Hospitalization due to fire-induced pollution in the Brazilian Amazon: a causal inference analysis with an assessment of policy trade-offs

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Abstract

In the Brazilian Amazon, thousands of kilometres of vegetation are annually burned, releasing pollutants that impact the health of 24 million inhabitants. The paper seeks to fill two crucial informational gaps for policy planning, namely, the size of the impact on the most pollution-susceptible groups, i.e., children and the elderly, and the priority locations for health-oriented intervention on fires. A municipal-monthly panel covering ten years of the Amazonian territory was analysed by relying on exogenous and high-resolution wind direction variation to identify the effect of fires on pollution and hospitalizations. As the result, one extra standard deviation of "upwind" fires was estimated to increase asthma-related hospitalization of the elderly in 0.03 days/month, an effect whose size decayed with the distance between fires and hospitals. A policy assessment uncovered the trade-off between respiratory health of the elderly and nutritional health of fire-dependent subsistence farmers, presenting a priority map for tackling the issue with municipal-level interventions. The targeting of non-subsistence fires is advised, what could avoid 28 hospital-days per year. It is thus demonstrated that the trade-offs inherent to agricultural fires could be better balanced by evidence-based targeting of fire prevention policy.

Keywords: hospitalization, causal inference, fires, Amazon, policy.

Resumo

Na Amazônia brasileira, milhares de quilômetros de vegetação são queimados anualmente, liberando poluentes que impactam a saúde de 24 milhões de habitantes. Procurou-se preencher duas lacunas de informação cruciais para o planejamento de políticas públicas, a saber, a magnitude do impacto sobre os grupos mais suscetíveis à poluição, i.e., crianças e idosos, e os locais prioritários para intervenção voltada a evitar danos à saúde. Um painel municipal-mensal compreendendo dez anos do território amazônico foi analisado, utilizando-se da variação exógena da direção do vento, observada com alta resolução, para identificar o efeito das detecções de fogo em poluição e hospitalizações. Como resultado, um aumento de um desvio padrão das detecções de fogo a favor do vento aumentou a hospitalização de idosos acometidos com asma em 0,03 dias-leito/ mês. O tamanho de tal efeito diminuiu com a distância entre detecções de fogo e hospitais. Uma avaliação de política pública revelou o *trade-off* entre a saúde respiratória dos idosos e a saúde nutricional de agricultores de subsistência dependentes do fogo, apresentando um mapa de prioridades para intervenções em nível municipal. Aconselha-se a priorização de queimadas não associadas à subsistência, o que poderia evitar 28 leitos-dias / ano de hospitalizações. Fica, pois, demonstrado que os *trade-offs* inerentes às queimadas agrícolas poderiam ser mais bem equilibrados por uma política pública direcionada com base em evidências.

Palavras-chave: hospitalização, inferência causal, fogo, Amazônia, políticas públicas

JEL codes: C33, Q52, Q58.

Área ANPEC 11 - Economia Agrícola e do Meio Ambiente

1 Introduction

The agricultural burning of vegetation is a common practice in the developing world which release toxic pollutants, creating or exacerbating respiratory illnesses (Edwards et al., 2020, Cassou, 2018, Kunii et al., 1999, Jacobson et al., 2014, Reddington, 2015). A great cost is imposed on nations, including the further widening of an already large health care supply gap during annual burning seasons. Internationally outstanding cases of large health impacts are Indonesia and India (Edwards et al., 2020, Shi et al., 2014, Cassou, 2018, Kumar et al., 2015), where burnings are conducted both by medium-to-large scale farmers seeking profit and small scale farmers seeking mainly self-subsistence (Edwards et al., 2020, Marlier et al., 2015, Kumar et al., 2015).

Health consequences are also pronounced in the Brazilian Amazon, where seven thousand km^2 are deforested each year, 75% of this area being burned in the same year, putting at risk the health of 24 million people (Morello, 2021). Of them, 165 thousand are annually hospitalized due to respiratory illnesses, overloading a local health system with physicians per capita thirty fold below the world average and able to provide inpatient care to only 14% of the population (INPE, 2020a and 2020b, IBGE, 2020a, DATASUS, 2020a and 2020b[1], WB, 2021). Many policies have been attempted in the Amazon, ranging from burning bans to subsidizing of alternatives to fire, but hospitalization due to respiratory illnesses during the burning season (August to November) has remained stable from 2008 to 2017 at the rate of 5 for each 10,000 people (DATASUS, 2020a).

Amazon fires generally receive great attention in years where they achieve catastrophic proportions and their health consequences are emphasized by scientists as another strong reason for reducing deforestation in the region (Barlow et al., 2020, Silveira et al., 2020, Reddington et al., 2015). Notwithstanding, two crucial gaps diminish the usefulness of published studies as basis for amending existing policies. First, available statistical studies are subjected to two sources of bias, as clarified next, thus not providing estimates of the causal effect of Amazon fires on health. Secondly, the trade-offs inherent to fire governance are frequently ignored, failing to inform policymakers about the most challenging aspects of policy planning (Sletto, 2020, Edwards et al., 2020).

Starting with the causal effect gap, the first bias is due to omitted observables. Many studies are based, as it is the case of this paper, on hospitalization records, whose geographical and temporal scope and resolution, and as well as its reliability, are unparalleled in Brazil (Machado-Silva et al., 2020, Sacramento et al., 2020). Nevertheless, determinants of health care demand and supply are seldom controlled for, thus ignoring health economics literature (Wagstaff, 1993, Gaddah et al., 2015, Harris and Kohn, 2018). Also studies of health and development in the Amazon, stressing the role of, for instance, urbanization and poverty (Davies et al., 2017, Parry et al., 2019, Galvão et al., 2019), are disregarded in covariate selection. These two covariate gaps, which are also observed in multivariate studies such as Smith et al. (2014), are even more notorious in papers relying exclusively on bivariate statistical approaches (mean-difference testing and single time-series analysis) or only on a few weather controls (see Machado-Silva et al., 2020, Rodrigues et al., 2010, Ignotti et al., 2010, Carmo et al., 2013 and Sacramento et al., 2020). The bias from insufficient controls is avoided in this paper by relying on a covariate set matching health economics, development and atmospheric research, as informed by a transdisciplinary literature review (section 2 below).

Secondly, published studies are subjected to bias due to two key non-observables. First, the agricultural seasonality that is clearly reflected on fire's time series shapes the unobserved subannual pace of patients' incomes (Rangel and Volg, 2019), moulding demand for health care. Second, the unobservable and

[1] All figures are averages across 2015 to 2017. The share of area burned annually was estimated as the percent of deforestation polygons with at least two fire detections that occurred in the same year that the polygon was detected by the deforestation measurement algorithm (details are found in INPE, 2019). The percent of population that could be served with inpatient health care was calculated as the quotient of (i) hospital beds in 2017 multiplied by the 365 days of the year, (ii) total population in 2017 multiplied by the average inpatient days (4.29). There are 2.1 hospital beds per 1,000 inhabitants in Brazil, 3.2 in the world and 0.09 in the Amazon (WB, 2021, DATASUS, 2021).

heterogeneous vulnerability of individuals to pollution (Deryugina et al., 2019, Makri and Stilianakis, 2008), is correlated not only with hospitalizations but also with fire-dependent subsistence agriculture via food insecurity (Piperata et al., 2013, Bezencry et al., 2016). These sources of bias are addressed in this paper with an identification strategy (IS) exploring the exogeneity of the relationship between fires and wind direction, as proposed by Rangel and Volg (2019). For this, high time and medium space resolution data were used to detect "upwind fires", i.e., fires that occurred when, in a three-hour time window, and where, in a 11 km cell grid, the wind blew towards municipal capitals, which are the locations were Amazonian hospitals are concentrated.

Now regarding fire trade-offs to be accounted for while planning policy, whereas medium-to-large scale agriculture holds the resources needed to move towards lower reliance on fires and deforestation, what it is been observed (Thaler et al., 2019, Cammelli and Angelsen, 2019, Godar et al., 2014), the same is not true for fire-dependent low-income smallholders and traditional people (indigenous and protected area inhabitants; Thaler et al., 2019, Carmenta et al., 2019, Godar et al., 2014). The latter are credit-constrained and weakly integrated to markets, having no access to alternative technologies. Targeting them with the dominant fire policy approach, which is based on monitoring and fining, is hardly effective and highly socially costly (Carmenta et al., 2019, Cammelli and Angelsen, 2019). To avoid this, the paper explicitly accounts for subsistence fires in identifying priority locations for fire prevention policy.

This paper therefore answers two policy-relevant questions asked in the Amazonian fire-hospitalization branch of literature with methods from the econometric pollution-health branch - the latter also including, for instance, Deryugina et al., (2019) and Chagas et al., (2016). First, whether and how strongly the most susceptible age groups of children and elderly are impacted by fire-induced pollution and second, which particular locations should be prioritized by effective fire reduction intervention. The importance of the latter question is also attested by current fire policy sparing effort across many locations over 1,000 km far from each other along the immense 5 million km^2 Amazonian territory (Prevfogo, 2018, IBGE, 2020b)[2]. Another remarkable contribution of the paper is delivering a whole-Amazon estimate for fires' effect, across 763 municipalities and from 2008 to 2017, thus capturing the wide heterogeneity of the region, whereas some previous studies were circumscribed to specific and particularly fire-critical subregions, potentially biasing the estimate upward (see, e.g., Ignotti et al., 2010, Carmo et al., 2013, Machado-Silva et al., 2020).

One of the main advantages of the IS employed is the refutability of one key assumption sustaining its validity, that upwind fires should have a larger impact on pollution than non-upwind fires, what was confirmed. The findings revealed that upwind fires increased the days the elderly remained hospitalized due to asthma in 0.03 hospital days for a one standard deviation rise in upwind fires. This effect, as well as the effect on pollution, was shown to decrease with the distance between fires and municipal capitals. No impact was found on the hospitalization of children, which was probably due to the effect of seasonal pollution on health increasing with accumulated lifetime exposure, being, thus smaller for children and, probably, less statistically detectable than compared with the elderly case, as far as hospitalization data could reveal (Pope III, 2000, Liu and Ao, 2021; Deryugina et al., 2019 for instance, estimated mortality from pollution to be 30 times more probable for a life expectancy of one rather than 11 years). Also, the size of estimated effects was probably diminished by a seasonal pattern of hospitalizations that mainly reproduced that of rain and air humidity, with peaks during the fire season being visually smaller (Machado-Silva et al., 2020, Silva et al., 2009). Tests exploring alternative distance and angular thresholds for wind direction and alternative covariate sets suggested by machine learning, confirmed the robustness of estimates. In addition, a policy assessment mapped municipalities based on the ratio of the benefit of avoided elderly hospitalization and the cost of eliminating subsistence fires and thus jeopardizing the health of food insecure fire-dependent subsistence farmers. The assessment also

[2] The average distance statistic refers to federal fire brigades from 2015 to 2017 (not including brigades in protected areas; mean = 1242 km, sd = 676 km).

estimated that 28 hospital-days / month would be avoided whether non-subsistence fires were suppressed from the Amazon.

The remainder of the paper begins, in section 2, with a literature review on the appropriate covariate set. Section 3 presents the methodology detailing the identification strategy. Results are provided in sections 4, followed by a coupled discussion and conclusion section.

2 Literature review

This section justifies the selection of covariates for the econometric models by succinctly revising theoretical and empirical studies. Three branches of research are explored, health economics, Amazon health and development studies and atmospheric science. Model covariates are classified as factors of health care demand [D], health care supply [S], society and economy [E] or of weather or pollution [W]. Classification is omitted whether data for the factor was unavailable. Proxies are also indicated when needed (e.g., "actual health level [D: infant mortality; chronic disease mortality]") and further justified.

2.1 Observable factors

Health care supply and demand factors determine the level of hospitalizations as emphasized in the health economics literature (Wagstaff, 1993, Gaddah et al., 2015, Harris and Kohn, 2018). Regarding demand, it is coherent with Wagstaff's (1993) version of Grossman's model, to explain it by price but also by age [D], education [D], income [D/E: GDP] and actual health level [D: infant mortality; chronic disease mortality]. Kunz and Winkelman (2016) estimated the effect of co-payment on doctor visits for Germany controlling for age [D], gender [D] and years of schooling [D]. Thorton's (2002) health production function for USA's states included education [D], income [D], race and gender [D] as covariates. Following Aquino et al. (2009) and Barufi et al. (2012), health level, a key theoretical predictor of health care demand (Wagstaff, 1993, Gaddah et al., 2015, Harris and Kohn, 2018), may be proxied, in Brazil, with infant mortality [D]. Liu and Ao (2021) also controlled, when estimating the impact of pollution on health, for physicians [S], for education [D] and income [E].

Regarding health care supply, Nunes et al. (2013) explained elderly mortality in the Amazon as a function of pollution by controlling for intensive care beds [S: hospital beds], primary care units per capita [S: ambulatories] and municipal human development index [S/E]. Herwartz and Schley (2018) estimated a stochastic frontier for Germany with health care provision explained by, among other factors, general practitioners [S: physicians], hospital beds [S], population density [D: population], GDP per capita [D/E: GDP] and measures of regional deprivation [D/E: poverty alleviation participation]. Health care supply is largely urban-biased [E] in the Amazon (Parry et al., 2019, Mattos and Mazetto, 2019), with 7 and 38 fold more hospitals and physicians in municipalities with at least 100,000 inhabitants (DATASUS, 2021, IBGE, 2021a). Coherently, in the investigations on health and development in the Amazon by Davies et al. (2017), Parry et al. (2019), Galvão et al. (2019) and Nunes et al. (2013), regional health care was influenced by urbanization [E], remoteness [E: road extension], development level [E: human development index] and poverty [E], etc. The latter proxiable by enrolment in "Bolsa Família", Brazil's main poverty alleviation program (Torrens et al., 2016, Brauw et al., 2015).

Atmospheric scientists and economists have been elucidating the influence of weather factors, mainly wind [W], rainfall [W] and air humidity [W], on pollution and on health outcomes. Deryugina et al. (2019) measured, at USA county level, the causal effect of pollution on elderly mortality and health care demand, controlling for precipitation [W], temperature [W] and wind speed and direction [W], the latter also used as an instrumental variable. Rangel and Volg (2019) also relied on wind direction but for identifying the effect of sugarcane burning on health at birth in Brazil. In Chagas et al. (2016), wind direction based specification of a neighbourhood matrix for a spatial diff-in-diff estimate of sugarcane burning's effect on hospitalization in Brazil. Importance of non-fire sources of pollution, such as road transport and vehicle fleet [W], was also demonstrated (e.g., Mendonça et al. 2004).

2.2 Non-observable factors

Let two key non-observables be detailed. First, the local economic activity level, which is observable at annual time scale with its subannual variation being left to the disturbance term (Rangel and Volg, 2019). The main source is the agricultural cycle, involving burning and generating variable amounts of employment and income across the months of the year (Rangel and Volg, 2016, figure B.0 in supplementary appendix[3]) in a region whose agricultural share of GDP is 2.4 fold that of the country (IBGE, 2021b). Demand for hospitalization may respond to such seasonality, especially among smallholders, the indigenous and residents of protected areas, whom are both liquidity-constrained thus facing large seasonal fluctuations of income (Thaler et al., 2019, Morello et al., 2018), and live far from urban areas where most hospitals are located. Also, urban-rural distances are large and linking roads are mostly unpaved and non-weatherproof (Garnelo et al., 2020). Other well-documented seasonal drivers of health care demand in the Amazon comprise water level of rivers travelled for reaching urban areas (Garnelo et al., 2020, Parry et al., 2018), floods and droughts whose effect is amplified by poor sanitation and geographical inequities (Parry et al., 2018) and state of roads and bridges.

The second unobservable is vulnerability to air pollution, understood as the likelihood of an individual's health to be affected by, and also of coping with and responding in a particular intensity to air-borne pollutants[4]. It is potentially variant across individuals along with innate and acquired characteristics, the latter including health status, chronic diseases and nutrition (Deryugina et al., 2019, Makri and Stilianakis, 2008), which are all ignored since hospitalization data omits individuals' characteristics. Importantly, omitted vulnerability may be related with fires as these are more frequent in Amazon's rural areas where subsistence production is widespread, food security is more dependent on (seasonal) weather and malnutrition was found to be significant (Bezencry et al., 2016, Parry et al. 2018 and 2019). Particularly, Piperata et al. (2013) found food insecurity to be highly frequent across Amazonian rural riverine households relying on slash-and-burn agriculture for subsistence, with mothers reducing own energy and protein intake to save for their children.

3 Method and data

3.1 The main equation and identification strategy

The research objective is to estimate the coefficient "c_1" in equation (1), at municipal ("i" index) and monthly ("t") level, with the disturbance term containing time-invariant (a_i) and time-variant ($u_{i,t}$) components:

$$\text{Hospitalization}_{i,t} = c_0 + c_1.\text{fires}_{i,t} + a_i + u_{i,t} \tag{1}$$

Since, as argued in section 2.2, standard estimation of c_1 is biased, the identification strategy (IS) of disentangling fires based on wind direction, developed by Rangel and Volg (2019), is adopted. The key identification assumption is that fires have a larger coefficient with pollution replacing hospitalization in equation (1) where wind blows towards the reference location, i.e., whether fires are classifiable as "upwind". Conveniently, such assumption becomes refutable with a "non-upwind" fire covariate included. A second feature is mitigation of omitted variable bias (OVB), especially of its cross-sectional component, through the within variation the two fire covariates create. Thirdly, validity also depends on the assumption that the process assigning fires to upwind and non-upwind classes - i.e., "the interaction of

[3] Accessible at: https://tinyurl.com/pjm6xmye

[4] More precisely, vulnerability unfolds into susceptibility, sensitivity and exposure (Makri and Stilianakis, 2008), with the two first dimensions, which are intrinsic to the individual, being more relevant for this text.

fire locations and wind direction" (Rangel and Volg, 2019) - is exogenous to the processes through which fire impacts on pollution and hospitalization. What could only be violated whether burning decision explored wind direction in order to send pollutants to particular municipal capitals, a behaviour not detected in the literature consulted. Nevertheless, such type of bias is avoided by controlling for wind speed and direction and other weather factors, and also by year and month dummies, in fixed-effects estimation (Rangel and Volg, 2019, Liu and Ao, 2021).

3.2 Classification of fires as upwind and non-upwind

As in Rangel and Volg (2019), fires were classified at high temporal and medium spatial resolutions regarding the direction of wind in the grid cell they were detected into. Over 99% of fires detected from 2008 to 2017 occurred in the 4 to 6 PM window, within which, thus, both wind direction was averaged and fire detections were retrieved. With "cell" referring to 11.4 km resolution gridded wind data, a fire detection was deemed upwind in respect to a reference municipal capital whether it occurred in a cell (Figure 1):

1. whose centroid was 5 km from the reference municipal capital or;
2. whose wind direction both…
    a. fell in the opposite trigonometric quadrant compared with the direction of the straight line arrow terminating at cell's centroid and starting at the reference municipal capital and;
    b. differed from the straight line direction in less than 45 angle degrees (hereafter "fire angle").

Contrariwise, the fire detection was deemed non-upwind. The classification criteria 2.a and 2.b are illustrated in figure 1. The cell at NE is considered to be upwind, for both (i) having wind blowing (black arrow) in a quadrant which is the opposite of the straight line distance quadrant and (ii) presenting a wind-distance angle difference in the [157.5; 202.5] interval. The same is not true for the case at SW, albeit the opposite quadrant condition being satisfied, since the wind angle threshold was exceeded.

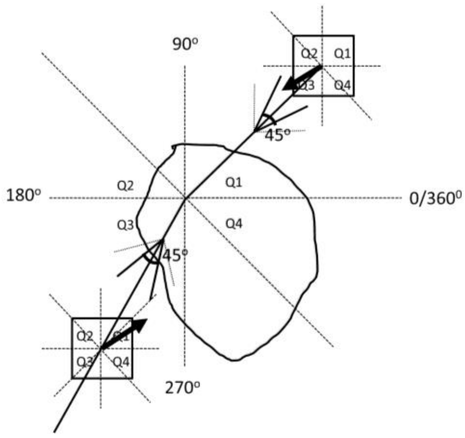

Figure 1 Cell classification criteria, wind direction indicated by the black arrow; the reference municipality is the grey polygon

Municipal capitals were matched with wind cells within 50 and 100 km distance, the former the Rangel and Volg's (2019) threshold, and the latter an alternative accounting for the larger municipal size in the Amazon as compared with authors' study region in southeastern Brazil (IBGE, 2021c). Capitals are focussed for being the main municipal urban (and population) centres thus concentrating hospitals. This is not in detriment of the amount of fires accounted for, as 74% of them were detected within 50km of capitals. Moreover, the identification power of wind direction (i.e., the IS's strength) should fall with distance according with atmospheric research, due to the increasing influence of confounders such as topography and forces driving air-borne transport including advection of smoke and climate zones (Mishra et al. 2015, Freitas et al., 2009).

3.3 Robustness tests

The first robustness test explored alternative radii around municipal capitals within which pollution level was averaged (25, 50, 100 km; hereafter "pollution radii") and fire types were counted (50 or 100 km around municipal capitals; "fire radii"), what is reported together with the main results. Additionally, the less restrictive fire angles of 60^o and 90^o were explored.

The second test, on covariate set, targeted, firstly, the consistency-efficiency trade-off inherent to the multiplicity of covariates (34 time-variant controls). The latter avoids OVB but may induce overfitting, inflating standard errors and menacing generality of the effect estimated (StataCorp, 2019, p.4, Belloni et al., 2014). As a data-driven balancing of the trade-off, controls were selected with "lasso" machine-learning for inference (Belloni et al., 2014)[5]. Secondly, robustness to time-invariant factors was verified by interacting them with a deterministic time trend thus avoiding automatic exclusion by the fixed-effects (FE) estimator. Thirdly, an additional specification test added to the panel FE models quadratic terms for all weather controls as in Liu and Ao (2021). Only the 50km fire radius was considered.

3.4 Estimated models

After Hausman and Mundlak tests, FE estimator was selected and implemented with municipality-clustered disturbances. This generated the main estimates which were confronted, in the robustness test, with lasso-based regressions. Since double selection and partialling out lasso-inference methods returned statistically equivalent results, only the latter is reported, for being conceptually equivalent to controlling for observables (StataCorp, 2019), a foundation of the FE-based IS[6]. Lasso was fit with the plugin approach (StataCorp, 2019, p.14) and with standard errors clustered at municipal level as in FE estimation.

3.5 Data

For weather covariates, satellite data were relied on due to the sparsity of Amazonian meteorological station network. Hourly wind direction and speed at 10 metres height were retrieved from the ERA 5 database of the European Centre for Medium-Range Weather Forecasts (Muñoz-Sabater, 2019), the highest spatial resolution satellite wind data available online, with cells of 11.4 km. Fire detections were those reprocessed by the Brazilian National Institute for Space Research (INPE), corresponding only to the reference satellite (Aqua Afternoon; INPE, 2019).

Pollution was measured as atmospheric optical depth (AOD), as common in atmospheric research (Gonçalves, 2018, Martins et al., 2017, Mishra et al., 2015), which is derived from smoke and captures the intensity with which light is blocked by aerosols (NASA, 2021, Mishra et al., 2015). The variable was processed by the Multiangle Implementation of Atmospheric Correction (MAIAC) algorithm from data generated by the MODIS sensors of NASA's Aqua and Terra satellites (Martins et al., 2017, LAADS, 2021). This is the only pollution measurement available for the whole Amazon (Gonçalves et al., 2018), being correlated at over 80% with fine particulate matter concentration (Gonçalves et al., 2018) and at over 95% with ground AOD measurements (Martins et al., 2017).

Hospitalizations capture patient admissions into public and private hospitals funded by the Brazilian National Health System (SUS) (Machado et al., 2016). This datum is the only source of morbidity

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[5] Sparsity is not a concern based on the size of the approximate threshold ratio of $s.\log(p)/\sqrt{N}$= 0.000974576, which was thus small as it should be (StataCorp, 2019, p.14),with (i) s = p = number of time-variant and invariant covariates = 52, so that all potential covariates are in the true model, and (ii) N = 91,560 in the whole panel.

[6] The two methods are "asymptotically equivalent" (StataCorp, 2019). The more computationally intensive cross-fit partialling out method was ignored for subdividing the sample, violating the cross-sectional dependence of panel data. Robustness test was thus based in "poregress" command of Stata 16.

information for the whole study region where over 90%[7] of inhabitants depends exclusively on SUS for health care (ANS, 2021, IBGE, 2021a). It has also been frequently used by health scientists to estimate the health impact of fire-induced pollution in the Amazon (Ignotti et al., 2010, Rodrigues et al., 2010, Carmo et al., 2013, Sacramento et al., 2020).

Hospitalization is apprehended in terms of duration, i.e., as bed-days, seeking to capture severeness, which is ignored by the hospitalization frequency used in previous studies (Machado-Silva, 2020, Carmo et al., 2013, Chagas et al., 2016). As a consequence, the dependent variable's conditional average estimated by the econometric models, $E[Y|X]$, captures both the "extensive margin" of hospitalization, i.e., the frequency aforementioned, $P(Y>0|X)$, but also the "intensive margin", or the average hospital-days among the hospitalized, $E[Y|X,Y>0]$[8]. Indeed, since hospital-days (Y) is a non-negative variable, $E[Y|X] = E[Y|X,Y>0].P(Y>0)$.

Only hospitalizations due to asthma, bronchitis and chronic obstructive pulmonary diseases (COPD)[9] were considered, seeking to mitigate confounders such as microorganisms and allergens. The three conditions were found by previous studies to be correlated with fire-induced pollution (Arbex, 2007, Rodrigues et al., 2010, Mascarenhas et al., 2008, Carmo et al., 2013, Phonboon et al., 1998, Duclos et al., 1987, Chatkin et al., 2020, Machado-Silva, 2020). Besides condition, only the extreme ages of 0 to 4, 5 to 14 and above 64 were accounted for, due to the higher susceptibility to pollution, as common in epidemiological literature (Nunes et al., 2013, Jacobson et al., 2014, Carmo et al., 2013, Machado-Silva et al., 2020, Makri and Stilianakis, 2008).

Covariates' summary and data sources' references are found in the supplementary appendix (SA), sections A.0 and C[10]. Controls outside the [0:1] interval were transformed to log(1+x). The panel comprised 763 of the 771 Amazonian municipalities across 120 months from January 2008 to December 2017. The eight municipalities excluded were due to missing data for pollution, temperature or vehicle fleet.

As visible in figure B.0 of SA, hospitalization peaks from March to May, thus out of the dry season period when most fires occur (August to October), and synchronously with humidity and precipitation and also with the temperature valley. This was documented elsewhere (Machado-Silva et al., 2020, Smith et al., 2014, figure 2, Rodrigues et al., 2010, figure 2, Silva et al., 2009) and diminishes the significance and size of fire's coefficient in hospitalization models. Nevertheless, peaks in the dry season, specifically in October are also clear with 39% of hospitalizations from July to November occurring in September or October. These seasonal patterns on observables are controlled for with month dummies, complementing the IS treatment of seasonal non-observables (section 3.1).

3.6 Assessment of priority municipalities for policy

Seeking to demonstrate the usefulness of the fire effect estimate and also to better inform Amazonian policymakers, a generic "fire policy" seeking to reduce respiratory-related hospitalizations by eliminating upwind fire detections is assessed. Two key parameters must be chosen while planning such a policy, the "centre" or reference municipal capitals to be prioritized, and the "radius", or distance within capitals to be covered. Choice is here based in the two step procedure of first selecting best radii for municipality classes then, based on such thresholds, identifying priority capitals.

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[7] Estimated as the residual percentage after accounting for the number of private health care beneficiaries informed by the Brazilian regulatory agency of the private care industry (ANS, 2021).

[8] The notions of intensive and extensive margin were inspired in physician visit models common in health economics literature such as Alessie et al. (2020) and Schmitz (2013).

[9] Including chronic bronchitis, emphysema and other illnesses classified as lung-obstructive by SUS.

[10] The supplementary appendix is available in the link: https://tinyurl.com/pjm6xmye

For the first step, municipalities were classified in three population groups, namely: (i) population $\leq$ 10,000 ("small towns"), (ii) 10,000 < population $\leq$ 100,000 ("medium towns") and (iii) population > 100,000 ("big towns"). Population is a catch-all variable significantly correlated with hospitalizations (> 90% correlation, p-value < 0.1%) and health care supply (idem). It was also statistically significant in the elderly asthma equation basing policy assessment.

An important information for policymakers is the high social cost of supressing upwind subsistence fires, owing to the hazard to a population whose health is highly vulnerable, as argued in the introduction and in section 2.2[11]. Therefore, subsistence fires were identified as occurring inside federal government lands inhabited by traditional people (indigenous and protected area residents) and smallholders (agrarian settlements), in consonance with previous studies (Sorrensen, 2009, Carmenta et al. 2013, Peña-Venegas et al. 2017 and Pivello, 2011). This both exposes the cost subsistence fires represent, as their reduction may require technological subsidies (Watts et al., 2019, Mburu, 2006, Cammelli and Angelsen, 2019), and the degree in which policy options trade-off nutritional health of fire-dependent social groups for respiratory health. Additionally, it leads to a more realistic estimate of avoidable hospitalizations since an indiscriminate fire ban is unlikely to be complied with by subsistence farmers (Carmenta et al., 2019, Cammelli and Angelsen, 2019, Thaler et al., 2019).

Coherently, fire policy performance was measured by a gross benefit-cost ratio with avoided hospitalizations divided by subsistence fires. Whereas radius selection was aggregately sought to capture the best central tendency within population classes, priority municipalities is by definition a non-aggregate result. In this case, a non-negligible frequency of zero subsistence fires (19%) turning the ratio partially unavailable was circumvented by a simple procedure that was also useful to reveal the intensity of the trade-off. This consisted in calculating, for the i-th municipality, $Q_{m,i} = (Q_{h,i} + Q_{r,i})/2$, with $Q_{h,i}$ being a quintile based on the ratio's numerator (avoided hospitalization), and $Q_{r,i}$ a quintile obtained by adjusting ratio quintiles for municipalities with subsistence fires by assigning those without fires to the top quintile[12].

The counterfactual policy considered supposedly eliminates upwind fires, and the factual state without policy corresponded to the observed fire level, without any further difference between states. Thus, and due to the linearity of the panel models, in the first stage, equation (2) below was applied to the fire radii r = 50 and 100 km and to the three population groups, k = small, medium, big, with $\hat{\beta}_{uf,r}$ being the radius-specific estimate for the upwind fire coefficient. In the second stage, equation (3) was applied at municipal level to the r* radius defined in the previous stage. In the two stages, subsistence fires were also counted within a specific radius and all fire counts referred to the three most recent years in the dataset, 2015 to 2017.

$$\text{Av. hosp}_{2015-2017,\text{r,k,1st}} = \hat{\beta}_{uf,r} \sum_{\substack{i=1 \\ pop_i=pop_k}}^{N_k} \sum_{y=2015}^{2017} \text{upwind\_fires}_{\text{i,y,r}} \quad (2)$$

$$\text{Av. hosp}_{2015-2017,\text{i,r}^*,\text{2nd}} = \hat{\beta}_{uf,\text{r}^*} \sum_{y=2015}^{2017} \text{upwind\_fires}_{\text{i,y,r=r}^*} \quad (3)$$

[11] Accounting for subsistence fires in the policy assessment is also a way to emphasize the important subject of vulnerable health of those relying on fires for subsistence (Piperata et al. 2013), which could not be directly addressed with econometrics due to the lack of a health vulnerability measure for the whole Amazon.

[12] Both $Q_{h,i}$ and $Q_{r,i}$ were taken as integers so that $Q_{m,i}$, i=1,..,N was a near-discrete variable whose quantiles were not evenly distributed across the sample.

4 Results

4.1 Pollution model

As in Rangel and Volg (2019), having pollution as the dependent variable aims mainly to test IS validity, since the effect of fires on pollution in the Amazon is well-documented (see, e.g., Mishra et al., 2015, Pereira et al., 2011, Marenco et al., 2016). Results revealed upwind and non-upwind fires to have positive coefficients in the pollution equation, with a larger coefficient for the former (Table 1). This was robust to pollution and fire radii. The only exception was the insignificance of upwind fires for a fire radius of 50km and a pollution radius of 100 km, a result that was part of a broader pattern of decay of the upwind/non-upwind coefficient ratio and of the upwind coefficient along with the expansion of the pollution radius for a fixed fire radius (see table A.1.1 of the supplementary appendix). Therefore, the IS proved valid in consequence of the systematically larger coefficient of upwind fire but its strength decayed with the expansion of the realm within which pollution was assessed. What demonstrates that fires' impact on pollution was spatially limited, being larger on more proximate locations.

Let it be now considered the expansion of the domain within which fires were counted while keeping a fixed pollution averaging domain[13]. The estimated upwind fire coefficient ratio was smaller whether a radius of 100 rather than 50 km was accounted for (Table 1), replicating the pattern of decay highlighted in the previous paragraph for the pollution radius and further confirming the spatially limited effect of upwind fires on pollution. Conversely, the upwind/non-upwind fire coefficient was larger at 50 km, what was due to the denominator decreasing faster. A possible reason for the latter was the non-refined nature of non-upwind fires, what may favour a greater increase of captured "noise fires", i.e., fires not causing pollution in the circular polygon around the reference municipal capital. In summary, in the pollution model a double confirmation of IS validity was achieved as its limited strength adhered to atmospheric science research as argued in section 3.2 above.

Table 1 FE estimates for pollution at different radius from municipal capitals

	AOD 25 km	AOD 50 km	AOD 100 km
Upwind fires, 50 km	0.452**	0.337*	0.221+
	[0.139]	[0.137]	[0.133]
Non-upwind fires, 50 km	0.154***	0.167***	0.167***
	[0.0233]	[0.0236]	[0.0234]
Upwind fires, 100 km	0.247***	0.214***	0.152**
	[0.0516]	[0.0509]	[0.0484]
Non-upwind fires, 100 km	0.0399***	0.0436***	0.0475***
	[0.00749]	[0.00756]	[0.00749]

Notes: Robust SE clustered at municipality level in brackets and significance reported as + p<0.10, * p<0.05, ** p<0.01, *** p<0.001. All time-variant controls included (but no time-invariant controls) together with year and month dummies. All equations were globally significant at less than 1%, observations amounted to 91,559 for AOD 25km and to 91,560 for the remaining equations. See SA, A.2, for details.

[13] It is useful to remind that both frequency of fire types and average pollution are calculated from circular polygons centred in municipal capitals. Thus, when the "fire radius" is expanded with the "pollution radius" remaining unaltered, the circular domain for counting fire types is extended within or beyond the one for which the average pollution is calculated.

4.2 Health model

Confirmation of IS validity enables examination of the health models. With a 50 km fire radius, upwind fires increased hospitalization of only the elderly and due to asthma (Table 2). None of the remaining hospitalization measures was significantly related with upwind and non-upwind fires. With the 100km fire radius, the only differences were the significantly negative effects of upwind fires in the bronchitis equations of children aged 4 to 15 and of non-upwind fires in the elderly asthma equation. The only significant coefficient in the two fire radii, elderly asthma, was about threefold larger under 50km, attesting that the effect of fires' on hospitalization is also spatially limited (what was confirmed by robustness estimates, see table A.1.2 of SA)[14].

Table 2 FE estimates for alternative hospitalization measures

	Asthma 0-4	Asthma 5-14	Asthma ≥ 65	Bronchitis 0-4	Bronchitis 5-14	Bronchitis ≥ 65	COPD 0-4	COPD 5-14	COPD ≥ 65
Upwind fires, 50 km	-0.00753+	-0.00359+	0.00359*	-0.000144	-0.00107	0.000653	0.00470+	0.000145	0.00243
	[0.00457]	[0.00203]	[0.00172]	[0.00591]	[0.000718]	[0.000744]	[0.00283]	[0.000642]	[0.00400]
Non-upwind fires, 50 km	-0.00046	0.000186	-0.000288	0.0000355	0.0000684	-0.0000872	-0.00045	-0.000214	0.00000665
	[0.000971]	[0.000447]	[0.000279]	[0.000664]	[0.000156]	[0.000109]	[0.000393]	[0.000132]	[0.000683]
Upwind fires, 100 km	-0.0072	-0.00118	0.00121*	-0.00501	-0.000587**	-0.000185	0.000429	-0.0000271	-0.00104
	[0.00575]	[0.00126]	[0.000536]	[0.00408]	[0.000220]	[0.000210]	[0.000474]	[0.000345]	[0.00140]
Non-upwind fires, 100 km	0.00017	0.00000849	-0.000177+	0.000312	0.000023	0.00000911	0.0000205	-0.0000391	0.000258
	[0.000286]	[0.000148]	[0.0000913]	[0.000249]	[0.0000380]	[0.0000468]	[0.0000997]	[0.0000527]	[0.000184]

Notes: observations amounted to 91,560 in all equations. See SA, A.2, for details.

4.3 Robustness check

Regarding the pollution model, for all fire degrees, fire radii and pollution radii, upwind fires exhibited a larger coefficient than non-upwind fires and the two coefficients were significantly positive (SA, table A.1.1). A larger identification power, measured by the upwind/downwind coefficient ratio, was achieved in the 45^{o} model for most fire radius and pollution radius, demonstrating that larger conservativeness in "congruent" wind direction was best (SA, table A.1.1). The same results were obtained for alternative fire angles regarding the upwind and non-upwind coefficients in the hospitalization models (SA, table A.1.2), what includes the negative coefficients of upwind fires in the children bronchitis model and of the non-upwind fires in the elderly asthma model. Nevertheless, the latter two were significant only with a fire radius of 100 km.

The covariate sensitivity test based on lasso inference, achieved the same pollution model results (SA, tables A.4.1, A.4.4. and A.4.7). In particular, as in FE estimation, upwind fires were insignificant with 100 km pollution radius and 50 km fire radius, what was the case for a 45^{o} fire angle and, deviating from FE estimates, also for a 60^{o} fire angle. Regarding the health models, the joint significance of upwind and

[14] Fire radii of 150 and 200 km were also accounted for in the many estimation batteries conducted while writing the paper. However, results for such radii were omitted because (i) atmospheric science literature suggest that influence of confounders increase with distance (as argued in section 3.2), (ii) coherently, upwind and non-upwind fires' coefficients in the pollution model decayed, respectively, to 37% and 12% at 150 km and to 24% and 7% at 200 km, of their 50 km levels, (iii) also coherently, results for the health models did not added to what's already in the text, with zero coefficients for upwind and non-upwind fires for all hospitalizations measures considered (the only two exceptions, observed only for 200km and for no other radius, were a positive coefficient of non-upwind fires for children aged 0 to 4, and a negative coefficient of upwind fires for elderly bronchitis).

non-upwind fires was taken as an imperfect substitute for the non-available global significance test. Joint significance was achieved only for asthma of children aged up to four years and of elderly, at a 50 km fire radius and, at 100 km fire radius, only for elderly asthma (SA, section A.4). In all cases, a positive coefficient of upwind fires was estimated in the elderly asthma model and non-upwind fires had a null coefficient for all dependent variables, thus confirming FE estimation. Considering only a 45^{o} fire angle and fire radius of 50 km and 100 km, the effect on elderly asthma was 2 or 2.5 fold larger with lasso, revealing a larger conservativeness of FE.

No qualitative change in results was observed either with time-variant covariates in FE estimation or with quadratic weather terms, except, in the latter case, with a significant coefficient for upwind fires in the model with 50 km fire radius and 100 km pollution radius (SA, A.3 and A.5).

4.4 Summary of estimation results

The key message inherent to results is that the IS was valid and able to identify fires' effect on hospital-days due to elderly asthma. One extra upwind fire detection would increase elderly hospital-days with asthma in the average municipal capital in 0.00359 or 0.00121 days/month for an extra fire within 50km or 100km, respectively. A one standard-deviation increase in upwind fires detections at any of the two distances would result into 0.03 additional hospital-days/month.

4.5 Policy assessment

For all municipality classes, the avoided hospitalizations/subsistence fire ratio was largest with the 50km radius, which was due to subsistence fires increasing with distance and the estimated effect of fires decreasing, two changes whose combined magnitude exceeded that in which total upwind fires increased (table 3). The ratio at 50km (2.59%) was outstandingly higher for big towns, what is reasonable since subsistence fires tend to be less frequent in highly populated and more urbanized towns. Notwithstanding, a considerably smaller ratio (1.39%) prevailed for most of the Amazon, given the dominance of medium, and less urbanized, towns.

Table 3 Avoided total fires, prevented subsistence fires and avoided hospitalizations in the fire policy scenarios (fires detected from 2015 to 2017).

Distance (km)	Municipal population	Number of municipalities	Avoided upwind fires	Prevented subsistence fires	Avoided hospitalizations (bed-days)	Ratio = avoided hosp./prevented subsistence
50	Small towns	268 (35%)	30360	6472	108.9924	1.68%
100			117795	25663	142.53195	0.56%
50	Medium towns	472 (61%)	57168	14811	205.23312	1.39%
100			213206	55607	257.97926	0.46%
50	Big towns	31 (4%)	2980	413	10.6982	2.59%
100			14893	3193	18.02053	0.56%

A consequence of table 3 is that 28 hospital-days/year would be avoided in the whole Amazon with the complete elimination of non-subsistence upwind fires within 50 km of capitals[15]. What amounted to 3% of the annual average hospital-days from 2015 to 2017 during August to October. This being a more realistic estimate of fire policy's outcome than the 41 hospital-days/year from the suppression of all upwind fires within 50 km[16].

[15] This was calculated by counting only once each non-subsistence fire detection within 50 km of any municipal capital, circumventing the fact that a detection could be upwind in respect to multiple capitals. The result was then multiplied by the average share and coefficient of upwind fires.
[16] Estimated analogously as in the previous footnote.

In the second stage, the avoided hospitalizations quintiles (benefit, figure 2-A) and the avoided hospitalizations/subsistence fires ratio quintiles (benefit/cost, figure 2-B) were equitably mixed into a synthetic quintile set (figure 2-C). In the latter, the top quintile had the largest share of small towns (42%) and the most equitable split between small and medium towns. The visible differences in the location of the top quintiles across the three maps exposes the trade-off between avoided hospitalizations and subsistence fires, a visual expression of a 60% positive correlation between the variables (p-value < 0.1%).

The "wicked" nature of the policy problem facing Amazonian governments becomes even clearer with the levels of two reasonable fire policy targets, deforestation and one its main causes, cattle ranching (Thaler et al., 2019, Tasker and Arima, 2016, AC, 2020, Morello, 2021), being lower in the top quintile of the mixed ranking (t test's p-value < 0.1%). Thus, even with the total fire count being highly correlated with deforestation (at 83%, p-value < 0.01%), this may not be a justifiable target for a fire policy seeking health benefits, since subsistence fires were also significantly correlated with deforestation (at 20%, p-value < 0.01%). Such complication having as a main source the overlap, at municipal level, of subsistence and non-subsistence fires (SA, figure B.1), a dimension of the sharp contrasts characterizing the Amazon (Thaler et al., 2019), with federal lands sided by private lands where medium to large scale deforestation takes place (SA, figure B.2). In addition, the priority municipalities also presented smaller amounts of physicians per capita (correlation test p-value < 5%), adding coherence to the prioritization here proposed.

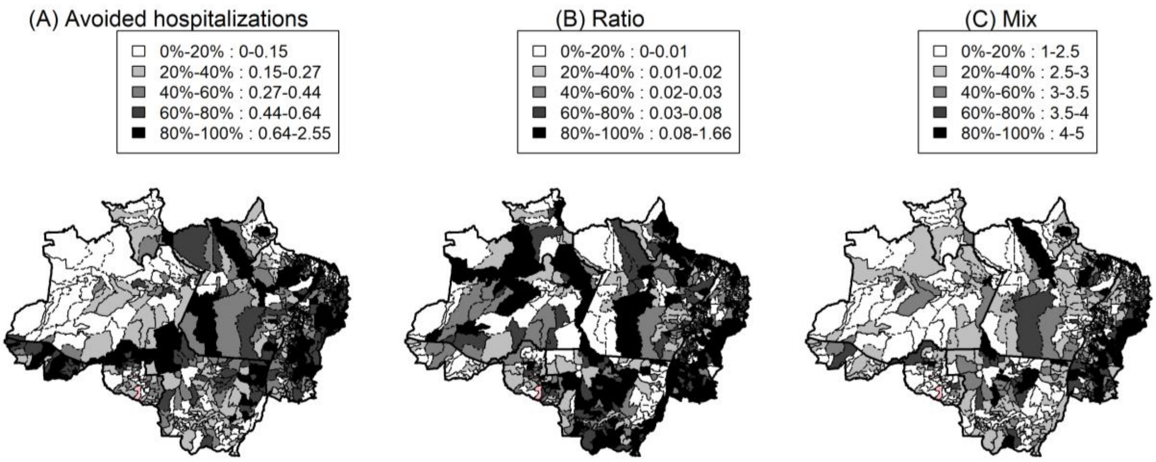

Figure 2 Alternative policy prioritization quintile maps (Amazonian states' boundaries drawn with solid line and municipal boundaries with dashed line)

5 Discussion and conclusion

The assessment presented was both broad and deep in space and time for covering the enormous territory of the Brazilian Amazon along ten years with high-resolution data on fire, wind and pollution. Accuracy was achieved, even under unobservability of economic seasonality and of vulnerability to air pollution, as attested by a significant and, consistently with atmospheric science, spatially limited power of wind direction to identify fire's effect on pollution and hospitalizations. A policy trade-off between respiratory health and nutrition was evidenced, with a priority map for addressing it formulated and the benefit of targeting non-subsistence fires also estimated.

In line with the findings, the elderly are commonly reported as highly susceptible to respiratory illnesses (Kunii, 1999, Machado-Silva et al., 2020, Deryugina et al., 2019). Asthma exacerbation by air pollution was also reported by health scientists during wildfires in Indonesia, with severe symptoms more frequently developed by the elderly (Kunii, 1999). Asthma hospitalization was estimated to increase with sugarcane burning in southern Brazil (Arbex et al., 2007) and also with agricultural burnings in the Amazon (Machado-Silva et al., 2020, section 4).

The null impact on children may be due to a greater responsiveness of hospitalization to long rather than short term exposure as compared to less severe outcomes (Liu and Ao, 2021). Even with elderly and children being the population groups with more vulnerable health, the former has a larger accumulated exposure what may augment the likelihood of morbimortality (Pope III, 2000). Silva et al. (2009) also found asthma-related hospitalizations of Amazonian children to increase during the wet season, being thus not related, across time, with agricultural burnings.

With the coincidence of hospitalization, precipitation and humidity peaks (section 3.5), and the sharp change from a precipitation level of 33 mm/month in the high dry season (August to October) to 146 mm/month in the rest of the year, fire cannot be deemed a determinant of the seasonal pattern of hospitalizations (Machado-Silva et al. 2020, Silva et al., 2009). But it was, nevertheless, powerful enough to cause an “off-peak” increment in the hospitalization of the age group with the longest lifetime exposure to pollution.

The literature warns against policy interventions designed in ways that may, as a side-effect, jeopardize subsistence agriculture (Carmenta et al., 2019, Cammelli et al., 2019, Tacconi and Ruchiat, 2006). Similar trade-offs involving rural air pollution were observed in other developing countries. Reyes et al. (2019) evidenced the trade-off between reduction of air pollution and heating of energy-poor Chilean households during a winter with temperature ten degrees Celsius below the healthy threshold. The reliance on firewood generated a pollution level over threefold the international standard. Nevertheless, the policy temporarily banning and fining firewood usage jeopardized the poor. Burning of crop residues by Indian farmers of multiple sizes, including the small (Kumar et al., 2015, p.39 and 139), was show to impair children's and adults' health (Agarwal et al., 2012). Smallholders' slash-and-burn, albeit not the main source of Indonesia's seasonal rise in air pollution and respiratory illnesses (Kunii, 1999, Dawud, 1999), is still a relevant factor (Edwards et al., 2018, sec. 4.3, Marlier et al., 2015, sec.3.4, Watts et al., 2019). Since small-scale farming was associated with poverty and food insecurity in India and Indonesia (Edwards et al., 2018, Vel et al., 2016, Niles and Salerno, 2018), it is not only in the Amazon where fire is a “wicked” policy problem.

In the same direction, it is also not only in the Amazon where refined policy, based on evidence about the options available to fire users, may better address challenging trade-offs. In fact, the highlighting of subsistence fires as a social cost to be either avoided by targeting non-subsistence fires or faced with subsidies for alternative technologies, parallels recommendations found in papers explicitly accounting for policy trade-offs. Reyes et al. (2019) proposed subsidized thermal insulation of houses of mid-to-low income Chilean families as an alternative to the fining of their firewood usage. In similar fashion, Sletto et al. (2008) pointed that the promotion of prescribed burning in the Latin American Gran Sabana, based in the systematization of traditional people's knowledge, could achieve environmental conservation goals without threatening traditional and fire-based livelihoods, improving upon the fire suppression policy in force. Edwards et al. (2018) argued that development of rural Indonesian villages would better address the fire-dependence of poor households than current regional economic growth policies incentivizing land use change.

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