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Winds of fire and smoke: Air pollution and health in the Brazilian Amazon

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In this paper we assess the effects of fire-related air pollution 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 air pollution in surrounding areas in order to exogenously shift exposure to air pollution at the locality. We find that exposure to air pollution, measured by PM2.5 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 PM2.5 is related to an increase of 1.5% of the monthly hospitalization rate for respiratory conditions. The latter estimate reaches 14% if monthly average PM2.5 crosses thresholds as high as 75 $\mu g/m^3$. We do not observe significant effects on hospitalization rates related to other health conditions nor on mortality rates.

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, Zheng, Chung, & Zhong, 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, Silva, Alencar, & and Moutinho, 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^2 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 pol-

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lution 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 (PM2.5) 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 PM2.5 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 PM2.5 concentration (SD = 17.3 $\mu g/m^3$) 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 PM2.5 levels cross thresholds as high as 75 $\mu g/m^3$—this corresponds to three times the threshold of 25 $\mu g/m^3$ in the 24 h 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 PM2.5 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 focused on urban environments and atmospheric pollution related to fossil fuels [eg.] (Deryugina, Heutel, Miller, Molitor, & Reif, 2019; He, Gouveia, & Salvo, 2019; Schlenker & Walker, 2016; Ward, 2015; Currie & 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, Duflo, & Greenstone, 2016; Johnston et al., 2012; Ezzati & 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, Liu, and and Zhou (1024) 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., 2742) and the major forest fires that hit Indonesia in the late 1990s [eg.] (Tan-Soo & Pattanayak, 2019; Jayachandran, 2009; Frankenberg, McKee, & Thomas, 2005). In that latter case, the 24 h total suspended particulate concentration reached atypically impressive levels as high as 4,000 $\mu g/m_3$ 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 & Vogl, 2019; Tan-Soo & 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, Massuda, Menezes-Filho, Andrade, & De Souza Noronha, 2019; Bhalotra, Rocha, & Soares, 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 & 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^2 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, Gandour, Rocha, & Rocha, 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). As mentioned by Barlow, Berenguer, Carmenta, and and França (2020), deforestation is key driver of fires ad forest clearance is a major source of ignition and augments the flammability of remaining forests. 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 CO2, CO, NOx and particulate matter, especially PM2.5, which refers to particles with aerodynamic diameter $\leq 2.5\mu m$, and consists of organic and black carbon components along with contributions from inorganic compounds (Johnston et al., 2012). PM2.5 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, Kabir, & Kabir, 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).[1] 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, sex and cause of hospitalization (ICD-10).[2] 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 PM2.5 and respiratory diseases, but extend our analysis to other conditions in additional exercises (infectious, circulatory, neoplasms and digestive diseases).[3] We also compute outcome indicators by age brackets separately to shed light on heterogeneities. He et al. (1024) 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 & 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. SISAM was officially developed to allow the analysis of environmental data and to support research on the effects of emissions and atmospheric pollution on human health. The system is particularly relevant for the Amazon region, which faces scarcity in infrastructure and relies on a limited number of ground-level meteorological stations that collect air pollutants. We mainly utilize data on the concentration of fine particulate near surface, PM2.5, as measured in $\mu g/m^3$. This variable is originally obtained from the Copernicus Atmosphere Monitoring Service (CAMS/ European Centre for Medium-Range Weather Forecasts). Original data are gathered at 6-h intervals

[1] While there does not exist any systematic assessments about its coverage and precision, SIM has gradually improved over time, particularly in the Northern Region, and is expected to be relatively more complete in more recent years (Frias, Szwarcwald, & and Lira, 2019).

[2] SIH is an administrative system of hospitalization payments that includes the universe of all admissions covered by SUS, both in public and in private hospitals accredited to SUS. According to data from the National Agency of Supplementary Health (ANS), the share of the population covered by private insurance plans in the municipalities of the Legal Amazon Region is the lowest in the country, oscillating between 8.5% around 2010 to 9.8% in the late 2010s. In that sense, SIH data are expected to cover the greatest share of hospital admissions in the region. Also important to mention, SIH has not undergone through any major revisions since 1998. Payment schedules for specific procedures have changed over time, and this is expected to affect incentives regarding misclassification of causes, but we have not identified any specific revisions during the period of analysis that could influence our results.

[3] Respiratory conditions refer to events classified under ICD-10 J00-J99.

and have a spatial resolution of $12.5km^2$. The CAMS models deliver near surface measures of air pollution after reanalysis of satellite imagery through modelling systems and validation with existing ground-based observations.[4] INPE performs numerical and satellite imagery analysis and provides a dataset at the municipality level, still with a 6-h 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) 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 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. For each municipality and time, wind direction is measured as upcoming wind in azimuth degrees, which indicate the direction from which the wind is blowing according to the location in latitude/longitude degrees of the municipality's population centroid – where the main district is located in. The original data are available on daily basis and 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 Forescasting Model (for 2019 only).

Our final sample contains 92,640 observations (10 years $\times$ 12 months $\times$ 772 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 Fig. 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 Fig. 2, which displays the patterns of PM2.5 concentration and fire activity. The horizontal line represents the Air Quality Guideline threshold at 25 $\mu g/m^3$ for PM2.5 concentration, established by the World Health Organization for the 24 h-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 24 h-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 Fig. 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:

$$Y_{mt} = \alpha_m + \gamma_t + \beta AirPollution_{mt} + \mathbf{X}\prime_{mt}\Theta + \upsilon_{mt} \tag{1}$$

where Y_{mt} is an outcome of interest for municipality m in time $t, AirPollution_{mt}$ indicates PM2.5 concentration, and α_m and γ_t are municipality and time fixed-effects, respectively. The term α_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 γ_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 υ_{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 Fig. 3. The upper graphic shows that average PM2.5 concentra-

[4] CAMS measurement error is generally low for different pollutants, including species measured by aerosol optical depth, though larger errors and outliers may occur at high latitudes and close to specific sources such as volcanoes (Lambert et al., 2019; Flemming et al., 2017).

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

	Mean	Std. Dev.	Min	Max	Source	Period
Hospitalization Rates						
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
Mortality Rates						
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
Environmental Indicators						
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.

tion 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 $\mu g/m^3$. 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 $\mu g/m^3$ varies from about 20% to 60%. For levels superior to 75 $\mu g/m^3$, 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 β 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.[5] While municipality GDP and income data are observable in our setting in annual basis, unfortunately these indicators are not available in high-frequency level, such as on monthly basis, which is the unit of our analysis. This leaves open the potentially confounding role that omitted economic activity might play in the short-run, across months, within years. 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 mentioned in Deryugina et al. (2019), OLS estimates might be prone to bias because exposure to PM 2.5 is likely to be measured with error as pollution-monitor readings may not adequately measure the average pollution exposure for local residents due to the sparse placement of monitors.[6] As also remarked by Graff Zivin and Neidell (2013): "[g]iven the geographic information contained in large-scale data sets, studies often approximate contemporaneous pollution levels based on an individual's general location and the location of the monitor. This crude approach leads to measurement error that increases with an individual's distance from the monitor and the degree to which pollutants disperse nonuniformly. This measurement error will typically bias estimates downward" (pp.699–700). Second, 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 erogeneity concerns, we rely on two sets of robustness checks. First, we rely on Eq. (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. In our instrumental variable approach, the term $AirPollution_{mt}$ in Eq. 1 is instrumented by a composite interaction term between wind direction and air pollution in neighboring municipalities.[7] More specifically, the instrumental variable is defined by:

[5] This concern is mentioned in studies that have explored even finer-level temporal variation (e.g. Sheldon & Sankaran (2017)).

[6] A similar reasoning is presented in Rodrigues (2018).

[7] 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.

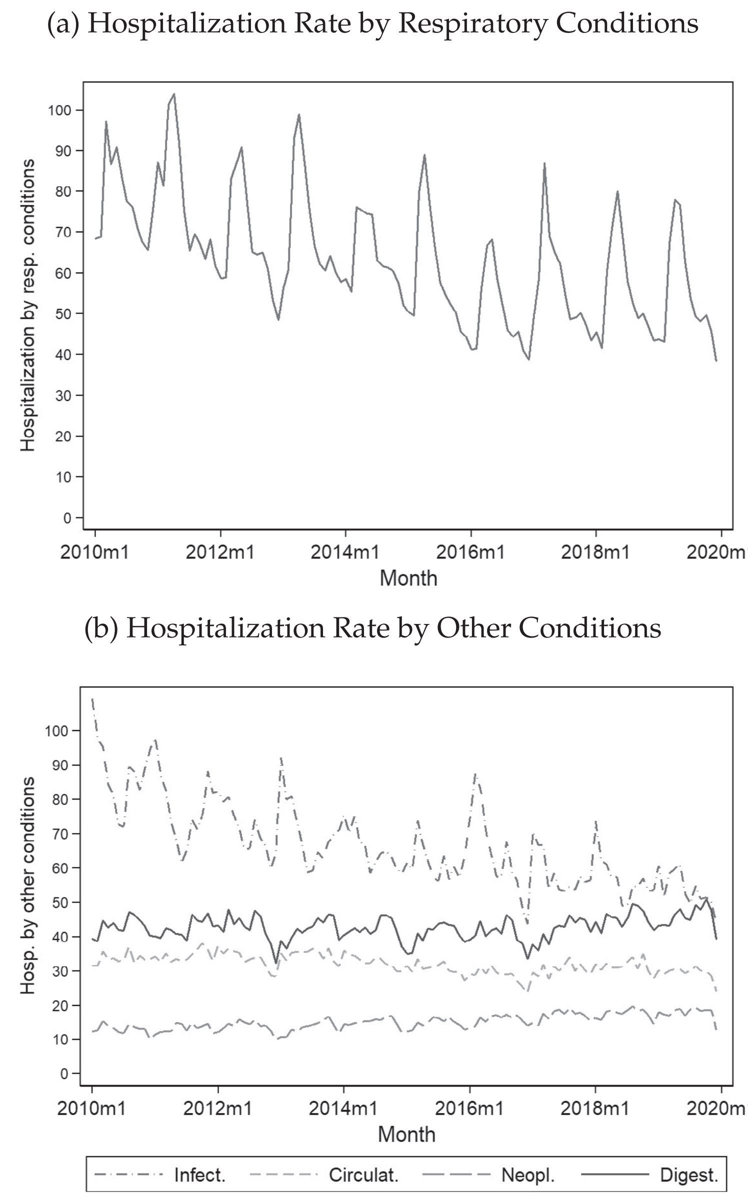


Fig. 1. Hospitalizations due to Respiratory Diseases and Other Conditions in the Brazilian Legal Amazon. (Notes: Microdata originally from Datasus/SIH. The plots show monthly averages for municipalities in the Brazilian Legal Amazon.)

$$AirPollution^N_{mt} = \sum_{i \in N} AirPollution_{it} \times \mathbb{1}(\mathrm{Location}^a_{it} * \mathrm{Wind}^a_{it}) \qquad (2)$$

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 $\mathbb{1}(\mathrm{Location}^a_{it} * \mathrm{Wind}^a_{it})$ 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. In that sense, we use the relative positions of each municipality (measured in degrees) and consider the group of all neighbor municipalities that share their borders with the reference municipality m, irrespective of the distance between their centroids. According to Eq. 2, we define that a neighboring municipality "exports" pollution to the reference municipality whenever the direction separating the two is diametrically opposite to the direction through which wind blows from the former. For 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 $AirPollution^N_{mt}$ 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.[8] Appendix Fig. A.1 depicts and further details the computation of the variable.

The term $AirPollution^N_{mt}$ 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 Eq. (1), but we replace the dependent variable by PM2.5 concentration. In the first column

[8] We are not able to compute wind nor air pollution at source in a given quadrant if the municipality meets terminus. Yet, the IV still captures variation in neighboring places through the sum of upwind pollution from other quadrants.

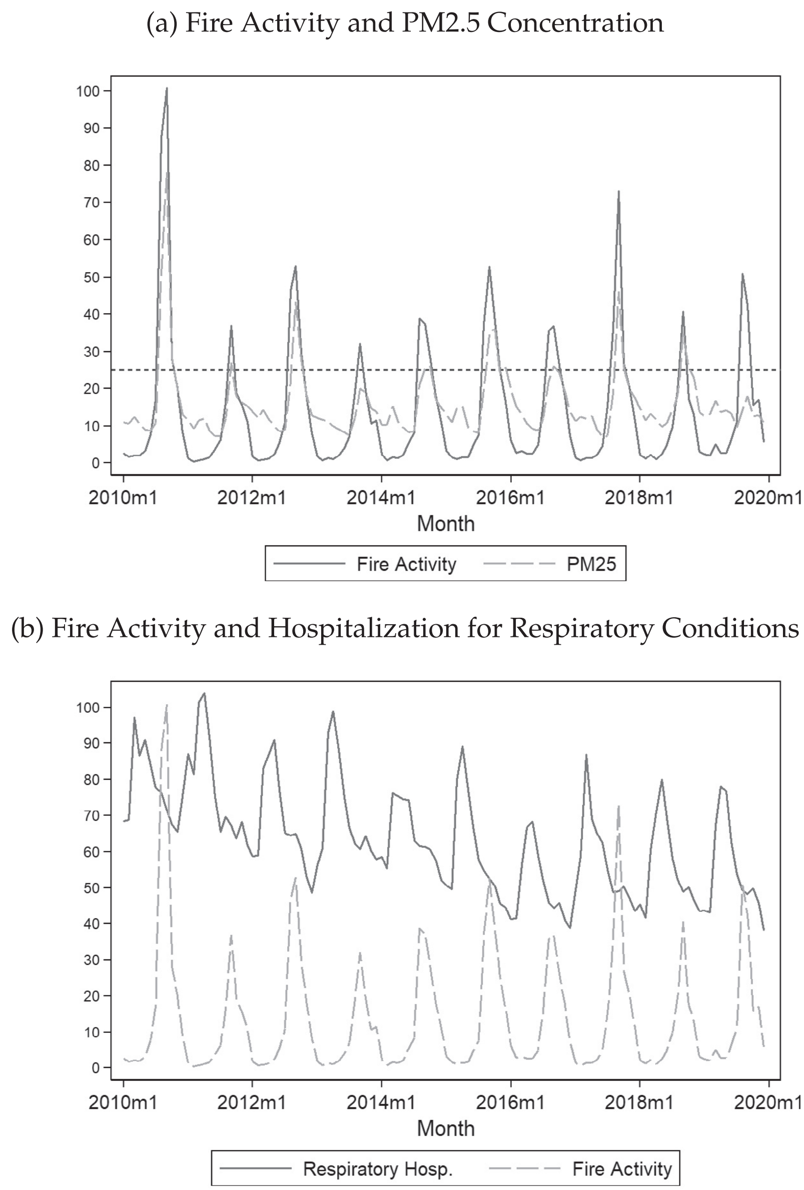


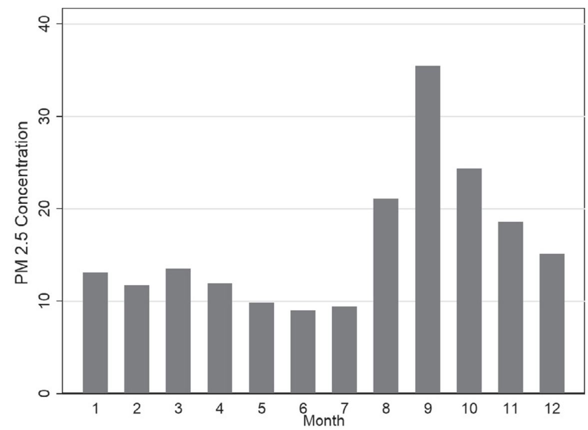
Fig. 2. Fire Activity, PM2.5 Concentration and Respiratory Diseases in the Brazilian Legal Amazon. (Notes: Data displayed on the upper plot are originally from the Environmental Health Information System (*Sistema de Informações Ambientais Integrado à Saúde*, SISAM). The trends show monthly averages 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.)

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 0.22–0.24, 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.

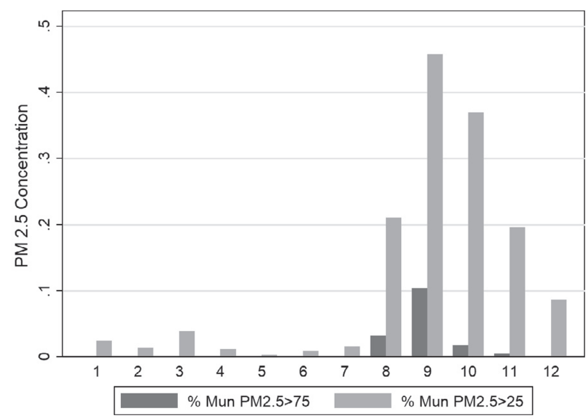
The exclusion restriction is valid if the instrumental variable is uncorrelated with any other latent determinant of health outcomes but air pollution in municipality m. Our identifying assumption is that, conditional on fixed-effects and time-varying controls in a high-frequency setting, the remaining variation in wind direction in neighboring municipalities is arguably exogenous to municipality m. If this assumption is valid, the term $AirPollution^{N}_{mt}$ 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 column 4 of Appendix Table A.1, 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. This is consistent with the fact that major atmospheric patterns generally blow air pollutants from SE Amazon, where the Arc of Deforestation is located, inwards the region. Yet, this pattern is only suggestive as neighboring air pollutants and winds are computed considering the only immediate surrounding municipalities. In the remaining column of Appendix Table A.1, we perform an additional consistency check.

(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

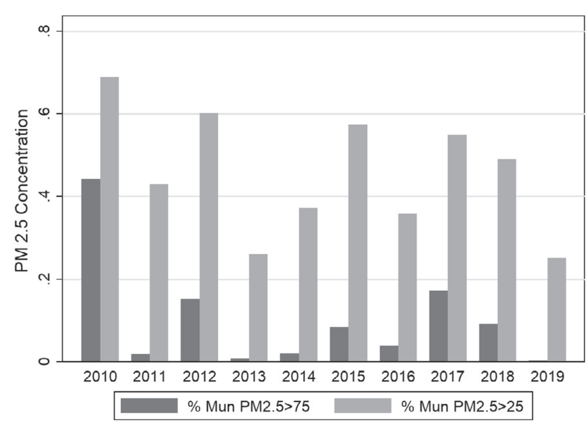


Fig. 3. Time and Cross-Sectional Variation in PM2.5 Concentration. (Notes: Data on PM2.5 concentration are originally from the Environmental Health Information System (*Sistema de Informações Ambientais Integrado à Saúde*, SISAM). Upper and middle graphics plot monthly averages while the bottom graphic displays averages computed for September in different years.)

We created a variable that takes into consideration prevailing winds and PM2.5 in all neighboring municipalities in order to capture a net dissipation effect. More precisely, for each reference municipality m and quadrant a from m, we compute the sum of PM2.5 in municipalities located in a multiplied by a dummy that indicates prevailing wind away from m. We also discount the sum of PM2.5 in municipalities located in the quadrant opposite to a multiplied by a dummy that indicates prevailing wind towards

m, i.e., the same prevailing wind. In that sense, we allow the computation of a net PM2.5 blowing through the same prevailing wind.[9] We analogously repeated the exercise for all quadrants and summed up a net dissipation effect: the net sum of neighboring PM2.5 that was moved away by winds. A positive indicator means that prevailing winds blew more PM2.5 outwards than inwards m. Column 5 of Table A.1 shows a specification in which the dependent variable is regressed on that net dissipation effect. We find a very small partial-F and a small but negative point estimate, i.e., we observe a reduction in local PM2.5 levels when the prevailing winds blew more PM2.5 outwards than inwards m.

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.[10] 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.[11] Regarding mortality rates, we observe small and statistically insignificant point estimates in the remaining columns, irrespective of the specification.[12] As discussed in Schlenker and Walker (2016), fluctuations in air pollution might not be fatal but result in treatable sickness where exposure to pollutants is generally low. In fact, air pollution levels in the Brazilian Amazon are generally low on average, but peak in September. Yet, even in September the share of municipalities with mean PM2.5 concentration above 75 $\mu g/m^3$ is only 10%. In that sense, variations in PM2.5 in the region have impacts on hospitalization, but would not lead to more extreme adverse outcomes such as death.

The point estimate of 0.055 means that a ten-unit increase (ten extra micrograms per cubic metre) in PM 2.5 is associated with an increase in hospitalizations in one half (0.55 units) or 0.9% of the average rate (63.5). The former shock corresponds to an observed variation of PM 2.5 as revealed roughly by 0.6 SD (10/17.3, where SD = 17.3 $\mu g/m^3$). Yet, air pollution can have nonlinear effects on health (Graff Zivin & 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. 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 $\mu g/m^3$; (ii) WHO IT 2 refers to the Interim Target 2, which corresponds to the range between 37.5 and 50 $\mu g/m^3$; (iii) WHO IT 1 refers to the Interim Target 1, between 50 and 75 $\mu g/m^3$; (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.

Fig. 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 $\mu g/m^3$, 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 $\mu g/m^3$. The point estimate is 8.88 (SD = 1.43), equivalent to 14% of the average rate.[13] 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 $\mu g/m^3$) is associated with an

[9] For instance, for the NE quadrant from m we calculated the PM2.5 in NE municipalities multiplied by a dummy that indicates prevailing wind in the NE quadrant blowing away from m minus the PM2.5 in SW municipalities of m multiplied by a dummy that indicates prevailing wind in the SW quadrant blowing towards m. Appendix Fig. A.1 depicts the computation of this variable.

[10] The point estimate increases when we include controls, but that comes together with a small reduction in sample size. Additional checks indicate that this is not led by changes in the number of observations as coefficients remain stable across identical estimation samples (available upon request).

[11] 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. The result also suggests a limited role for measurement error in our setting.

[12] The Amazon region is extremely vast and heterogeneous both across geographical and socioeconomic features, making the possibility of different seasonal patterns across subregions a lingering concern. In further robustness checks, we included month-of-the year × mesoregion fixed-effects, which are expected to absorb the seasonal influence of more specific geographies over the period of analysis. Point estimates remain stable (results upon request). 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.

[13] A F-test on the equality of the coefficients allows us to reject the null hypothesis that estimates are statistically equal ($F = 15.12$).

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)
				Panel A – OLS		
PM2.5	0.021	0.060	0.055	0.002	0.002	0.001
	(0.012)*	(0.012)***	(0.011)***	(0.001)	(0.001)	(0.001)
Observations	92,640	91,440	91,440	83,352	83,352	83,352
				Panel B – 2SLS		
PM2.5	0.007	0.063	0.055	0.001	0.001	0.000
	(0.025)	(0.027)**	(0.027)**	(0.002)	(0.002)	(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: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

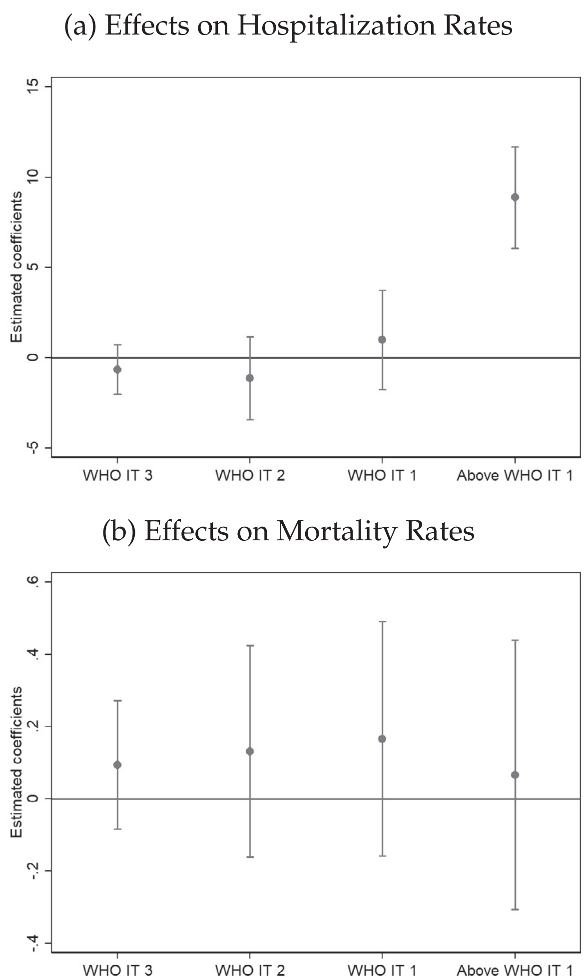


Fig. 4. Non-Linear Effects of PM2.5 Concentration on Hospitalization and Mortality Rates by Respiratory Conditions: OLS Results. (Notes: The graphics report results from regressions that follow the OLS specification reported in columns 3 and 6 of Table 2, but in which the PM2.5 variable is replaced by 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/m3; (ii) WHO IT 2 refers to the Interim Target 2, which corresponds to the range between 37.5 and 50 g/m3; (iii) WHO IT 1 refers to the Interim Target 1, between 50 and 75 g/m3; (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.)

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

	Resp (1)	Infec (2)	Circulat (3)	Neoplas (4)	Digest (5)	Total (6)
			Panel A – OLS			
PM2.5	0.055	0.040	0.010	-0.001	-0.006	0.055
	(0.011)***	(0.016)**	(0.006)	(0.004)	(0.007)	(0.035)
Observations	91,440	91,440	91,440	91,440	91,440	91,440
			Panel B - 2SLS			
PM2.5	0.055	0.014	0.006	0.011	-0.015	0.023
	(0.027)**	(0.028)	(0.015)	(0.007)	(0.014)	(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] (1)	[1y–5y] (2)	[6y–14y] (3)	[15y–59y] (4)	>60y (5)
			Panel A – OLS		
PM2.5	0.009	0.001	0.000	0.012	0.026
	(0.004)**	(0.003)	(0.002)	(0.003)***	(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
			Panel B – 2SLS		
PM2.5	0.012	−0.010	0.003	0.015	0.022
	(0.009)	(0.007)	(0.005)	(0.007)**	(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: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

increase in 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. (1024) 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.[14]

[14] 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 noisy result for neoplasms among infants.

5.4. Robustness checks

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.[15] 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.[16] 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 of local PM2.5 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 PM2.5 on respiratory health. Notably, we find pollution-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., 1024).

Other two relevant conceptual issues may reinforce the view that our benchmark estimates are conservative. First, our results are contemporaneous and measure the relationship between PM2.5 and hospitalizations or mortality in the same month of occurrence. However, the unobservable chain connecting atmospheric pollution to the onset of debilitating health consequences is challenging. A limitation of our modelling choice is that exposure to air pollution in a given month may have health consequences that eventually spillover into the following month. The timing of the connection between exposure to air pollution and debilitating health consequences can be relatively short, but it is still conceptually contrived and empirically open (Deryugina et al., 2019).[17] Our estimates can be attenuated as long as the effects of exposure to air pollution partially spillover into the future. Second, avoidance behavior can also attenuate adverse effects. Our estimates are reduced-form parameters that capture the overall effect of air pollution on health outcomes. Although not directly observable, if present in the Amazon region, avoidance behavior can be considered part of adaptive mechanisms that help mitigate adverse effects (e.g. see Graff Zivin & Neidell (2013) and Hsiang, Oliva, & and Walker (2019)).

Finally, the exclusion restriction is valid in high-frequency empirical settings (such as in daily, weekly or even monthly basis) should other local determinants of health respond only very weakly or relatively slowly in comparison to changes in wind patterns and PM2.5 (e.g health care supply and GDP). In fact, our main estimates are remarkably stable conditional upon the inclusion of economic variables measured in the reference municipality. While we conjecture that a similar or even weaker pattern should occur across geographies, spatial dependence in determinants of health outcomes may trivially exist in our empirical setting. A Moran's I tests for PM2.5 and hospitalization – by using a queen contiguity matrix, which considers every neighbor that shares a common edge or common vertex with the reference municipality – confirms the presence of spatial autocorrelation for air pollution (Moran's I value of 0.77), and a positive but smaller spatial autocorrelation for hospitalizations (Moran's I value of 0.24). Additionally, we have estimated a Bivariate Moran's I test between spatial lagged PM2.5 and hospitalization. This test considers the correlation between both variables, without taking into account the correlation between PM2.5 and hospitalization in the same municipality. We find that the Bivariate Moran's I statistic is not distinguishable from zero, which suggests that lagged PM2.5, eventually correlated with determinants of health and other confounders from neighbors, do not correlate with hospitalization in the reference municipality. We ran ordinary spatial panel models as an additional consistency check and to further test whether our results are robust to the inclusion of spatial lags. More specifically, we used a queen contiguity matrix and ran a spatial error model, a spatial autocorrelation model, and a spatial autoregressive model. We observe that point estimates for the impact of PM2.5 on hospitalization rates remain positive, statistically significant, and quantitatively similar to our OLS results across all specifications.[18]

6. Discussion and 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 compos-

[15] Deryugina et al. (2019) and Schlenker and Walker (2016) also include leads and lags in PM2.5 concentrations to assess dynamics.

[16] More specifically, we use Eq. (2) and replace the dummies that indicate upwind by dummies that indicate winds blowing to the opposite direction. The dummy "Non-Upwind" takes unitary value when wind is not blowing from neighbours towards the reference municipality.

[17] For the US context, for instance, Deryugina et al. (2019) estimate the dynamic effects of a 1-day shock in exposure to PM2.5 on elderly mortality, and find that the increase in the effect levels off throughout the following weeks, with the bulk of the variation occurring in the first days. Their benchmark specification considers a 3-day estimating window.

[18] The results are presented in Appendix Table B.3.

ite term that combines monthly variation in wind direction with air pollution in surrounding municipalities, we documented a robust association between exposure to PM2.5 concentration and an increase in hospital admissions for respiratory conditions. More specifically, our benchmark estimation indicates that an increase of one standard deviation in PM2.5 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 PM2.5 levels cross thresholds as high as 75 $\mu g/m^3$, which corresponds to three times the threshold of 25 $\mu g/m^3$ 24-h 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 degradation and biodiversity loss. In particular, we shed light on the detrimental health impacts that air pollution related to forest fires have on local populations.

The existing literature is not short of studies on the relationship between air pollution and health outcomes in the Amazon region, but has very often focused on specific sites or relied on more descriptive empirical methods, such as cross-sectional and time-series analysis (Rodrigues, Ignotti, & and Hacon,2013; Nunes, Ignotti, & Hacon, 2005; Rodrigues et al., 2013; Jacobson et al., 2014). As remarked by Smith, Aragao, Sabel, and and Nakaya (2014), the existing estimates from the literature range from increases of 2.9% to 5.6% in hospitalization rates for a positive variation of 10 $\mu g/m^3$ in PM2.5. These results are somewhat higher than our estimates, which are slightly less than 1% for the same increase in PM2.5. Our non-linear results nevertheless shed light on more extreme conditions as well, when air pollution peaks and effects are larger, and closer to estimates from sites that face relatively higher air pollution.

Our results reveal and characterize health costs associated with deforestation in the Brazilian Amazon, which are not usually considered in the discussion of land-use patterns and of development processes in the region. There is an important academic and policy debate on whether the current pattern of occupation of the Brazilian Amazon is conducive or not to development. This literature discusses the "boom and bust" hypothesis (Celentano et al., 2012; Hall & Caviglia-Harris, 2013; Weinhold, Reis, & and Vale, 2015), without reaching a conclusion. The adverse health effects of land-use patterns bring an additional layer of costs and complexity to the debate. In fact, the reduction in health effects of air pollution is recognized by the United Nations' Sustainable Development Goals, which explicitly state as target 3.9 that, by 2030, the number of deaths and illnesses from hazardous chemicals and air, water and soil pollution and contamination should be substantially reduced. The consideration of health-related costs associated with air pollution is therefore relevant for the assessment of alternative development strategies for the region.

Finally, it is possible to break-down the trade-off between agricultural expansion and forest conservation. As Barbier (2019) highlights, it is indeed important to decouple rural development from land-use expansion. This was achieved in Brazil from the mid-2000s until the early 2010s with a mix of policies intended to enhance forest conservation in the Brazilian Amazon. These policies did not harm agricultural development, which became more intensive (Assunção et al., 2020; **?**). The results of this paper reinforce the importance of strengthening previous successful conservation policies in the region by documenting that the welfare costs associated with deforestation and biomass burning are also leveraged by adverse health consequences.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Illustration of IV, first-stage and additional results

See Fig. A.1 and Tables A.1–A.3.

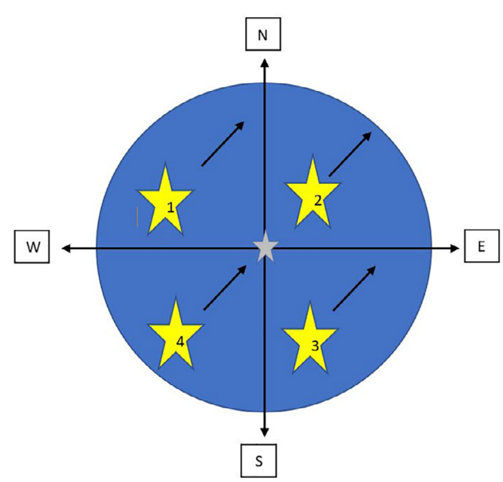

Fig. A.1. Computation of IV: Illustrative Figure. (Notes: This figure depicts an example to illustrate the computation of the IV (Eq. 2) and variations used in consistency checks. The municipality *m* of reference is represented by the gray star. Each yellow star represents a neighboring municipality (or group of municipalities). In this example, the wind is blowing towards *m* from the SW quadrant. Thus, only the air pollution from municipality 4 is assigned into the instrumental variable, as defined by Eq. (2). As regards the Wind-Reverted PM2.5 measure in column 5 of Table A.1, we compute the difference between the pollution in municipality 2 and in municipality 4.)

Table A.1
First-Stage Results.

	PM2.5				
	(1)	(2)	(3)	(4)	(5)
Instrument	0.243	0.227	0.227		
(Wind from Neighbors*PM2.5 in Neighbors)	(0.015)***	(0.014)***	(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)***	
Wind-Reverted PM2.5					-0.029
					(0.014)**
Observations	90,720	89,520	89,520	89,520	89,520
Partial-F IV	270.8	261.2	257.5	119.3	4.485
Common Specification:					
Time and Municipality FE	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	Yes	Yes	Yes
Time Trend	No	No	Yes	Yes	Yes

Notes: All specifications follow Eq. 1. In all columns the dependent variable is PM2.5. In columns 1–3, the instrument is defined by Eq. 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 (1)	Infec (2)	Circulat (3)	Neoplas (4)	Digest (5)	Total (6)
			Panel A – OLS			
PM2.5	0.001	−0.001	0.004	0.003	0.000	0.010
	(0.001)	(0.001)	(0.003)	(0.002)*	(0.002)	(0.005)**
Observations	83,352	83,352	83,352	83,352	83,352	83,352
			Panel B – 2SLS			
PM2.5	0.000	−0.002	0.004	0.004	0.001	0.007
	(0.002)	(0.002)	(0.005)	(0.003)	(0.002)	(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 (1)	Infec (2)	Circulat (3)	Neoplas (4)	Digest (5)	Total (6)
[0y–1y]	0.0005	−0.0008	−0.0000	−0.0003	0.0004	−0.0006
	(0.0007)	(0.0006)	(0.0002)	(0.0001)***	(0.0005)	(0.0019)
Observations	81,432	81,432	81,432	81,432	81,432	81,432
>60y	−0.0007	0.0007	0.0042	0.0040	−0.0003	0.0036
	(0.0021)	(0.0011)	(0.0044)	(0.0028)	(0.0012)	(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: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Appendix B. Robustness checks

See Tables B.1–B.3.

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)
			Panel A – OLS			
PM2.5	0.028	0.070	0.061	0.002	0.002	0.001
	(0.013)**	(0.014)***	(0.012)***	(0.001)	(0.001)	(0.001)
Observations	78,720	78,720	78,720	70,848	70,848	70,848
			Panel B – 2SLS			
PM2.5	0.025	0.075	0.067	0.001	0.000	-0.000
	(0.026)	(0.029)***	(0.029)**	(0.002)	(0.003)	(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)
				Panel A – OLS				
PM2.5	0.055	0.062	0.049	0.054	0.001	0.001	0.001	−0.001
	(0.011)***	(0.012)***	(0.011)***	(0.012)***	(0.001)	(0.001)	(0.001)	(0.002)
PM2.5 Neighb.*Non-Upwind				−0.007				0.002
				(0.007)				(0.002)
Observations	91,440	88,008	86,696	86,696	83,352	80,136	80,136	80,136
				Panel B – 2SLS				
PM2.5	0.055	0.072	0.060	0.066	0.000	−0.000	−0.001	−0.002
	(0.027)**	(0.028)***	(0.031)*	(0.034)*	(0.002)	(0.003)	(0.003)	(0.004)
PM2.5 Neighb.*Non-Upwind				−0.009				0.002
				(0.008)				(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: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table B.3
Spatial Regression Models.

	(1) OLS	(2) OLS	(3) SEM	(4) SAC	(5) SAR
PM2.5	0.055	0.054	0.051	0.032	0.046
	(0.011)***	(0.012)***	(0.013)***	(0.009)***	(0.012)***
rho				0.494	0.170
				(0.045)***	(0.013)***
lambda			0.170	−0.411	
			(0.013)***	(0.065)***	
Observations	91,440	92,640	92,640	92,640	92,640

Notes: The first column reproduces the results from column (2) of Table 2. The second column follows the same specification, but excludes specific controls which have some missing observations so as to allow us to run a balanced panel of municipalities. As spatial models need a strongly balanced panel, columns (3)-(5) present estimates without relative humidity as control. All specifications include municipality and time fixed-effects and weather controls (average precipitation and temperature). The spatial models from columns (3)-(5) are estimated based on a queen contiguity matrix, which considers every neighbor that shares a common edge or common vertex with the municipality of analysis. In the third column, it is estimated a Spatial Error Model, which considers a lag structure in the error term (the lambda estimated). The fourth column presents a Spatial Autocorrelation Model, which considers a lag structure both in the error term (lambda) and in the lagged dependent variable (rho). Finally, the Spatial Autoregressive Model considers a lag structure in the lagged dependent variable (rho). Standard errors clustered at the municipality level. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Appendix C. Supplementary data

Supplementary data associated with this article can be found, in the online version, at https://doi.org/10.1016/j.worlddev.2021.105722.

References

Assunção, J., Gandour, C., Rocha, R., & Rocha, R. (2020). The effect of rural credit on deforestation: Evidence from the Brazilian Amazon. *The Economic Journal, 130*(626), 290–330.

Barbier, E. B. (2020). Is green rural transformation possible in developing countries? World Development 131, 104955..

Barcellos, C., Xavier, D., Hacon, S., Artaxo, P., Gracie, R., Magalhães, M., et al. (2019). Queimadas na Amazônia e seus impactos na saúde: A incidência de doenças respiratórias no sul da Amazônia aumentou significativamente nos últimos meses. 3Informe técnico do Observatório de Clima e Saúde. Observatório de Clima e Saúde Instituto de Comunicação e Informação Científica e Tecnológica em Saúde (ICICT), Fundação Oswaldo Cruz (Fiocruz)..

Barlow, J., Berenguer, E., Carmenta, R., and França, F. (2020). Clarifying amazonia's burning crisis. Global Change Biology 26(2), 319–321..

Bhalotra, S., Rocha, R., & Soares, R. R. (2019). Does Universalization of Health Work? Evidence from Health Systems Restructuring and Maternal and Child Health in Brazil. *Working Paper*.

Brasil. (2018). Brazil's submission of a Forest Reference Emission Level (FREL) for reducing emissions from deforestation in the Amazonia biome for REDD+ results-based payments under the UNFCCC from 2016 to 2020. Brasília..

Burke, M., Driscoll, A., Xue, J., Heft-Neal, S., Burney, J., and Wara, M. (2020). The Changing Risk and Burden of Wildfire in the US. National Bureau of Economic Research, (27423)..

Carmo, C. N. d., Hacon, S., Longo, K.M., Freitas, S., Ignotti, E., Leon, A. P. d., and Artaxo, P. (2010). Associação entre Material Particulado de Queimadas e Doenças Respiratórias na Região Sul da Amazônia Brasileira. Revista Panamericana de Salud Pública 27, 10–16..

Castro, M., Massuda, A., Menezes-Filho, N., Andrade, M., De Souza Noronha, K., et al. (2019). Brazilian unified health system-the first 30 years and prospects for the future: modelling study..

D. Celentano, E. Sills, M. Sales, and A. Veríssimo. Welfare outcomes and the advance of the deforestation frontier in the brazilian amazon. World Development, 40 (4):850–864, 2012..

Currie, J., & Neidell, M. (2005). Air Pollution and Infant Health: What Can We Learn from California's Recent Experience? *The Quarterly Journal of Economics, 120*(3), 1003–1030.

de Oliveira Alves, N., Vessoni, A. T., Quinet, A., Fortunato, R. S., Kajitani, G. S., Peixoto, M. S., de Souza Hacon, S., Artaxo, P., Saldiva, P., Menck, C. F. M., et al. (2017). Biomass Burning in the Amazon Region Causes DNA Damage and Cell Death in Human Lung Cells. *Scientific Reports, 7*(1), 1–13.

Deryugina, T., Heutel, G., Miller, N. H., Molitor, D., & Reif, J. (2019). The Mortality and Medical Costs of Air Pollution: Evidence from Changes in Wind Direction. *American Economic Review, 109*(12), 4178–4219.

Ezzati, M., & Kammen, D. M. (2001). Quantifying the Effects of Exposure to Indoor Air Pollution from Biomass Combustion on Acute Respiratory Infections in Developing Countries. *Environmental Health Perspectives, 109*(5), 481–488.

Fearnside, P. M. (2018). Brazil1s amazonian forest carbon: The key to southern amazonia's significance for global climate. *Regional Environmental Change, 18*(1), 47–61.

Flemming, J., Benedetti, A., Inness, A., Engelen, R. J., Jones, L., Huijnen, Remy, V. S., et al. (2017). The cams interim reanalysis of carbon monoxide, ozone and aerosol for 2003–2015. Atmospheric Chemistry and Physics 17(3), 1945–1983..

Frankenberg, E., McKee, D., & Thomas, D. (2005). Health Consequences of Forest Fires in Indonesia. *Demography, 42*(1), 109–129.

Frias, P. G. d., Szwarcwald, C. L., and Lira, P. I. C. d. (2014). Avaliação dos sistemas de informações sobre nascidos vivos e óbitos no brasil na década de 2000. Cadernos de Saúde Pública 30, 2068–2280..

Garnelo, L. (2019). Specificities and Challenges of Public Health Policies in the Brazilian Amazon. *Cadernos de Saúde Pública, 35*(12).

Graff Zivin, J., & Neidell, M. (2013). Environment, Health, and Human Capital. *Journal of Economic Literature, 51*(3), 689–730.

Guan, W.-J., Zheng, X.-Y., Chung, K. F., & Zhong, N.-S. (2016). Impact of Air Pollution on the Burden of Chronic Respiratory Diseases in China: Time for Urgent Action. *The Lancet, 388*(10054), 1939–1951.

Hall, S. C., and Caviglia-Harris, J. (2013). Agricultural development and the industry life cycle on the brazilian frontier. Environment and Development Economics 18 (3), 326–353..

Hanna, R., Duflo, E., & Greenstone, M. (2016). Up in Smoke: The Influence of Household Behavior on the Long-Run Impact of Improved Cooking Stoves. *American Economic Journal: Economic Policy, 8*(1), 80–114.

He, G., Liu, T., and Zhou, M. (2020). Straw Burning, PM2.5, and Death: Evidence from China. Journal of Development Economics 102468..

He, J., Gouveia, N., & Salvo, A. (2019). External Effects of Diesel Trucks Circulating Inside the São Paulo Megacity. *Journal of the European Economic Association, 17*(3), 947–989.

Hsiang, S., Oliva, P., and Walker, R. (2019). The Distribution of Environmental Damages. Review of Environmental Economics and Policy 13(1), 83–103..

IBGE. (2004). Mapa de Biomas do Brasil e o Mapa de Vegetação do Brasil. Database, Instituto Brasileiro de Geografia e Estatística, Brasil. URL: https://ww2.ibge.gov.br/home/presidencia/noticias/21052004biomashtml.shtm..

Jacobson, L. d. S.V., de Souza Hacon, S., de Castro, H. A., Ignotti, E., Artaxo, P., Saldiva, P. H. N., et al. (2014). Acute Effects of Particulate Matter and Black Carbon from Seasonal Fires on Peak Expiratory Flow of Schoolchildren in the Brazilian Amazon. PLoS One 9(8), e104177..

Jayachandran, S. (2009). Air Quality and Early-Life Mortality: Evidence from Indonesia's Wildfires. *Journal of Human Resources, 44*(4), 916–954.

Johnston, F. H., Henderson, S. B., Chen, Y., Randerson, J. T., Marlier, M., DeFries, R. S., Kinney, P., Bowman, D. M., & Brauer, M. (2012). Estimated Global Mortality Attributable to Smoke from Landscape Fires. *Environmental Health Perspectives, 120*(5), 695–701.

Kim, K.-H., Kabir, E., & Kabir, S. (2015). A Review on the Human Health Impact of Airborne Particulate Matter. *Environment International, 74*, 136–143.

Lambert, J., Keppens, A., Hubert, D., Langerock, B., Eichmann, K., Kleipool, Q., et al. (2019). Quarterly validation report of the copernicus sentinel-5 precursor operational data products. S5P MPC Routine Operations Consolidated Validation Report series (03)..

Motta, R. S. d. (2002). Estimativa do custo econômico do desmatamento na Amazônia..

Nunes, Karine Vila Real, Ignotti, Eliane, & Hacon, Sandra de Souza (2015). Circulatory disease mortality rates in the elderly and exposure to PM2.5 generated by biomass burning in the Brazilian Amazon in 2005. *Cadernos de saude publica, 29*, 589–598.

Rache, B., Rocha, R., Nunes, L., Spinola, P., Malik, A. M., & Massuda, A. (2020). *Necessidades de Infraestrutura do SUS em Preparo à COVID-19: Leitos de UTI, Respiradores e Ocupação Hospitalar*. São Paulo: Instituto de Estudos para Políticas de Saúde.

Rangel, M. A., & Vogl, T. S. (2019). Agricultural Fires and Health at Birth. *Review of Economics and Statistics, 101*(4), 616–630.

Reddington, C., Butt, E., Ridley, D., Artaxo, P., Morgan, W., Coe, H., & Spracklen, D. (2015). Air Quality and Human Health Improvements from Reductions in Deforestation-Related Fire in Brazil. *Nature Geoscience, 8*(10), 768–771.

Rodrigues, P. C. d. O., Ignotti, E., and Hacon, S. d. S. (2013). Distribuição espaço-temporal das queimadas e internações por doenças respiratórias em menores de cinco anos de idade em Rondônia, 2001 a 2010. Epidemiologia e Serviços de Saúde 22(3), 455–464..

Ruiz-Tagle, J. C. (2018). Essays on the Effects of Air Pollution on Human Health. PhD thesis..

Schlenker, W., & Walker, W. R. (2016). Airports, air pollution, and contemporaneous health. *The Review of Economic Studies, 83*(2), 768–809.

Sheldon, T. L. and Sankaran, C. (2017). The impact of indonesian forest fires on singaporean pollution and health. American Economic Review P&P 107(5), 526–29..

Silvério, D., Silva, S., Alencar, A., and Moutinho, P. (2019). Amazônia em Chamas. Nota Técnica do Instituto de Pesquisa Ambiental da Amazônia – IPAM. Recuperado de: https://ipam.org.br/wp-content/uploads/2019/08/NT-Fogo-Amazo%CC%82nia-2019.pdf..

Smith, L. T., Aragao, L. E., Sabel, C. E., and Nakaya, T. (2014). Drought impacts on children's respiratory health in the brazilian amazon. Scientific Reports 4(1), 1–8..

Tan-Soo, J.-S., & Pattanayak, S. K. (2019). Seeking natural capital projects: Forest fires, haze, and early-life exposure in indonesia. *Proceedings of the National Academy of Sciences, 116*(12), 5239–5245.

Van der Werf, G. R., Randerson, J. T., Giglio, L., Collatz, G., Mu, M., Kasibhatla, P. S., Morton, D. C., DeFries, R., Jin, Y., & van Leeuwen, T. T. (2010). Global Fire Emissions and the Contribution of Deforestation, Savanna, Forest, Agricultural, and Peat Fires (1997–2009). *Atmospheric Chemistry and Physics, 10*(23), 11707–11735.

Viana, A. L. d. and Iozzi, F. L. (2019). Enfrentando desigualdades na saúde: impasses e dilemas do processo de regionalização no Brasil. Cadernos de Saúde Pública 35, e00022519..

Ward, C. J. (2015). It's an ill wind: The effect of fine particulate air pollution on respiratory hospitalizations. *Canadian Journal of Economics, 48*(5), 1694–1732.

Weinhold, D., Reis, E. J., and Vale, P. M. (2015). Boom-bust patterns in the brazilian amazon. Global Environmental Change 35, 391–399..

WTO. (2006). Air Quality Guidelines: Global Update 2005. Particulate Matter, Ozone, Nitrogen Dioxide, and Sulfur Dioxide. World Health Organization..