrm{occup}_{t-7} > 0.85] * 1[\text{p75 occup nb}_{t-7} < 0.85]$	155.24	155.24	155.24	155.24
Number of districts	157.00	157.00	157.00	157.00
Number of days	1088	1088	1088	1088
Observations	170078	170078	170078	170078

Notes: This table reports the IV estimated PM10 impacts on hospitalization rates for children between 1 and 5 years old. The hospitalization rate is measured as the number of hospital admissions per one million children. Panel A shows the results for respiratory illnesses, and Panel B shows the results for illnesses seemingly unrelated to pollution. $1[\mathrm{occup}_{t-7} > 0.85]$ is our *ex-ante* measure of hospital capacity constraints. We use a triple interaction on district PM, district high occupancy rate, and neighboring low occupancy rates defined as at least 75% of neighboring districts with occupancy rate less than 0.85%. Each column reports coefficients from a different regression, with hospitalizations classified based on ICD-10 categories. The units of analysis are districts of the Sao Paulo Metropolitan Area, observed daily over the period 2015-2017. We include district, day-of-week, month-of-year, and year fixed effects. We also add temperature and humidity in quadratic form as controls. Standard errors in parentheses are two-way clustered by district and calendar date. *** p<0.01, ** p<0.05, * p<0.1.

Table A8: PM impacts on children's hospitalization using different specifications and instruments – Respiratory illnesses

Panel A: Different specifications	Precipitation as control	Month by year FE	Admission day FE
	(1)	(2)	(3)
PM_t	2.56**	1.55	7.88
	(1.001)	(0.941)	(5.596)
$PM_t * 1[occup_{t-7} > 0.85]$	−3.90**	−3.79**	−4.56**
	(1.810)	(1.804)	(1.872)
Kleibergen-Paap rk Wald F-statistic	70.30	72.44	4.21
Panel B: Different instruments	PM_t on WS and WD	PM_t on WD	PM_t on WS and WD*region
	(4)	(5)	(6)
PM_t	2.74***	2.23	2.59***
	(0.926)	(1.980)	(0.903)
$PM_t * 1[occup_{t-7} > 0.85]$	−3.60***	−2.36*	−3.35***
	(1.279)	(1.353)	(1.173)
Kleibergen-Paap rk Wald F-statistic	35.56	9.96	19.76
Dep. var. mean	44.95	44.95	44.95
Number of districts	157	157	157
Number of days	1088	1088	1088
Observations	170078	170078	170078

Notes: This table reports the IV estimated PM10 impacts on hospitalization rates for children between 1 and 5 years old. The hospitalization rate is measured as the number of hospital admissions per one million children for respiratory illnesses. Panel A reports the results for different specifications. Column (1) includes precipitation (in mm/day) as control, column (2) uses the main specification but includes month-by-year fixed effects, column (3) also uses the main specification but includes day of admission fixed effects. Panel B uses different sets of instruments. Column (4) adds bins of wind direction ($[0°, 90°]$, $(90°, 180°]$, $(180°, 270°]$, $(270°, 360°]$) besides contemporaneous and lagged wind speed, and their interaction with high occupancy as instruments. Column (5) uses only bins of wind speed and their interaction with high occupancy as instruments, and column (6) adds the interaction of wind direction bins with district location (north, south, west and east) and their interaction with high occupancy to the specification from column (4). The units of analysis are districts of the Sao Paulo Metropolitan Area, observed daily over the period 2015-2017. We include district, day-of-week, month-of-year, and year fixed effects. We also add temperature and humidity in quadratic form as controls. Standard errors in parentheses are two-way clustered by district and calendar date. *** p<0.01, ** p<0.05, * p<0.1.

Table A9: PM impacts on children's hospitalization by different lags of occupancy rate – Respiratory illnesses

	All respiratory (1)	Acute respiratory infections (2)	Chronic lower respiratory diseases (3)	Others respiratory (4)
Panel A: Occupancy rate in t				
PM_t	2.40**	1.94**	0.65**	−0.19
	(0.977)	(0.792)	(0.323)	(0.275)
$PM_t * 1[occup_t > 0.85]$	−4.01*	−4.15**	−0.82	0.96
	(2.246)	(2.077)	(0.653)	(0.667)
Kleibergen-Paap rk Wald F-statistic	41.74	41.74	41.74	41.74
Panel B: Occupancy rate in t-6				
PM_t	2.26**	1.83**	0.55*	−0.13
	(0.994)	(0.811)	(0.315)	(0.264)
$PM_t * 1[occup_{t-6} > 0.85]$	−1.47	−2.00	0.29	0.24
	(1.447)	(1.242)	(0.652)	(0.543)
Kleibergen-Paap rk Wald F-statistic	71.11	71.11	71.11	71.11
Panel C: Occupancy rate in t-7				
PM_t	2.51**	2.04**	0.57*	−0.10
	(1.010)	(0.815)	(0.320)	(0.260)
$PM_t * 1[occup_{t-7} > 0.85]$	−3.88**	−3.91**	0.11	−0.07
	(1.813)	(1.681)	(0.634)	(0.529)
Kleibergen-Paap rk Wald F-statistic	67.06	67.06	67.06	67.06
Panel D: Occupancy rate in t-8				
PM_t	2.34**	1.88**	0.54*	−0.09
	(1.000)	(0.813)	(0.319)	(0.265)
$PM_t * 1[occup_{t-8} > 0.85]$	−2.30	−2.50*	0.33	−0.13
	(1.485)	(1.325)	(0.695)	(0.487)
Kleibergen-Paap rk Wald F-statistic	68.09	68.09	68.09	68.09
Dep. var. mean	44.95	31.76	7.11	6.08
Number of districts	157	157	157	157
Number of days	1088	1088	1088	1088
Observations	170078	170078	170078	170078

Notes: This table reports the IV estimated PM10 impacts on hospitalization rates for children between 1 and 5 years old. The hospitalization rate is measured as the number of hospital admissions per one million children for respiratory illnesses. $1[occup_{t-\Delta t} > 0.85]$ is our *ex-ante* measure of hospital capacity constraints. Panel A uses the occupancy rate of the same date of admission. Panel B uses the occupancy rate six days before the admission date. Panel C uses the occupancy rate seven days before the admission date, which is our preferred specification. Panel D uses the occupancy rate eight days before the admission date. Each column in each panel reports coefficients from a different regression, with hospitalizations classified based on ICD-10 categories. The units of analysis are districts of the Sao Paulo Metropolitan Area, observed daily over the period 2015-2017. We include district, day-of-week, month-of-year, and year fixed effects. We also add temperature and humidity in quadratic form as controls. Standard errors in parentheses are two-way clustered by district and calendar date. *** p<0.01, ** p<0.05, * p<0.1.

Table A10: PM impacts on children's hospitalization by different high occupancy rates – Respiratory illnesses

	All respiratory (1)	Acute respiratory infections (2)	Chronic lower respiratory diseases (3)	Others respiratory (4)
Panel A: Occupancy rate greater than 80%				
PM_t	2.29**	1.87**	0.52	−0.10
	(1.022)	(0.830)	(0.332)	(0.270)
$PM_t * 1[occup_{t-7} > 0.80]$	−0.99	−1.28	0.32	−0.03
	(1.312)	(1.179)	(0.456)	(0.370)
Kleibergen-Paap rk Wald F-statistic	69.39	69.39	69.39	69.39
Panel B: Occupancy rate greater than 85%				
PM_t	2.51**	2.04**	0.57*	−0.10
	(1.010)	(0.815)	(0.320)	(0.260)
$PM_t * 1[occup_{t-7} > 0.85]$	−3.88**	−3.91**	0.11	−0.07
	(1.813)	(1.681)	(0.634)	(0.529)
Kleibergen-Paap rk Wald F-statistic	67.06	67.06	67.06	67.06
Panel C: Occupancy rate greater than 90%				
PM_t	2.24**	1.74**	0.63*	−0.13
	(0.989)	(0.813)	(0.323)	(0.260)
$PM_t * 1[occup_{t-7} > 0.90]$	−4.14	−3.54	−1.45	0.85
	(2.856)	(2.884)	(0.961)	(0.681)
Kleibergen-Paap rk Wald F-statistic	65.71	65.71	65.71	65.71
Dep. var. mean	44.95	31.76	7.11	6.08
Number of districts	157	157	157	157
Number of days	1088	1088	1088	1088
Observations	170078	170078	170078	170078

Notes: This table reports the IV estimated PM10 impacts on hospitalization rates for children between 1 and 5 years old. The hospitalization rate is measured as the number of hospital admissions per one million children for all respiratory illnesses. $1[occup_{t-7} > 0.85]$ is our *ex-ante* measure of hospital capacity constraints. The 85% threshold (Panel B) has been highlighted by the Brazilian Ministry of Health as the maximum hospital utilization that would not adversely affect health outcomes. Panel A and C present robustness of the 85% threshold, considering 80% and 90% of hospital utilization, respectively. Each column reports coefficients from a different regression, with hospitalizations classified based on ICD-10 categories. The units of analysis are districts of the Sao Paulo Metropolitan Area, observed daily over the period 2015-2017. We include district, day-of-week, month-of-year, and year fixed effects. We also add temperature and humidity in quadratic form as controls. Standard errors in parentheses are two-way clustered by district and calendar date. *** p<0.01, ** p<0.05, * p<0.1.

Table A11: PM impacts on children's hospitalization by different high occupancy rates – Illnesses seemingly unrelated to air pollution

	All non-respiratory (1)	Genitourinary (2)	Skin and connective (3)	Others non-respiratory (4)
Panel A: Occupancy rate greater than 80%				
PM_t	0.38	0.04	0.12	0.21
	(1.308)	(0.468)	(0.234)	(0.962)
$PM_t * 1[occup_{t-7} > 0.80]$	−2.55	−1.58**	−0.29	−0.68
	(1.571)	(0.700)	(0.369)	(1.365)
Kleibergen-Paap rk Wald F-statistic	69.39	69.39	69.39	69.39
Panel B: Occupancy rate greater than 85%				
PM_t	0.30	−0.05	0.17	0.18
	(1.280)	(0.454)	(0.223)	(0.948)
$PM_t * 1[occup_{t-7} > 0.85]$	−3.61*	−1.87***	−0.88**	−0.87
	(1.860)	(0.705)	(0.425)	(1.645)
Kleibergen-Paap rk Wald F-statistic	67.06	67.06	67.06	67.06
Panel C: Occupancy rate greater than 90%				
PM_t	0.25	−0.12	0.14	0.23
	(1.279)	(0.451)	(0.221)	(0.942)
$PM_t * 1[occup_{t-7} > 0.90]$	−9.28***	−3.60***	−1.95**	−3.74
	(2.467)	(1.233)	(0.842)	(2.366)
Kleibergen-Paap rk Wald F-statistic	65.71	65.71	65.71	65.71
Dep. var. mean	70.17	13.70	6.03	50.45
Number of districts	157	157	157	157
Number of days	1088	1088	1088	1088
Observations	170078	170078	170078	170078

Notes: This table reports the IV estimated PM10 impacts on hospitalization rates for children between 1 and 5 years old. The hospitalization rate is measured as the number of hospital admissions per one million children for all illnesses seemingly unrelated to air pollution. $1[occup_{t-7} > 0.85]$ is our *ex-ante* measure of hospital capacity constraints. The 85% threshold (Panel B) has been highlighted by the Brazilian Ministry of Health as the maximum hospital utilization that would not adversely affect health outcomes. Panel A and C present robustness of the 85% threshold, considering 80% and 90% of hospital utilization, respectively. Each column reports coefficients from a different regression, with hospitalizations classified based on ICD-10 categories. The units of analysis are districts of the Sao Paulo Metropolitan Area, observed daily over the period 2015-2017. We include district, day-of-week, month-of-year, and year fixed effects. We also add temperature and humidity in quadratic form as controls. Standard errors in parentheses are two-way clustered by district and calendar date. *** p<0.01, ** p<0.05, * p<0.1.

Table A12: PM impacts on children's hospitalization by occupancy rate, income and rural districts – Respiratory illnesses and illnesses seemingly unrelated to air pollution

Panel A: Respiratory illnesses	All respiratory	Acute respiratory infections	Chronic lower respiratory diseases	Others respiratory
	(1)	(2)	(3)	(4)
PM_t	2.90**	2.55***	0.74	−0.39
	(1.260)	(0.945)	(0.470)	(0.308)
$PM_t * 1[occup_{t-7} > 0.85]$	−3.84**	−3.87**	0.14	−0.10
	(1.797)	(1.658)	(0.624)	(0.530)
$PM_t * 1[\text{high income}]$	−0.65	−0.98	−0.16	0.49**
	(0.936)	(0.750)	(0.467)	(0.223)
$PM_t * 1[\text{rural}]$	−0.29	−0.15	−0.36	0.23
	(1.046)	(0.821)	(0.496)	(0.280)
Dep. var. mean	44.95	31.76	7.11	6.08
Panel B: Illnesses seemingly unrelated to air pollution	All non-respiratory	Genitourinary	Skin and connective	Others non-respiratory
	(5)	(6)	(7)	(8)
PM_t	0.54	0.06	−0.13	0.62
	(1.573)	(0.543)	(0.273)	(1.236)
$PM_t * 1[occup_{t-7} > 0.85]$	−3.50*	−1.80***	−0.91**	−0.80
	(1.913)	(0.684)	(0.416)	(1.687)
$PM_t * 1[\text{high income}]$	0.34	0.21	0.53*	−0.40
	(1.122)	(0.440)	(0.285)	(0.929)
$PM_t * 1[\text{rural}]$	−1.61	−0.90*	0.19	−0.90
	(1.202)	(0.533)	(0.293)	(1.065)
Dep. var. mean	70.17	13.70	6.03	50.45
Kleibergen-Paap rk Wald F-statistic	28.21	28.21	28.21	28.21
F-stat: PM_t	36.43	36.43	36.43	36.43
F-stat: $PM_t * 1[occup_{t-7} > 0.85]$	25.53	25.53	25.53	25.53
F-stat: $PM_t * 1[\text{high income}]$	37.32	37.32	37.32	37.32
F-stat: $PM_t * 1[\text{rural}]$	28.04	28.04	28.04	28.04
Number of districts	157	157	157	157
Number of days	1088	1088	1088	1088
Observations	170078	170078	170078	170078

Notes: This table reports the IV estimated PM10 impacts on hospitalization rates for children between 1 and 5 years old. The hospitalization rate is measured as the number of hospital admissions per one million children. Panel A shows the results for respiratory illnesses, and Panel B shows the results for illnesses seemingly unrelated to pollution. $1[occup_{t-7} > 0.85]$ is our *ex-ante* measure of hospital capacity constraints. *High income* is a dummy variable that indicates whether the average income of each district is above the median according to Census-2010. *Rural* is a dummy variable that indicates whether the share of the rural population of each district is above the median according to Census-2010. Each column reports coefficients from a different regression, with hospitalizations classified based on ICD-10 categories. The units of analysis are districts of the Sao Paulo Metropolitan Area, observed daily over the period 2015-2017. We include district, day-of-week, month-of-year, and year fixed effects. We also add temperature and humidity in quadratic form as controls. Standard errors in parentheses are two-way clustered by district and calendar date. *** p<0.01, ** p<0.05, * p<0.1.

Table A13: PM impacts (lagged and contemporaneous) on children's hospitalization – Respiratory illnesses

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
PM_t	2.11**	1.05	2.14*	1.90	2.22*	2.17*	2.13*
	(0.982)	(1.053)	(1.191)	(1.188)	(1.210)	(1.219)	(1.217)
PM_{t-1}		2.33**	−0.02	1.91	1.35	1.62	1.66
		(0.905)	(1.218)	(1.385)	(1.402)	(1.413)	(1.428)
PM_{t-2}			2.34**	−0.69	0.92	0.41	0.44
			(0.974)	(1.392)	(1.485)	(1.509)	(1.537)
PM_{t-3}				2.79***	0.38	1.66	1.53
				(1.032)	(1.340)	(1.456)	(1.502)
PM_{t-4}					2.18**	0.30	0.57
					(0.949)	(1.277)	(1.437)
PM_{t-5}						1.76*	1.36
						(0.935)	(1.413)
PM_{t-6}							0.33
							(0.966)
Cumulative effects	2.11**	3.39***	4.45***	5.92***	7.05***	7.91***	8.01***
	(0.98)	(1.14)	(1.32)	(1.55)	(1.70)	(1.79)	(1.82)
Dep. var. mean	44.95	44.95	44.95	44.95	44.95	44.95	44.95
Kleibergen-Paap rk Wald F-statistic	130.45	71.20	53.47	28.17	20.06	16.01	12.76
Number of districts	157	157	157	157	157	157	157
Number of days	1088	1088	1088	1088	1088	1088	1088
Observations	170078	170073	170068	170063	170058	170053	170048

Notes: This table reports alternative second stage results for children between 1 and 5 years old, considering the hospitalization rate for all respiratory illnesses as the dependent variable. We include up to 6 lags of exposure to PM10. Hospitalization rate is measured as the number of hospital admissions for respiratory illnesses per one million children. Each column reports coefficients from a different regression. Cumulative effects are the sum of all PM coefficients. The standard errors associated with the cumulative effects are in parenthesis. We use districts of the Sao Paulo Metropolitan Area. We include district, day-of-week, month-of-year, and year fixed effects. We also add temperature and humidity in quadratic form as controls. Standard errors in parentheses are two-way clustered by district and calendar date. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A14: PM impact on hospitalization by different age groups - Respiratory illnesses

	All respiratory (1)	Acute respiratory infections (2)	Chronic lower respiratory diseases (3)	Others respiratory (4)
Panel A: Children younger than 1 year old				
PM_t	3.17	3.54	1.76**	−2.12***
	(5.549)	(4.981)	(0.821)	(0.793)
$PM_t * 1[occup_{t-7} > 0.85]$	−12.23	−7.30	−4.98	0.06
	(17.747)	(16.428)	(3.430)	(1.317)
Dep. var. mean	202.17	178.93	15.04	8.21
Kleibergen-Paap rk Wald F-statistic	25.24	25.24	25.24	25.24
Number of districts	156	156	156	156
Number of days	1088	1088	1088	1088
Observations	168990	168990	168990	168990
Panel B: Children between 1 and 5 years				
PM_t	2.51**	2.04**	0.57*	−0.10
	(1.010)	(0.815)	(0.320)	(0.260)
$PM_t * 1[occup_{t-7} > 0.85]$	−3.88**	−3.91**	0.11	−0.07
	(1.813)	(1.681)	(0.634)	(0.529)
Dep. var. mean	44.95	31.76	7.11	6.08
Kleibergen-Paap rk Wald F-statistic	67.06	67.06	67.06	67.06
Number of districts	157	157	157	157
Number of days	1088	1088	1088	1088
Observations	170078	170078	170078	170078
Panel C: Children between 6 and 14 years				
PM_t	0.34	0.25	0.11	−0.02
	(0.268)	(0.160)	(0.096)	(0.169)
$PM_t * 1[occup_{t-7} > 0.85]$	0.29	−0.14	−0.23	0.67**
	(0.588)	(0.344)	(0.286)	(0.304)
Dep. var. mean	9.46	4.16	1.88	3.42
Kleibergen-Paap rk Wald F-statistic	68.92	68.92	68.92	68.92
Number of districts	156	156	156	156
Number of days	1088	1088	1088	1088
Observations	168990	168990	168990	168990

Notes: This table reports the IV estimated PM10 impacts on hospitalization rates for children younger than 1 year old (Panel A), between 1 and 5 years old (Panel B), and between 6 and 14 years old (Panel C). The hospitalization rate is measured as the number of hospital admissions per one million children for respiratory illnesses. $1[occup_{t-7} > 0.85]$ is our *ex-ante* measure of hospital capacity constraints. Each column in each panel reports coefficients from a different regression, with hospitalizations classified based on ICD-10 categories. The units of analysis are districts of the Sao Paulo Metropolitan Area, observed daily over the period 2015-2017. Compared to Panel B, we lose one additional district in Panels A and C due to the lack of admissions for the respective age group when inferring their network. We include district, day-of-week, month-of-year, and year fixed effects. We also add temperature and humidity in quadratic form as controls. Standard errors in parentheses are two-way clustered by district and calendar date. *** p<0.01, ** p<0.05, * p<0.1.

Table A15: PM impact on 3-day hospitalization for elderly above 75 years

	Circulatory (1)	Respiratory (2)	Cancer (3)	Injury and external (4)	Others (5)
PM_t	3.46	0.02	4.17*	6.90***	14.28*
	(4.017)	(3.178)	(2.468)	(2.574)	(7.646)
$PM_t * 1[occup_{t-7} > 0.85]$	6.16	9.57*	−6.17	−8.22**	−13.83
	(6.088)	(5.542)	(4.259)	(3.489)	(11.989)
Dep. var. mean	320.54	182.70	130.64	106.68	584.20
Kleibergen-Paap rk Wald F-statistic	67.05	67.05	67.05	67.05	67.05
F-stat: PM_t	65.97	65.97	65.97	65.97	65.97
F-stat: $PM_t * 1[occup_{t-7} > 0.85]$	39.77	39.77	39.77	39.77	39.77
Number of districts	156	156	156	156	156
Number of days	1088	1088	1088	1088	1088
Observations	168990	168990	168990	168990	168990

Notes: This table reports the IV estimated PM10 impacts on 3-day hospitalization rates for elderly individuals aged 75 years or more. The hospitalization rate is measured as the number of hospital admissions per one million elderly occurred within three days following the pollution measurement. $1[occup_{t-7} > 0.85]$ is our *ex-ante* measure of hospital capacity constraints. Each column in each panel reports coefficients from a different regression, with hospitalizations classified based on ICD-10 categories. The units of analysis are districts of the Sao Paulo Metropolitan Area, observed daily from 2015-2017. Compared to our main analysis, we lose one additional district due to the lack of admissions for individuals aged 75 or older when inferring their network. We include district, day-of-week, month-of-year, and year fixed effects. We also add temperature and humidity in quadratic form as controls. Standard errors in parentheses are two-way clustered by district and calendar date. *** p<0.01, ** p<0.05, * p<0.1.

Table A16: PM impacts on children's 3-day hospitalization by occupancy rate – Respiratory illnesses and illnesses seemingly unrelated to air pollution

Panel A: Respiratory illnesses	All respiratory	Acute respiratory infections	Chronic lower respiratory diseases	Others respiratory
	(1)	(2)	(3)	(4)
PM_t	9.53***	7.91***	2.31***	−0.69
	(2.749)	(2.228)	(0.808)	(0.621)
$PM_t * 1[occup_{t-7} > 0.85]$	−8.93**	−7.78*	0.68	−1.83*
	(4.383)	(4.287)	(1.763)	(1.096)
Dep. var. mean	134.80	95.25	21.32	18.23
Panel B: Illnesses seemingly unrelated to air pollution	All non-respiratory	Genitourinary	Skin and connective	Others non-respiratory
	(5)	(6)	(7)	(8)
PM_t	0.52	0.46	−0.21	0.27
	(3.509)	(1.095)	(0.626)	(2.607)
$PM_t * 1[occup_{t-7} > 0.85]$	−10.71**	−4.33***	−3.00**	−3.38
	(5.020)	(1.577)	(1.281)	(4.450)
Dep. var. mean	210.36	41.06	18.06	151.24
Kleibergen-Paap rk Wald F-statistic	67.06	67.06	67.06	67.06
F-stat: PM_t	66.66	66.66	66.66	66.66
F-stat: $PM_t * 1[occup_{t-7} > 0.85]$	46.69	46.69	46.69	46.69
Number of districts	157	157	157	157
Number of days	1088	1088	1088	1088
Observations	170078	170078	170078	170078

Notes: This table reports the IV estimated PM10 impacts on 3-day hospitalization rates for children between 1 and 5 years old. The hospitalization rate is measured as the number of hospital admissions per one million children occurred within three days following the pollution measurement. Panel A shows the results for the number of hospital admissions per one million children for respiratory illnesses, and Panel B shows the results for illnesses seemingly unrelated to pollution. $1[occup_{t-7} > 0.85]$ is our *ex-ante* measure of hospital capacity constraints. Each column in each panel reports coefficients from a different regression, with hospitalizations classified based on ICD-10 categories. The units of analysis are districts of the Sao Paulo Metropolitan Area, observed daily from 2015-2017. We include district, day-of-week, month-of-year, and year fixed effects. We also add temperature and humidity in quadratic form as controls. Standard errors in parentheses are two-way clustered by district and calendar date. *** p<0.01, ** p<0.05, * p<0.1.

Table A17: PM impacts on children's hospitalizations in public hospitals versus philanthropic hospitals - Respiratory illnesses

	All respiratory (1)	Acute respiratory infections (2)	Chronic lower respiratory diseases (3)	Others respiratory (4)
Panel A: Public hospitals				
PM_t	2.48**	1.97**	0.48	0.04
	(0.966)	(0.798)	(0.303)	(0.217)
$PM_t * 1[occup_t > 0.85]$	−3.65**	−3.57**	0.02	−0.09
	(1.745)	(1.687)	(0.604)	(0.437)
Dep. var. mean	40.69	29.66	6.28	4.75
Panel B: Philanthropic hospitals				
PM_t	0.03	0.07	0.09	−0.13
	(0.228)	(0.139)	(0.083)	(0.132)
$PM_t * 1[occup_t > 0.85]$	−0.23	−0.34	0.09	0.02
	(0.414)	(0.384)	(0.116)	(0.209)
Dep. var. mean	4.26	2.10	0.83	1.33
Kleibergen-Paap rk Wald F-statistic	67.06	67.06	67.06	67.06
F-stat: PM_t	66.66	66.66	66.66	66.66
F-stat: $PM_t * 1[occup_{t-7} > 0.85]$	46.69	46.69	46.69	46.69
Number of districts	157	157	157	157
Number of days	1088	1088	1088	1088
Observations	170078	170078	170078	170078

Notes: This table reports the IV estimated PM10 impacts on hospitalization rates for children between 1 and 5 years old. The hospitalization rate is measured as the number of hospital admissions per one million children for illnesses seemingly unrelated to air pollution. Panel A reports the results considering only admission in public hospitals. Panel B reports the results considering only admissions in philanthropic hospitals. $1[occup_{t-7} > 0.85]$ is our *ex-ante* measure of hospital capacity constraints. Each column in each panel reports coefficients from a different regression, with hospitalizations classified based on ICD-10 categories. The units of analysis are districts of the Sao Paulo Metropolitan Area, observed daily over the period 2015-2017. We include district, day-of-week, month-of-year, and year fixed effects. We also add temperature and humidity in quadratic form as controls. Standard errors in parentheses are two-way clustered by district and calendar date. *** p<0.01, ** p<0.05, * p<0.1.