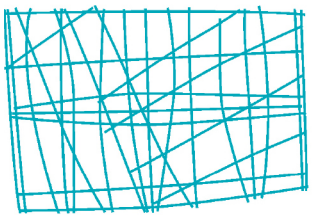

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ABSTRACT

Ecosystem degradation and contact with wildlife is often linked to infectious diseases such as COVID-19 and malaria, a major cause of death and incapacitation worldwide. This paper investigates a quasi-experiment involving two forest protection policies for the Brazilian Amazon region and their consequences to malaria incidence. The first inadvertently increased forest degradation in part of the Amazon, whereas the second curbed deforestation in the entire region. Using actual malaria case data distributed across space and over 17 years, we estimate the causal link between deforestation and malaria. The results imply that effective forest protection reduced malaria incidence by over 50%.

Keywords: Malaria, deforestation, forest protection policies.

JEL Codes: D04, I18, Q23, Q56, Q57, Q58.

1 Introduction

Ecosystem degradation has been linked to adverse health outcomes, with most of the emerging infectious diseases, such as COVID-19, stemming from contact with animals, especially wildlife.[1] Among the diseases often associated with deforestation and land use changes, malaria takes center stage globally. According to the World Health Organization, in 2021, almost half of the world population was at risk of malaria and there were an estimated 247 million cases and over 600 thousand deaths worldwide.[2] In addition, a number of studies suggest that malaria has significant economic consequences by negatively impacting human capital formation and lifetime earnings,[3] influencing violent conflict in vulnerable economic settings,[4] and hindering economic development.[5]

Although the control of infectious diseases seems to call for conservationist policies, little is known about the health impacts of forest protection. In addition, some scholars ponder that natural forests act as a wild reservoir that in fact propitiates disease outbreaks,[6] and others even argue that malaria itself may contribute to curbing deforestation.[7] At the center of the conservation and health debate is the need to better understand the complex interactions between social, environmental and epidemiological processes in space.[8] In this paper we take advantage of a quasi-experiment stemming from two conservation policies and estimate the impact of deforestation on the incidence of malaria in the Brazilian Amazon.

The first policy prohibited the market for big leaf mahogany, a valuable timber species native to the Americas, in response to predatory extraction in the Brazilian Amazon. The policy was

[1] Myers et al. (2013) discusses the negative impact of ecosystem degradation on human health. Jones et al. (2008) claims that most infectious diseases are zoonoses, whereas Andersen et al. (2020) argues that this is likely the case for the COVID-19 pandemic.

[2] https://www.who.int/news-room/fact-sheets/detail/malaria accessed on April 4, 2023.

[3] See for example, Cirera et al. (2022), Kuecken et al. (2021), Barofsky et al. (2015), Cutler et al. (2010), Lucas (2010) and Barreca (2010).

[4] Cervellati et al. (2022) and Acemoglu et al. (2020) explore different channels through which malaria can impact civil unrest.

[5] See for example, Carstensen and Gundlach (2006) and Sachs and Malaney (2002).

[6] De Coster et al. (2014).

[7] MacDonald and Mordecai (2019).

[8] Albers et al. (2020).

expected to not only safeguard the species but also curb large-scale deforestation that usually follow extraction of high-value timber. Although the direct impact of mahogany extraction on the forest cover is small, harvesting of high-value timber species creates infrastructure that reduces the overall cost of deforestation for other economic activities.[9] Nevertheless, due to a lack of adequate monitoring and enforcement, the ban on mahogany inadvertently resulted in the emergence of an illicit market that surpassed the size of its legal counterpart, as indicated by Chimeli and Boyd (2010) and Chimeli and Soares (2017). This, in turn, was conducive to increased deforestation and malaria incidence in areas where the species naturally occurs.

The second policy was the second phase of the Action Plan for Prevention and Control of Deforestation in the Legal Amazon (PPCDAm). PPCDAm II increased monitoring and enforcement in both mahogany and non-mahogany areas of the Brazilian Amazon, successfully reducing deforestation in the entire region.

Mahogany prohibition was therefore expected to have led to a differential increase in deforestation in mahogany occurring areas and PPCDAm II was expected to have done just the opposite. This setting provides us with a unique scenario for the estimation of the causal link between deforestation and the incidence of malaria.

Other papers associate malaria with deforestation, with most studies coming from the medical or natural sciences literature. For example, MacDonald and Mordecai (2019) estimate a fixed effects model for the Brazilian Amazon using an IV approach to account for possible reverse causality and find that deforestation increases malaria incidence. Chaves et al. (2018) estimate a positive correlation between deforestation and malaria. In a field study, Barros and Honório (2015) found that forest fringes were hotspots for larvae of the *Anopheles darlingi* mosquito, one of the most important malaria vectors in the Americas.

In the still small economics literature on the topic, Garg (2019) estimates a positive rela-

[9] See for example, Cropper et al. (1999), Amelung and Diehl (1992), Barbier et al. (1995) and Andersen et al. (2002). Verissimo et al. (1995) discusses the specific case of Mahogany in the Brazilian Amazon region.

tionship between deforestation and malaria outbreaks. He uses village-level survey data for Indonesia for the years 2003, 2006 and 2008 and constructs a panel with binary variation on the occurrence of malaria outbreaks. Because deforestation is likely to be non-random, he accounts for possible endogeneity through falsification tests with the incidence of other diseases as outcomes. Berazneva and Byker (2017) study malaria in young children with high resolution survey data for Nigeria for the years 2008 and 2013. In their sample, incidence of malaria is estimated through mothers' perception of their children's health in the two weeks prior to the survey. They address endogeneity concerns with a set of fixed-effects, time-effects, time-region trends, physical characteristics of the areas in their sample and socieconomic controls at the household and local levels.

Our approach differs from the existing literature in two important ways. First, to the best of our knowledge, we are the first to estimate the causal effect of forest loss on malaria by exploring a quasi-natural experiment with variation in deforestation over time and space. Second, because reporting of malaria cases are mandatory in Brazil, we use annual data on the number of actual cases (per 100 thousand) receiving medical attention over a time span of 17 years. Therefore, our data allow us to investigate both the intensity and the dynamics of malaria incidence over time due to deforestation.

Santos and Almeida (2018) run a spatial econometric model for the Brazilian Amazon and estimate that deforestation increases the number of cases of malaria. We address their insight by conducting robustness checks allowing standard errors to follow a general spatial correlation structure.

In our identification strategy, we take advantage of exogenous variation in incentives to deforest over space (municipalities) and time and the fact that there is only one group of treated regions during the entire span of the treatment. We rely on two-way fixed effects models and event studies linking forest protection and the incidence of malaria per 100 thousand inhabitants.

We estimate that PPCDAm II led to a decrease of over 250,000 cases, 100 deaths and around 5,072 disability-adjusted life years (DALYs) in the mahogany area alone between 2009 and 2019. This implies a 58% reduction in the number of cases relative to the counterfactual scenario without the forest protection policy. From our back-of-the envelope calculations this translates into health benefits of US$ 36 to US$ 109 million in terms of the value of a statistical life (VSL) and around US$ 26.8 million with respect to gains of years with full health.

Our results are robust to placebo treatments, spatial correlation, restricted time series, different intervention dates, propensity score weighting, different measures of malaria infection and population changes. We also perform falsification tests with hospitalizations and deaths by diseases that we do not expect to have been influenced by PPCDAm II. Overall, our results suggest that effective forest protection indeed leads to a decrease in malaria incidence.

Our results communicate with readers interested in conservation policies, public health, market prohibition policies, policy integration and policy evaluation more generally. In addition, by investigating the effects of a policy that seems to have failed and another that seems to have succeeded in fulfilling their main goals, we bring empirical evidence on the impact of monitoring and enforcement in the context of a developing country. We therefore hope the evidence we present here can contribute to policy design and implementation in lower- and middle-income countries.

Following this introduction, the background section discusses the relationship between malaria, deforestation and the conservation policies that form the basis of the malaria-deforestation quasi-experiment. Moving forward, in Section 3, we discuss the data employed in our study, while Section 4 outlines our empirical strategy. In Section 5, we present and discuss the findings derived from our research, while Section 6 contextualizes these results by providing back of the envelope calculations regarding the social costs of malaria that was averted relative to the counterfactual scenario of no forest protection policy. Finally, section 7 concludes.

2 Background

Malaria and deforestation

Malaria is transmitted by different species of the Anopheles mosquitoes. Although the relationship between land use change and malaria transmission is complex, deforestation and human intervention often contribute to increased sun exposure, higher temperatures, accumulation of standing water and elimination of mosquito predators. These environmental changes alongside the outer rims of forests create ideal breeding conditions for some Anopheles vector species (Yasuoka and Levins, 2007). Increased human presence in these areas then leads to increased malaria incidence.[10]

Mahogany market prohibition

This section is based on Chimeli and Boyd (2010) and Chimeli and Soares (2017), who provide a more detailed description of the institutional setting for the mahogany market.

Big-leaf mahogany (*Swietenia macrophylla King*) is a native tree species of the Americas originally ranging from Mexico to South America. Its timber characteristics led to intensive extraction over the centuries, restricting the remaining stocks of the species to the Amazon region by the 1990s. Concerns with respect to predatory harvesting motivated the Brazilian government to regulate the mahogany market starting in the mid 1990s.

A federal decree from 1994 determined that mahogany logging required a license and a forest management plan to guarantee preservation of the species. Systematic evidence of fraud by mahogany loggers, however, led the Brazilian government to suspend 85% of existing licenses in March of 1999. Later, in October of 2001, the government prohibited extraction, transportation, and trade of the species. When the mahogany market was legal, the state

[10] Among the studies that describe this process, see for example Vittor et al. (2006, 2009); da Silva-Nunes et al. (2008); Olson et al. (2010); de Oliveira et al. (2013); Barros and Honório (2015); Tucker Lima et al. (2017).

of Pará dominated the production of mahogany timber, exporting over 70% of its output to both the United States and the European Union.

Chimeli and Boyd (2010) and Chimeli and Soares (2017) present evidence that mahogany continued being formally exported after prohibition under the guise of "other tropical species". Not only that, they show that the volume of illegal exports surpassed the quantities traded before prohibition. If the extraction of high-timber value indeed leads to large-scale deforestation by other activities as the literature suggests, then the larger illegal market for mahogany resulting from prohibition is expected to have led to a relative increase in deforestation and malaria incidence in mahogany occurring areas.

PPCDAm

The Action Plan for Prevention and Control of Deforestation in the Legal Amazon (PPCDAm) was a novel policy involving coordination among 14 ministries of the federal government, and it was implemented in four phases, starting in 2004. Phase I (2004-2008) promoted the creation of conservation units and demarcation of indigenous lands. It also introduced a real time deforestation detection system (DETER) using satellite images that drastically improved deforestation monitoring capacity.[11]

Although monitoring improved with PPCDAm's phase I, enforcement remained weak and only a small fraction of fines imposed by regulators was actually collected (Assunção et al., 2023). Starting in 2009, phase II (2009-2011) introduced a number of measures that improved enforcement and caused deforestation in the Brazilian Amazon region to fall by 40% (Assunção et al., 2022). Among the measures that have been put into action, two prominent initiatives stand out. Firstly, a priority list of municipalities facing substantial deforestation rates was established. Secondly, the involvement of both public and private financial institutions has been instrumental. These institutions have taken a proactive approach by limiting

[11] Assunção et al. (2023) show how DETER played an important role in reducing deforestation in the Brazilian Amazon.

[Figure 1 approximately here.]

credit access for landowners in the identified high-risk regions (Mello and Artaxo, 2017).

Phase III (2012-2015) kept much of the measures adopted in the previous phases and additionally dealt with the challenge of monitoring more pulverized deforestation (Mello and Artaxo, 2017). Finally, phase IV (2016-2020) was marked by the weakening of deforestation monitoring and enforcement institutions in the country as well as an increasing trend in forest loss.

Mahogany policy, PPCDAm and malaria

The underlying feature of our empirical strategy is the variation in illegal mahogany extraction, which induced differential deforestation in mahogany occurring areas. Chimeli and Soares (2017) document how exports of "other tropical species" (disguised mahogany) jumped in 1999 following suspension of most mahogany extraction licenses, and then fell drastically around the time when PPCDAm II was introduced.[12]

The successful implementation of PPCDAm II resulted in a significant reduction of deforestation across the Amazon region (Assunção et al., 2022). Consequently, we anticipate that deforestation rates in mahogany-rich areas will have decreased to levels comparable to those in other regions. As a result, we also expect a convergence of malaria incidence in both mahogany and non-mahogany regions following the implementation of PPCDAm II.

Figure 1 illustrates the expected incidence of Malaria in the mahogany region relative to areas without mahogany. With the larger illegal market for mahogany starting in 1999/2001 inducing increased deforestation, we expect a relative increase in malaria in mahogany areas. Following the implementation of PPCDAm II, however, we expect convergence towards similar levels in both regions. Figure 1 also illustrates that malaria data in Brazil is only

[12]Chimeli and Soares (2017), figure 1, page 37.

[Table 1 approximately here.]

[Figure 2 approximately here.]

available from 2003, therefore, that we only have information for the mahogany prohibition period.

Table 1 presents descriptive statistics for deforestation, forest cover and malaria incidence in mahogany and non-mahogany regions within the state of Pará, before and after implementation of PPCDAm II. As the series for malaria starts in 2003, the pre-intervention period is defined as 2003 to 2008. Deforestation as a fraction of the municipal territory was 3 times larger in mahogany occurring areas before PPCDAm II and fell by 78% after the policy was implemented (in contrast to a 67% drop in non-mahogany areas). Likewise, malaria incidence in mahogany municipalities was more than twice as high as in non-mahogany areas before PPCDAm II and the indices in both regions converged to similar levels in the post policy introduction period. The table further suggests that malaria incidence is also related to the fraction of the municipality covered by forests. We control for baseline differences in deforestation in our benchmark specifications and for baseline forest cover in a robustness exercise available in Appendix A.

Figure 2 depicts malaria incidence in both regions over time. The vertical line marks the first year of PPCDAm II. The graph shows a large gap in malaria incidence before the stronger deforestation policy enforcement was introduced and a convergence in rates afterwards.

3 Data

Malaria

Starting in 2003, the Brazilian Malaria Control Program (PNCM) made it mandatory for health professionals to report all cases of the disease that received treatment in both private

[Figure 3 approximately here.]

and public health institutions. The information is entered in both the SIVEP-Malaria and DataSus systems under the Ministry of Health. We collect the data on cases of the disease from SIVEP-Malaria as it is the primary and more up to date data system. The data basis also contains information on the patient's municipality of residence, the municipality where the case was reported and the place of probable infection. Because the place of residence is an objective measure, whereas the place of probable infection is inferred by the health professional following a set of questions he/she asks the patient, we use the number of cases in the municipality of residence in our main specification.[13] We also conduct robustness checks with the other two pieces of information.

We normalize our outcome variable as a rate per 100 thousand inhabitants by dividing the number of cases of malaria by the municipal population times 100,000. Population data at the municipal level comes from the Brazilian Institute of Geography and Statistics (IBGE). Our annual data on malaria incidence spans from 2003 to 2019.

Treatment and control variables

Our treatment variable is the occurrence of mahogany in municipalities in the state of Pará. Following Chimeli and Soares (2017) we overlap the map with municipal borders in Pará and the area of natural occurrence of mahogany in the Brazilian territory provided by Lentini et al. (2003) based on Lamb et al. (1966). Figure 3 shows the mahogany (dark green) and non-mahogany (light green) municipalities that we use as treatment and control groups, respectively.

[13] See Wiefels et al. (2016) and Braz et al. (2006) for more detailed information on the SIVEP-Malaria system.

Forest and cloud controls

We hypothesize that the incidence of malaria may be affected by deforestation. Deforestation in a given municipality, in turn, is likely to be affected by the amount of forest cover in its territory. We therefore collect data on forest cover and deforestation at the municipal level from the MapBiomas database built from satellite images.[14] We also use information from the same database on areas covered by clouds, as Assunção et al. (2023) show that cloud cover is correlated with deforestation monitoring and enforcement.

In our econometric models, we use forest cover, deforestation and cloud cover at the municipal level as the fraction of the areas of the municipalities covered by each of these variables. Because data on forest cover and deforestation are likely endogenous to our specifications, we use baseline levels interacted with year dummies. We also use 1 and 2-year lagged deforestation as controls, following Berazneva and Byker (2017) who estimate that malaria incidence is positive and statistically significant in the first and second years after deforestation takes place.

Socioeconomic controls

As both malaria incidence and deforestation are likely affected by socioeconomic forces, we control for a number of additional variables. To capture local trends in health, we control for deaths by neoplasms, heart and infectious diseases. Controlling for health trends is particularly important to the extent that malaria might be under-reported and health habits may change over time due to municipal characteristics that may be correlated with the probability of a patient paying a visit to a health unit. This might be due, for example, to heterogeneous transportation and health service infrastructure.

We account for economic activity, economic development and urbanization by controlling for the log of GDP per capita, the share of agriculture in municipal GDP, and death rates of

[14] https://mapbiomas.org/en, extracted on 08/08/2019

both children under 5 years of age and by traffic accidents. We also account for the expansion of the agricultural frontier by including bovine density and deaths due to land conflicts in our econometric models.

The data comes from IBGE (GDP, population, bovine herds and agricultural GDP), DataSus (number of deaths by traffic accidents, neoplasms, heart diseases, infectious diseases and deaths of children under 5) and "Comissão Pastoral da Terra," a catholic organization that monitors and mediates land conflicts in Brazil. We also use DataSus data on hospitalizations due to bronchitis, accidental tetanus infections, diphtheria and deaths by neoplasms as outcome variables in our falsification tests.

Our socioeconomic control variables are expected to be endogenous and therefore we use baseline values interacted with year dummies in our specifications.

4 Empirical Strategy

We investigate the impact of legislative changes in 2009 in conjunction with the presence of mahogany across various municipalities in order to establish a causal relationship between malaria incidence and deforestation. Our hypothesis is that if the reduction in malaria incidence starting in 2009 is more pronounced in municipalities where mahogany occurs, it can be attributed to the second phase of the PPCDAm. The timing of this intervention was unique to the entire Amazon region, allowing us to identify the impact based on a differential responses in mahogany-rich municipalities, which were previously affected by the illegal logging market.

To analyze the data, we create a treatment dummy variable that is set to one for the interval between 2009 and 2019, the final year of our sample. This period encompasses the years of increased forest policy enforcement by the Brazilian government, resulting in a subsequent reduction in illegal deforestation. In contrast, the period from 2003 to 2008 is characterized

by a large volume of illegal extraction of mahogany resulting from prohibition combined with poor enforcement.

We begin with the following two-way fixed effects model:

$$Malaria_{it} = \beta_0 + \beta_1 D_{2009} \times mahog_i + \mathbf{x'_{it}}\gamma + \theta_i + \mu_t + \epsilon_{it}. \quad (1)$$

where $Malaria_{it}$ is the malaria incidence rate for municipality i in the year t; D_{2009} is a dummy variable equal to one for 2009 and all the following years; $mahog_i$ is a dummy variable equal to one if the municipality is located in the area of natural occurrence of mahogany; θ_i is the municipality fixed effect, μ_t is a time effect and ϵ_{it} is a random term. $\mathbf{x'_{it}}$ is a vector of control variables including socioeconomic, health, forest and cloud controls. Under the usual hypotheses that $E[\epsilon_{it}|D_{2009} \times mahog_i, \mathbf{x'_{it}}, \theta_i, \gamma_t] = 0$ and the stable unit treatment values assumption, OLS estimation of the above equation provides unbiased estimates of β_1, the average treatment effect on the treated. A statistically significant negative sign for β_1 is therefore indicative of a causal relationship between deforestation and malaria transmission.

Because most of our explanatory variables could be endogenous to our treatment, we use the interaction between their baseline (2000) levels and year dummies as controls. To allow for differential dynamics of the disease according to its pre-intervention rate and given that malaria data starts in 2003 only, we control for the interaction between the 2008 malaria incidence rate (just before PPCDAm II) and time dummies. Moreover, the use of baseline value interactions allows municipalities to have arbitrarily different non-linear dynamics of malaria incidence as a function of a large set of initial characteristics. Finally, following the findings in Berazneva and Byker (2017) we also include one and two-year lagged deforestation rates in our set of controls.

We address some potential threats to our identification with a number of checks and robustness exercises. As the variance of malaria incidence is related to population size, we weigh our baseline regressions by population. Additionally, we cluster standard errors at the

municipality level to account for temporal correlation of the residuals. In a robustness exercise, we estimate the impact of PPCDAm II in an unweighted regression using propensity score weights to guarantee better comparability between the treatment and control groups. In another exercise, we also report regression results with Driscoll-Kraay standard errors, which are robust to general forms of cross-sectional and temporal dependence.

Our analysis allows for the possibility of municipality-specific linear trends, placebo treatments, different years of initial impact to account for a lag between deforestation and malaria, and alternative control for baseline forest status in each municipality. Additionally, in one triple differences specification, we check for the role of initial deforestation and forest cover on the reduction in malaria. Also importantly, the transmission of malaria may be a function of population density, and deforestation may only indirectly affect the disease. We check for this possibility by using municipal population as an outcome variable.

The 2009 to 2019 intervention period is arguably heterogeneous, especially because anecdotal evidence suggests that monitoring and enforcement of illegal deforestation during the final years of our sample were relaxed. In addition, PPCDAm I was introduced in 2004 and caused a significant drop in deforestation between 2004 and 2005. To address these issues, we estimate our baseline regression in a sample restricted to the 2006-2013 period.

Interpretation of β_1 relies on parallel trends for the control and treated groups. To further investigate this hypothesis and the dynamics of the impact of PPCDAm II on malaria we estimate the following event-study specification with the outcome and control variables defined as before:

$$(y_{it} - y_{i2008}) = \alpha_0 + \sum_{\tau=2003}^{2019} \alpha_\tau mahog_i + \mathbf{x}'_{\mathbf{it}}\gamma + \epsilon_{it}. \tag{2}$$

Finally, we estimate equation 2 to run falsification tests with health outcomes that we do not expect to have been affected by deforestation.

[Table 2 approximately here.]

5 Results

A. Benchmark Results

Table 2 presents the results for equation 1. Column (1) includes fixed, time effects and non-linear trends in malaria by interacting 2000 incidence rates in each municipality with time dummies. Columns (2), (3), (4), (5) and (6) add deforestation lags, socioeconomic, health, bovine density and cloud area, and deforestation controls, respectively. Like in the case of malaria, columns (3)-(6) allow for non-linear time trends of the regressors by interacting baseline values with time dummies. Column (7) further explores differential trends by adding the interaction between municipal dummies and a linear time trend.

The estimated coefficients in all of the different specifications consistently suggest a relative decrease in malaria incidence in mahogany municipalities after 2009. Adding lagged deforestation to our simplest regression reduces the magnitude and precision of our coefficient of interest, but including additional controls, especially socioeconomic and bovine density, the economic activity that tends to immediately follow deforestation in the Brazilian Amazon, produces estimates that are larger in absolute value and significant at the 5% level. Municipality-specific linear time trends do not impact our estimates in any important way (column 7) and, therefore, we focus on model (6) as our benchmark specification.

Compared to the average annual rate of incidence in mahogany municipalities between 2003 and 2008, the -1,148 coefficient suggests a relative drop of around 35% after PPCDAm II was introduced. Given the average population of 46,501.16 in the 44 mahogany municipalities in Pará, our results imply a reduction of 533.83 cases per municipality per year, or roughly 258,374 less cases between 2009 and 2019 for the entire region. During the post PPCDAm II period a total of 185,013 cases of malaria were actually registered, implying a 58% decrease in the number of cases in the mahogany region alone relative to the counterfactual scenario

[Table 3 approximately here.]

[Figure 4 approximately here.]

without the forest protection policy.

The results in table 2 rely on the assumption of no preexisting trends for malaria in mahogany regions. To address this concern, we first re-estimate model (6) with four definitions of placebo treatments during the pre-intervention years. Table 3 reports the results for the four placebo treatments, each defined as the interaction between the mahogany municipality dummy and a dummy for a different set of years during the pre-intervention period: $pretreat0\tau = D_{2003 \leq t \leq 200\tau} \times mahog_i$, where $D_{2003 \leq t \leq 200\tau} = 1$ and τ represents the last digit of the years 2007, 2006, 2005 or 2004. If mahogany areas were already experiencing a relative decrease in malaria incidence before 2009, the placebo coefficients should capture these trends. However, none of the placebo treatments are significant and all treatment coefficients remain negative, although they have smaller absolute values and the $treat2009$ coefficient in column (6.p.1) is less precisely estimated (p-value of 0.108).[15]

Next, we explore the relative dynamics of malaria incidence in the mahogany region by estimating equation 2. Figure 4 (a) plots the annual coefficients for the event-study that mirrors specification (6) in table 2. The results indicate higher incidence levels up to 2010, followed by a downward trend and stabilization with significantly negative coefficients starting in 2013. This pattern may suggest a lagged effect of the stronger deforestation monitoring policy, an observation that is consistent with the findings in Barofsky et al. (2015), who estimate a significant increase in malaria incidence one and two years after deforestation takes place.

The probable reason for the lagged effect is that human exposure to malaria induced by deforestation may take some time until new economic activities settle along the forest fringe.

[15] In tables 3 through 5 and in Appendix A, columns are labeled so that the first number refers to the specification in table 2 and the following letter indicates the overall characterization of the set of results: "p" for placebo tests, "r" for robustness checks, "t" for triple differences and "a" for appendix.

[Table 4 approximately here.]

In our case, a decrease in deforestation may have taken up to two years to translate into a slowdown in the rate of contamination in municipalities with previously more intensive forest loss. To help us to visualize this possibility, figures 4 (b) and (c) re-estimate equation 2 with 2010 and 2011 as reference years – one and two years after the introduction of PPCDAm II, respectively. The corresponding two-way fixed effects coefficient estimates appear in table A.1 in Appendix A. As expected, the estimated average treatment on the treated increases in magnitude and we proceed with the more conservative results from table 2, column (6).

B. Selection bias, spatial correlation and treatment variation

A common issue in the analysis of the effect of policies is selection bias and comparability between treatment and control groups. To address this concern, we match units from the treatment and control groups on the year 2000 baseline values of the control variables, and use propensity scores as weights in our baseline regression (Abadie, 2005). The results are reported in column (6.r.1) in table 4 . Because propensity-score weighted regression restricts the sample to units with common support, we lose about 4% of our observations. Nevertheless, the qualitative result remains and significance of the treatment coefficient increases.

Deforestation and malaria are naturally placed in a spatial context and spatial correlation may affect significance of our estimates. Column (6.r.2) reports regression results with Driscoll-Kraay standard errors, which are robust to general forms of cross-sectional spatial and temporal dependence. As in the case of the PS weighted regression, the coefficient of interest remains significantly negative, increases in magnitude and is more precisely estimated.

Interpretation of the two-way fixed effects estimator relies on the assumption that the policy treatment is stable over time. This raises two possible concerns: (i) PPCDAm I was introduced in 2004 and deforestation in the Brazilian Amazon measured by the National In-

stitute of Space Research (Inpe/PRODES) fell by over 30% between 2004 and 2005; and (ii) deforestation data between 2014 and 2019 indicate an upward trend along with economic slowdown and allegedly weakening of enforcement effort. Taking into consideration these identification threats, we estimated our baseline regression using a restricted sample that spans the years 2005 to 2013. The results in column (6.r.3) remain robust to these changes.

C. Alternative outcomes

We use four alternative outcome variables in our regressions as robustness checks and additional tests of the validity of the interpretation of our results. The first two are robustness checks with different measures of malaria infection reported in SIVEP-Malaria. The outcome variable in column (6.r.4) of table 4 is the rate of malaria per 100 thousand inhabitants according to the municipality of notification (the municipality where the patient sought treatment), and the corresponding coefficient is of smaller magnitude and less precisely estimated. This is not surprising, as infected individuals may seek treatment in the more convenient health care units, which may not be in the same municipality of residence or of probable infection. Column (6.r.5) reports the coefficient for the municipality of probable infection (inferred by health professionals based on questions they ask the patients including, for example, place of work and recent travels), and the result is in line with the one in our baseline specification.

Column (6.r.6) addresses an issue pointed by Garg (2019): to the extent that the rate of infection may depend on the total human population, cases of malaria may be a consequence of population changes in deforested areas and not deforestation itself. In our context, the implementation of PPCDAm II may have diminished the region's economic attractiveness, resulting in a subsequent decline in population. To examine this hypothesis, we estimate a difference-in-differences model using municipal population as the outcome. The coefficient for the intervention dummy ($Treat2009$) is statistically insignificant, providing reassurance that we are not inadvertently measuring the impact of population decrease in our benchmark

[Table 5 approximately here.]

results.

Column (6.r.7) estimates the impact of PPCDAm II on the percentage of the municipal area covered by forests. This regression differs from our preferred specification in three important ways. We do not use population weights, as they do not seem to be applicable in this context, we do not use lagged variables for forest cover or deforestation and, like in column (6.r.3), we restrict our sample to the 2005 to 2013 period to minimize concerns with respect to changes in enforcement and monitoring effort. Our estimates suggest a significant relative decrease in deforestation in the mahogany municipalities following the implementation of PPCDAm II.[16]

D. Triple differences: Mahogany, PPCDAm and baseline deforestation

If malaria is associated with forest loss, we would expect treated municipalities with different baseline levels of deforestation and forest cover to experience different changes in infection rates.

To explore this hypothesis, we first estimate triple differences models by interacting our treatment variable with forest cover as a fraction of the municipal area in the year 2000, just after most extraction licences were cancelled and just before complete shut down of the market. The results appear in the first three columns of results in table 5. Column (5.t.1) omits our non-linear forest trend control (analogous to model (5) in table 2). Column (6.t.1) controls for non-linear forest trends by interacting time dummies with the fraction of the municipality area that was deforested between 2000 and 2001. In column (6.t.2) we use an alternative forest trend control by replacing deforestation with the fraction of the municipality covered by forests in 2000. In all three cases the triple interaction coefficients

[16] A detailed analysis of the impact of PPCDAm on relative land use changes in the mahogany area is beyond the scope of this paper and is pursued in a separate study.

[Figure 5 approximately here.]

are negative and large relative to the estimates in table 2, although they are less precisely estimated (p-values of 0.105, 0.102 and 0.11, respectively).

Next, in columns (5.t.2), (6.t.3) and (6.t.4), we define our triple differences by interacting our treatment variable with deforestation between the years 2000 and 2001. The estimated coefficients are all negative, relatively large and marginally significant.

Overall, our triple differences results suggest that municipalities with a larger rate of deforestation and larger forest cover around the time of the intervention in the mahogany market experienced a larger drop in malaria incidence.

E. Falsification tests

Lastly, we investigate the linkage between malaria and PPCDAm II by estimating the differential dynamics between mahogany and non-mahogany municipalities for four health indicators: hospitalization rates by bronchitis, accidental tetanus and diphtheria, and death rates by neoplasms. We do not expect any of these variables to be affected by increased monitoring and enforcement of illegal deforestation.

Hospitalizations by bronchitis, tetanus and diphtheria can capture potential short-term changes in health outcomes in the mahogany region around the time PPCDAm II was implemented, but that were not related to forest protection. Death by neoplasms capture potential long-term changes in health outcomes in the region.

The event study coefficients and 95% confidence intervals are shown in figure 5 . None of the graphs depict any systematic changes suggesting an omitted variable bias in our estimates of the impact of PPCDAm II on malaria. The estimates for neoplasms suggest and upward trend in the final portion of the sample, but this goes in the opposite direction of our malaria estimates and nothing peculiar seems to have happened around the time PPDCAm II was implemented.

6 Discussion on Avoided Social Costs of Malaria

Data on the costs of PPCDAm or comprehensive expenditures on malaria treatment and prevention in Brazil are not readily available, which prevents us from conducting a detailed cost-benefit analysis of the policy from its health perspective. Nevertheless, in this section, we provide some back-of-the-envelope calculations to provide some context to the health impacts of our results.

The estimated reduction of 258,374 cases combined with a case fatality rate of 0.04% results in 103 less deaths due to malaria in the mahogany region between 2009 and 2019.[17] Pereira et al. (2020) estimate that the value of a statistical life in Brazil varies between US$ 0.349 and US$ 1.056 million in 2015 values, which results in social benefits of around US$ 36 to US$ 109 million for those lives saved.[18]

An alternative measure of the burden caused by a disease is its Disability-Adjusted Life Year (DALY). One DALY represents the loss of one year of full health and is calculated as the sum of Years of Life Lost (YLL) due to mortality and Years of Life with Disability (YLD). Starting from the total number of cases, YLL is calculated based on the case fatality rate of the disease and the life expectancy of the deceased. YLD is calculated based on a disability weight associated with the disease and the average amount of time until the individual is cured.

For the 258,374 avoided cases of malaria in the mahogany region of Pará we calculate 4,571.08 additional years of full health lost due to avoided deaths (YLL) and 500.53 additional years of full health due to avoided morbidity (YLD). In total, PPCDAm contributed to an additional 5,071.61 years of full health (DALYs) in the mahogany area between 2009 and 2019. The average GDP per capita for the mahogany municipalities in Pará in 2015 was US$ 5,281.53.[19]

[17] The case fatality rate comes from Brazilian Ministry of Health (2021)

[18] Pereira et al. (2020) estimates that the VSL for Brazil range from R$ 1.088 to R$ 3.294 million in 2015 values. We converted those values to US$ using the exchange rate of 3.1185 from July 01, 2015 provided by the Central Bank of Brazil website: https://www.bcb.gov.br/conversao.

[19] GDP per capita comes from IBGE and Pará's state government. See

Multiplying GDP per capita to avoided DALYs results in a gain of around US$ 26.8 million.[20]

7 Concluding Remarks

Whereas many scholars argue that ecosystem degradation is the source of important infectious diseases, large-scale evidence that supports this hypothesis is still limited. In this paper we advance in the direction of causal estimation of the link between malaria and deforestation. We take advantage of a unique quasi-experiment induced by two forest protection policies and analyze a dataset covering actual cases of malaria distributed across space in the Brazilian Amazon region and over 17 years.

The first policy severely restricted and eventually prohibited the market for big-leaf mahogany, a tree species which naturally occurs in part, but not all the Brazilian Amazon. Mahogany prohibition was poorly enforced and the evidence suggests that it led to an increase in extraction of the species, induced deforestation and malaria incidence. The second policy, PPCDAm II, improved forest protection enforcement and monitoring efforts reducing deforestation in the entire Amazon region. We find compelling evidence that PPCDAm II effectively curbed the incidence of malaria in the mahogany region compared to other parts of the Amazon. This led to a remarkable convergence of malaria incidence rates between both regions, resulting in a reduction of over 50% specifically in the mahogany area.

The decrease in malaria we document is not related to changes in agricultural or farming activities, pre-existing trends in the dynamics of transmission, intrinsic characteristics of the population in the municipalities or to changes in population dynamics due to economic changes driven by the enforcement.

Our paper adds to different streams of the economics literature concerned with market

https://www.fapespa.pa.gov.br/sistemas/anuario2020/tabelas/economia/2.4-pib/tab-2.4.8-evolucao-do-produto-interno-bruto-per-capita-dos-municipios-paraenses-2013-a-2017.htm accessed on July 19, 2023.

[20] Detailed calculations appear in Appendix B.

prohibition, environmental protection policies, public health and policy design and implementation in the developing world. The main implication of our findings is that effective monitoring and enforcement of ecosystem protection policies can be an important tool to reduce transmission of infectious diseases with potentially large social costs.

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Figures and Tables

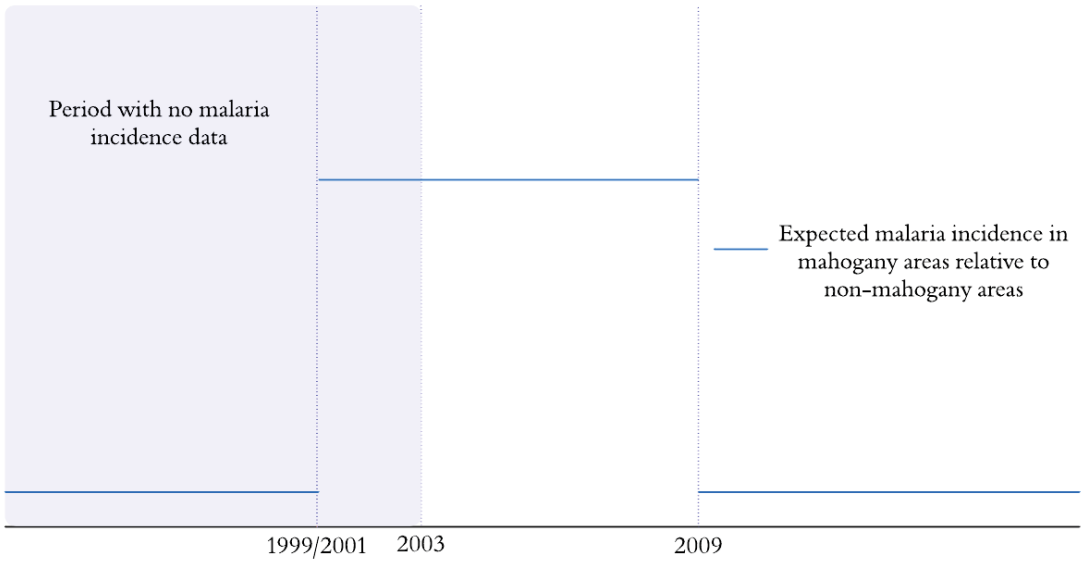


Figure 1: Expected Malaria Incidence Rates in Mahogany area relative to non-Mahogany areas.

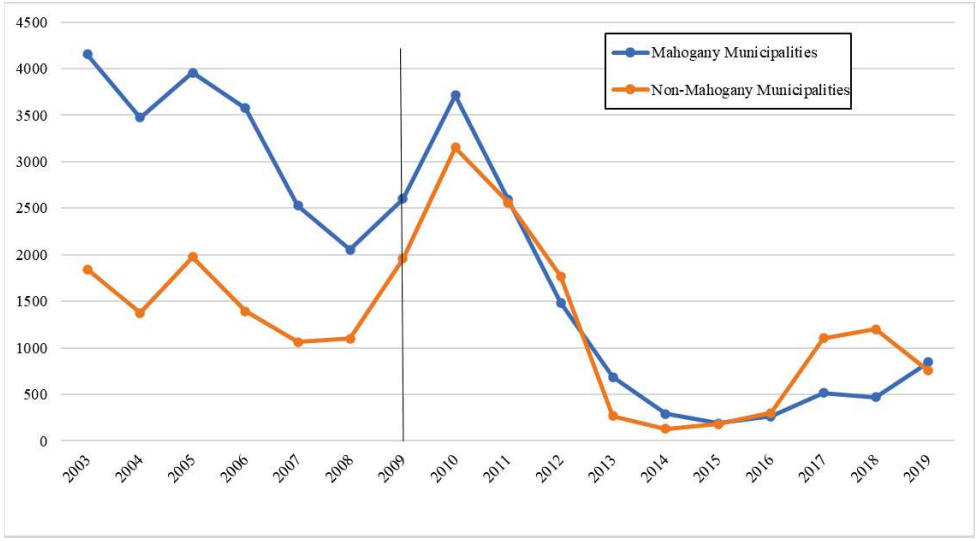


Figure 2: Malaria incidence (per 100,000 inhabitants) per municipality of residency from SIVEP-Malaria database, Pará, Brazil, 2003-2019.

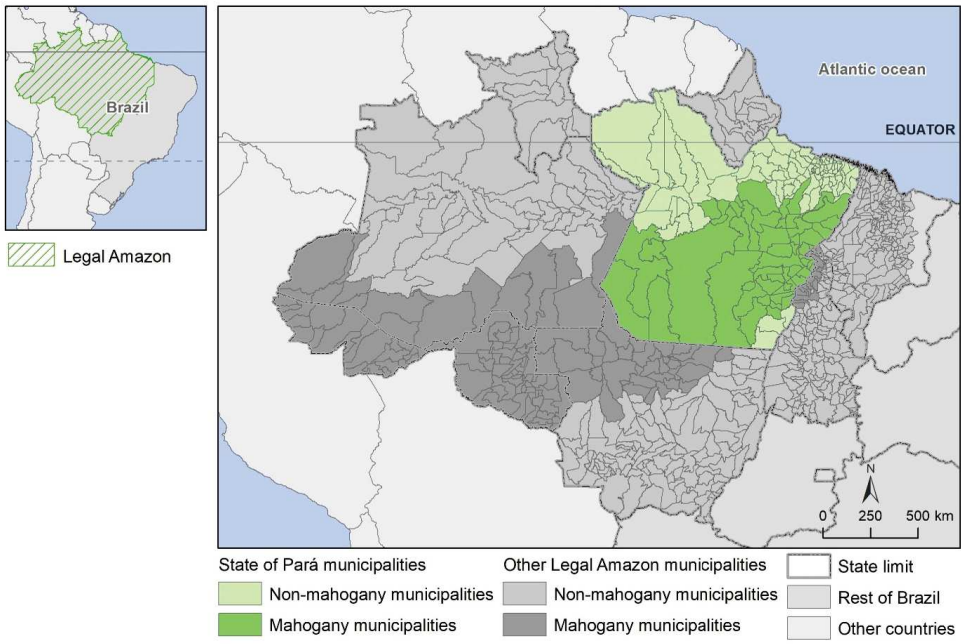
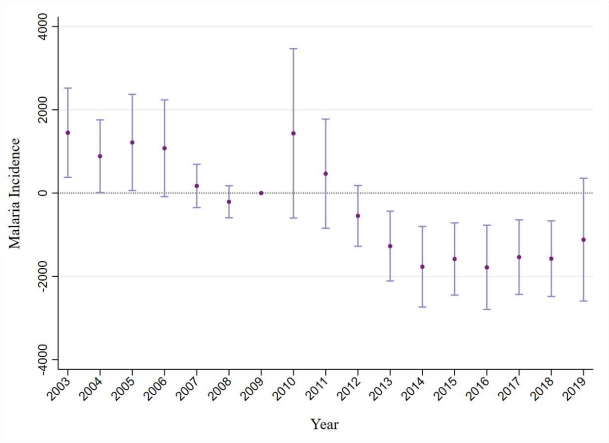
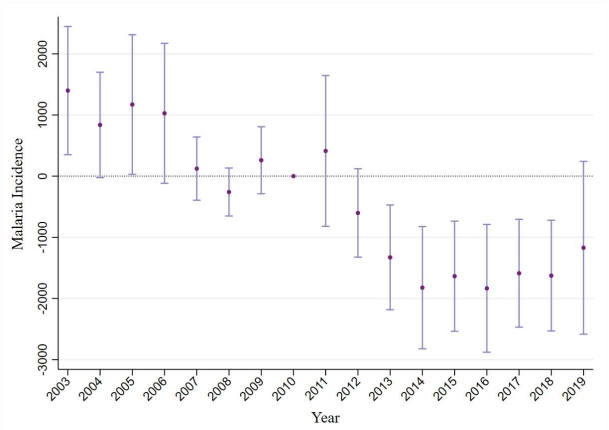


Figure 3: Municipalities with natural mahogany occurrence, Legal Brazilian Amazon States, Brazil.

(a) 2009 as base year.



(b) 2010 as base year.



(c) 2011 as base year.

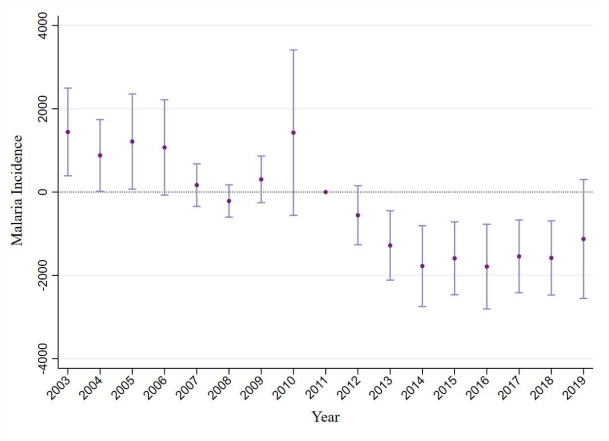


Figure 4: Dynamics of malaria incidence in mahogany municipalities, relative to non-mahogany municipalities, Pará, Brazil, 2003-2019.

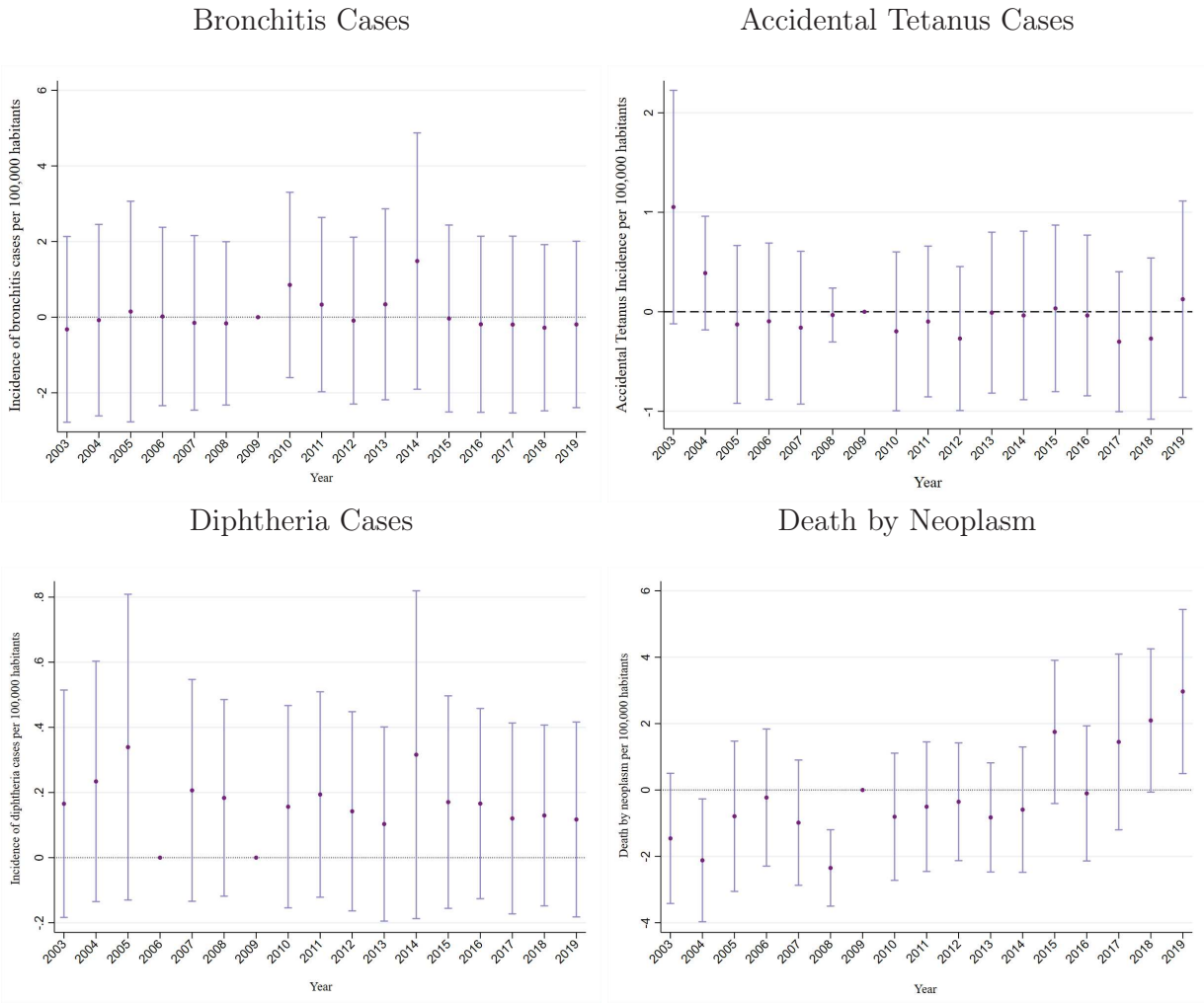


Figure 5: Dynamics of other diseases' incidence in mahogany municipalities, relative to non-mahogany municipalities, Pará, Brazil, 2003-2019, 2009 as base year.

Table 1: Descriptive statistics, selected variables.

		Non-Mahogany Municipalities		Mahogany Municipalities	
		Mean	sd	Mean	sd
Malaria Incidence	2003-2008	1,408.2	4,774.9	2,950.3	4,453.6
(cases per 100,000 inhabitants)	2009-2019	1,184.3	6,396.2	1,188.0	4,058.9
Deforestation	2003-2008	0.3%	0.8%	0.9%	1.1%
(Variation in % of forest Area)	2009-2019	0.1%	0.3%	0.2%	0.3%
Forest Cover	2003-2008	20.9%	29.5%	50.4%	32.4%
(% of forest Area)	2009-2019	19.6%	26.2%	47.2%	32.0%

Table 2: Evidence of causality between PPCDam II and malaria incidence decrease, municipalities in Pará, difference-in-differences, 2003 - 2019.

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)
treat2009	-1,441***	-831.4*	-1,041**	-975.2**	-1,153**	-1,148**	-1,141**
	(472.3)	(424.6)	(435.8)	(443.9)	(480.2)	(490.2)	(482.2)
Fixed effects	X	X	X	X	X	X	X
Time effect	X	X	X	X	X	X	X
Deforestation lags		X	X	X	X	X	X
Municipality-specific time trend							X
Socioeconomic controls (baseline 2000)			X	X	X	X	X
Health controls (baseline 2000)				X	X	X	X
Bovine density & cloud area (baseline 2000)					X	X	X
Deforestation trend control (baseline 2000)						X	X
Average malaria incidence per 100,000 inhabitants in mahogany municipalities between 2003 and 2008	3,291.19	3,291.19	3,291.19	3,291.19	3,291.19	3,291.19	3,291.19
Observations	2,431	2,431	2,137	2,137	2,137	2,137	2,137
R-squared	0.746	0.757	0.779	0.782	0.787	0.788	0.789

Robust standard errors in parentheses, clustered at municipal level. *** p<0.01, ** p<0.05, * p<0.1. All regressions include a constant and are weighted by the population. The dependent variable is the malaria incidence rate (per 100,000 inhabitants), generated via the number of malaria cases reported by municipality of residency of the victim, via the database SIVEP MALARIA. The treatment variable (treat2009) is a dummy equal to 1 if the year is 2009-2019 interacted with a dummy equal to 1 if the municipality has areas with natural occurrence of mahogany.

Table 3: Evidence of causality between PPCDam II and malaria incidence decrease, testing for pre-treatment trends, municipalities in Pará, difference-in-differences, 2003 - 2019.

VARIABLES	(6.p.1)	(6.p.2)	(6.p.3)	(6.p.4)
treat2009	-612.2	-810.7**	-1,006**	-1,036**
	(380.8)	(398.2)	(410.5)	(416.6)
pretreat07	660.4			
	(440.2)			
pretreat06		526.2		
		(445.0)		
pretreat05			298.3	
			(484.9)	
pretreat04				357.8
				(534.5)
Fixed effects	X	X	X	X
Time effect	X	X	X	X
Deforestation lags	X	X	X	X
Socioeconomic controls (baseline 2000)	X	X	X	X
Health controls (baseline 2000)	X	X	X	X
Bovine density & cloud area (baseline 2000)	X	X	X	X
Deforestation trend control (baseline 2000)	X	X	X	X
Observations	2,137	2,137	2,137	2,137
R-squared	0.788	0.788	0.788	0.788

Robust standard errors in parentheses, clustered at municipal level. *** p<0.01, ** p<0.05, * p<0.1. All regressions include a constant and are weighted by the population. The dependent variable is the malaria incidence rate (per 100,000 habitants), generated via the number of malaria cases reported by municipality of residency of the victim, via the database SIVEP MALARIA. The treatment variable (treat2009) is a dummy =1 if the year is 2009-2019 interacted with a dummy =1 if the municipality has areas with natural occurrence of mahogany.In this specification, we also include different placebo terms, the interactions between a dummy variable equal to one for mahogany areas and pre-treatment periods (pretreat07: 2003-2007; pretreat06: 2003-2006; pretreat05: 2003-2005 or pretreat04: 2003-2004).

Table 4: Evidence of causality between PPCDam II and malaria incidence decrease, further checks, municipalities in Pará, difference-in-differences, 2003- 2019.

VARIABLES	(6.r.1)	(6.r.2)	(6.r.3)	(6.r.4) Malaria incidence per municipality of notification as outcome variable	(6.r.5) Malaria incidence per municipality of probable infection as outcome variable	(6.r.6) Population as outcome variable	(6.r.7) Percentage of forest area as outcome variable
treat2009	-1,131**	-1,294***	-1,315**	-948.0*	-1,252**	1,581	-0.0369**
	(442.9)	(201.9)	(514.8)	(483.4)	(568.3)	(2,533)	(0.0177)
Fixed Effects	X	X	X	X	X	X	X
Time effect	X	X	X	X	X	X	X
Deforestation lags	X	X	X	X	X	X	
Socioeconomic controls (baseline 2000)	X	X	X	X	X	X	X
Health controls (baseline 2000)	X	X	X	X	X	X	X
Bovine density & cloud area (baseline 2000)	X	X	X	X	X	X	X
Deforestation trend control (baseline 2000)	X	X	X	X	X		X
Weights by population		X	X	X	X		
Propensity Score matching weights	X						
Driscoll-Kraay Standard errors		X					
Reduced sample			X				X
Different outcome variable				X	X	X	X
Observations	2,018	2,137	1,152	2,120	2,137	2,137	1,152
R-squared	0.874		0.830	0.799	0.778	0.998	0.922

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. The treatment variable (treat2009) is a dummy =1 if the year is 2009-2019 interacted with a dummy =1 if the municipality has areas with natural occurrence of mahogany.

Table 5: Evidence of causality between no illegal deforestation policy enforcement and malaria incidence decrease, municipalities in Pará, triple-differences, 2003 - 2019.

VARIABLES	(5.t.1)	(6.t.1) Deforest as trend control	(6.t.2) Forest area as trend control	(5.t.2)	(6.t.3) Deforest as trend control	(6.t.4) Forest area as trend control
treat2009	662.2	672.6	697.2	-165.7	-20.57	-91.98
	(1,014)	(984.2)	(1,020)	(620.8)	(614.3)	(728.4)
treat2009*forest_area_base00	-3,016	-3,019	-3,144			
	(1,846)	(1,833)	(1,953)			
treat2009*deforest_area_base00-01				-48,960*	-52,809*	-49,297*
				(27,539)	(27,582)	(27,710)
Fixed effects	X	X	X	X	X	X
Time effect	X	X	X	X	X	X
Deforestation lags	X	X	X	X	X	X
Socioeconomic controls (baseline 2000)	X	X	X	X	X	X
Health controls (baseline 2000)	X	X	X	X	X	X
Bovine density & cloud area (baseline 2000)	X	X	X	X	X	X
Deforestation trend control (baseline 2000)		X	X		X	X
Observations	2,137	2,137	2,137	2,137	2,137	2,137
R-squared	0.789	0.789	0.790	0.793	0.794	0.794

Robust standard errors in parentheses, clustered at municipal level. *** p<0.01, ** p<0.05, * p<0.1. All regressions include a constant and are weighted by the population. The dependent variable is the malaria incidence rate (per 100,000 habitants), generated via the number of malaria cases reported by municipality of residency of the victim, via the database SIVEP MALARIA. The treatment variable (treat2009) is a dummy =1 if the year is 2009-2019 interacted with a dummy =1 if the municipality has areas with natural occurrence of mahogany. We further interact the treatment variable with baseline values of the municipality's forest area in 2000 or with the variation of forest area in municipalities from 2000 to 2001.

A Appendix

Table A.1: Robustness check: Changing treatment year and deforestation trend control

VARIABLES	(6.a.1) Forest area as trend control	(6.a.2)	(6.a.3)
treat2009	-1,075*		
	(567.5)		
treat2010		-1,268**	
		(522.1)	
treat2011			-1,173**
			(525.7)
Fixed effects	X	X	X
Time effect	X	X	X
Deforestation lags	X	X	X
Socioeconomic controls (baseline 2000)	X	X	X
Health controls (baseline 2000)	X	X	X
Bovine density & cloud area (baseline 2000)	X	X	X
Deforestation trend control (baseline 2000)	X	X	X
Observations	2,137	2,137	2,137
R-squared	0.789	0.622	0.626

Robust standard errors in parentheses, clustered at municipal level. *** p<0.01, ** p<0.05, * p<0.1. All regressions include a constant and are weighted by the population. The dependent variable is the malaria incidence rate (per 100,000 habitants), generated via the number of malaria cases reported by municipality of residency of the victim, via the database SIVEP MALARIA.

B Appendix

To interpret the estimated decrease in malaria cases as a decrease in the Years of Life with Disability (YLD), we use the eq. 3 below, where I is the number of cases, DW is the disability weight and L is the average length of malaria disease until cured. Disability weights for malaria range from 0.004 to 0.625, depending on the severity of the consequences of the

disease to the individual. As an approximation, we use the value of 0.051 associated with "Moderate malaria", from the Institute for Health Metrics and Evaluation (IHME) (2020). For the value of L, we use 0.038.[21]

$$YLD = I \times DW \times L \tag{3}$$

The estimated reduction in YLD, therefore, is equal to $258,374 \times (1 - 0.0004) \times 0.051 * 0.038 = 500.52$ years.

Similarly, we calculate the decrease in Years of Life Lost (YLL) as follows, where I is the number of deaths, N is the number of deaths and LE is the average life expectancy.

$$YLL = N * LE \tag{4}$$

Using the case fatality rate of 0.04%, the average life expectancy by age group from Brazil's institute of geography and statistics (Instituto Brasileiro de Geografia e Estatistica (IBGE), 2019) and the distribution of cases of malaria in the population of Brazil in 2008 per age group from Xavier (2020) we calculate a reduction in YLL of 4,571.08 years.

A full breakdown of YLL values per age co-hort category is presented in table B.2 below.

The Disability-Adjusted Life Year (DALY) is calculate as the sum of the YLD and YLL. One DALY represents the loss of the equivalent of one year of full health due to malaria. Therefore, the reduction in cases due to the PPCDAmII policy is estimated to have lead to an increase in 5,071.6 years of full health. Multiplying that with the average GDP per capita for the mahogany municipalities in Pará in 2015,[22] we have a total benefit of USD 26,785,860.36.

[21] Xavier (2020), page 33.

[22] Data for GDP per capita for Pará's municipality comes from IBGE and the Pará state government: https://www.fapespa.pa.gov.br/sistemas/anuario2020/tabelas/economia/2.4-pib/tab-2.4.8-evolucao-do-produto-interno-bruto-per-capita-dos-municipios-paraenses-2013-a-2017.htm, accessed on July 19, 2023.

Table B.2: Years of Life Lost (YLL), per municipality

Age group	**Decrease in cases***	**Avoided deaths****	**Average life expectancy*****	**YLL**
0-14	22,597.96	9.04	71.24	643.95
15-24	60,871.88	24.35	58.13	1415.47
25-34	54,261.24	21.70	48.90	1061.35
35-44	44,431.44	17.77	39.73	706.16
45-54	33,803.81	13.52	30.90	417.82
55-64	25,088.77	10.04	22.77	228.48
65+	17,318.89	6.93	14.13	97.85
Total	25,8374.00	103.35		4,571.08

*Based on proportions calculated from rates by age group presented in Xavier (2020), table 4, page 47.
** Using fatality rate of 0.04%.
*** Calculated based on Instituto Brasileiro de Geografia e Estatistica (IBGE) (2019) as follows. For age group 0-14, we calculated the average life expectancy for ages 0, 5, 10 and 15. Similar averages were calculated for 15-24 (15, 20 and 25), 25-34 (25, 30 and 35), 35-44 (35, 40 and 45), 45-55 (45, 50 and 55), 55-64 (55, 60 and 65) and 65+ (65, 70, 75 and 80+).