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DISCUSSION PAPER

IMPACTS OF DEFORESTATION ON THE INCIDENCE OF DISEASES IN THE BRAZILIAN AMAZON

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CONTENTS

ABSTRACT

The limited knowledge about the effect of deforestation on human health is an important gap for environmental and health management in Brazil and worldwide. In order to assess its occurrence and magnitude, we performed a panel analysis, linking data on deforestation and reportable diseases by municipality and year, covering 773 municipalities in the Amazon between 2004 and 2012. We conducted estimates separately for each disease, with the inclusion of controls for fixed effects of municipality, socioeconomic features and provision of public health services. Among the diseases that had sufficient data for analysis, we found that deforestation has a significant effect on leishmaniasis and malaria: on average, annual increases of 1% in the municipal deforested area lead to an increase between 14.5% and 23.2% in the incidence of malaria and between 5.12% and 9.26% in the incidence of leishmaniasis. On the other hand, statistically significant effects were not detected for diseases indicated as strong candidates by some authors. The results confirm the existence of health-related deforestation costs, although these do not apply to a wide range of diseases. We highlight the existence of deforestation costs related to health in the Amazon, which must be taken into account both in the management of public health and in decision making regarding natural capital.

Keywords: environmental degradation; infectious diseases; public health.

1 INTRODUCTION

Most of the debate on deforestation emphasizes its global and continental impacts through climate change, ignoring important local effects, such as those on health outcomes. The scientific evidence on the link between deforestation and health is limited. This lack of knowledge about the impact of environmental disturbances on human health hinders good management of natural capital, precluding the design of more integrated health and environmental public policies.

The impact of deforestation on the incidence of diseases is especially important in the Brazilian Amazon, where most of the country's deforestation takes place, and where social vulnerability can amplify the impact of environmental imbalances. Thus, knowing more about the relationship between deforestation and disease can both highlight neglected costs in environmental valuation efforts as well as allow better integration of environmental and health policies.

For decades, the scientific literature has provided evidence that environmental imbalances, particularly those related to deforestation, may increase the incidence of diseases (Patz *et al.*, 2000; Vora, 2008; Gottwalt, 2013). Some studies suggest deforestation raises the incidence of a wide range of diseases (Barcellos *et al.*, 2009; Alho, 2012; Confalonieri, Margonari and Quintão, 2014). There is a certain consensus on the positive association between deforestation and malaria (Pattanayak et al., 2006; Vanwambeke *et al.*, 2007; Yasuoka and Levins, 2007; Vittor *et al.*, 2009; Olson *et al.*, 2010; Parente, Souza and Ribeiro, 2012; Braz, Duarte and Tauil, 2014; Hahn *et al.*, 2014; Stefani *et al.*, 2013). However, this association is unclear for other diseases (Gottdenker *et al.*, 2011; Garg, 2014; Gottdenker *et al.*, 2014). The use of different methodological approaches, spatial and temporal scales in the cited studies also hinders the comparison of the magnitude of impacts on each disease.

We investigate the impact of deforestation on a wide number of diseases, for all municipalities in the Brazilian Amazon between 2004 and 2012. We construct a novel dataset, combining disease incidence, deforestation rates and a wide range of control variables, implementing estimates that allow comparison of impacts between diseases. Information on disease incidence comes from the National Health System (Sistema Único de Saúde - SUS). This system of mandatory notification collects information on the diseases with higher epidemiological impact, risk, and availability of control measures. Diseases are included in the mandatory notification system according to incidence rates, dissemination potential, vulnerability, and availability of control measures as stated in the International Health Regulations (Brazil, Ordinance No. 1271 of 6 June 2014).

2 MATERIALS AND METHODS

We create a dataset combining yearly information on disease incidence, deforestation rates and a series of socioeconomic and health provision controls at the municipal level between 2004 and 2012 for all 773 municipalities in the Brazilian Amazon.[1] This eight year period is the one for which the most complete dataset for deforestation detection and diseases notification is available.

We use data on diseases of mandatory notification to the National Health System (Sistema Único de Saúde - SUS). The SUS is decentralized, with disease detection and basic care responsibilities falling on municipalities and states. Because of this, the Ministry of Health created a series of systems to collect information on the diseases of higher epidemiological impact. We combine data from these systems: the Notifiable Diseases Information System (SINAN/MS),[2] the National Program of Information System for Malaria Control (SISMAL/MS; 2001-2003), and the System for Epidemiological Surveillance Information on Malaria (SIVEP-MALARIA/MS, 2003-2012),[3] responsible for monitoring the disease in the Amazon region. The data is updated up to August 2014.

Table 1 presents descriptive statistics and the variables used for locating cases in time and space for the studied diseases. Because municipalities in the Brazilian Amazon are very large, rural population is scattered and health service quality is uneven, people often seek treatment at different municipalities and sometimes only years after

1. We include all municipalities in the Brazilian Legal Amazon, which is the definition used by the deforestation monitoring system.
2. Data are available in <http://dtr2004.saude.gov.br/sinanweb>.
3. We thank the General Coordination of the National Program for Malaria Control of the Ministry of Health (MS),_which unified information from SINAN/MS, SISMAL/MS and SIVEP-MALARIA/MS.

developing the symptoms. The notification system requires local health workers to estimate, as best as possible, infection time and place, and this information is available for most variables. We selected all diseases for which data on infection municipality were available. We also included Schistosomiasis, for which only municipality of notification is available. Despite this limitation, the disease was included because of its relatively high incidence in the Brazilian Amazon and existing evidence of its association with modifications on landscape structure (Anaruma-Filho *et al.*, 2010).

TABLE 1
Descriptive statistics on diseases of mandatory notification in the Brazilian Legal Amazon (2004-2012)

	Total cases, 2001 to 2012 (1000)	Cases by municipality				Identification variables	
		Mean per 1000 people	Mean	s.d	Zero inflation share:	Municipality of:	Year of:
Accidents caused by venomous animals	144.3	1.1	20.5	34.8	0.07	occurrence	accident
Dengue Fever	551.7	2.3	78.4	723.7	0.30	infection	1st symptom
Chagas Disease (American trypanosomiasis)	1.1	0.0	0.2	1.8	0.97	infection	1st symptom
Schistosomiasis	1.4	0.0	0.2	2.3	0.96	notification	1st symptom
Typhoid Fever	1.8	0.0	0.3	3.4	0.95	infection	1st symptom
Cutaneous Leishmaniasis	129.8	1.1	18.4	37.1	0.14	infection	diagnosis
Visceral Leishmaniasis	9.8	0.1	1.4	6.9	0.76	infection	2001-2006: notification 2007-2012: 1st symptom
Leptospirosis	3.3	0.0	0.5	5.9	0.91	infection	1st symptom
Malaria	3,475.1	19.0	493.8	2.287.3	0.35	infection	1st symptom
Measles and Rubella	0.7	0.0	0.1	2.0	0.98	infection	1st symptom

Sources: SINAN/MS, SISMAL/MS, SIVEP-malária/MS, Datasus/MS, MDS, IDH-M/PNUD.

As time indicator, we used "year of the first symptom", which is the closest variable to the unobserved year of infection in the available dataset. Thus, a case reported in 2010 whose first symptoms occurred in 2009 is counted as a 2009 case in our estimates. For cutaneous and visceral leishmaniasis, the year of first symptom was not available, so we used the closest alternative. For cutaneous leishmaniasis we used "year of diagnosis". For visceral leishmaniasis we used "year of notification" between 2004 and 2006 and "year of the first symptom" afterwards. Finally, for accidents caused by venomous animals we used "year of accident".[4]

4. For brevity, through the text, we refer to "diseases" in a broad sense, including accidents caused by venomous animals, which are not technically diseases.

As indicated in table 1, incidence rates in the region are quite high for dengue fever, cutaneous leishmaniasis, accidents caused by venomous animals and especially malaria. We were unable to analyze other diseases available in the original dataset (plague, yellow fever, rabies, hantavirus, cholera and pesticide poisoning) due to the reduced number of occurrences in Amazonian municipalities or to the reduced number of years of disease notification.

Deforestation data come from the Project for Monitoring Deforestation in the Legal Amazon (PRODES) by the National Institute for Space Research (INPE), which has been monitoring the Brazilian Amazon rainforest using visual classification of satellite images since 1988.[5] We use the rate of deforestation per year and municipality, which is calculated as the increase in deforested area, measured in km^2, in the year divided by the municipal area. While our reference period is 2004 to 2012, we also use deforestation data from 2002 and 2003 to capture the lagged effects in our estimates.

Our estimates also include a large set of control variables, as explained further below. We obtained data on monthly rainfall and temperature from the National Institute of Meteorology (INMET). Municipal HDI data are from the United Nations Development Program (UNDP).[6] Health services data, such as the number of doctors and other health professionals, are from the National Register of Health Facilities in Brazil (CNES/MS).[7] Finally, data for the Bolsa Família program come from the Ministry of Social Development.[8]

For each of the diseases we estimate the impact of deforestation using count fixed effects regressions. The dependent variable in the regressions is the incidence of disease in each municipality-year, given the number of confirmed cases (per thousand inhabitants). These are count data, that is, taking nonnegative integer values, and with high frequency of zeros. Therefore, we estimate the impact of deforestation on disease using Poisson models, which are characterized by the following equations:

$$E[y|X] = \mu = e^{X\theta}. \quad (1)$$

5. Available at: <http://www.dpi.inpe.br/prodesdigital/prodesmunicipal.php>.
6. Available at: <http://www.pnud.org.br/IDH/DH.aspx>.
7. Available at: <http://cnes.datasus.gov.br>.
8. Available at: <http://aplicacoes.mds.gov.br/sagi/miv/miv.php>.

$$f(y|\mu) = \frac{e^{-\mu}\mu}{y!}. \tag{2}$$

The model establishes a multiplicative relationship between the expected value of the dependent variable, μ, and the explanatory variables, X (eq. 1). This expected value serves as a parameter that determines the link function (eq. 2), which is the Poisson probability distribution function. The model parameters, θ, are estimated by quasi maximum likelihood (Cameron and Trivedi, 2013).

A restrictive aspect of the usual Poisson model is that the average should be equal to the variance of the dependent variable. As seen in table 1, as is common in most empirical applications, for all diseases studied in this article the variance exceeds the average. To overcome this problem there are two alternatives: robust Poisson models or less restrictive link functions, usually the negative binomial, which allows the variance to be greater than the average. Cameron and Trivedi (2013) show that, despite the variance constraint, Poisson estimators with robust standard errors are nonbiased. On the other hand, estimators based on the Negative Binomial can be more efficient if that is the true underlying distribution, but can be biased if that is not the case. Thus, we present estimates for Poisson models with robust standard errors.[9]

After applying the logarithm to equation (1), we obtain equation (3), which details the temporal structure and the covariates included in the analysis:

$$\ln(E[y_{it}|x_{it}, \alpha_i]) = \delta_t + \ln(\propto_i) + ln(POP_{it}) + \beta * deforest_{i,t} + x'_{it}. \tag{3}$$

Where:

- i : municipality index;
- t : year index;
- y_{it} : number of confirmed cases of disease in i and t;

9. We also estimated regressions using a negative binomial (type 1), available upon request from the authors. The results were similar.

- $deforest_{i,t}$: deforestation rate in i and t;
- x_{it} : controls;
- α_i : municipality fixed effect;
- δ_t : period fixed effect; and
- POP_{it} : population in i and t.

Equation (3) details the important features of the model. For each disease we estimate regressions where the dependent variable is the number of confirmed cases of disease y_{it}. The log-linear form in eq. (3) means the coefficients in the model indicate the percentage change in disease due to changes in deforestation and other covariates.

The period fixed effects, δ_t, capture idiosyncratic year shocks which are common to all municipalities. The municipality fixed effects, α_i, capture unobservable characteristics of municipalities that are time invariant and influence the incidence of diseases. If these fixed municipal characteristics were also correlated with deforestation, their omission would bias the estimates of the effect of deforestation on disease, β. Thus we use count data fixed effects estimators, which eliminate α_i by the usual within transformation. As is common in fixed effects models, the standard errors must be corrected to account for serial correlation of idiosyncratic effects within municipalities. To achieve this, our standard errors are estimated by bootstrap estimators, wherein the sampling unit is the municipality (Cameron and Trivedi, 2013).

While diseases affect individuals, we use data at a more aggregated level, the municipality. Amazon municipalities vary greatly in terms of area and population. These differences in size and population could bias our results. Thus, we treat this in two ways. First, to take into account the size differences, we use the rate of deforestation, i.e. the deforested area divided by the total area of the municipality. Second, we control for the number of people potentially exposed to diseases induced by deforestation. As is common in epidemiological studies, we include the logarithm of the municipal population, $ln(POP_{it})$, as a dependent variable whose coefficient is pre-set to equal one.[10]

10. In Stata this can be done routinely by including "exposure (pop)" as the regression command option.

We also include controls to allow for a more flexible temporal effect of deforestation. The impact of deforestation on disease can be lagged, especially considering we use the year of the 1st symptom as a proxy for the year of infection, and symptoms may take some time to develop. Therefore, we estimate models including two time lags of deforestation.

We also include a series of climatic, socioeconomic and existing public health controls, which could have varied over the period within municipalities. We include controls for temperature and rainfall. In addition to increasing the accuracy of estimates, these controls may be important because of the influence of climate on the incidence of diseases and the pace of deforestation. Climatic data were obtained from monthly time series meteorological station of INMET. For the period there are 41 stations in the Brazilian Amazon. The data were interpolated to the urban center of each municipality using the inverse of distance weighting (IDW) for each weather station (Pebesma, 2004).[11] Because the effects of weather on disease can be heterogeneous throughout the year, the regressions include separate controls for temperature and rainfall in each of the twelve months.

To proxy for quality of health services and the ability of the health system to notify diseases, we include controls for the number of doctors and other health professionals in each municipality and year.[12] These proxies can capture two effects that work in opposite directions. First, health services can implement prevention activities, reducing the incidence of diseases. On the other hand, the existence of health services increases the detection and reporting of existing diseases.

We include controls for local socioeconomic characteristics. We use the three components of the municipal human development index (municipal-HDI) calculated by UNDP: longevity, education and income. Because the HDI is only available for the years 2000 and 2010, we interpolated data linearly for the years 2004 to 2012. In addition, we include controls for the number of beneficiary families and the total amount received from "Bolsa Família", a conditional cash transfer program targeting the poor, which expanded rapidly in the period in the region.

11. We used the idw function in the gstat package.

12. Controls for health services availability are common in the literature, as in Achcar *et al.* (2011), Garg (2014) and Hahn *et al.* (2014).

These variables can be interpreted either as controls for confounding factors that change within municipalities over the period but are not caused by deforestation, or as socio-economic changes that are induced by deforestation, thus a channel through which deforestation affects diseases. The fundamental point, however, is that, as we will see in the results section, the inclusion of these control variables, whether they act as controls for confounding factors or channels, does not significantly alter the results.

3 RESULTS

We summarized our results in table 2, in which rows indicate the impacts of deforestation on different diseases and columns represent different controls included in the regression models. Each cell of the table represents the estimated coefficient and standard error of a separate regression on the impact of deforestation on the incidence of each disease. For each disease, estimates were made using: only contemporary effect of deforestation (column 1), contemporary effect and lags (column 2), contemporary effect and controls (column 3), and contemporary effect, lags and controls (column 4).

TABLE 2
Impact of deforestation on disease incidence

	(1)	(2)	(3)	(4)
Accidents caused by venomous animals	3.57 (1,53)**	3.55 (1,73)**	3.37 (2,30)	3.25 (1,73)*
Dengue Fever	2.32 (11,2)	9.62 (13,1)	1.25 (9,8)	5.71 (12,9)
Chagas Disease (American trypanosomiasis)	45.26 (31,3)	32.39 (30,9)	42.71 (30,8)	36.31 (48,9)
Schistosomiasis	-19.64 (20,7)	-26.86 (20,9)	-25.4 (38,4)	-23.13 (45,0)
Typhoid Fever	41.93 (32,2)	38.5 (41,4)	-19.55 (26,5)	-29,23 (44,1)
Cutaneous Leishmaniasis	9.26 (2,76)***	6.85 (2,26)***	5.12 (1,04)***	2.44 (2,55)
Visceral Leishmaniasis	8.05 (4,3)*	4.65 (5,3)	5.82 (4,2)	6.75 (5,8)
Leptospirosis	-17.86 (12,9)	-25.23 (45,5)	-2.58 (20,8)	-2.6 (28,7)
Malaria	23.16 (9,03)**	18.45 (6,07)***	18.82 (2,91)***	14.54 (5,59)***
Measles and Rubella	136.07 (64,1)**	182.29 (101,8)*	-9.33 (79,7)	-19.45 (176,9)

Note: * p<0,1; ** p<0,05; *** p<0,01. Each cell represents the estimated coefficient and standard error of a separate Poisson regression on the impact of deforestation on the incidence of each disease. Columns indicate additional controls in each regression: only contemporary effect of deforestation (1), contemporary effect and lags (2), contemporary effect and socioeconomic controls (3), and contemporary effect, lags and socioeconomic controls (4). All regressions control for municipality and year fixed effects, average temperature and total precipitation for each month. Standard deviations are adjusted to city cluster, robust and estimated by bootstrap. Sources: SINAN/MS, SISMAL/MS, SIVEP-malária/MS, Datasus/MS, MDS, IDH-M/PNUD.

The results indicate that deforestation increases the incidence of malaria, cutaneous leishmaniasis and visceral leishmaniasis. Results are robust to the inclusion of lagged deforestation and a wide range of socio-economic controls. Tables 3, 4 and 5 show the complete regression output for these three diseases, including the coefficients associated with the controls. We do not find an impact of deforestation on the other diseases in the table, except for effects of very small magnitude on the incidence of accidents caused by venomous animals and measles.[13]

The results indicate that a yearly increase of 1% in deforestation is associated with a 14.5% to 23.2% increase in the incidence of malaria and a 5.12% and 9.26% increase in the incidence of cutaneous leishmaniasis. Unlike these diseases, the results for visceral leishmaniasis are only significant at the 10% level, and when lags are included, only the lagged deforestation coefficients are significant.

TABLE 3
Impact of deforestation on Malaria incidence

	(1)	(2)	(3)	(4)
Deforestation_rate	23.2 (9,03)**	18.5 (6,07)***	18.8 (2,91)***	14.5 (5,59)***
L.Deforestation_rate		14.6 (4)***		13.6 (4,92)***
L2.Deforestation_rate		10.2 (3,52)***		7.47 (4,21)*
# doctors			0,00 (0,00)	0,00 (0,00)
# other health workers			0,00 (0,00)	0,00 (0,00)
Municipal_HDI_Education			-10.8 (3,31)***	-9.69 (4,85)**
Municipal_HDI_Health			-6.94 (6,94)	-5.83 (7,89)
Municipal_HDI_Income			2.89 (3,75)	1.27 (5,45)
Bolsa Família: # famílies			0,00 (0,00)	0,00 (0,00)
Bolsa Família: R$ transfered			0,00 (0,00)	0,00 (0,00)
N	6.345	6.345	5.440	5.440
# Municipalities		705	680	680

Note: * p<0,1; ** p<0,05; *** p<0,01. Poisson regressions with municipality and year fixed effects and controls for average temperature and total precipitation for each month. Standard deviations are adjusted to city cluster, robust and estimated by bootstrap. Sources: SINAN/MS, SISMAL/MS, SIVEP-malária/MS, Datasus/MS, MDS, IDH-M/PNUD.

13. Full regression tables for the remaining diseases were omitted for brevity, but are available from the authors upon request.

TABLE 4
Impact of deforestation on cutaneous leishmaniasis

	(1)	(2)	(3)	(4)
Deforestation_rate	9.26 (2,76)***	6.85 (2,26)***	5.12 (1,04)***	2.44 (2,55)
L.Deforestation_rate		3.61 (1,98)*		7.48 (2,18)***
L2.Deforestation_rate		4.36 (1,69)**		3.04 (1,89)
# doctors			0,00 (0,00)	0,00 (0,00)
# other health workers			0,00 (0,00)	0,00 (0,00)
Municipal_HDI_Education			-2.81 (1,30)**	-2.03 (1,28)
Municipal_HDI_Health			5.94 (1,68)***	5.08 (2,24)**
Municipal_HDI_Income			3.08 (2,32)	1.81 (2,10)
Bolsa Família: # famílies			0,00 (0,00)	0,00 (0,00)
Bolsa Família: R$ transfered			0,00 (0,00)	0,00 (0,00)
N	7.011	7.011	6.232	6.232
# Municipalities		779	779	779

Note: * p<0,1; ** p<0,05; *** p<0,01. Poisson regressions with municipality and year fixed effects and controls for average temperature and total precipitation for each month. Standard deviations are adjusted to city cluster, robust and estimated by bootstrap. Sources: SINAN/MS, SISMAL/MS, SIVEP-malária/MS, Datasus/MS, MDS, IDH-M/PNUD.

TABLE 5
Impact of deforestation on visceral leishmaniasis

	(1)	(2)	(3)	(4)
Deforestation_rate	8.05 (4,26)*	4.65 (5,34)	5.82 (4,19)	6.75 (5,76)
L.Deforestation_rate		8.99 (3,68)**		8.95 (4,77)*
L2.Deforestation_rate		8.05 (2,62)***		9.45 (6,83)
# doctors			0,00 (0,00)	0,00 (0,00)
# other health workers			0,00 (0,00)	0,00 (0,00)
Municipal_HDI_Education			7.61 (5,60)	7.91 (5,10)
Municipal_HDI_Health			1.63 (5,22)	0.996 (7,32)
Municipal_HDI_Income			-2.27 (4,43)	-4.68 (6,96)
Bolsa Família: # famílies			0,00 (0,00)	0,00 (0,00)
Bolsa Família: R$ transfered			0,00 (0,00)	0,00 (0,00)
N	3.924	3.924	3.392	3.392
# Municipalities		436	424	424

Note: * p<0,1; ** p<0,05; *** p<0,01. Poisson regressions with municipality and year fixed effects and controls for average temperature and total precipitation for each month. Standard deviations are adjusted to city cluster, robust and estimated by bootstrap. Sources: SINAN/MS, SISMAL/MS, SIVEP-malária/MS, Datasus/MS, MDS, IDH-M/PNUD.

4 DISCUSSION

We are unaware of any other study in Brazil that uses such a granular dataset, covering such a large area and time period and investigating such a wide range of diseases. In addition, the spatial scale employed - the municipality - facilitates the use of results by environmental and health policy makers.

To grasp the magnitude of our findings on health outcomes we need to look at the distribution of deforestation rates. Mean yearly deforestation in the Amazon was 0.65%. The distribution is skewed, with many municipalities with zero deforestation. Median deforestation rate was 0.06%. Even the 75th percentile, at 0.37%, was still only half the deforestation average. Therefore, given the abovementioned estimates, the impacts on malaria and leishmaniasis at municipalities where deforestation takes place can be significant.

In accordance with the studies cited here on malaria carried out in various parts of the world with many different methods and at different scales, our results showed that deforestation has a major impact on the incidence of this disease. Therefore, any health measures related to malaria should necessarily take into account deforestation rates. Given the magnitude of the malaria incidence in the region, with 3.4 million cases over 8 years, it is clear that deforestation caused a high social cost that is little considered in making decisions about forest preservation.

In line with the studies of Chaves *et al.* (2008), Gottwalt (2013), Confalonieri, Margonari and Quintão (2014) and Nieves *et al.* (2014), we also found a clear link betwen deforestation and leishmaniasis. Its different manifestations – cutaneous and visceral – are recorded as separate diseases by DATASUS/MS. These different clinical forms refer to the diversity of protozoa of the same genus, Leishmania, associated with differences in the immune capacity of infected individuals. We find a significant impact on the incidence of the cutaneous manifestation, but a less pronounced impact on the visceral manifestation.

The finding that deforestation is unrelated to the incidence of dengue, Chagas disease, schistosomiasis, leptospirosis and typhoid fever contradicts the view of some authors, such as Patz *et al.* (2000), Vora (2008), Alho (2012) and Confalonieri, Margonari and Quintão (2014), who suggest that environmental imbalances can affect a wider range of diseases. It also differs from some studies of specific diseases, such as Barcellos *et al.* (2009), who suggest that water-borne diseases can be impacted by deforestation, and Anaruma-Filho *et al.* (2010), who find a positive association between Schistosomiasis and environmental modification. Gottdenker *et al.* (2011) shows an association between deforestation and triatomine vectors of Chagas disease. However, the author warns that an increased abundance of vectors does not necessarily result in higher disease incidence. On the other hand, our results are in line with those of Garg (2014), who finds no significant effect of deforestation on dengue, measles and diarrhea. Therefore, while our results indicate the existence of heath costs associated with deforestation, these impacts seem restricted to a small set of diseases.

In particular, deforestation activity could attract migrants to informal settlements that lack proper sanitation in urban areas. This in turn could lead to the spread of diseases, biasing our results. Our analysis, however, indicates that this is not a major channel of influence, because we do not find significant effects of deforestation on other diseases commonly associated with urbanization and improper sanitation. We find no association between deforestation and dengue fever, which occurs more frequently in urban environments, or leptospirosis, which is associated with improper sanitation. Therefore we can conclude that the increases in the incidence of malaria and leishmaniasis are a direct consequence of ecological imbalance and not a consequence of poor urban conditions.

Our results have two main implications for public policies in the Amazon: a) deforestation imposes costs to the health system that must be taken into account; b) there is synergy between malaria and leishmaniasis prevention and control policies and policies to combat deforestation.

Therefore, valuation models used for government decision making, as well as environmental impact and mitigation assessment, should include the effect of deforestation on the incidence of malaria and leishmaniasis and its associated costs. The integration between environmental and health policies, in turn, can be based on joint actions for environmental surveillance, and prevention and mitigation of malaria and leishmaniasis, taking into account the spatial distribution of recent deforestation.

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