Deforestation and Infant Health: Evidence from an Environmental Conservation Policy in Brazil

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**Abstract**

This study provides evidence of a negative externality of deforestation in infant health. As identification strategy, we exploit the introduction of a change in the forest policy which caused a marked reduction in deforestation by municipalities in the Amazon region of Brazil. We show that this policy of forest reduced the rates of preterm birth and low birth weight in those municipalities that were potentially exposed to the intervention. Importantly, our results are insensitive to a variety of robustness exercises.

**Key words:** Infant Health; Environmental Quality; Deforestation; Brazil

**Resumo**

Este estudo fornece evidências significativas de uma externalidade negativa do desmatamento na saúde das crianças. Como estratégia de identificação, explora-se a introdução de uma política de conservação da floresta que causou uma acentuada redução no desmatamento nos municípios da Região Amazônica no Brasil. O trabalho mostra que essa política de conservação de florestas reduziu as taxas de prematuridade e baixo peso ao nascer nos municípios que foram potencialmente expostos à intervenção. Mais importante, os resultados encontrados são insensíveis a uma variedade de exercícios de robustez.

**Palavras-chave:** Saúde Infantil; Qualidade Ambiental; Desmatamento; Brasil

**Área ANPEC:** Economia Agrícola e do Meio Ambiente

**Classificação JEL:** I12, K32, Q51

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## 1. Introduction

There is a growing consensus that deforestation has a significant impact on the environment. Among these, one of the most important is its contribution to emissions of greenhouse gases. Globally, deforestation accounts for about 17% of total emissions of such gases (IPCC, 2014). Other changes in the environment are related to the propagation of vectors, such as malaria-inducing ones (VITTOR, 2009). These changes in the environment have potential health externalities. Previous studies have consistently shown that the emission of particles implies worse mortality outcomes (CONEUS; SPIESS, 2012; CURRIE et al., 2009), while in some countries diseases such as malaria remain a major cause of death[5]. For all this, the control of illegal deforestation of forests has been of general interest. Thus, the design of an optimal forest policy requires an estimation of the benefits of reducing the rate of deforestation. Previous studies have focused on the global effects of deforestation due to concerns about global warming but have typically ignored "local" effects.

In this study, we investigated the effects of deforestation on health considering the introduction of a new forest policy that caused a marked variation in deforestation within the Amazon region of Brazil. Assunção, Gandour and Rocha (2011) show that the launch of the *Plano de Ação para a Prevenção e Controle do Desmatamento na Amazônia Legal* (PPCDAM) drastically reduced deforestation rates. We investigated the effect of PPCDAM on birth outcomes of children born in municipalities that were potentially exposed to the intervention.

Understanding the extent to which deforestation affect infant health is important for several reasons. First, there is a growing consensus that fetal adverse shocks have negative economic consequences in the long run. Indeed, previous studies have shown that better health outcomes at birth are associated with greater human capital accumulation (ALMOND; CURRIE 2011; ALMOND, 2006; CASE et al., 2002, 2005; Currie, 2011a)[6].This is especially important given that health shocks during childhood are often transmitted from generation to generation (CURRIE, 2011a). Hence, understanding how deforestation affects birth outcomes could impact the design of forest policies. Second, studying newborns has several methodological advantages to understanding the deforestation-health link. One is that the time of exposure to the environmental quality of the newborn is easier to identify than the adult population. As is argued in Currie (2011b):

> "The study of newborns overcomes several difficulties in making the connection between pollution and health because, unlike adult diseases that may reflect pollution exposure that occurred many years ago, the link between cause and effect is immediate" (CURRIE 2011b, p.p. 66).

Third, the long-term effects of health shocks in early life may be larger in developing countries due to limited ability to offset these shocks (CURRIE; VOGL, 2013).Therefore, to extrapolate estimates from developed countries to developing economies could lead to less accurate policy designs.

The relationship between environmental quality and health is the subject of a voluminous empirical literature. Nevertheless, we are unaware of any previous study that raised a link between deforestation and child health. Remarkably, the literature on the influence of the environment on health has focused on the effects of particulate pollutant emission (CHAY; GREENSTONE, 2003; CONEUS; SPIESS, 2012;

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[5]http://www.ncbi.nlm.nih.gov/pubmed/11425172

[6]A detailed summary of this literature is presented in Almond and Currie (2011) and Currie and Vogl (2013).

CURRIE; NEIDELL, 2005; CURRIE et al., 2009). The evidence from these studies, however, is insufficient to inform the effects of deforestation because there are multiple mechanisms through which the deterioration of the forest area could affect health. Several epidemiological studies provide some evidence of such mechanisms. Vittor et al. (2006) found that the incidence of mosquito bites that induce malaria is substantially higher in deforested areas. Meanwhile, Chaves et al. (2008) show that the incidence of Lymey's pathology (leishmaniasis) is also associated with deforestation. In addition, an association between deforestation and the incidence of SARS, Ebola and other bat viruses has been found (LEROY et al., 2005; LOOI; CHUA, 2007; FIELD, 2009). Failure to observe these mechanisms could result in an underestimation of the effects of deforestation on health.

Estimating the effect of deforestation on health outcomes is not a simple task, however. A simple Ordinary least squares (OLS) regression of a health outcome on deforestation does not provide causality because deforestation in this regression may be endogenous. Individuals with higher incomes and strong preferences for a "good" environment can migrate to less deforested areas. This would overestimate the true effect of deforestation. Alternatively, if the deforested areas are replaced with infrastructure (such as roads, schools, etc.) so that capitalize on higher prices of housing, then the high-income families who value these improvements will choose to be localized in areas that have been most deforested. This would bias to zero the true effect deforestation. Therefore, simple correlations are unlikely to provide convincing evidence.

Our identification strategy exploits a change in a policy of environmental conservation that caused a large reduction in deforestation rates. In particular, we exploit the differential changes in deforestation attributable to geographic variation of PPCDAM effects within a short window of time. The PPCDAM was introduced in 2004 and emphasized those municipalities with critical levels of deforestation. Evidence suggests that this policy substantially reduced deforestation in those municipalities that had critical levels of deforestation in 2004, while those with low levels of deforestation this policy had little or no effect (ASSUNÇÃO; GANDOUR; ROCHA, 2011). This suggests that the latter group of municipalities may be a useful control group. Thus, our analysis compares the infant health outcomes before and after the intervention of municipalities with large reductions in the rate of deforestation with those who had little or no reduction in deforestation.

Brazil provides a compelling setting to explore the effects of deforestation for several reasons. First, the country has the world's largest rainforest, with an extension that is equivalent to nearly half the total area of Europe. Therefore, the consequences of deforesting the Amazon rainforests of Brazil are of global concern. Second, Brazil is an emerging country that has experienced rapid economic growth in recent years. This represents significant challenges since Brazil is in the development stage in where the deterioration of the environmental quality is increasing with economic development (GROSSMAN, 1995). Third, deforestation contributes about 50% of emissions of carbon dioxide ($CO_2$) in Brazil (MINISTÉRIO DA CIÊNCIA E TECONOLOGIA, 2010), suggesting that the emission of this gas could be a particularly important mechanism in deforestation-health link. Finally, Brazil has detailed information about deforestation rates at the municipal level data since 2000, allowing us to study the effects of deforestation with a large panel data.

There are several threats that our empirical approach is exposed. Among them, one of the most important is the introduction of new social programs that coincide with the adoption of PPCDAM. If the targeting of other social programs is correlated with the PPCDAM then we could underestimate or exaggerate the effects of deforestation on child health outcomes. The evidence we present below suggests that the introduction of such programs have little effect on our estimates of the effect of PPCDAM. In the section 4 we discuss the major threats and how we face them.

We find suggestive evidence that deforestation has a robust effect on infant health. Our preferred specifications suggest that PPCDAm reduced the incidence of extreme preterm birth in 0.45% and very low birth-weight in 0.38%. Importantly, these findings are insensitive to a variety of robustness exercises. For example, we found no evidence that changes in other potentially confounding factors (such as the characteristics of mothers) explain the improvements in child health.

The next section of this article presents a brief review of the channels through which deforestation may affect children's health. Section 3 describes the PPCDAM. Section 4 presents the empirical strategy we use to identify the effect of PPCDAM on birth outcomes. Section 5 describes the data used. The section 6 shows the results. Section 7 presents some robustness checks. Finally, the last section concludes.

## 2. Deforestation-Infant-health linkages

We can draw from existing literature insights to identify the main mechanisms underlying the effects of deforestation on infant health. Through the process of logging, deforestation alters important elements of the ecosystem such as aquatic conditions and the microclimate. It has been demonstrated that deforestation reduces rainfall levels and increases the temperature levels (IPCC, 2014; KURUKULASURIYA; ROSENTHAL, 2013; SERÔA DA MOTTA, 2011; DORE, 2005; NOBRE; ASSAD, 2005). The effect on the rainfall occurs because deforestation reduces the natural recycling cycle through which vegetation absorbs moisture from the ground and sends it to the atmosphere, where as rain it returns. In turn, climate warming occurs through the connection between deforestation and greenhouse gases. The forest plays an important role in the absorption of such gases. By reducing the size of forests an increased pollution is emitted into the atmosphere and therefore the greater the speed of global warming. These changes in climate may have implications for children's health. Both water scarcity and a higher climate warming may affect the household's demand for health inputs through reductions in agricultural production, which means less income and higher food prices. The direct consequence of this is fetal exposure to poor intake of vitamins and iron, and a decreased ability of the mother to invest in prenatal care (WORLD HEALTH ORGANIZATION, 2012; TRUJILLO; CARRILLO; IGLESIAS, 2013). If reduction in the amount of water means less water quality, then it would increase the risk of diarrhea and respiratory infections (WORLD HEALTH ORGANIZATION, 2012).

Importantly, the effect of deforestation on child health through income is theoretically ambiguous. On the one hand, the restrictive policies of deforestation can contribute to improving agricultural productivity through reductions in fluctuations in rainfall and temperature. Moreover, such policies can become an impediment for farmers to expand their production levels. At least in the short term these expansion constraints to farmers could result in less income for households that depend on this activity. Therefore, the net effect of the restrictive policies of deforestation depend in part on the magnitude of these two impacts on production.

In addition, changes in the ecosystem also influence the survival of vectors that induce malaria. Indeed, the survival of mosquitoes is mainly determined by the temperature and humidity. Empirically, the relationship between deforestation and malaria risk has been documented by previous studies. Vittor et al. (2006) shows that the risk of malaria is 278 times higher in deforested areas in the Amazon region of Peru. For Brazil, Olson et al. (2010) shows that 48% of the increase in the incidence of malaria is explained by the increase of deforestation between 1997 and 2000. This transmission channel of deforestation is important in view of the mortality rates due to malaria. According to the World Health Organization (WHO), in 2010, 660,000 people died across the globe because of this condition.

There are other diseases that are also associated with climate change. Examples of these diseases are: dengue, the Lymey's pathology (leishmaniasis), SARS, Ebola, and those induced by the black fly and other viruses of bats (WLSON et al., 2002; LEROY et al., 2005; LOOI; CHUA, 2007; CHAVES et al., 2008; FIELD, 2009; MORIN; COMRIE; ERNST, 2014). The transmission of these infectious diseases not only occurs because deforestation provides the optimal environment for the breeding of carrier insects but also through increased human contact with animals (WOLFE et al., 2005; WOLFE et al., 2007).The incidence of these diseases, however, varies across the globe. For example, the incidence of SARS and Ebola is specific in countries of Asia and Africa. Thus, this channel is likely to play a minor role in Brazil. By contrast, dengue is expected to be a more important explanatory factor for this country.

The interaction of these factors could exacerbate the effect of deforestation on birth outcomes. This will depend on the rate at which deforestation affects climate change and the magnitude of the impact of climate changes on the outcome at birth. In this regard, there is a set of studies in the literature that attempts to estimate the effects of exposure to extreme climates in the uterus. Deschênes, Greenstone, and Guryan (2009) find that exposure to extreme heat during pregnancy reduces birth weight. They then predict that the end of the XXI century global climate change would reduce by 0.22% the birth-weight of white children and 0.36% that of African-American children. In addition, they find that the probability of low birth weight[7]will increase by about 5.9%. Lawlor, Leon, and George (2005) find heterogeneous effects by period of gestation. They find that birth weight has a negative relationship with temperature exposure in the first trimester of pregnancy, whereas exposure in the third quarter the relationship found is positive. All this evidence of the effects of climate change, however, is concentrated to developed countries. Many of the channels that can operate in developing countries are likely to have little or no effect in developed countries. For example, malaria is virtually non-existent in those developed economies as well as the incidence of dengue. Moreover, this is compounded by the fact that higher-income families are better able to compensate for an adverse impact on the environment.

While the evidence on the link between temperature and birth-outcomes for developing countries is smaller, there is a large literature exploring the link between water scarcity and child health (KIM, 2010; KUDAMATSU et al., 2010; AGUILAR; VICARELLI, 2011; SKOUFUAS et al., 2011; BURGESS et al., 2011; ROCHA; SOARES, 2012). The results of Kudamatsu et al. (2010) for a set of African countries indicate that fluctuations in precipitation levels have a negative impact on child mortality and malnutrition. For Mexico, Aguilar and Vicarelli (2011) find that the *Fenómeno del Niño* affects the height and weight of infants. The authors present some evidence to suggest that the fall in income from agriculture explains their results. Finally, Rocha and Soares (2012) investigate the effect of fluctuations in precipitation levels for the semiarid region of Brazil. They find that negative shocks in rainfall levels imply higher rates of low birth weight and premature births. In short, the whole body of evidence suggests that fluctuations in rainfall could be an important mechanism through which deforestation exerts its influence on children's health.

The greenhouse gas emissions can also affect birth outcomes independent of changes in climate. As is well known, the forest areas have an important role in the absorption of pollutant gases. Therefore, the deforestation reduces the natural ability of the forest to absorb such gases. Thus, further deforestation equals more air pollution. The contribution to air pollution through deforestation is greater if the method used to deforest is large-scale burning. According to IPCC (2014), deforestation contributes 17% of total emissions of greenhouse gases over the world. For Brazil, which has the world's largest forest, deforestation contributes almost half of the total $CO_2$ emissions. This figure is similar to the total emissions from vehicles in the U.S. (QUADRELLI; PETERSON, 2007; CERRI et al. 2009). Given the immense territorial dimension of Brazil,

[7]Low birth weight is defined as less than 2500 grams.

the relative contribution of deforestation to greenhouse gas emissions should be significantly higher in the Amazon region of Brazil.

Air pollution can affect children's health in various ways. To the extent that a pregnant woman is exposed to polluted air, the development of the fetus may be adversely affected. This is due to toxins carried in the blood of the mother that can be transmitted to the uterus, which increases the risk of health and developmental problems. The main health risks caused by fetal exposure to air pollution are the negative effects on birth weight and gestation period. Among the most recent studies on the subject, which also found negative effects on other child health indicators, are Beatty and Shimshack (2011) Knittel, Miller, and Sanders (2011), and Currie (2011).

While the above evidence suggests that deforestation may be an environmental factor that contributes to worse birth outcomes, we are unable to find any studies that have proposed a link between these variables. Our study therefore contributes to exploring the effects of deforestation on birth weight and the length of the gestation period.

## 3. Policy Context - PPCDAm

Perhaps one of the places in the world that best represents the consequences of deforestation is Brazil. Indeed, this country is among the six countries that account for 60% of global deforestation (FAO, 2010).[8] A retrospective analysis of deforestation in the Brazilian Amazon region proves to be useful. It is estimated that by 1980 deforestation reached about 300 thousand square kilometers, which represents 6% of its total area. However, this pace became more intense during the first years of the 2000s. According to *Instituto Nacional de Pesquisas Espaciais* (INPE) figures, approximately 19,000 square kilometers of forest per year were lost on average between 1996 and 2005. Given this scenario, Brazilian conservation policies for prevention and control of deforestation in the Amazon had to undergo an intensive review. Indeed, the Brazilian government to take stringent measures to curb deforestation. Therefore, in 2004, the government adopted the *Plano de Ação para a Prevenção e Controle do Desmatamento na Amazônia Legal* (PPCDAM). In the same year, the deforestation of the Brazilian Amazon reached its peak, registering a loss of 27,000 square kilometers.

The PPCDAM was based on a new way to combat deforestation. It integrated the whole efforts of federal, state and municipal governments with specialized agencies and civil society. The management and integrated action facilitated the implementation of innovative processes for monitoring, environmental control and territorial management. The mutual collaboration between the different stakeholders enabled the increased intensity of monitoring activities. This ability has improved significantly with the implementation of *Sistema de Detecção de Desmatamento em Tempo Real* (DETER) of the INPE and the creation of *Centro de Monitoramento Ambiental* (CEMAM) within the *Instituto Brasileiro de Meio Ambiente e Recursos Naturais Renováveis* (IBAMA).

The PPCDAm is structured into three main areas, namely i) land and land use planning, with special attention given disputes over land ownership; ii) environmental monitoring and control, to improve monitoring, licensing and inspection; and iii) promotion of sustainable production activities, including better use of already deforested land and development of transport infrastructure and sustainable energy. The implementation of the actions can be directed to municipalities, according to criteria considered as priorities and critical to each municipality observed. The intention is to reduce deforestation by 80% by 2020. Until 2012, the figures indicated that this goal is not far from being achieved. In fact, in 2011, one of the lowest

[8]Nearly 12,343 square miles of forest are deforested each year in the Brazilian Amazon. This area is equivalent to almost five times the territory of the Duchy of Luxembourg.

rates of deforestation since official data became available was recorded, yielding 78% less deforestation than in 2004.

Some studies in the literature have attempted to estimate the effects of PPCDAM (KATOS, 2010; ASSUNÇÃO et al., 2011; ASSUNÇÃO et al., 2012; ASSUNÇÃO; GANDOUR; ROCHA, 2013). In particular, Assumption et al. (2012) investigated the underlying causes of the decline in observed rates of deforestation in the Amazon since 2004. The authors evaluated the impact of PPCDAM. The identification strategy of these authors takes advantage of the heterogeneity in local politics to win transverse variation. The authors' results indicate that deforestation rates have been sensitive to the prices of agricultural production. After controlling for the effects of prices, they found that conservation policies implemented have contributed significantly to the reduction of deforestation since mid-2000s. According to the study in question half of avoided deforestation between 2005 and 2009 can be attributed to conservation policies introduced in the period. The simulations suggest that the developed plans accounted for approximately 62,000 km2 of avoided deforestation. This amount represents about 52% of the total area to be deforested in the absence of policies.

In order to show what were the associated PPCDAM policies that contributed to the reduction of deforestation in the Amazon, Assunção et al. (2012) and Assunção et al. (2013) evaluated the impact of some changes in the plan, especially the command and control. Assunção et al (2012) analyzed the new policy of providing rural credit[9] in the Amazon Biome, introduced in 2008. The authors found that about U.S. $ 2.9 billion in rural credit were not contracted between 2008 and 2011 due to the new restrictions. This reduction prevented the deforestation of over 2,700 km2 of forest area, meaning a 15% drop in deforestation in the period. Importantly, the impact of the resolution on the deforestation was significant only in municipalities that have livestock production as their main economic activity. In another study, Assunção et al. (2013) estimated that policies of command and control based on *Sistema de Detecção de Desmatamento em Tempo Real* (DETER) prevented the deforestation of over 59,500 km2 of Amazon rainforest between 2007 and 2011. Should the policy had not been changed, deforestation in the region would have been 59% higher. The analysis also revealed that agricultural production in the region was not affected by such changes.

In summary, the evidence suggests that PPCDAM was primarily responsible for the large reduction in deforestation observed after 2004. Nevertheless, we do not know any study that has tried to evaluate the externalities of PPCDAM in other dimensions different to deforestation. In particular, the angle of health is important given its direct link with the welfare. Our study contributes to the literature estimating the effects of PPCDAM on child health. Know the extent to which the PPCDAM affects child health would contribute to better information for cost-benefit analysis of changes in forest policy. For example, from 2012 to 2013, there was a 370% increase in deforestation that coincides with the approval of the Forest Code of 2012. This policy change includes among its actions the exemption from responsibility of those who directly cause deforestation. Thus, a detailed analysis of the targets affected by deforestation is required to quantify the costs of the adoption of this policy.

## 4. Empirical Strategy

Our identification strategy exploits variation across Brazilian municipalities induced by the intervention PPCDAm. We estimate the following model for each outcome variable of child health:

[9] The Resolution 3545 was responsible for the changes in granting credit and deforestation in the Amazon Biome.

$$O_{it} = \alpha + \beta * Post\,2004 * Deforestation_{i2004} + \delta * year * Deforestation_{2004} + \theta \mathbf{Z}_{\mathrm{it}} + \mu_i + \omega_t + \varepsilon_{it} \quad (1)$$

$O_{it}$ is the outcome variable of interest in child health for the municipality $i$ and year $t$. The dummy variable *Post 2004* denotes the years after 2004. This is the intervention period that witnessed a rapid escalation in controlling deforestation. $Deforestation_{i2004}$ is the rate of municipal deforestation of 2004. To facilitate interpretation, we normalize this variable by standardizing it with the mean and standard deviation. The interaction between this variable and the linear trend *year* capture differential trends in the dependent variable. The inclusion of this interaction term is relevant because it is possible that the municipalities with the highest deforestation rates in 2004 are systematically different from other municipalities in characteristics that we do not observe. The vector includes a set of **Z** municipal controls. The terms $\mu$ y $\omega$ represent municipality and year fixed effects. Finally, $\varepsilon_{it}$ is the idiosyncratic error term. Standard errors are robust and clustered at municipality level. This allows us to perform statistical inference robust to heterocedasticity and autocorrelation.

The coefficient of interest is β, which measures the impact of deforestation policy. Our identification strategy lies on pre-existing variation in deforestation due to geographical factors or unique natural conditions, through the Brazilian Amazon. Therefore, one would expect that municipalities with high deforestation rates have benefited most. This is the same strategy behind Assunção, Gandour and Rocha (2011). Therefore, if deforestation has negative effects on children's health, then one would expect that child health indicators have improved more in those municipalities that benefited most from the intervention.

There are several potential threats to estimate (1), however. The first one is that the introduction of PPCDAM coincides with the launch of the *Bolsa Familia* program. If the focus of this social program is correlated with that of PPCDAM, then ignoring this could lead to a biased estimate of the parameter of interest. We face this threat by including the interaction between the variable *Post2004* and the municipality GDP of 2004. We use the municipality GDP of 2004 as a proxy for the *Bolsa Familia* program targeting. This variable is a good proxy because it is plausible that the government has placed emphasis on those municipalities that had higher levels of poverty in 2004. Therefore, the inclusion of the interaction term would allow us to control indirectly by the influence of the *Bolsa Familia* program and any other social program whose focus has been the poorest municipalities. As a robustness exercise, we use alternative proxies, such as the Gini index of inequality. Also, we control for the share of expenditure on education and health, to capture different dimensions of local policy that could be correlated with the PPCDAM. More importantly, we also control for the percentage of beneficiaries of *Bolsa Familia* in each municipality for each year since 2004. As discussed below, our baseline results are robust to these exercises.

Another potential threat has to do with the fact that pregnant women with higher incomes and greater concern for the care of their infants could after the intervention period relocate to municipalities with healthier environment. We believe that this is implausible given the costs of mobility and the fact that a municipality with a healthy environment is probably not a neighboring municipality. That is to say, municipalities with high deforestation are usually surrounded by municipalities with high deforestation. Therefore, to find a town with low deforestation levels would imply travel many miles, which increases transaction costs. To additional confidence, we conduct a robustness exercise that consists of estimating the following regression on observable characteristics of mothers:

$$MChar_{it} = \alpha + \beta * Post\,2004 * Deforestation_{i2004} + \delta * year * Deforestation_{2004} + \mu_i + \omega_t + \varepsilon_{it} \quad (2)$$

$MChar$ are indicator variables of the characteristics of mothers, such as educational attainment, race, and teen pregnancy. If mothers choose not to systematically change its municipal location after surgery then the $\beta$ coefficient should not be statistically different from zero. That is, there should be no systematic changes in the characteristics of mothers that are explained by the intervention.

An additional concern that arises is the fall in agricultural prices that coincided with the period of intervention. The fall in agricultural prices may discourage deforestation and therefore the effect of the coefficient of interest in (1) would reflect more than the influence of PPCDAM. In order to mitigate this possible problem, we include variables that represent state-specific trends. If the variation in agricultural prices is more or less uniform within states, then these variables would capture the influence of agricultural prices. Furthermore, the introduction of these variables allows us to control indirectly by the influence of any other confounding factor that varies in time and government level. As a robustness exercise, we include specific micro-region trends, which is a bit demanding in terms of computational load.

## 5. Data

In this study, we use data for the Legal Amazon region of Brazil, which is constituted of 782 municipalities. The source of information on children's health in our study comes from the Brazilian National System of Information on Birth Records (SINASC/Datasus)[10]. In relation to infant and maternal characteristics such as educational attainment, age and place of residence, all this information is available in the system since 1996. However, we focus on the period 2000-2007 for infants who were born around the introduction of PPCDAM. Ideally, an analysis of the effects of deforestation on the health outcomes should be taken as the unit of analysis the individual. However, SINASC only provides aggregate information on live births and mothers. Given this restriction, in this study the unit of analysis is the municipality. The municipality where the mother lives is taken as the reference municipality for the panel. This is an important point because not always the municipality where the mother resides is the same where she gave birth.

Using this information, we construct a set of control variables related to the characteristics of mothers: educational attainment, percentage of whites (with the approximate percentage of white births), teen mother and marital status. As outcome variables of infant health, we focus on: very low birth-weight rate (percentage of infants less than 1500 grams), low birth-weight rate (percentage of infants less than 2500 grams), extreme prematurity rate (percentage of infants born before 28 weeks of gestation), and prematurity rate (percentage of infants born before 38 weeks gestation).

Regarding the data on deforestation, we extract the information from the *Instituto Nacional de Pesquisas Espaciais* (INPE). This institute provides information on the area deforested for each municipality since 2000. The INPE uses remote sensing detection technology to map increases in deforested area from year to year. Deforestation is given as the total deforested area in square kilometers for each of the municipalities. As we mentioned in the previous section, we use the rate of deforestation in 2004 to capture pre-existing variation in deforestation due to geographic or regional specific factors as a strategy to identify the impact of PPCDAM. This variable is normalized by subtracting the mean and dividing by the standard deviation.

The remaining variables that we use throughout the study as additional controls or checks for robustness are agricultural production per capita, per capita GDP in 2004, and the percentage of spending on education and health. The source of information of the first two variables comes from the Brazilian Institute of Geography and Statistics (IBGE, for its acronym in Portuguese), while for the other two comes from *Ministério da Fazenda*. In addition, an attempt to control for the influence of the *Bolsa Familia* program we

[10]This information is available free of charge at http://www2.datasus.gov.br/DATASUS/index.php?area=0205&VObj=http://tabnet.datasus.gov.br/cgi/deftohtm.exe?sinasc/cnv/nv

present estimates where we control for the percentage of beneficiaries. This information comes from the *Ministério do Desenvolvimento Social e Combate à Fome*. Finally, we use the variable Gini inequality index to control for the targeting of other social programs and access to basic sanitation. The information of these two variables comes from the population census 2000. Descriptive statistics for all variables used in this study are presented in the Table 1.

**[Table 1]**

## 6. Results

We begin by examining the distribution of the main variables before and after intervention. For this we present the average of the variables used in the pre and post intervention periods according to the level of deforestation observed in 2004. Specifically, the table compares municipalities with low deforestation (those located to the 75th percentile of the distribution) to those with high deforestation (those located above the 75th percentile of the distribution). In the table it is also reported that the p-values are obtained from testing mean differences among the municipalities with low and high rate of deforestation. A higher percentage of white infants are born in municipalities with high deforestation, but the educational level of mothers is lower. The biggest difference between the two groups was observed in agricultural production, which is about 100% in both periods. This is consistent since one of the incentives to deforest is to expand agricultural production. The percentage of the health budget is slightly higher in municipalities with less deforestation, although only in the post-intervention period a statistically significant difference is observed. In the child health variables significant differences are observed both in low birth-weight and preterm birth rate, with the highest incidence of both indicators in municipalities with less deforestation. The results in the table does not allow us to infer that there is any significant change in trend in child health variables, possibly due to the influence of other confounding factors.

We now present regression models controlling for several confounding factors and assess whether there are significant differentials in the trends of child health variables. The results of estimating equation (1) are presented in Table 2. Each column adds different set of controls. The table is divided into four panels. The first panel presents the results for very low birth weight rate; the second for low birth weight rate; the third for extreme preterm rate and the fourth for preterm rate.

The results for the first panel show that the incidence of very low birth weight decreased relatively more in those municipalities where deforestation was reduced more. Column 1 only by controlling the interaction between deforestation in 2004 and a linear trend and the fixed effects of year-municipality yields an estimate of -0.000735 (with a standard error = 0.000349) coefficient, which is significant at 5%. Column 2 adds the interaction between initial per capita GDP and the post 2004 dummy. This interaction term captures the influence of other social programs created in the year of the launch of the PPCDAM. The inclusion of this term has little effect on the estimated coefficient of interest reducing it in absolute terms while remaining significant at 10%. The inclusion of the characteristics of mothers has a negligible effect on the estimated coefficient. When adding nonlinear state specific trends the estimated coefficient becomes -0.000705.

Panel B estimates suggest that PPCDAM had positive effects on the incidence of low birth weight, reducing it in the intervention period. The parameter of interest is estimated at -0.00136 in column 1, but is statistically insignificant. Once is indirectly controlled the influence of other social programs, the coefficient passes to -0.00148 and becomes slightly significant. Again, the inclusion of variables related to maternal characteristics has no effect on the estimated parameter. With the addition of state-specific trends, the estimated parameter of the impact of PPCDAM is estimated in -0.00172 and significant at 10%.

The results for extreme prematurity (Panel C) suggest that PPCDAM helped to reduce the incidence of birth outcome. The coefficient of interest is relatively stable to the inclusion of various controls, being between -0.000365 and -0.000353, and statistically significant in all cases. By contrast, the results for Preterm Birth are less stable and the estimation results indicate that PPCDAM did not significantly improve, once this indicator was controlled by the specific state trends (Panel D).

To interpret the magnitude of the estimated coefficients, we proceed to evaluate how much would be the reduction in each outcome variable if the rate of deforestation in 2004 happens to be three standard deviations higher, which is equivalent to comparing municipalities in the lowest quintile with those in the highest quintile. The results of this exercise indicate reductions of 0.38% in the incidence of very low birth-weight rate, of 0.09% in the low birth-weight rate, of 0.45% in extreme preterm rate, and of 0.06% in preterm rate. This analysis suggests that the effects of PPCDAM on child health are modest.

**[Table 2]**

We now investigate whether the large observed reduction in deforestation after 2004 resulted in a reduction in agricultural production. This is important because deforestation is closely linked to agricultural production, and the profits or losses of income in this sector can have a direct impact on birth outcomes. We estimate again equation (1) but now the dependent variable is the logarithm of per capita agricultural production. The results of these estimates are presented in Table 3. There are no significant reductions in agricultural production that may explain the effects of PPCDAM on child health presented above. Indeed, while the estimated coefficient of the impact of PPCDAM on agricultural production is negative, it is only marginally significant in the most parsimonious specification.

**[Table 3]**

The above evidence suggests that household income was not one of the mechanisms by which the reduction in deforestation influenced the birth-outcomes in the period 2005-2007. This could be an indication that there is a compensation effect: the positive effect of reducing deforestation (through less variability in climate and rainfall) is offset by a negative effect (via less agricultural expansion), making that the final effect is zero.

## 7. Robustness of findings

In this section, we perform a number of robustness tests designed to assess the validity of our identification strategy. Specifically, we explore alternative specifications to examine whether our findings are insensitive to the introduction of contemporary social programs, pre-existing trends, mean reversion, sorting and serial autocorrelation. In general, the results from these robustness checks are reassuring. Given space constraints, we do not present robustness exercises to sorting and serial autocorrelation.

### *7.1. Contemporaneous Social Programs*

It is possible that differential trends in child health indicators in municipalities with large reductions in deforestation are not necessarily influenced by the PPCDAM, but by the introduction of other social programs in 2004. The most important social program introduced in that year was the *Bolsa Familia*. Our strategy to address this potential problem in our baseline estimates above was to include the interaction between per capita GDP in 2004 and the indicator variable of the intervention period. The assumption behind this strategy is that the program focused on the poorest municipalities based on income levels. This assumption may fail if GDP is a poor proxy of the degree of poverty of the municipalities or if the targeting of programs took into account other dimensions. In Table 4, we explore a variety of alternative specifications to check the robustness of our baseline results.

Column 1 replicates our main estimates, while column 2 shows the results of a specification that includes the share of spending on health and education as control variables. The inclusion of these variables should capture different dimensions of local policy that could be correlated with the implementation of PPCDAm. The results in the table show that our main estimates are robust to the inclusion of these variables. For example, in Panel A, the coefficient of interest changes from -0.000705 to -0.000811 and is now estimated more precisely.

Alternatively, columns 3-6 use interactions between the indicator variable of the intervention period and the Gini index, the rate of child labor, the illiteracy and the percentage of appropriate houses[11]. Each of these interactions is added separately and not all at once. Note that the inclusion of these interaction terms allows us to control indirectly by pre-existing differential trends in infant health. As can be seen, our results are robust to the inclusion of these variables and in some cases the coefficients are estimated more precisely.

Column 7 directly controls the influence of the *Bolsa Familia* Program. Indeed, now we include in our estimates the percentage of beneficiaries as a control variable, as well as the interaction between this variable and the dummy of the intervention period. Our results hardly change with the inclusion of these variables.

Column 8 controls simultaneously for all variables used in previous columns. Naturally, this can create problems of collinearity, but our interest is to evaluate how the coefficients of interest change with this exercise. Assuming that our research design is valid and the other social programs is no threat to our estimates, then the addition of these variables should only reduce the sampling variance while leaving unchanged the estimated parameters of interest. The results of this exercise suggest that our identification strategy is valid and that the inclusion of these control variables does not significantly affect our estimates. Again, the coefficients are estimated more precisely. Indeed, those coefficients that were significant at 10% are now 5%, while those that were significant at 5% became significant at 1%.

**[Table 4]**

*7.2.Pre-existing trends and Mean Reversion*

The identifying assumption of our approach is that in the absence of PPCDAM, municipalities with different levels of deforestation have experienced the same proportional changes in infant health. We investigate the validity of this assumption in two related complementary ways. First, we include microrregion specific linear trends. This results in the inclusion of about a hundred additive terms given that on average a microrregion is made up of seven municipalities. Assuming that variations in agricultural prices and the degree of dependence on the agricultural sector are homogeneous across municipalities within each microrregion, the inclusion of these micro-region specific trends allow us to control indirectly by the influence of the dynamics in the agricultural prices. Additionally, we include a lagged term of the dependent variable. This allows us to control for mean reversion also.

The results of this exercise are presented in Table 5. As usual, Column 1 replicates our baseline estimates. The results in column 2 show that adding specific trends of microrregion has no noticeable effect on our main estimates. Column 3 adds the lagged of the dependent variable as a control variable. Most of our

[11]These variables are taken from the 2000 population census.

results remain robust to the inclusion of this variable. However, the coefficient that measures the effect on low birth-weight is substantially reduced (in absolute terms) and becomes statistically insignificant.

Column 4 presents a second complementary way of investigating whether there are pre-existing trends affecting our results. Specifically, we exclude municipalities in states with very low rates of deforestation in 2004. This increases the comparability across municipalities and thus helps minimize the likelihood of differential trends in child health. The specification in column 4 is the same as column 3, but now the number of observations is substantially reduced due to the restriction that we impose. Despite this reduction in the number of observations, the coefficients of interest remain very similar to our baseline results. Very similar results are obtained when we include the interaction between the lagged dependent variable and the year *dummies* (not shown). This suggests that it is unlikely that our results are influenced by the existence of pre-existing trends.

**[Table 5]**

## 8. Conclusion

This study provides the first estimates of the effects of deforestation on children's health. We show that the change in forest policy introduced in 2004 reduced the incidence of very low birth-weight by 0.38% and extreme preterm 0.45%. Our findings are robust to a variety of robustness exercises. We check for possible mean reversion including the lag of each outcome variable and the results are qualitatively and quantitatively similar. Also, our results are insensitive to a variety of variables that capture the influence of local policy. In addition, we also directly control the influence of the *Bolsa Familia*, the main intervention for poverty alleviation program introduced in 2004, and our findings remain similar. Finally, our findings are not explained by pre-existing micro-regional trends.

The effects of deforestation on child health that we found in this study are modest. We argue that this is because forest policy had no significant impact on agricultural production. This null effect may be due to two offsetting effects that reducing deforestation implies. On the one hand, less deforestation involves increased agricultural productivity due to less variability in temperature and rainfall. On the other hand, less deforestation implied lower productivity due to the reduction in the expansion of agricultural land. The combination of these two effects seem to explain the null effect of forest policy on agricultural production and, in turn, explain the modest impact of reducing deforestation on child health. We leave for future studies to further evaluate this argument.

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# TABLES

Table 1. Summary Statistics

| | Pre-intervention (2000-2004) | | | Post-intervention (2005-2007) | | |
|---|---|---|---|---|---|---|
| | Low Deforestation | High Deforestation | P-values | Low Deforestation | High Deforestation | P-values |
| Married | 31.83 | 32.07 | 0.65 | 25.52 | 28.67 | 0.00 |
| Teen Mother | 32.27 | 32.23 | 0.83 | 30.69 | 30.07 | 0.02 |
| Mother Education | 26.56 | 23.86 | 0.00 | 37.14 | 34.12 | 0.00 |
| Log of Agricultural GDP | -0.498 | -0.039 | 0.00 | -0.401 | 0.071 | 0.00 |
| Helth Spending Share | 30.93 | 30.01 | 0.14 | 40.33 | 36.97 | 0.00 |
| Education Spending Share | 50.66 | 50.89 | 0.72 | 54.68 | 55.06 | 0.60 |
| Very Low Birth-Weight Rate | 0.55 | 0.55 | 0.95 | 0.75 | 0.66 | 0.02 |
| Low Birth-Weight Rate | 5.87 | 5.49 | 0.00 | 6.23 | 5.91 | 0.01 |
| Extreme Preterm Birth | 0.25 | 0.24 | 0.80 | 0.31 | 0.28 | 0.36 |
| Preterm Birth | 6.98 | 5.84 | 0.00 | 5.20 | 4.98 | 0.45 |
| Observations | 3845 | | | 2307 | | |

Source: Author's elaboration, from the survey data.
Agricultural GDP per capita is in constant 2000 prices. High Deforestation refers to municipalities that had rates of deforestation in 2004 above the 75th percentile of the distribution. Mother Education refers to the percentage of mothers who reported an education level equal to or greater than 8 years.

Table 2. Effects of PPCDAm on infant health

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Panel A: Dependent variable is Very Low Birth-Weight Rate | | | |
| Post 2004 x Deforestation 2004 | -0.000735** | -0.000643* | -0.000666** | -0.000714* |
| | (0.000349) | (0.000343) | (0.000339) | (0.000374) |
| | Panel B: Dependent variable is Low Birth-Weight Rate | | | |
| Post 2004 x Deforestation 2004 | -0.00136 | -0.00148* | -0.00149* | -0.00170* |
| | (0.000894) | (0.000894) | (0.000889) | (0.000968) |
| | Panel C: Dependent variable is Extreme Preterm Birth | | | |
| Post 2004 x Deforestation 2004 | -0.000353** | -0.000320* | -0.000325** | -0.000361** |
| | (0.000175) | (0.000167) | (0.000165) | (0.000170) |
| | Panel D: Dependent variable is Preterm Birth | | | |
| Post 2004 x Deforestation 2004 | -0.00124 | -0.00319* | -0.00304 | -0.00108 |
| | (0.00179) | (0.00185) | (0.00188) | (0.00189) |
| 2004 GDP per capita x Post 2004 | No | Yes | Yes | Yes |
| Maternal Characteristics | No | No | Yes | Yes |
| State-Specific trends | No | No | No | Yes |
| Year x 2004 Deforestation | Yes | Yes | Yes | Yes |
| Year and Municipality Fixed Effects | Yes | Yes | Yes | Yes |
| Observations | 6152 | 6152 | 6152 | 6152 |

Source: Author's elaboration, from the results of this paper.
*Notes:* Maternal Characteristics contains Married (%),Teen Mother (%), and Mother Education. Robust standard errors clestared at municipality level are into parentheses. ** P<0.1; ** P<0.05; P<0.01.*

Table 3. Effects of PPCDAm on agricultural production

| | (1) | (2) | (3) |
|---|---|---|---|
| | Dependent variable is log of agricultural production | | |
| Post 2004 x Deforestation 2004 | -0.000306* | -0.000203 | -0.000248 |
| | (0.000169) | (0.000168) | (0.000158) |
| 2004 GDP per capita x Post 2004 | No | Yes | Yes |
| State-Specific trends | No | No | Yes |
| Year x 2004 Deforestation | Yes | Yes | Yes |
| Year and Municipality Fixed Effects | Yes | Yes | Yes |
| Observations | 6152 | 6152 | 6152 |

Source: Author's elaboration, from the results of this paper.
*Notes:* Robust standard errors clestared at municipality level are into parentheses. The agricultural GDP is in logs and 2000 constant prices. ** P<0.1; ** P<0.05; P<0.01.*

Table 4. Effects of PPCDAm on infant health (Contemporaneous Social Programs)

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| | Panel A: Dependent variable is Very Low Birth-Weight Rate | | | | | | | |
| Post 2004 x Deforestation 2004 | -0.000705* | -0.000811** | -0.000797** | -0.000765** | -0.000743** | -0.000864** | -0.000725* | -0.000968** |
| | (0.000376) | (0.000406) | (0.000377) | (0.000384) | (0.000378) | (0.000400) | (0.000376) | (0.000446) |
| | Panel B: Dependent variable is Low Birth-Weight Rate | | | | | | | |
| Post 2004 x Deforestation 2004 | -0.00172* | -0.00187* | -0.00168* | -0.00180* | -0.00169* | -0.00192** | -0.00177* | -0.00231** |
| | (0.000966) | (0.00109) | (0.000969) | (0.000971) | (0.000971) | (0.000970) | (0.000970) | (0.00115) |
| | Panel C: Dependent variable is Extreme Preterm Birth | | | | | | | |
| Post 2004 x Deforestation 2004 | -0.000365** | -0.000441** | -0.000434** | -0.000393** | -0.000385** | -0.000456** | -0.000349** | -0.000531*** |
| | (0.000171) | (0.000189) | (0.000172) | (0.000176) | (0.000175) | (0.000181) | (0.000172) | (0.000201) |
| | Panel D: Dependent variable is Preterm Birth | | | | | | | |
| Post 2004 x Deforestation 2004 | -0.00121 | -0.00115 | -0.00112 | -0.000681 | -0.000527 | -0.000523 | -0.000394 | -0.00203 |
| | (0.00188) | (0.00199) | (0.00201) | (0.00190) | (0.00191) | (0.00195) | (0.00193) | (0.00204) |
| Education and heatlh spending share | No | Yes | No | No | No | No | No | Yes |
| Gini x Post 2004 | No | No | Yes | No | No | No | No | Yes |
| Child labor x Post 2004 | No | No | No | Yes | No | No | No | Yes |
| Illiteracy rate x Post 2004 | No | No | No | No | Yes | No | No | Yes |
| Adequate housing x Post 2004 | No | No | No | No | No | Yes | No | Yes |
| Bolsa Familia Program | No | No | No | No | No | No | Yes | Yes |
| 2004 GDP per capita x Post 2004 | Yes | No | No | No | No | No | No | Yes |
| Maternal Characteristics | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| State-Specific trends | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year x 2004 Deforestation | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year and Municipality Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 6152 | 5540 | 6152 | 6152 | 6152 | 5128 | 6152 | 4636 |

Source: Author's elaboration, from the results of this paper.

*Notes:* Maternal Characteristics contains Married (%),Teen Mother (%), and Mother Education. Robust standard errors clestared at municipality level are into parentheses. Gini, child labor, Illiteracy and Adequate housing are taken from the 2000 population census. Bolsa Familia Program: we include in our estimates the percentage of beneficiaries as a control variable, as well as the interaction between this variable and the dummy of the intervention period. * *P<0.1; ** P<0.05; P<0.01.*

Table 5. Effects of PPCDAm on infant health (Pre-existing regional trends and Mean Reversion)

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Panel A: Dependent variable is Very Low Birth-Weight Rate | | | |
| Post 2004 x Deforestation 2004 | -0.000714* | -0.000690** | -0.000668* | -0.000822** |
| | (0.000374) | (0.000345) | (0.000374) | (0.000404) |
| | Panel B: Dependent variable is Low Birth-Weight Rate | | | |
| Post 2004 x Deforestation 2004 | -0.00170* | -0.00149* | -0.000232 | -0.0000812 |
| | (0.000968) | (0.000902) | (0.000870) | (0.000894) |
| | Panel C: Dependent variable is Extreme Preterm Birth | | | |
| Post 2004 x Deforestation 2004 | -0.000361** | -0.000341** | -0.000421** | -0.000450** |
| | (0.000170) | (0.000166) | (0.000199) | (0.000210) |
| | Panel D: Dependent variable is Preterm Birth | | | |
| Post 2004 x Deforestation 2004 | -0.00108 | -0.00299 | -0.00174 | -0.000870 |
| | (0.00189) | (0.00195) | (0.00163) | (0.00154) |
| Microrregion-Specific trends | No | Yes | Yes | Yes |
| Year lagged dependent variable | No | No | Yes | Yes |
| State-Specific trends | Yes | No | No | No |
| 2004 GDP per capita x Post 2004 | Yes | Yes | Yes | Yes |
| Maternal Characteristics | Yes | Yes | Yes | Yes |
| Year x 2004 Deforestation | Yes | Yes | Yes | Yes |
| Year and Municipality Fixed Effects | Yes | Yes | Yes | Yes |
| Observations | 6152 | 6152 | 5383 | 2940 |

Source: Author's elaboration, from the results of this paper.

*Notes:* Maternal Characteristics contains Married (%),Teen Mother (%), and Mother Education. Robust standard errors clestared at municipality level are into parentheses. ** P<0.1; ** P<0.05; P<0.01.*