Health Impacts of Deforestation-Related Fires in the Brazilian Amazon[*]

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Introduction

This report aims to assess correlations between the deforestation-related fires in the Brazilian Amazon and health outcomes, especially respiratory illness. In this document, we discuss the methodology that will be utilized for the statistical study linking active fire hotspots, ambient air pollution and health. Finally, we provide the main results as well as aggregate estimates of the effects of ambient air pollution related to fires and deforestation on health in the Brazilian Amazon. For the purposes of this report, we define the Brazilian Amazon as the Amazon Biome within Brazil's borders, excluding the municipalities pertaining to the Brazilian Legal Amazon that are not part of the Amazon Biome.

Data and Methodology

Health outcomes

Brazil has a universal health system (Sistema Único de Saúde, SUS, as its acronym in Portuguese), which provides free health care to Brazilian citizens. The SUS has an informatics department (DATASUS) that assembles data on hospitalizations – which includes the days a person remains hospitalized and the cost to the SUS- mortality and births at the individual level. From DATASUS, therefore, we obtained administrative data on health outcomes.

We gathered monthly data at the municipality level from January 2010 to December 2019. There are 546 municipalities in the Brazilian Amazon (Amazon biome). Given the size of the region and the demographic density, not all municipalities are equipped with hospitals. Hence, we track the municipality of residence of each person that was hospitalized. Following the literature on the effects of air quality - related to fires – and health, we focused on: respiratory diseases. [1] [2]

As regards the age structure of the population mostly affected, He et al. [2] argue that older people in China suffer more from ambient air pollution related to straw burning. Rangel and Vogl [3] focus on infant health in a study on the effects of agricultural fires at São Paulo state, Brazil. Jacobsen et al. [4] study the effects of particulate matter and black carbon from seasonal fires in schoolchildren's health in the Brazilian Amazon. Hence, our focus will be on infants (0-1-year-old), children between 1 and 5 years old and those with more than 60 years old.

For every health outcome, we standardize data to facilitate comparisons across municipalities and time. Because monthly, age-stratified population is not available, we will compare health outcomes in relation to monthly number of admissions/100,000 total inhabitants per municipality. We use the same approach to age-specific groups rates of hospital admissions. However, there is not, for the years in the sample, estimates of municipal population by age groups. Therefore, we utilize the rate of hospitalization by age group divided by total population. To the extent that the age distribution of the population does not vary substantially, this should not affect our estimates.

Deforestation, Fires and Ambient Air Pollution

Monthly data on deforestation and active fire hotspots by municipality used in this project were assembled by the Instituto de Pesquisa Ambiental da Amazônia (IPAM), a partner institution in this project. IPAM obtained and analyzed data from the Brazilian National Institute for Space Research (INPE) databases on deforestation and active fire hotspots. The data is structured in a panel at the municipality level and with a monthly structure.

The data on deforestation is based on DETER-B which represents periodical deforestation alerts that were aggregated by month from August 2016 to December 2019. Its main difference from previous DETER data is the spatial resolution that increased from 250m to 60m by adding these other satellites to Modis daily product. In addition, DETER-B brings many classes indicating disturbances in native vegetation such as mining, logging, forest degradation by fire and deforestation (forest clear cut). For this study, we only considered the classes associated with deforestation. [1] DETER-B data gives a good perspective of the deforestation trends since it presents daily information that can be aggregated by month or year.

The data on fires measures specifically number of active fire hotspots collected from the reference satellite used by INPE to monitor the spatial and temporal dynamics of fires in Brazil. This data is based on the MODIS sensor on board of the Aqua satellite. This data correlates with the area burned and is a reliable indicator on the overtime trends of fire activity.[2] The active fire hotspots dataset represents the best dataset to compare with health issues since it captures the dynamics of fires over time.

Data on monthly ambient air pollution at the municipality level was obtained from the System of Environmental Information Related to Health (Sistema de Informações Am-

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[1] The DETER data is available in the INPE website (access on Jun. 18 2020)

[2] The data is available in the INPE website (access on Jun. 18 2020)

bientais Integrado à Saúde, SISAM). We will mainly utilize data on $PM_{2.5}$ but will also inspect correlations with other pollutants such as CO, SO_2, NO_2 and O_3.[3]

Additional variables

In order to understand or control for some covariates that might be related to hospitalization rates in the Brazilian Amazon, we will include data on precipitation, relative humidity and temperatures, extracted from INPE.

Table A.1 in the appendix provides descriptive statistics on each variable as well as their source. All variables are at the municipality level and are monthly.

Methodology

We will conduct a statistical analysis to assess the correlation between ambient air pollution from fires related to deforestation and health outcomes in the Brazilian Amazon. Ideally, we would like to recover a causal estimate, as our estimates will control for some observable variables, as temperature, rainfall and moisture, and unobservable variables specific to each municipality that do not vary in time. This design eliminates confounding from seasonality and climate shocks such as *El Niño* years. However, even after conditioning our results on those variables, determining causality is challenging due to omitted variable bias. One likely confounder is the association between fires and economic activity, which might affect health outcomes through other channels. As there is not available monthly economic data at the municipal level, we will add specific municipality trends to account for specific trends that might be related to economic activity as well as health policies at the municipal level.[4]

We hypothesize that ambient air pollution due to fire activity in a given municipality might lead to an increase in hospitalizations and mortality due to respiratory illnesses. We address this correlation by relying on the panel structure of the data, which allows us to control for unobservable variables from municipalities and common monthly shocks, by including municipality and month by year fixed effects. Therefore, our benchmark model to be estimated is:

$$Y_{mt} = \beta_0 + \beta_1 * AirPollution_{mt} + \gamma * X_{mt} + \lambda_m + \alpha_t + \varepsilon_{mt}$$

Where Y_{mt} is a variable that measures health output. In our case, we will use alternative health outcomes, such as hospitalizations and mortality due to respiratory diseases by age groups. $AirPollution_{mt}$ is a variable that measures the concentration of a given pollutant ($PM_{2,5}$, CO, NO_2 and SO_2) in the municipality *m* during month *t*. O The coefficient - β_1 - is our coefficient of interest and recovers our studied correlation conditional on our control variables. X_{mt} is a vector of covariates that might also affect health outcomes. Control variables are mean rainfall, mean temperature and mean humidity. The term α_t is a time fixed effect, which captures month by year shocks common to all municipalities, whereas λ_m is the municipality fixed effect, which captures effects of unobservable and invariant variables in time. The model error term is ε_{mt}.

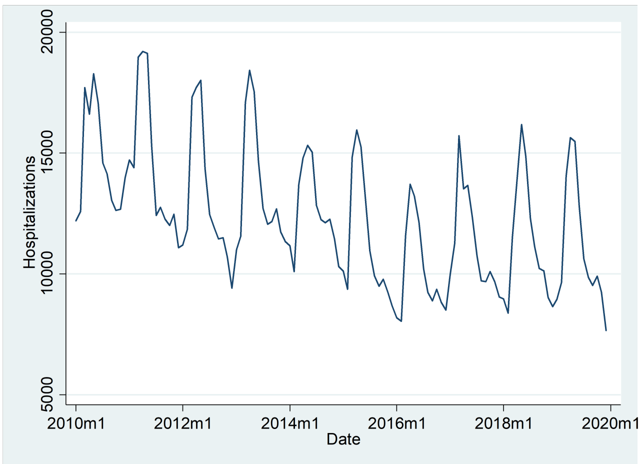
[3] http://queimadas.dgi.inpe.br/queimadas/sisam/v2/dados/download/

[4] Another possible omitted variable that might lead to inconsistent estimator is indoor air pollution from cooking fires. However, we believe that the inclusion of municipality fixed effects as well as municipality trends might deal with this caveat. Moreover, as Gioda et al. [5], report, cooking with firewood represents a relatively small fraction, between 3.2% and 4.5% of households in Brazil.

Trends in respiratory health in the Brazilian Amazon

As regards respiratory diseases, hospitalizations in the Brazilian Amazon biome follow a seasonal pattern, which reach a maximum around May – which marks the beginning of the driest season in the Amazon. Figure 1 plots hospitalizations related to respiratory diseases from January 2010 to December 2019.

Figure 1. Hospitalizations due to respiratory diseases in the Amazon biome



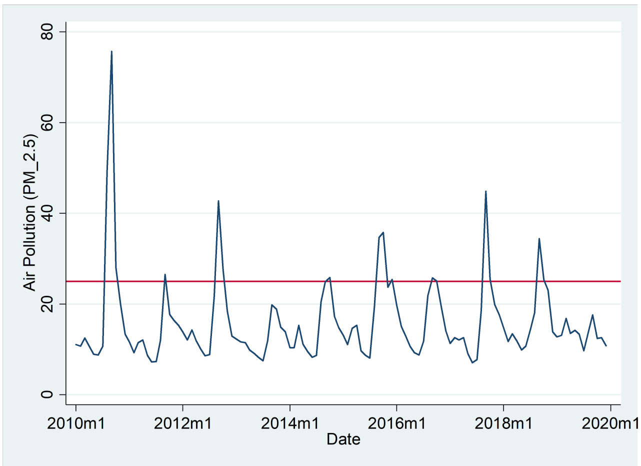
Source: DATASUS

Overall, there was a declining trend in hospitalizations due to respiratory diseases in the Amazon. It seems, however, that this trend has achieved a certain stability from 2015 and there is a clear seasonal peak around May.

In the Brazilian Amazon, the concentration of pollutants is mainly related to fires from deforestation [6]. This is why we are able to observe a peak in the atmospheric concentration of pollutants, as $PM_{2.5}$ from August to October. Figure 2 displays the pattern of $PM_{2.5}$ concentration. The horizontal line in Figure 2 represents the Air Quality Guideline threshold established by the World Health Organization for 24h mean.

On Figure 3, we observe the trends, from 2016 to 2019, of focus of active fire hotspots in the Brazilian Amazon Forest. The period of active fire counts reflects the same period of data from DETER-B. As it is clear, there is a seasonal pat-

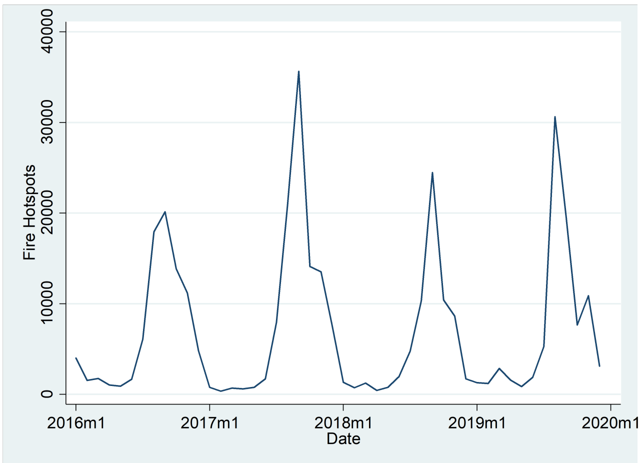
Figure 2. Mean of $PM_{2.5}$ concentration in the Amazon biome



Source: INPE

tern where fires start around July and last until September each year.

Figure 3. Active fire hotspots in the Brazilian Amazon Biome



Source: IPAM, based on data from INPE/BDqueimadas

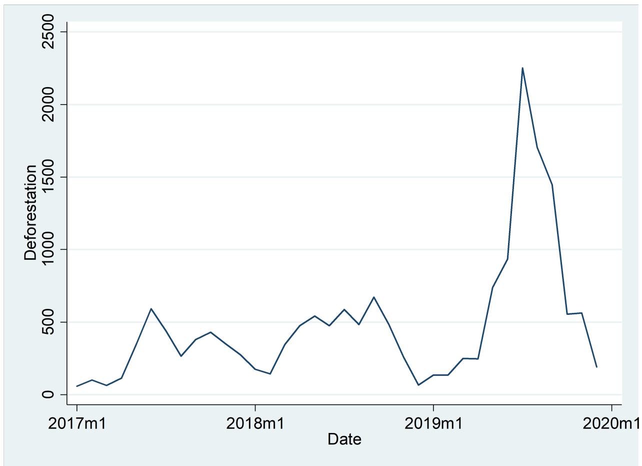
In addition to active fire hotspots, we make a visual inspection of the trends regarding deforestation. As shown on Figure 4, there is a clear peak in deforestation from July 2019 to September 2019 that does not have a parallel in previous years. The surge in deforestation last year helps in understanding the extent of the problems associated to smoke from fires last year.

Results

Ambient Air Pollution, Fires and Deforestation

The majority of deforested plots in the Brazilian Amazon is burned to clean land, in preparation for cattle ranching, agriculture and mining activities [7]. The burned biomass generates many pollutants, as CO_2, CO, NO_x and particulate matter (especially $PM_{2.5}$) [8]. As Barcellos et al. [9] argue, particulate matter may travel hundreds of kilometers,

Figure 4. Deforestation (km^2/month) in the Brazilian Amazon Biome



Source: INPE

spreading pollution even to regions not affected by deforestation.

Ultimately, the health impacts of fires related to deforestation in the Amazon can be sensed distant from the fire sources. Therefore, when assessing health impacts, the main independent variable to be utilized in this report is the concentration of particulate matter, which has significant impacts in human health [10]. The effects of vegetation fire events are so expressive that they have even deserved a guideline document produced by the World Health Organization [11].

Table A.2, in the annex, displays the relationship between the concentration of different pollutants and fire and deforestation activities. All pollutants have a positive correlation between their concentration in the atmosphere and fires related to deforestation.

Health and Ambient Air Pollution

Hospitalization and overall population

Table 1 displays the relationship between hospitalization rates due to respiratory diseases and the monthly mean of fine particulate matter ($PM_{2.5} \mu g/m^3$). From Columns (1)-(3), the dependent variable is the overall hospitalization rate (per 100,000 inhabitants) due to respiratory illness. In column (4), we assess the effects on the number of hospitalization days due to the same kind of diseases. From columns (1) to (3), we estimate the effect of the level of $PM_{2.5}$5 concentration on hospitalization rates, by controlling for municipality and month-by-year fixed effects (Column (1)); weather covariates (Column (2)) and a municipality trend (Column (3)). We add these specific municipality trends to account for the consistent reduction in hospitalization in time, as seen on Figure 1.

Results point to a positive relationship between ambient air pollution and hospitalization rates. From column (3), an increase of one standard deviation (17.88) in pollution levels relates to an increase of 0.82 in hospitalization rates,

Table 1. Hospitalization rates due to respiratory illness and ambient air pollution

VARIABLES	(1) Hosp. Rate Resp.	(2) Hosp. Rate Resp.	(3) Hosp. Rate Resp.	(4) #Days of Hosp.
$PM_{2.5}$	0.026*	0.053***	0.046***	0.070**
	(0.013)	(0.013)	(0.012)	(0.033)
Observations	65,520	65,520	65,520	65,520
R-squared	0.502	0.503	0.598	0.931
Municipality FE	Y	Y	Y	Y
Month by Year FE	Y	Y	Y	Y
Weather variables	N	Y	Y	Y
Municipality Trend	N	N	Y	Y
Number of municipalities	546	546	546	546
Mean of Dep. Var.	61.90	61.90	61.90	106.9

Notes: Table reports OLS estimates with municipality and month-by-year fixed effects. In columns (1)-(3), dependent variable is the rate of hospitalization (per 100,000 inhabitants) due to respiratory illness. In column (4), dependent variable is the overall number of monthly hospitalization days due to respiratory illness. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Source: own elaboration.

or 1.33% of the mean of the dependent variable. A one standard deviation in $PM_{2.5}$ concentration is equal to an increase from the total average (16.42) to the average in September, the month where pollution levels are at their highest (34.33). As regards the number of hospitalization days, an increase of one standard deviation in our measure of ambient air pollution relates to 1.25 more days in hospital, or 1.17% of the average number of hospitalization days.

On Table 1, we have focused on particulate matter. As argued by Chan [12]), health risks related to particulate matter (both PM_{10} and $PM_{2,5}$) are especially well documented. This is so because fine particulate matter can penetrate deep into the lung. However, other pollutants also impose a risk on health [13]. Hence, on Table A.3 of the Annex, we focus on CO, NO_2 and SO_2 and their respective relationships with respiratory diseases. We estimate the same specification as in Column (3) from Table 1, with municipality trends.

An important point raised by Graff-Zivin and Neidell [14]) is that pollution can have nonlinear effects on health. Thus, we allow for nonlinear effects by examining how hospitalization rates vary according to dummies related to the World Health Organization Air Quality Guidelines thresholds [15]. We follow the procedure proposed by Currie et al. [16]), who used instead the U.S. National Air Quality Standards. Figure A.1 in the appendix displays the estimated coefficients for the thresholds proposed by WHO [15].The results show a non-linear relationship, where it is only above interim target 1 that we see a statistically significant relationship between air pollution and hospitalizations, which confirms the nonlinear effects found in the literature. This result means that when ambient air pollution is above 75 $\mu g/m^3$ in 24-hour mean, the hospitalization rate due to respiratory diseases is 8.7 per 100,000 people higher as compared to WHO air quality guideline for $PM_{2.5}$. This can also be interpreted as an increase of 14.8% as compared to average hospitalization rate in 2019 due to respiratory diseases.

Hospitalization and Health by Age Groups

We utilize the rate of hospitalization by age group divided by total population (Hosp. by Age Group/100,000 total population). Table 2 provides estimates of hospitalization due to respiratory diseases by age groups. The age group on column (1) comprises children with less than one year old. Column (2) displays estimates of hospitalization in children with more than one year old and less than six years old.[5] On column (3), the age group is of children between six and fourteen years old.[6] Finally, on column (4), we provide estimates for hospitalization among those with more than 60 years old.[7]

Results from Table 2 follow as expected, given the literature review. Both children and older people suffer with respiratory diseases as ambient air pollution increases. However, among children, the effects are only felt among those with less than one year old. Using the estimated coefficient from column (1), a one standard deviation in ambient air pollution is related to an increase 1.5% in mean hospitalization rates to infants. The same evaluation for the elderly implies a related increase of 3.0% in hospitalization rates.

It seems that the extremes of the age groups are more susceptible to the effects of ambient air pollution on health. However, this correlation appears to be even stronger among older people, where pollution peaks can have important morbidity effects.

[5] Rodrigues et al. [17] analyze the distribution of hospitalization for respiratory diseases in children with less than 5 years old in the state of Rondônia. Carmo et al. [18] also focus on children with less than 5 years old in Alta Floresta, MT.

[6] Jacobson et al. [4] describe the effects of air pollution from fires in the Brazilian Amazon on peak expiratory flow on children between 6 to 15 years old living in the municipality of Tangará da Serra, MT.

[7] Carmo et al. [18] discuss the respiratory problems related to fires and particulate matter among people with more than 64 years old.

Table 2. Hospitalization rates due to respiratory illness and ambient air pollution

VARIABLES	(1) [0y-1y]	(2) [1y-5y]	(3) [6y-14y]	(4) >60y
$PM_{2.5}$	0.011**	-0.002	-0.001	0.023***
	(0.004)	(0.003)	(0.003)	(0.005)
Observations	64,296	64,296	64,296	64,296
R-squared	0.397	0.433	0.412	0.397
Municipality FE	Y	Y	Y	Y
Month by Year FE	Y	Y	Y	Y
Weather variables	Y	Y	Y	Y
Municipality Trend	Y	Y	Y	Y
Number of municipalities	546	546	546	546
Mean of Dep. Var.	13.37	9.917	6.915	13.72

Notes: Table reports OLS estimates with municipality, month-by-year fixed effects and municipality trends. Dependent variable is the rate of hospitalization (per 100,000 inhabitants) due to respiratory illness. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Source: own elaboration.

Mortality and overall population

After analyzing morbidity, in this subsection, we estimate the correlation between mortality rates and ambient air pollution. Mortality rates are represented as the number of deaths related to a specific source divided by total population (deaths per 100,000 inhabitants). Table 3 displays the results for deaths related to respiratory diseases.

Overall, it seems that there is not, conditional on fixed effects, a correlation in the short term between mortality due to respiratory conditions and ambient air pollution in the Brazilian Amazon.[8] These results seem to be general: as we inspect the relationship among distinct age groups, the estimated coefficient cannot be distinguished from zero in any age group, as shown on Table A.4, in the annex.

Discussion of results

This report has analyzed morbidity and mortality related to ambient air pollution in the Brazilian Amazon, defined as the Amazon Biome in Brazil. Our results show a statistically significant relationship between hospitalizations due to respiratory diseases and the concentration of particulate matter. Moving forward, it is important for policy makers to understand the scope of the public health impact in the Amazon region and the strain it places on its precarious health infrastructure, with a view to formulate preventive and proactive protective measures for affected communities and, particularly, vulnerable groups. Thus, natural questions arise such as how many people were hospitalized in 2019 due to the decrease in air quality related to the outbreak of fires and the extent of deforestation in the Brazilian Amazon? Given that, what was the fiscal cost to the public health system? Which age groups were mainly affected?

In this section, we will address these questions, based on the estimates presented in the previous section. Firstly, we take the predicted values of ambient air pollution, based on the estimates of Table 1, Column (3). Then, we apply these values to assess how many people were hospitalized in 2019 linked to the decrease in air quality related to deforestation and fires, based on estimates from Table 1. In other words, we compare the number of hospital admissions in 2019 related to air pollution from fires and deforestation with a counterfactual of zero deforestation and zero fires. We aggregate the results and use each municipality population to have overall figures for the number of total hospitalizations in 2019 related to the outbreak of fires and deforestation.

In 2019, we estimate that there was a total of 2,195 hospitalizations (with a 95% confidence interval between 1,098 and 3,291) due to respiratory diseases linked with ambient air pollution from deforestation-related fires. This led to a total of 6,698 days of hospitalization (with a 95% confidence interval between 1,292 and 12,105 days). In 2019, the average cost for hospitalizations due to respiratory diseases in the Brazilian Amazon was R$ 858.15 (USD 217.50) per hospitalization which we apply to the 2,195 hospitalizations. The amount of reimbursements made by the federal government was of R$ 1.88 million (USD 477,551). However, as highlighted by Américo and Rocha [20], state and municipal governments also add funds on top of federal transfers, in a ratio that proxies 2:1. Hence, applying this ratio, we estimate that total costs associated to hospitalizations due to deforestation-related fires was R$ 5.64 million (USD 1.4 million).

For the same year, during the period of June-October which encompasses the dry season in the Amazon [21], we estimate, that there was a total of 1,012 hospitalizations (with a 95% confidence interval between 506 and

[8] This result should be viewed with since we are investigating short-term correlations. For an analysis of the effects of biomass burning on DNA damage and human lung cells, see De Oliveira Alves et al. [19]

Table 3. Mortality rates due to respiratory illness and ambient air pollution

VARIABLES	(1) Mort. Rate Resp.	(2) Mort. Rate Resp.	(3) Mort. Rate Resp.
$PM_{2.5}$	0.000	0.000	-0.000
	(0.001)	(0.001)	(0.001)
Observations	58,944	58,944	58,944
R-squared	0.066	0.066	0.081
Municipality FE	Y	Y	Y
Month by Year FE	Y	Y	Y
Weather variables	N	Y	Y
Municipality Trend	N	N	Y
Number of municipalities	546	546	546
Mean of Dep. Var.	2.844	2.844	2.844

Notes: Table reports OLS estimates with municipality and month-by-year fixed effects. Dependent variable is the rate of mortality (per 100,000 inhabitants) due to respiratory illness. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Source: own elaboration.

1,517) due to respiratory diseases associated with ambient air pollution from deforestation-related fires. This led to a total of 3,021 days of hospitalization (with a 95% confidence interval between 583 and 5,460 days). The cost to the public healthcare system (SUS) between June and October 2019 resulting from hospitalizations due to respiratory diseases linked to deforestation-related fires was of R$ 2.6 million (USD 660,000).

The remarkable spike in fire hotspots in August 2019 was accompanied by an increase in excess hospitalizations linked to ambient air pollution. Hospitalizations due to respiratory diseases linked to the increase in ambient air pollution from deforestation-related fires increased by 65% between July and August, the month when the fires peaked. The burden of ambient air pollution among age groups shows that infants and older people were the most affected. In 2019, there were 467 (with a 95% confidence interval between 109 and 824) hospitalizations of infants aged 0-1-year-old and 1,080 (with a 95% confidence interval between 608 and 1,552) hospitalizations of older people aged 60 years old and over due to respiratory diseases linked to the increase in ambient air pollution from deforestation-related fires. For the period concerning only the dry season, between June and October, there were 215 hospitalizations of infants and 47 older persons. The sum of these two age groups amounts to 70% of total hospitalizations due to respiratory diseases linked to air pollution from deforestation-related fires in 2019.

As a conclusion, our estimates show an important effect of the outbreak of fires and deforestation in 2019 on hospitalizations due to respiratory diseases. In 2020, with higher rates of deforestation and, relatedly, a higher risk of fires, as well as the devastating toll of COVID-19 in the Amazon region, there is a justifiable fear of a serious threat to the population in the Brazilian Amazon and its strained public health system.

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Table 4. Estimates for absolute hospitalizations due to respiratory diseases linked to increased ambient air pollution from deforestation-related fires in the Brazilian Amazon Biome

Month (year of 2019)	Total number of excess hospitalizations attributable to deforestation related fires	Average Total number of hospitalizations (2016-2018)	Total number of hospitalizations of infants (0-1 year old)	Total number of hospitalizations of older people (60 years and older)
January	148	9,311	31	75
February	143	9,646	30	76
March	154	13,652	33	82
April	148	14,650	32	82
May	122	15,120	26	67
June	109	13,465	23	59
July	141	11,335	30	67
August	232	10,314	49	103
September	288	9,898	61	134
October	242	10,202	52	113
November	255	9,498	54	119
December	213	8,744	45	104
TOTAL	2,195	135,835	467	1,080

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Annex

Table A.1 – Descriptive Statistics

Variable	Mean	Std. Dev	Min	Max	Obs	Period	Source
Hosp. rate – resp. (per 100,000 people)	61.90	68.12	0	1471.47	65,520	Jan 2010 – Dec 2019	DATASUS
Mort. rate – resp. (per 100,000 people)	2.84	5.19	0	96.18	58,944	Jan/2010 – Dec/2018	DATASUS
$PM_{2.5}$ ($\mu g/m^3$)	16.38	17.88	2.6	657.71	65,520	Jan/2010 – Dec/2019	INPE
Active fire hotspots	14.07	70.26	0	35577	24,336	Jan/2016 – Dec/2019	INPE
Deforestation (in km^2)	0.89	4.56	0	178.64	22,386	Aug/2016-Dec/2019	INPE

Table A.2 – Correlation between active fire hotspots, deforestation and ambient air pollution

	(1)	(2)	(3)	(4)
VARIABLES	Ln_$PM_{2.5}$	Ln_CO	Ln_SO_2	Ln_NO_2
Ln(active fire hotspots)	0.151***	0.126***	0.064***	0.109***
	(0.007)	(0.005)	(0.004)	(0.005)
Ln(Deforestation)	0.022***	0.014***	0.005***	0.010***
	(0.003)	(0.002)	(0.001)	(0.002)
Rainfall	0.032***	0.027***	0.005***	0.012***
	(0.002)	(0.001)	(0.001)	(0.001)
Temperature	0.104***	0.113***	0.098***	0.100***
	(0.007)	(0.007)	(0.007)	(0.008)
Observations	22,386	15,834	15,834	15,834
R-squared	0.591	0.781	0.744	0.677
Municipality FE	Y	Y	Y	Y
Month by Year FE	Y	Y	Y	Y
Municipality Trend	Y	Y	Y	Y
Number of municipalities	546	546	546	546
Mean	2.704	4.975	0.306	0.431

Notes: Table reports Ordinary Least Squares estimates with municipality, month-by-year fixed effects and municipality trends. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Source: own elaboration.

Table A.3 – Hospitalization rates due to respiratory illness and other pollutants

VARIABLES	(1) Hosp. Rate Resp.	(2) Hosp. Rate Resp.	(4) Hosp. Rate Resp.
CO	0.008***		
	(0.002)		
NO_2		1.088***	
		(0.235)	
SO_2			1.555***
			(0.377)
Observations	58,944	58,944	58,940
R-squared	0.609	0.609	0.609
Municipality FE	Y	Y	Y
Month by Year FE	Y	Y	Y
Weather variables	Y	Y	Y
Municipality Trend	Y	Y	Y
Number of municipalities	546	546	546
Mean	62.83	62.83	62.83

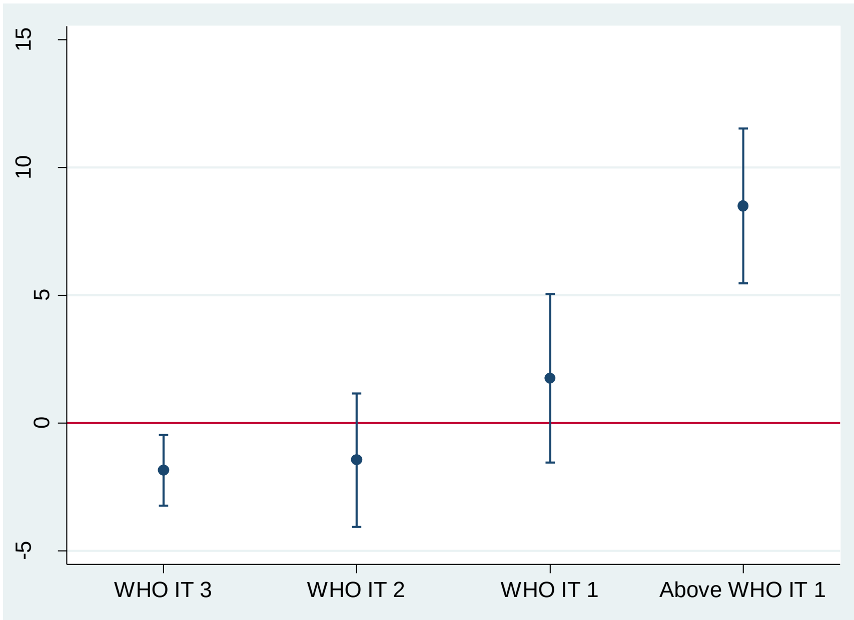
Notes: Table reports OLS estimates with municipality, month-by-year fixed effects and municipality trends. Dependent variable is the rate of hospitalization (per 100,000 inhabitants) due to respiratory illness. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A.4 – Mortality rates due to respiratory illness and ambient air pollution, among age groups

VARIABLES	(1) [0-1yr)	(3) [1-5yr]	(5) >60yr
$PM_{2.5}$	-0.000	-0.000	-0.001
	(0.000)	(0.000)	(0.001)
Observations	58,728	56,568	58,944
R-squared	0.066	0.032	0.081
Municipality FE	Y	Y	Y
Month by Year FE	Y	Y	Y
Weather variables	Y	Y	Y
Municipality Trend	Y	Y	Y
Number of municipalities	544	524	546
Mean	0.174	0.0924	2.016

Notes: Table reports OLS estimates with municipality and month-by-year fixed effects. Dependent variable is the rate of mortality (per 100,000 inhabitants) due to respiratory illness. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Source: own elaboration.

Figure A.1 – Estimated coefficients for the World Health Organization's Air Quality Guidelines (2006) thresholds for PM 2.5 concentration in 24-hour mean



Source: own elaboration.

The estimated parameters must be interpreted as a difference to benchmark pollution, which is WHO air quality guidelines and refers to $PM_{2.5}$ less than 25 μg/m^3 in 24-hour mean. WHO IT 3 refers to the Interim Target 3, which is between 25 and 37.5 μg/m^3 in 24-hour mean. WHO IT 2 refers to the Interim Target 2, which is between 37.5 and 50 μg/ m^3 in 24-hour mean. WHO IT 1 refers to the Interim Target 1, which is between 50 and 75 μg/m^3 in 24-hour mean. Finally, Above WHO IT 1 refers to air pollution above interim target 1 and is, therefore, a significant amount of air pollution.

On Figure 5, we plot the values of the estimated coefficients having the WHO Air Quality Guidelines (WHO ACG) as a benchmark. In other words, the estimated coefficients are compared to a case where the parameter of WHO ACG is set equal to zero.