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Rudi Rocha  
André Sant'Anna

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Rua Itapeva 286 | 81-84  
Bela Vista, São Paulo – SP  
01332-000 - Brasil

[www.ieps.org.br](http://www.ieps.org.br)  
+55 11 4550-2556  
[contato@ieps.org.br](mailto:contato@ieps.org.br)

# Winds of Fire and Smoke: Air Pollution and Health in the Brazilian Amazon\*

Rudi Rocha

IEPS & FGV

André Sant'Anna

BNDES & UFF

## Abstract

In this paper we assess the effects of fire-related smoke on population health in the Brazilian Amazon. Our empirical strategy is based on a municipality-by-month fixed effects model, coupled with an instrumental variables approach that explores wind direction and smoke in surrounding areas in order to exogenously shift exposure to smoke at the locality. We find that exposure to smoke, measured by PM<sub>2.5</sub> concentration levels, is robustly associated with an increase in hospital admissions for respiratory conditions. The effects are higher among children and the elderly, and increase non-linearly with pollution levels. Our benchmark estimates indicate that an increase of one standard deviation in PM<sub>2.5</sub> is related to an increase of 1.5% of the monthly hospitalization rate for respiratory conditions. The latter estimate reaches 14% if monthly average PM<sub>2.5</sub> crosses thresholds as high as  $75\mu\text{g}/\text{m}^3$ . We do not observe significant effects on hospitalization rates related to other health conditions nor on mortality rates.

**Key Words:** fires, air pollution, health outcomes, Amazon.

**JEL Codes:** I14, I18, H23, Q53.

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# 1 Introduction

Some of the poorest regions of the world have been severely exposed to greenhouse gas emissions originated from landscape fires, which release around two petagrams of carbon into the atmosphere every year, in particular stemming from tropical forests, grasslands and the savanna (Van der Werf et al., 2010). While there exist increasingly concerns as well as understanding about how fire activity and related deforestation have contributed to global greenhouse gas emissions, reshaped the environment, and influenced the Earth system, less attention has been paid to their potentially detrimental health impacts on local populations (Johnston et al., 2012; Van der Werf et al., 2010). Yet, many of the chemical components in biomass smoke are known to be hazardous to human health, specially fine particulate matter, which can penetrate the pulmonary alveolus, reach the blood, accumulate in other human organs and cause DNA damage (de Oliveira Alves et al., 2017; Guan et al., 2016).

In this paper we assess the effects of fire-related air pollution on population health in the Brazilian Amazon, which is home of 23 million inhabitants and spans over a large and heterogeneous area in terms of population characteristics and patterns of land-use and deforestation. The economic activity is mostly driven by agriculture, the region is sparsely inhabited and there are relatively few and scattered urban settlements. In that sense, ambient air pollution is mainly related to fires and biomass burning (Reddington et al., 2015). While fire activity tends to increase with droughts in specific years, it is often related to anthropogenic degradation and agricultural practices. Most deforested plots in the Brazilian Amazon are burned in preparation for cattle ranching, crop and mining activities (Motta, 2002). Approximately 42% of the total Brazilian greenhouse gas emissions have originated from land cover change in the region, which has recently witnessed an outbreak of deforestation-related fires and a surge in biomass smoke (Silvério et al., 2019; Brasil, 2018).

More specifically, in this paper we empirically assess and characterize the extent to which air pollution, as a relevant by-product of fire activity and environmental degradation, affects health outcomes in the Amazon. We focus on the Brazilian Legal Amazon, which is a sociopolitical division that encompasses 772 municipalities, covers approximately 5 million km<sup>2</sup> and 59% of the Brazilian territory. Our empirical strategy is based on a municipality-by-month fixed effects model, coupled with an instrumental variables approach, which exploits sources of exogenous variation in air pollution to elicit causality and overcome identification concerns — in particular those related to the potentially confounding influence of economic activity as well as to measurement error in environmental indicators. Our instrument is a composite term that combines monthly variation in wind direction with air

pollution in surrounding municipalities. More precisely, the first-stage relationship relies on the fact that air pollution levels in a given municipality and time positively respond to levels in neighboring municipalities when winds blow from these surrounding areas. Our identifying assumption is that, conditional on fixed-effects and time-varying controls, in a high-frequency setting, the remaining variation in wind direction in neighboring areas is arguably exogenous to the municipality. If this assumption is valid, the instrument is expected to exogenously shift local air pollution levels.

Our analysis is based on a panel of monthly data at the municipality level on concentrations of fine particulate matter (PM<sub>2.5</sub>) and health outcomes throughout the 2010 decade. We use administrative microdata on mortality and hospital admissions from the Brazilian Ministry of Health (MS/Datasus), which are converted into monthly death and hospitalization rates by age groups and specific causes (ICD-10). We mainly focus on respiratory conditions but also analyze other infectious and chronic diseases. These data are matched at the municipality of residence level and time of the event (death or hospital admission) to monthly data on air pollution, wind direction and other weather indicators, originally collected from satellite imagery and processed by the Environmental Health Information System (*Sistema de Informações Ambientais Integrado à Saúde*, SISAM), a joint-initiative by the National Institute for Space Research (INPE), Fiocruz, and the Brazilian Ministry of Health.

We find that exposure to PM<sub>2.5</sub> concentration is robustly associated with an increase in hospital admissions for respiratory conditions. Our benchmark estimates indicate that an increase of one standard deviation in PM<sub>2.5</sub> concentration ( $SD = 17.3\mu\text{g}/\text{m}^3$ ) is related to an increase of 0.95 hospital admissions per 100,000 inhabitants per month, or 1.5% of the monthly average rate. Yet, we uncover relevant heterogeneous and non-linear effects. We find that children and the elderly are hit the most, and that hospital admissions by respiratory conditions increase as much as 14% of the average rate if monthly PM<sub>2.5</sub> levels cross thresholds as high as  $75\mu\text{g}/\text{m}^3$  — this corresponds to three times the threshold of  $25\mu\text{g}/\text{m}^3$  in the 24h mean, above which we can expect higher risk for acute and chronic health effects from air pollution according to the WHO air quality guidelines for short-term exposures (WTO, 2006). We do not observe any significant effects on hospitalization rates related to other conditions nor on mortality rates. In short, we find that acute variation in exposure to air pollution in the Brazilian Amazon, as marked by monthly changes in PM<sub>2.5</sub> concentration levels, is associated with an increase in hospital admissions for respiratory conditions specifically, in particular among age groups that are typically more sensitive to air pollution.

The dense research on the health consequences of exposure to air pollution has mainly fo-

cused on urban environments and atmospheric pollution related to fossil fuels (eg. [Deryugina et al., 2019](#); [He et al., 2019](#); [Schlenker and Walker, 2016](#); [Ward, 2015](#); [Currie and Neidell, 2005](#)), while the causal effects of pollutants released by biomass smoke have been less extensively examined. Much of the existing evidence comes from indoor environments where pollutants stem from household solid fuel use or from global accounting exercises (eg. [Hanna et al., 2016](#); [Johnston et al., 2012](#); [Ezzati and Kammen, 2001](#)). Evidence on the causal effects of outdoor air pollution related to biomass burning is scarcer in general. [Rangel and Vogl \(2019\)](#) document that *in utero* exposure to upwind smoke related to agricultural fires in the state of São Paulo, Brazil, has detrimental impacts on birth outcomes. [He et al. \(2020\)](#) show that the elderly in China are sensitive to exposure to air pollution related to straw burning. Causal evidence related to forest fires is even scarcer, and comes from context-specific massive pollution shocks, as in the case of wildfires in the US ([Burke et al., 2020](#)) and the major forest fires that hit Indonesia in the late 1990s (eg. [Tan-Soo and Pattanayak, 2019](#); [Jayachandran, 2009](#); [Frankenberg et al., 2005](#)). In that latter case, the 24h total suspended particulate concentration reached atypically impressive levels as high as  $4,000\mu\text{g}/\text{m}_3$  in October 1997 in parts of Sumatra. Regarding the Amazon context, the existing literature often relies on correlational methods and concentrates on case studies targeted at specific localities. For instance, [Jacobson et al. \(2014\)](#) study the effects of biomass smoke from seasonal fires on schoolchildren's health in Tangará da Serra, a municipality of the state of Mato Grosso. [Carmo et al. \(2010\)](#) study the time-series relationship between particulate matter and respiratory diseases in the municipality of Alta Floresta, also in Mato Grosso.

We contribute novel evidence to the literature by assessing and fully characterizing the causal effects of deforestation-related smoke on health outcomes in the Brazilian Amazon. Whether routine, moderate variations in exposure to biomass smoke affect health conditions in a vast, open and sparsely inhabited setting is an open question. Yet, it is relevant as local populations are overwhelmingly poor and generally underserved by public services and economic opportunities, as is typically the case of agricultural contexts of developing countries. Still, the Amazon hosts a large stock of carbon at risk of being released to the atmosphere as greenhouse gas emissions, with consequences that might extend far beyond the limits of the region ([Fearnside, 2018](#)). Particulate matter may travel hundreds of kilometers and reach regions not directly affected by deforestation ([Barcellos et al., 2019](#)).

We also characterize the results in a series of heterogeneity analyses, by documenting effects by age, specific health conditions, and by intensity of exposure. Most studies on biomass burning focus on infant health (eg. [Rangel and Vogl, 2019](#); [Tan-Soo and Pattanayak, 2019](#); [Jayachandran, 2009](#)), with scant evidence on older ages and across specific causes.

By providing a comprehensive characterization of biomass smoke effects on health outcomes, we contribute potentially informative evidence to policymaking by revealing socioeconomic costs beyond those directly associated with environmental degradation and biodiversity loss. In particular, we document that air pollution related to forest fires has detrimental health impacts on local populations.

The remainder of this paper is organized as follows. Section 2 provides the background. Section 3 describes the data, while Section 4 presents our empirical strategy. We present the main results in Section 5, together with heterogeneity analyses, robustness checks and additional discussion. Section 6 concludes.

## 2 Health and Air Pollution in the Brazilian Amazon

In 1988, Brazil established universal and egalitarian access to health care as a constitutional right, and in the following years introduced the Unified Health System (*Sistema Único de Saúde*, SUS). The system follows a social insurance model of financing of health care, designed with the aim of guaranteeing free universal health coverage. Over the last decades, SUS has successfully expanded access to health services throughout the country, improved health outcomes, and reduced health inequalities (Castro et al., 2019; Bhalotra et al., 2019). However, inequalities in access to health care persist and many regions and populations remain underserved. This is particularly the case of the Brazilian Amazon, where hospital capacity as well as physical and human resources in health are scarce (Rache et al., 2020). Yet, the 23 million inhabitants of the region are overwhelmingly poor and typically resort to SUS for health care (Garnelo, 2019; Viana and Iozzi, 2019).

The Brazilian Amazon spans over a large and heterogeneous area in terms of ethnical settlements, demographics, epidemiological characteristics, drivers of economic growth and patterns of land-use and deforestation. In this paper we focus on municipalities located in the Brazilian Legal Amazon, which is a sociopolitical division that encompasses the states of Acre, Amapá, Amazonas, Mato Grosso, Pará, Rondônia, Roraima, Tocantins, and the western part of Maranhão state, and has long been used to territorially define and implement public regulation and policy efforts. The Brazilian Legal Amazon covers approximately 5 million km<sup>2</sup> and 59% of the Brazilian territory (IBGE, 2004). Much of its Southern area overlaps with the so-called Arc of Deforestation, a region strained by the agricultural frontier and that has experienced acute deforestation (Assunção et al., 2020).

In the Amazon, economic activity is mostly driven by agriculture, the region is sparsely inhabited and there are relatively few and scattered urban settlements. In that sense, air

pollution is mainly related to fires and deforestation (Reddington et al., 2015). Most deforested plots in the Amazon are burned in preparation for cattle ranching, crop and mining activities (Motta, 2002). Fire activity tends to increase because of droughts as well, which are often triggered by El Niño in specific years. The burned biomass generates many pollutants, such as CO<sub>2</sub>, CO, NO<sub>x</sub> and particulate matter, especially PM<sub>2.5</sub>, which refers to particles with aerodynamic diameter  $\leq 2.5\mu\text{m}$ , and consists of organic and black carbon components along with contributions from inorganic compounds (Johnston et al., 2012). PM<sub>2.5</sub> may have significant impacts on human health as they can penetrate the pulmonary alveolus, reach the blood, accumulate in other human organs and cause DNA damage (de Oliveira Alves et al., 2017; Guan et al., 2016; Kim et al., 2015).

Fires, air pollution and health outcomes are thus potentially linked in the region. In this paper, we empirically assess whether and to what extent air pollution, as a relevant by-product of fires and deforestation, affects health outcomes in the Brazilian Legal Amazon. In what follows, we describe the data used in our analysis and document descriptive statistics for our main variables.

### 3 Data and Descriptive Analysis

#### 3.1 Data

Our analysis relies on a balanced panel of monthly data at the municipality level on air pollution and health outcomes throughout the 2010 decade. The sample covers all the 772 municipalities of the Brazilian Legal Amazon.

We use data on mortality and hospital admissions from the Brazilian Ministry of Health (MS/Datasus). We obtain mortality microdata from the Brazilian National System of Mortality Records (Datasus/SIM), which collects records on every death officially registered in Brazil and includes the deceased's age, gender, as well as the diagnostic codes according to the International Classification of Diseases, 10th Revision (ICD-10). Hospitalization microdata are obtained from the National System of Information on Hospitalizations (Datasus/SIH), which contains administrative information at the hospital admission level and are managed by the Health Care Agency (SAS/Ministry of Health). The system includes all hospital admissions covered by SUS, both in public facilities and private hospitals accredited by the government, and provides information on patients' age, gender and cause of hospitalization (ICD-10). Both SIM and SIH microdata sets include patients' municipality of residence and the date of the event (death or hospital admission). The date of the event and the code of the municipality of residence are used to aggregate the microdata into a

municipality-by-month data set and to match with data from other sources.

We follow the literature on the effects of air pollution on health and focus specifically on concentration of PM<sub>2.5</sub> and respiratory diseases, but extend our analysis to other conditions in additional exercises (infectious, circulatory, neoplasms and digestive diseases).<sup>1</sup> We also compute outcome indicators by age brackets separately to shed light on heterogeneities. He et al. (2020) document that the elderly in China suffer more from ambient air pollution related to straw burning. Rangel and Vogl (2019) focus on birth outcomes in a study on the effects of agricultural fires at São Paulo state, Brazil. Most of the research on air pollution related to forest fires concentrates on infant outcomes (eg. Tan-Soo and Pattanayak, 2019; Jayachandran, 2009; Frankenberg et al., 2005). We therefore analyze in detail outcomes for children (<1yo and 1-5yo) and the elderly (>60yo) as these groups are potentially the most susceptible to variations in air pollution in our empirical setting as well.

We standardize health outcomes in order to facilitate comparisons across municipalities and time. Age-stratified population is not available at the municipality-by-month level, so we compute health outcomes (such as hospitalizations related to respiratory diseases) in rates per 100,000 municipality inhabitants, which is estimated in an annual basis by the Brazilian Institute of Geography and Statistics (IBGE). Our analysis relies on a fixed-effects estimation and focus on a relatively short period of time, so the age distribution of the population is not expected to vary substantially nor to affect our estimates.

We use monthly data on ambient air pollution at the municipality level also from January 2010 throughout December 2019, originally collected by the Environmental Health Information System (*Sistema de Informações Ambientais Integrado à Saúde*, SISAM), a joint-initiative by the National Institute for Space Research (INPE), Fiocruz, and the Ministry of Health. We mainly utilize data on the concentration of fine particulate, PM<sub>2.5</sub>, as measured in  $\mu\text{g}/\text{m}^3$ . This variable is originally obtained from the Copernicus Atmosphere Monitoring Service, from the European Centre for Medium-Range Weather Forecasts. Original data are gathered at intervals of 6-hour and have a spatial resolution of  $12.5 \text{ km}^2$ . INPE performs numerical and satellite imagery analysis and provides a dataset at the municipality level, still with a 6-hour interval. We average the data at the monthly level, which is considered informative and methodologically recommended by INPE guidelines.

In order to characterize the relationship between air pollution and fires in a descriptive analysis, we use monthly data on fire occurrence as measured by the number of active fire hotspots. These data are collected by the National Institute for Space Research (INPE)

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<sup>1</sup>Respiratory conditions refer to events classified under ICD-10 J00-J99.

to monitor the spatial and temporal dynamics of fires in Brazil. The data are originally obtained from the MODIS sensor on board of the Aqua satellite, which captures fire heat at a resolution as small as  $100\text{m}^2$ . The data are available from January 2010 to December 2019 and are converted into a dataset at the municipality-by-month level containing indicators of fire activity.

Finally, we also collect weather variables to be used as controls in our estimations as well as wind direction. Control variables include monthly data on precipitation, relative humidity and temperature. Wind direction is measured in azimuth degrees and is averaged at the month-municipality level. All weather variables are extracted from SISAM and cover the January 2010 throughout December 2019 period, with few missing observations. As in the case of other indicators, INPE gathers original data from the European Centre for Medium-Range Weather Forecasts as well as from the Weather Research and Forecasting Model (for 2019 only).

Our final sample contains 92,640 observations ( $10 \text{ years} \times 12 \text{ months} \times 772 \text{ municipalities}$ ). Mortality outcomes are available only until December 2018. There are 100 municipalities with missing observations in weather indicators in 2019, and 16 municipalities with missing observations for wind direction in surrounding areas in total. In our main tables and figures we present results based on samples with valid observations, and provide robustness checks for balanced samples in Appendix Section B, where we consider only municipalities without any missing observations during the entire period of analysis. The results are quantitatively similar.

## 3.2 Descriptive Statistics

Table 1 provides descriptive statistics for our main variables as well as their source of information and period of time for which the data are available. All variables and descriptive statistics are computed at the municipality-by-month level. We observe that the monthly average hospital admission rate for respiratory conditions ranks relatively high, at 63.5 per 100,000 inhabitants, together with hospital admissions for infectious diseases, while mortality rates are relatively lower. The average death rate for respiratory conditions is 3 per 100,000 inhabitants.

The average hospitalization rate for respiratory conditions is relatively high, but masks substantial seasonality within years. The upper graphic of Figure 1 plots hospitalizations related to respiratory diseases from January 2010 to December 2019 and shows that the monthly average peaks in the first semester, specifically around May of each year, which marks the beginning of the driest season in the Amazon. We also observe a salient rebound

amidst the decay of the series throughout the beginning of the second semester. The bottom graphic plots hospitalization rates for other conditions. We observe a stable pattern for most conditions, except for infectious diseases, which generally follow a more erratic seasonal trend within years.

As previously mentioned, in the Amazon the concentration of air pollutants is mainly determined by fires related to deforestation and land use (Reddington et al., 2015). This is clearly shown on the upper plot of Figure 2, which displays the patterns of PM2.5 concentration and fire activity. The horizontal line represents the Air Quality Guideline threshold at  $25\mu\text{g}/\text{m}^3$  for PM2.5 concentration, established by the World Health Organization for the 24h-mean (WTO, 2006). We observe a seasonal pattern in which both PM2.5 and fires trends go upwards around July and last until September. It is also clear that PM2.5 concentration often crosses the 24h-threshold of air quality, above which we can expect increased risk for acute and chronic health effects from short-term exposure to air pollution. Notably, the bottom plot of Figure 2 shows that fire activity is closely related to an upward rebound along the decay of hospitalization rates for respiratory conditions in the second semester. This suggests a positive association between fire-related pollution and hospital admissions. Indeed, while the rebound seems small in light of the seasonal aggregated trend, not all municipalities are exposed to fires and PM2.5 concentration in the region. In that sense, local effects can be sizable. In the following sections, we assess in detail the relationship between air pollution and health outcomes in the Brazilian Legal Amazon.

## 4 Empirical Model

In this paper we empirically estimate the effects of air pollution and health outcomes in the municipalities of the Brazilian Legal Amazon. To do so, we rely on a municipality-by-month panel of data and explore idiosyncratic variation in air pollution across municipalities for causal identification. The following equation provides the conceptual setup:

$$Y_{mt} = \alpha_m + \gamma_t + \beta \text{AirPollution}_{mt} + \mathbf{X}'_{mt} \Theta + v_{mt} \quad (1)$$

Where  $Y_{mt}$  is an outcome of interest for municipality  $m$  in time  $t$ ,  $\text{AirPollution}_{mt}$  indicates PM2.5 concentration, and  $\alpha_m$  and  $\gamma_t$  are municipality and time fixed-effects, respectively. The term  $\alpha_m$  absorbs the confounding influence of persistent municipality characteristics, such as climate and local epidemiological features as well as access to public services and

physical infrastructure that are not expected to vary within a short span of time. The term  $\gamma_t$  control for common time trends, such as macroeconomic conditions, the political cycle and meteorological phenomena that might potentially affect the region at large (e.g. droughts episodes triggered by El Niño). The term  $\mathbf{X}_{mt}$  is a vector of time-varying weather controls, which should help absorb the independent influence of temperature, rainfall and humidity conditions on outcome variables. In our most saturated specifications, the term  $\mathbf{X}_{mt}$  also includes municipality-specific linear trends in order to absorb any confounding influence of non-observable time trends across municipalities. The term  $v_{mt}$  is the error component, and we cluster standard errors at the municipality level to allow for serial correlation within cross-sectional units, over time, as idiosyncratic disturbances may be persistently correlated within municipalities on a monthly basis.

We rely on seasonal and cross-sectional variation in air pollution for identification, in particular on the fact that air pollution levels vary across years as well as across municipalities, for a given point in time and irrespective of the calendar month. This is shown in Figure 3. The upper graphic shows that average PM2.5 concentration varies across calendar months, sharply increasing during the dry season up to September. Notwithstanding that aggregated pattern, the plot just below shows that not all municipalities are exposed to high levels of air pollution, even in September, when about 45% of the municipalities are exposed to average levels of PM2.5 above  $25\mu\text{g}/\text{m}^3$ . The bottom figure plots the same statistics for the month of September, across different years. We observe that the share of municipalities exposed to levels of PM2.5 above  $25\mu\text{g}/\text{m}^3$  varies from about 20% to 60%. For levels superior to  $75\mu\text{g}/\text{m}^3$ , we find a range generally from 5% to nearly 20%.

Should variation in air pollution be random, conditional on fixed-effects and time-varying controls, our parameter of interest  $\beta$  would capture its causal effects on outcome variables. Air pollution indeed carries exogenous variation as winds tend to reallocate air pollutants across different areas. [Rangel and Vogl \(2019\)](#), for instance, explore wind direction as a source of exogenous variation for exposure to fire-related pollution in the state of São Paulo, Brazil. As [Barcellos et al. \(2019\)](#) argue, particulate matter may travel hundreds of kilometers in the Brazilian Amazon as winds can spread pollution to distant regions and away from fire sources.

However, even conditional on time and municipality fixed-effects, there might still exist some remaining variation in air pollution potentially endogenous to the municipality. The first main potential confounder is economic activity, unobserved at high-frequency, which might affect health outcomes through income and other competing channels. We conjecture that the confounding influence of the economic activity may attenuate our estimates

as income is expected to be positively correlated with health. In fact, fire-related pollution is typically led by deforestation and land use choices in our empirical setting. We may also face measurement error in our variables of interest as they are collected from satellite imagery analysis and reprocessed at the municipality level. In particular, weather conditions might correlate both with health outcomes and imagery quality, potentially leading to another source of attenuation bias. This is expected if clouds and humidity are correlated both with better respiratory conditions and worse imagery quality and detection capacity.

In order to overcome concerns related to omitted variables and measurement error, we rely on two sets of robustness checks. First, we rely on equation 1 to provide falsification tests by assessing patterns in other health conditions that are supposedly less directly affected by air pollution. We also check the sensitivity of our estimates to the inclusion of weather controls as a way of testing not only for the influence of other omitted variables but also measurement error. Overall, we find a robust contemporary effect of air pollution on respiratory conditions specifically. We also find larger point estimates whenever we control for weather indicators. These patterns help reassure the existence of a causal impact of air pollution on respiratory conditions, albeit eventually recovered as a lower bound of the true effect.

Second, we complement our analysis by following an instrumental variable approach with the particular aim of exogenously shifting and gaining variation in local air pollution irrespective of local economic activity related to fire occurrence and land-use patterns.<sup>2</sup> In our instrumental variable approach, the term  $AirPollution_{mt}$  in equation 1 is instrumented by a composite interaction term between wind direction and air pollution in neighboring municipalities. More specifically, the instrumental variable is defined by:

$$AirPollution_{mt}^N = \sum_{i \in N} AirPollution_{it} \times \mathbb{1}(Location_{it}^a * Wind_{it}^a) \quad (2)$$

Where  $N$  refers to the group of municipalities  $i$  that share their borders with municipality  $m$ , and  $AirPollution_{it}$  corresponds to PM2.5 concentration recorded in municipality  $i$  and month  $t$ . The term  $\mathbb{1}(Location_{it}^a * Wind_{it}^a)$  is a dummy that indicates whether (i) the centroid of municipality  $i$  is located in the quadrant  $a \in (0^\circ - 90^\circ, 91^\circ - 180^\circ, 181^\circ - 270^\circ, 271^\circ - 360^\circ)$ , in respect to  $m$ 's centroid, and (ii) the average wind direction in municipality  $i$  and month  $t$  blowing towards municipality  $m$  as measured in terms of quadrants as well. For

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<sup>2</sup>The use of variation in wind direction as IV to local air pollution was originally proposed by [Deryugina et al. \(2019\)](#) for the US context.

instance, suppose that a given municipality  $i$  is located Northeastern from municipality  $m$ . In this case, we assign the air pollution recorded in  $i$  and month  $t$  to municipality  $m$  if the average wind direction recorded in  $i$  and  $t$  blew towards the Southwestern quadrant of  $i$ . The term  $AirPollution_{mt}^N$  thus computes a proxy for the total PM2.5 that was carried by the wind from  $m$ 's neighboring municipalities  $i \in N$  and reached out municipality  $m$  in time  $t$ .

The term  $AirPollution_{mt}^N$  is a valid instrument as long as we have sufficient variation in the first-stage relationship and the exclusion restriction holds. We formally inspect the first stage in Appendix Table A.1. All specifications follow equation 1, but we replace the dependent variable by PM2.5 concentration. In the first column we include only municipality and time fixed-effects. We add weather controls in the second specification, and municipality-specific linear time trends in the remaining one. We find robust and stable coefficients in the range of 0.22 to 0.24, with partial F-statistics no lower than 257. The point estimate in the third column suggests an implicit conversion of 1:0.24 PM2.5 of neighboring air pollution into local air pollution.

The exclusion restriction is valid if the instrumental variable is uncorrelated with any other latent determinant of health outcomes but air pollution in municipality  $m$ . Our identifying assumption is that, conditional on fixed-effects and time-varying controls in a high-frequency setting, the remaining variation in wind direction in neighboring municipalities is arguably exogenous to municipality  $m$ . If this assumption is valid, the term  $AirPollution_{mt}^N$  is therefore expected to exogenously shift air pollution levels in municipality  $m$ . In fact, conditioned upon fixed-effects and time-varying controls, the remaining variation in the instrument should capture changes in local air pollution arguably attributable to idiosyncratic changes in wind direction. In this case, we do not rely on typical prevailing wind directions, which means that our approach is expected to capture the effects of exposure of acute variation in air pollution rather than in climatic conditions.

In the remaining column of Appendix Table A.1 we examine whether the patterns underneath the first-stage relationship between local and surrounding air pollution are generally consistent with the geography of our empirical setting. As mentioned in Section 2, much of the Southern area of the Brazilian Legal Amazon overlaps with the so-called Arc of Deforestation, a region strained by the agricultural frontier and that has experienced acute deforestation and fire activity. In this case, we expect increased air pollution should winds blow from the southeast to northwest. Consistent with that, in column 4 we observe that local PM2.5 is positively associated with an interaction term between a dummy indicating winds blowing from southeast and PM2.5 levels in southeastern neighbors, and negatively associated with a similar interaction term, but computed with a dummy indicating winds

blowing from northwestern neighbors.

## 5 Results

In this section we first report our main results on hospitalization and mortality rates for respiratory conditions. We then explore heterogeneity by intensity of exposure, extend our analysis to other health conditions and different age brackets, provide robustness checks and discussion.

### 5.1 Air Pollution and Respiratory Conditions

Table 2 presents the effects of air pollution on hospital admission and mortality rates for respiratory conditions. Panels A and B report the results of OLS and 2SLS specifications, respectively. The first three columns present results for hospital admissions. In the first column we include only municipality and time fixed-effects. We add weather controls in the second specification, and municipality-specific linear time trends in the remaining one. Columns 4-6 replicate the same series of specifications for mortality rates. In the first column of Panel A, we find a positive but small and borderline significant coefficient of 0.021 for hospitalization rates, which increases to 0.06 and remain stable and robust at 0.055 as we include weather controls and municipality specific time trends, respectively. The same pattern is observed across 2SLS specifications, standing out a remarkably similar point estimate of column (0.055) in comparison to the OLS results. This suggests a limited role for concerns related to attenuation bias in our empirical setting.<sup>3</sup> Regarding mortality rates, we observe small and statistically insignificant point estimates in the remaining columns, irrespective of the specification.<sup>4</sup>

The point estimate of 0.055 means that an increase of one standard deviation in PM2.5 concentration ( $SD = 17.3\mu\text{g}/\text{m}^3$ ) is associated with an increase in increase of 0.95 hospital admissions per 100,000 inhabitants per month, or 1.5% of the average rate (63.5). Yet, air pollution can have nonlinear effects on health (Graff Zivin and Neidell, 2013). We allow for nonlinear effects by examining how outcomes vary in response to whether average monthly PM2.5 levels crossed the World Health Organization Air Quality thresholds.

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<sup>3</sup>This result suggests that, conditional on fixed-effects and controls, the remaining variation in economic activity is not a relevant confounder in our empirical setting. This pattern can be explained should pecuniary gains from fire-related activity be accrued by few individuals.

<sup>4</sup>Appendix Table B.1 presents the same series of results for balanced samples of municipalities, i.e., those without any missing observations during the entire period of analysis. We observe slightly higher, but statistically similar coefficients.

More specifically, we rely on our most complete OLS specification, the same as reported in columns 3 and 6 of Table 2, and assess the relationship between health outcomes and the following indicators: (i) WHO IT 3 refers to the Interim Target 3, which is equal to one if average PM2.5 is in the range between 25 and  $37.5\mu\text{g}/\text{m}^3$ ; (ii) WHO IT 2 refers to the Interim Target 2, which corresponds to the range between 37.5 and  $50\mu\text{g}/\text{m}^3$ ; (iii) WHO IT 1 refers to the Interim Target 1, between 50 and  $75\mu\text{g}/\text{m}^3$ ; (iv) finally, the marker above WHO IT 1 refers to air pollution above interim target 1. We run the same specification for hospitalization and mortality rates.

Figure 4 reports point estimates and confidence intervals at 95% for hospitalization and death rates of respiratory conditions, respectively in the upper and bottom graphics. In both regressions the omitted category is PM2.5 below  $25\mu\text{g}/\text{m}^3$ , so interpretation of point estimates refers to benchmark levels below which we can expect lower risk for acute and chronic health effects from air pollution. We observe a clear non-linear relationship for hospitalization rates, with a statistically significant and large coefficient for the indicator of PM2.5 levels above  $75\mu\text{g}/\text{m}^3$ . The point estimate is 8.88 (SD = 1.43), equivalent to 14% of the average rate. Regarding mortality rates, we observe again insignificant and smaller point estimates across all markers.

## 5.2 Effects on Other Health Conditions

In Table 3 we assess whether air pollution has detrimental effects on hospital admissions by other health conditions as well as on the total hospitalization rate. In the first column, we replicate again our most complete OLS and 2SLS specifications for hospital admissions by respiratory conditions. We follow the same specifications in the following four columns, which report results for infectious and cardiovascular diseases, neoplasms, and digestive diseases. In the remaining column we assess effects on total hospitalization rates, which consider all causes. Overall, we find a robust effect of air pollution on respiratory conditions specifically. While the point estimate for hospital admissions for infectious diseases is relatively large and statistically significant in the OLS panel, it drops in magnitude and become insignificant in the 2SLS specification. We observe statistically insignificant coefficients across all the remaining conditions and for total hospital admissions.

Appendix Table A.2 replicates the same series of specifications for mortality rates. Overall, we find small and statistically insignificant point estimates across the board. Point estimates are generally positive, except for infectious diseases, and borderline significant for neoplasms and significant at 5% for total mortality in the OLS specification. Point estimates remain small in magnitude and are always statistically non-significant in the 2SLS

specifications. Considering the point estimate of 0.07 in the last column of Panel B, we find that an increase of one standard deviation in PM2.5 concentration ( $SD = 17.3\mu\text{g}/\text{m}^3$ ) is associated with an increase of 0.12 in the total number of deaths per 100,000 inhabitants per month, or 0.3% of the average rate (35.3). The magnitude of the effects on death rates by circulatory conditions and neoplasms is relatively larger, but cannot be statistically distinguished from zero.

### 5.3 Heterogeneity by Age

In Table 4 we assess whether effects are heterogeneous across age groups. Given the results from the previous sections, we now look specifically at hospitalization rates by respiratory conditions. As mentioned in Section 3, many studies have focused on age groups that are potentially the most susceptible to exposure to air pollution. [Deryugina et al. \(2019\)](#) find detrimental effects of high levels of PM2.5 concentration on hospital admissions and deaths among the elderly in the US, while [He et al. \(2020\)](#) document that the elderly in China suffer more from air pollution related to straw burning. [Rangel and Vogl \(2019\)](#) focus on infant health in a study on agricultural fires in the state of São Paulo, Brazil, and find negative effects of exposure to upwind fires on birth outcomes. We analyze outcomes separately for younger and older children, adults and the elderly. The age group in column 1 of Table 4 refers to children with less than one year old, in columns 2 and 3 we look at children of age between 1-5 and between 6-14 years old, respectively. The remaining two columns report results for individuals aged 15-59 and 60 or more. We follow our most complete OLS and 2SLS specifications, the ones reported in column 3 of Table 2.

Overall, we find that both children and the elderly are those who suffer the most with exposure to air pollution. The 2SLS coefficient for children below 1 year old is not statistically significant, as the standard error is relatively large, but is greater in magnitude in comparison to the OLS point estimate. Considering 2SLS estimates, we find that an increase in one standard deviation in PM2.5 levels is associated with an increase of 0.20 and 0.37 hospital admissions by respiratory conditions per 100,000 inhabitants per month, or 1.5% and 2.5% of the average rate, respectively for children and the elderly. Similarly to what is observed in other contexts, these are the age groups that suffer the most with air pollution in the Brazilian Amazon. Together with results from the previous sections, the overall findings indicate that the relationship between exposure to air pollution and health conditions in the Brazilian Amazon follows specific patterns by age and cause.<sup>5</sup>

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<sup>5</sup>For the sake of completeness, in Appendix Table A.3 we report effects on mortality by age and specific cause. We focus on infants and the elderly, and report only the results from the complete 2SLS specification so to keep the table concise. We generally find small and insignificant coefficients, except for a potentially

## 5.4 Robustness Checks and Discussion

We relied on alternative estimating approaches and checked the sensitivity of our estimates to the inclusion of time-varying controls in order to overcome identification concerns. We also explored the sensitivity of the effects in a series of heterogeneity analyses to further characterize the relationship between air pollution and health outcomes in the Brazilian Amazon as well as to check the overall consistency of the results in light of the main hypotheses and the previous evidence in the literature. We now perform an additional set of robustness tests and provide further discussion on the results.

We first test how sensitive are our main estimates to autocorrelation in weather and air pollution. In Appendix Table B.2, we replicate our benchmark results in columns 1 and 4, respectively for hospital admissions and mortality by respiratory conditions. In the following columns 2 and 5, we control for two lags of local weather indicators as well as for two lags of our instrument, as variation in weather and surrounding air pollution can be potentially autocorrelated and have lagged effects on health conditions. We observe that point estimates for hospital admissions increase both in the OLS and 2SLS specifications, while the effects remain very small and statistically insignificant for death rates. In the following columns 3 and 6 we include two lags and two leads of local PM2.5 in order to test how sensitive is the contemporary effect of PM2.5 on health outcomes. We observe that the estimates for hospital admissions slightly decrease but remain roughly in the range of 0.05 to 0.07. This result helps us reassure the interpretation that the estimated effect of PM2.5 concentration levels on hospitalization rates is contemporary and relatively stable across specifications. The effects of death rates remain small and statistically insignificant.

Finally, in columns 4 and 8 we include an alternative composite term that is the counterpart of our instrument, in the sense that it computes a proxy for the total PM2.5 in surrounding areas that is blew away from the municipality.<sup>6</sup> As similarly discussed in [Rangel and Vogl \(2019\)](#), this variable would capture potentially positive spillovers of economic activity in surrounding areas on health outcomes, eventually net of the negative effects of exposure to air pollution. In column 4, we still observe robust positive effects of local PM2.5 on hospital admissions by respiratory conditions, in the range of 0.05 to 0.07. The point estimates for the alternative composite term is actually negative, as predicted by the spillover hypothesis, but small in magnitude and statistically insignificant.

In sum, the results from Appendix Table B.2 reinforce the existence of a direct causal effect

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noisy result for neoplasms among infants.

<sup>6</sup>More specifically, we use equation 2 and replace the dummies that indicate upwind by dummies that indicate winds blowing to the opposite direction.

of local PM<sub>2.5</sub> levels on hospitalization rates for respiratory conditions. We also observe that point estimates are statistically similar across specifications in columns 1-4 and, among them, our benchmark coefficient of 0.055 can be interpreted as a conservative parameter for the contemporary effect of local PM<sub>2.5</sub> on respiratory health. Notably, we find smoke-related detrimental effects specifically on hospital admissions for respiratory conditions, particularly among infant and the elderly. We do not observe significant effects on hospitalization rates related to other health conditions (eg. on cardiovascular diseases) nor on mortality rates, as documented in other contexts (eg. [Deryugina et al., 2019](#); [He et al., 2020](#)).

## 6 Final Remarks

In this paper we evaluated the causal links between fire-related air pollution on health outcomes in the Brazilian Amazon. Despite being sparsely inhabited and driven by agriculture, the region experiences important peaks in air pollution, which are mainly related to fires and deforestation.

Relying on a municipality-by-month fixed effects model, coupled with an instrumental variables approach based on a composite term that combines monthly variation in wind direction with air pollution in surrounding municipalities, we documented a robust association between exposure to PM<sub>2.5</sub> concentration and an increase in hospital admissions for respiratory conditions. More specifically, our benchmark estimation indicates that an increase of one standard deviation in PM<sub>2.5</sub> concentration is related to an increase of 1.5% of the monthly average rate. Moreover, we also characterized the results in a series of heterogeneity analyses, by documenting effects by age, specific causes, and by intensity of exposure. We find that children and the elderly are hit the most, and that hospital admissions by respiratory conditions increase as much as 14% of the average rate if monthly PM<sub>2.5</sub> levels cross thresholds as high as  $75\mu\text{g}/\text{m}^3$ , which corresponds to three times the threshold of  $25\mu\text{g}/\text{m}^3$  24-hour mean according to the WHO air quality guidelines for short term exposures.

Our results contribute novel evidence to the literature. Despite being a relevant topic, there has been scarce causal evidence on the effects of ambient air pollution from biomass burning on health outcomes. As deforestation-related fires rebound, these results evince important negative externalities related to the process of land-use change in the Brazilian Amazon. Indeed, by providing a comprehensive characterization of biomass smoke effects on health outcomes, we contribute potentially informative evidence to policymaking by revealing socioeconomic costs beyond those directly associated with environmental degra-

dation and biodiversity loss. In particular, we shed light on the detrimental health impacts that air pollution related to forest fires have on local populations. Our results reveal further costs associated with deforestation in the Brazilian Amazon, which are not usually considered.

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# Main Tables and Figures

Table 1: Descriptive Statistics and Main Sources of Data on Health Outcomes and Environmental Indicators

	Mean	Std. Dev.	Min	Max	Source	Period
<b>Hospitalization Rates</b>						
Respiratory	63,5	71,2	0	1471	Datasus	Jan 2010/Dec 2019
Circulatory	32,0	33,8	0	1477	Datasus	Jan 2010/Dec 2019
Infectious	66,8	85,0	0	1687	Datasus	Jan 2010/Dec 2019
Neoplasms	15,2	18,3	0	322	Datasus	Jan 2010/Dec 2019
Digestive	42,7	37,1	0	845	Datasus	Jan 2010/Dec 2019
Total	480,7	254,7	0	4984	Datasus	Jan 2010/Dec 2019
<b>Mortality Rates</b>						
Respiratory	3,0	6,0	0	124	Datasus	Jan 2010/Dec 2018
Circulatory	9,9	11,7	0	181	Datasus	Jan 2010/Dec 2018
Infectious	1,5	3,9	0	92	Datasus	Jan 2010/Dec 2018
Neoplasms	4,1	7,2	0	134	Datasus	Jan 2010/Dec 2018
Digestive	1,6	4,4	0	93	Datasus	Jan 2010/Dec 2018
Total	35,3	22,9	0	286	Datasus	Jan 2010/Dec 2018
<b>Environmental Indicators</b>						
PM2.5	16,1	17,3	0,87	658	INPE	Jan 2010/Dec 2019
PM2.5 (upwind * PM2.5 in neighbors)	23,6	36,8	0,00	1822	INPE	Jan 2010/Dec 2019
Precipitation	4,2	3,9	0,00	34	INPE	Jan 2010/Dec 2019
Temperature	26,4	1,5	19,05	32	INPE	Jan 2010/Dec 2019
Relative Humidity	80,9	13,7	25,69	99	INPE	Jan 2010/Dec 2019
Fire Activity (n. of hotspots)	13,9	63,1	0	6383	INPE	Jan 2010/Dec 2019

Notes: Descriptive statistics computed at the municipality-by-month level for the entire period of analysis for which data are available. Sources of information and reference to the period for which data are available are reported in the last two columns, respectively.

Table 2: PM2.5 Effects on Hospitalization and Mortality Rates by Respiratory Conditions: OLS and 2SLS Specifications

	Hospitalization Rate			Death Rate		
	(1)	(2)	(3)	(4)	(5)	(6)
<b>Panel A - OLS</b>						
PM2.5	0.021 (0.012)*	0.060 (0.012)***	0.055 (0.011)***	0.002 (0.001)	0.002 (0.001)	0.001 (0.001)
Observations	92,640	91,440	91,440	83,352	83,352	83,352
<b>Panel B - 2SLS</b>						
PM2.5	0.007 (0.025)	0.063 (0.027)**	0.055 (0.027)**	0.001 (0.002)	0.001 (0.002)	0.000 (0.002)
Observations	90,720	89,520	89,520	81,648	81,648	81,648
Time and Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	Yes	No	Yes	Yes
Time Trend	No	No	Yes	No	No	Yes

Notes: Panels A and B report the results of OLS and 2SLS specifications, respectively. The first three columns present results for hospital admissions. In the first column we include only municipality and time fixed-effects. We add weather controls in the second specification, and municipality-specific linear time trends in the third one. Weather controls include average precipitation, relative humidity and temperature. Columns 4-6 replicate the same series of specifications for mortality rates. Standard errors clustered at the municipality level. Significance: \*\*\* p<0.01, \*\* p<0.05, \* p<0.1.

Table 3: PM2.5 Effects on Hospitalization Rates by Other Conditions: OLS and 2SLS Specifications

	Resp	Infec	Circulat	Neoplas	Digest	Total
	(1)	(2)	(3)	(4)	(5)	(6)
<b>Panel A - OLS</b>						
PM2.5	0.055 (0.011)***	0.040 (0.016)**	0.010 (0.006)	-0.001 (0.004)	-0.006 (0.007)	0.055 (0.035)
Observations	91,440	91,440	91,440	91,440	91,440	91,440
<b>Panel B - 2SLS</b>						
PM2.5	0.055 (0.027)**	0.014 (0.028)	0.006 (0.015)	0.011 (0.007)	-0.015 (0.014)	0.023 (0.079)
Observations	89,520	89,520	89,520	89,520	89,520	89,520
Time and Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Time Trend	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Panels A and B report the results of OLS and 2SLS specifications, respectively. Dependent variables are hospital admission rates by specific conditions (columns 1-5) and all-cause hospitalization rate (column 6). OLS and 2SLS specifications follow the same as reported in column 3 of Table 2, respectively in Panels A and B. Standard errors clustered at the municipality level. Significance: \*\*\* p<0.01, \*\* p<0.05, \* p<0.1.

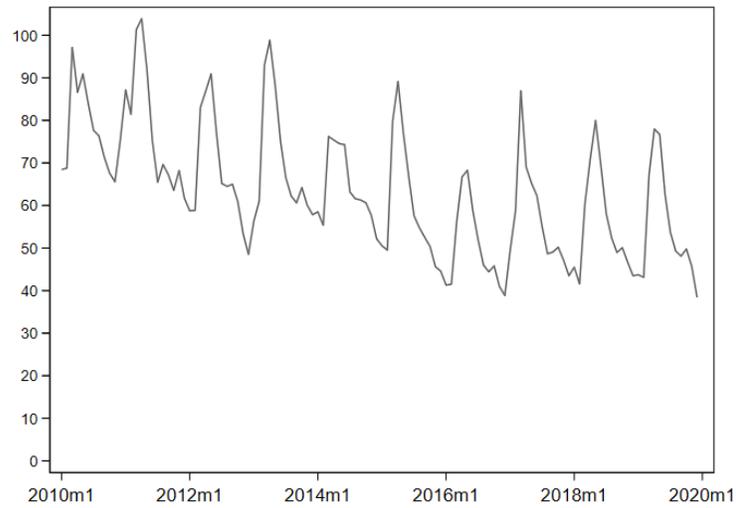
Table 4: PM2.5 Effects on Hospitalization Rates for Respiratory Conditions by Age Brackets: OLS and 2SLS Specifications

	[0y-1y]	(1y-5y]	[6y-14y]	[15y-59y]	>60y
	(1)	(2)	(3)	(4)	(5)
<b>Panel A - OLS</b>					
PM2.5	0.009 (0.004)**	0.001 (0.003)	0.000 (0.002)	0.012 (0.003)***	0.026 (0.005)***
Dep Var Mean	13.45	9.82	7.05	11.38	14.76
Observations	91,416	91,416	91,416	91,416	91,416
<b>Panel B - 2SLS</b>					
PM2.5	0.012 (0.009)	-0.010 (0.007)	0.003 (0.005)	0.015 (0.007)**	0.022 (0.009)**
Dep Var Mean	13.41	9.91	7.13	11.51	14.89
Observations	89,520	89,520	89,520	89,520	89,520
Time and Municipality FE	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Time Trend	Yes	Yes	Yes	Yes	Yes

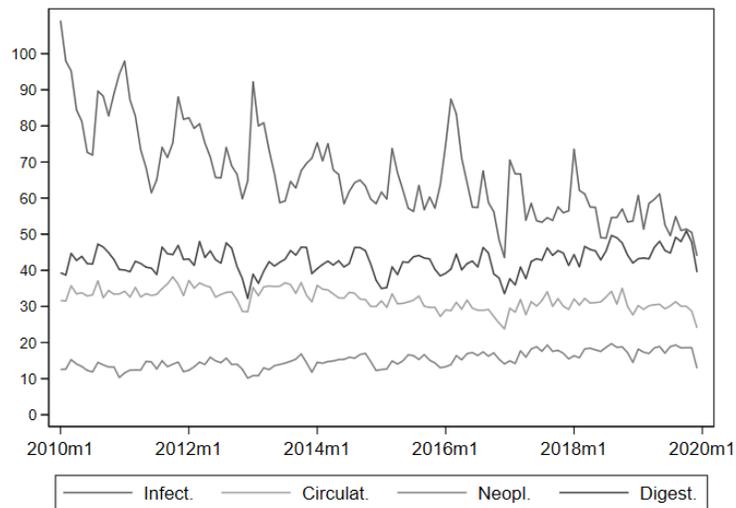
Notes: Panels A and B report the results of OLS and 2SLS specifications, respectively. Dependent variables are hospital admission rates for respiratory conditions by age groups. OLS and 2SLS specifications follow the same as reported in column 3 of Table 2, respectively in Panels A and B. Standard errors clustered at the municipality level. Significance: \*\*\* p<0.01, \*\* p<0.05, \* p<0.1.

Figure 1: Hospitalizations due to Respiratory Diseases and Other Conditions in the Brazilian Legal Amazon

(a) Hospitalization Rate by Respiratory Conditions



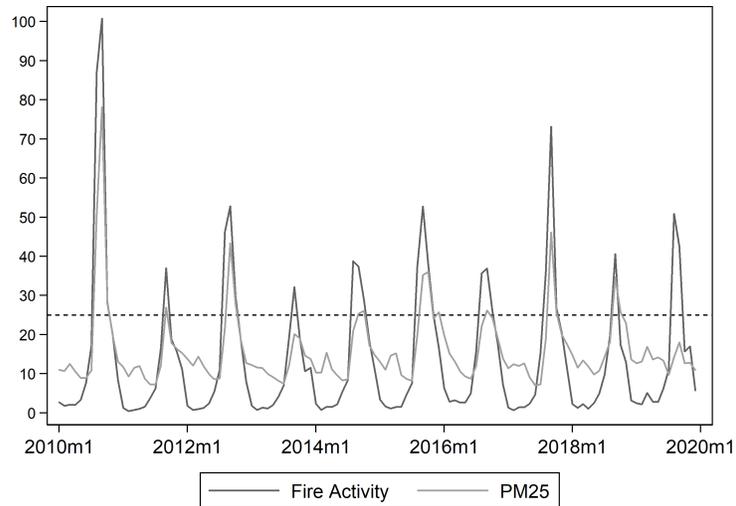
(b) Hospitalization Rate by Other Conditions



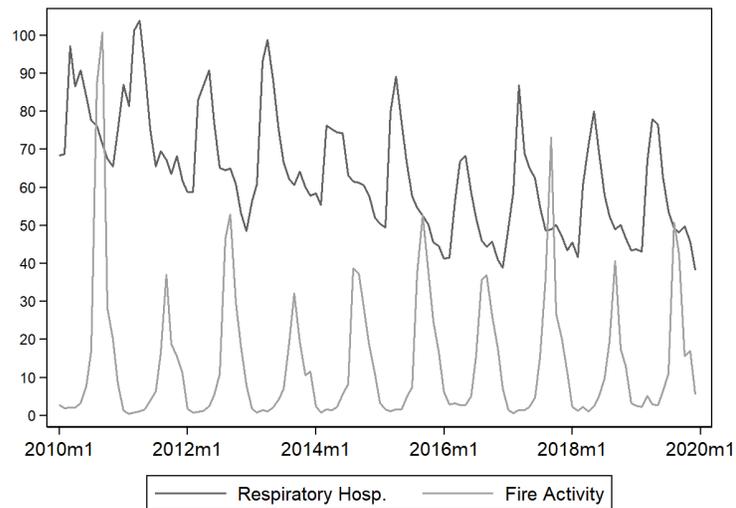
Notes: Microdata originally from Datasus/SIH. The plots show monthly averages for municipalities in the Brazilian Legal Amazon.

Figure 2: Fire Activity, PM2.5 Concentration and Respiratory Diseases in the Brazilian Legal Amazon

(a) Fire Activity and PM2.5 Concentration



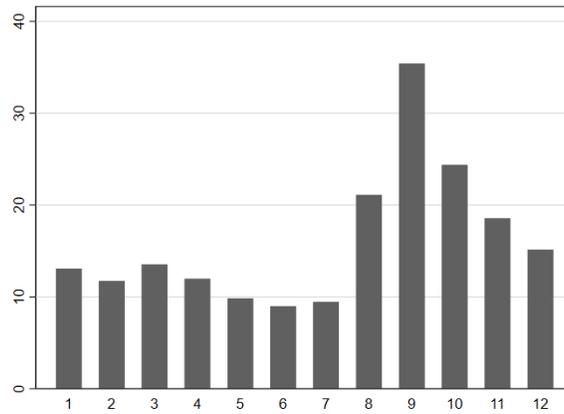
(b) Fire Activity and Hospitalization for Respiratory Conditions



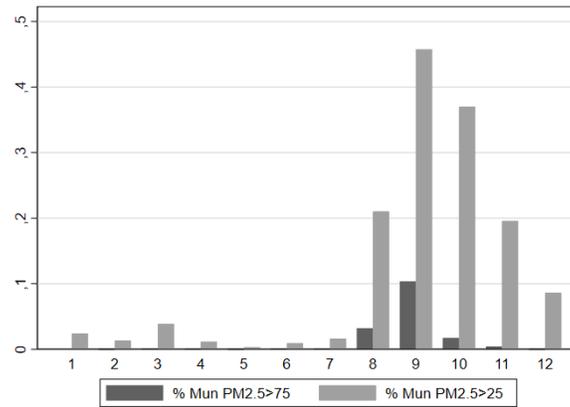
Notes: Data displayed on the upper plot are originally from the Environmental Health Information System (*Sistema de Informações Ambientais Integrado à Saúde, SISAM*). The trends show monthly averages on fire activity (number of hotspots) and PM2.5 concentration for municipalities in the Brazilian Legal Amazon. On the bottom plot, data on hospital admissions are originally from Datasus/SIH.

Figure 3: Time and Cross-Sectional Variation in PM2.5 Concentration

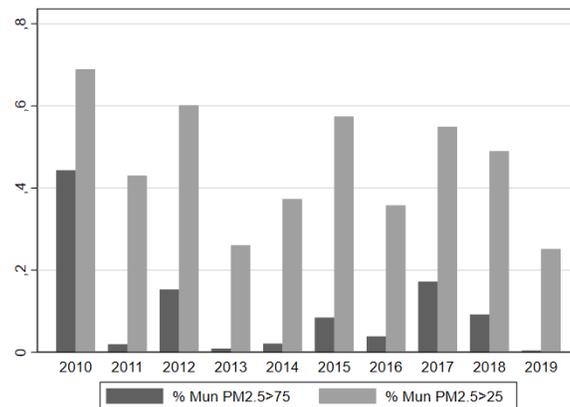
(a) PM2.5 Concentration: Monthly Averages



(b) PM2.5 Concentration: Monthly Share of Municipalities Above PM2.5 Thresholds



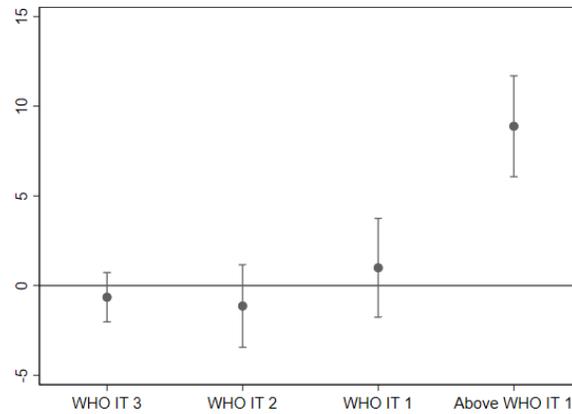
(c) PM2.5 Concentration: Share of Municipalities Above PM2.5 Thresholds in September



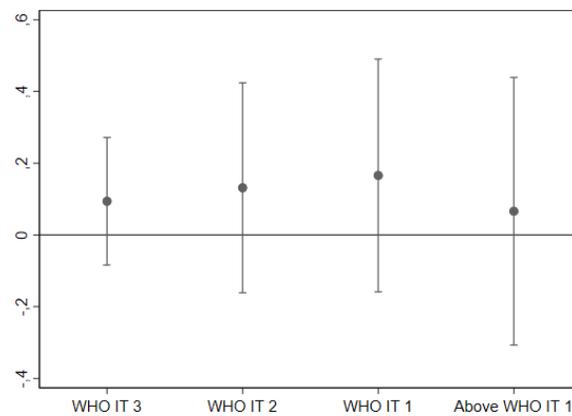
Notes: Data on PM2.5 concentration are originally from the Environmental Health Information System (*Sistema de Informações Ambientais Integrado à Saúde, SISAM*). Upper and middle graphics plot monthly averages while the bottom graphic displays averages computed for September in different years.

Figure 4: Non-Linear Effects of PM2.5 Concentration on Hospitalization and Mortality Rates by Respiratory Conditions: OLS Results

(a) Effects on Hospitalization Rates



(b) Effects on Mortality Rates



Notes: The graphics report results from regressions that follow the OLS specification reported in columns 3 and 6 of Table 2, but in which the PM2.5 variable is replaced by dummies that indicate monthly average concentration levels within different ranges: (i) WHO IT 3 refers to the Interim Target 3, which is equal to one if average PM2.5 is in the range between 25 and 37.5 g/m<sup>3</sup>; (ii) WHO IT 2 refers to the Interim Target 2, which corresponds to the range between 37.5 and 50 g/m<sup>3</sup>; (iii) WHO IT 1 refers to the Interim Target 1, between 50 and 75 g/m<sup>3</sup>; (iv) above WHO IT 1 refers to air pollution above interim target 1. Confidence intervals estimated at 95% from standard errors clustered at the municipality level.

# Appendix Tables

## A First-Stage and Additional Results

Table A.1: First-Stage Results

	PM2.5			
	(1)	(2)	(3)	(4)
Instrument (Wind From Neighbors * PM2.5 in Neighbors)	0.243 (0.015)***	0.227 (0.014)***	0.227 (0.014)***	
Wind From SE Neighbors * PM2.5 in SE Neighbors				0.238 (0.017)***
Wind From NW Neighbors * PM2.5 in SE Neighbors				-0.280 (0.049)***
Observations	90,720	89,520	89,520	89,520
Partial F-Stat	270.8	261.2	257.5	119.3
<b>Common Specification:</b>				
Time and Municipality FE	Yes	Yes	Yes	Yes
Controls	No	Yes	Yes	Yes
Time Trend	No	No	Yes	Yes

Notes: All specifications follow equation 1. In all columns the dependent variable is PM2.5. In columns 1-3, the instrument is defined by equation 2. In the first column we include only municipality and time fixed-effects. We add weather controls in the second specification (average precipitation, relative humidity and temperature), and municipality-specific linear time trends in the remaining ones. Standard errors clustered at the municipality level. Significance: \*\*\* p<0.01, \*\* p<0.05, \* p<0.1.

Table A.2: PM2.5 Effects on Mortality Rates by Other Conditions and All-Cause Mortality: OLS and 2SLS Specifications

	Resp	Infec	Circulat	Neoplas	Digest	Total
	(1)	(2)	(3)	(4)	(5)	(6)
<b>Panel A - OLS</b>						
PM2.5	0.001 (0.001)	-0.001 (0.001)	0.004 (0.003)	0.003 (0.002)*	0.000 (0.002)	0.010 (0.005)**
Observations	83,352	83,352	83,352	83,352	83,352	83,352
<b>Panel B - 2SLS</b>						
PM2.5	0.000 (0.002)	-0.002 (0.002)	0.004 (0.005)	0.004 (0.003)	0.001 (0.002)	0.007 (0.009)
Observations	81,648	81,648	81,648	81,648	81,648	81,648
Time and Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Time Trend	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Panels A and B report the results of OLS and 2SLS specifications, respectively. Dependent variables are mortality rates by specific conditions (columns 1-5) and all-cause mortality (column 6). OLS and 2SLS specifications follow the same as reported in column 3 of Table 2, respectively in Panels A and B. Standard errors clustered at the municipality level. Significance: \*\*\* p<0.01, \*\* p<0.05, \* p<0.1.

Table A.3: PM2.5 Effects on Mortality Rates by Age and Specific Causes: 2SLS Results

	Resp	Infec	Circulat	Neoplas	Digest	Total
	(1)	(2)	(3)	(4)	(5)	(6)
[0y-1y]	0.0005 (0.0007)	-0.0008 (0.0006)	-0.0000 (0.0002)	-0.0003 (0.0001)***	0.0004 (0.0005)	-0.0006 (0.0019)
Observations	81,432	81,432	81,432	81,432	81,432	81,432
>60y	-0.0007 (0.0021)	0.0007 (0.0011)	0.0042 (0.0044)	0.0040 (0.0028)	-0.0003 (0.0012)	0.0036 (0.0068)
Observations	81,648	81,648	81,648	81,648	81,648	81,648
Time and Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Time Trend	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The upper and bottom panels report the results of our most complete 2SLS specification, respectively for infants and the elderly. Dependent variables are mortality rates by specific conditions (columns 1-5) and all-cause death rate (column 6). In all regressions, the 2SLS specification follows the same as reported in column 3 of Table 2, Panel B. Standard errors clustered at the municipality level. Significance: \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ .

## B Robustness Checks

Table B.1: PM2.5 Effects on Hospitalization and Mortality Rates of Respiratory Conditions: OLS and 2SLS Specifications in Balanced Samples

	Respiratory Hospitalization Rate			Respiratory Death Rate		
	(1)	(2)	(3)	(4)	(5)	(6)
<b>Panel A - OLS</b>						
PM2.5	0.028 (0.013)**	0.070 (0.014)***	0.061 (0.012)***	0.002 (0.001)	0.002 (0.001)	0.001 (0.001)
Observations	78,720	78,720	78,720	70,848	70,848	70,848
<b>Panel B - 2SLS</b>						
PM2.5	0.025 (0.026)	0.075 (0.029)***	0.067 (0.029)**	0.001 (0.002)	0.000 (0.003)	-0.000 (0.003)
Observations	78,720	78,720	78,720	70,848	70,848	70,848
Time and Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	Yes	No	Yes	Yes
Time Trend	No	No	Yes	No	No	Yes

Notes: Panels A and B report the results of OLS and 2SLS specifications, respectively. The samples are balanced and include municipalities without any missing observations during the entire period of analysis. The first three columns present results for hospital admissions. In the first column we include only municipality and time fixed-effects. We add weather controls in the second specification, and municipality-specific linear time trends in the remaining one. Weather controls include average precipitation, relative humidity and temperature. Columns 4-6 replicate the same series of specifications for mortality rates. Standard errors clustered at the municipality level. Significance: \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ .

Table B.2: PM2.5 Effects on Hospitalization and Death Rates by Respiratory Conditions: OLS and 2SLS Specifications With Additional Controls

	Respiratory Hospitalization				Respiratory Death Rate			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
<b>Panel A - OLS</b>								
PM2.5	0.055 (0.011)***	0.062 (0.012)***	0.049 (0.011)***	0.054 (0.012)***	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	-0.001 (0.002)
PM2.5 Neighb.*Non-Upwind				-0.007 (0.007)				0.002 (0.002)
Observations	91,440	88,008	86,696	86,696	83,352	80,136	80,136	80,136
<b>Panel B - 2SLS</b>								
PM2.5	0.055 (0.027)**	0.072 (0.028)***	0.060 (0.031)*	0.066 (0.034)*	0.000 (0.002)	-0.000 (0.003)	-0.001 (0.003)	-0.002 (0.004)
PM2.5 Neighb.*Non-Upwind				-0.009 (0.008)				0.002 (0.002)
Observations	89,520	88,008	86,696	86,696	81,648	80,136	80,136	80,136
Time and Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Weather Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Dynamic Controls	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Two Lags and Leads of PM2.5	No	No	Yes	Yes	No	No	Yes	Yes
Time Trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Panels A and B report the results of OLS and 2SLS specifications, respectively. Dependent variables are hospital admission rates and death rates by respiratory conditions. OLS and 2SLS specifications in columns 1 and 5 follow the same as reported in columns 3 and 6 of Table 2, respectively in Panels A and B. Specifications in columns 2 and 6 add lagged weather variables and lagged instrument in two periods. Specifications in columns 3 and 7 add two lags and two leads of local PM2.5. Specifications in columns 4 and 8 add the composite term of PM2.5 concentration in neighbor municipalities interacted non-upwind dummies. Standard errors clustered at the municipality level. Significance: \*\*\* p<0.01, \*\* p<0.05, \* p<0.1.