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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 an identification strategy, we exploit the introduction of a change in the forest policy that caused a marked reduction in deforestation in the Amazon region of Brazil. We demonstrate that this forest policy 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.

Keywords: Brazil; Deforestation; Environmental Quality; Environmental Policy; Infant Health.

JEL codes: I14, Q58

1. Introduction

There is a growing consensus that deforestation has a significant impact on the environment. Among these concerns, one of the most important is its contribution to emissions of greenhouse gases. Globally, deforestation accounts for approximately 17% of the total emissions of such gases (IPCC, 2007). Other changes in the environment are related to the propagation of vectors, such as those that induce malaria (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, and Spiess, 2012; Currie et al., 2009), while in some countries diseases such as malaria remain a major cause of death[1]. Thus, the design of an optimal forest policy requires an estimation of the benefits of reducing the rate of deforestation.

While previous studies have focused on the global effects of deforestation due to concerns about global warming, they have typically ignored the local effects. In this study, we investigate the effects of deforestation on health by examining the effect of a forest policy change 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 investigate the effect of PPCDAM, and thus the sharp reductions in deforestation, on birth outcomes of children born in municipalities that were potentially exposed to the intervention.

Understanding the extent to which deforestation affects infant health is important for a number of reasons. First, there is a growing consensus that fetal adverse shocks have negative economic consequences in the long term. Indeed, previous studies have shown that better health outcomes at birth are associated with greater human capital accumulation (Almond and Currie 2011; Almond, 2006; Case et al., 2002, 2005; Currie, 2011)[2]. This is especially important given that health shocks during childhood are often transmitted from generation to generation (Currie, 2011). 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 a newborn's exposure to environmental quality is easier to identify than that of the adult population. As is argued by Currie and Walker (2011),

> *"The study of newborns overcomes several difficulties in making the connection between pollution and health because, unlike adult diseases*

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

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

that may reflect pollution exposure that occurred many years ago, the link between cause and effect is immediate" (Currie and Walker 2011, p.p. 66).

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

Despite the above, we are unaware of any previous study that raises 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 emissions (Chay and Greenstone, 2003; Coneus and Spiess, 2012; Currie, and Neidell, 2005; Currie et al., 2009). The evidence from these studies, however, is insufficient to inform on the effects of deforestation because there are multiple mechanisms through which the deterioration of the forest area could affect health. Several epidemiological studies provide 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 and 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. For example, an 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, which would overestimate the true effect of deforestation. Alternatively, if the deforested areas are replaced with infrastructure (such as roads, schools, etc.) that in turn capitalizes by increasing housing prices, then high-income families who value these improvements will choose to relocate in these deforested areas, thus biasing to zero the true effect of 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 significant reduction in deforestation rates. In particular, we exploit the differential changes in deforestation attributable to geographic variations of effects of the PPCDAM 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 the policy had little or no effect on those with low levels of deforestation (Assunção, Gandour, and Rocha, 2011). This suggests that the latter group of municipalities may be a useful control group. Thus, our analysis compares infant health outcomes before and after the intervention in municipalities with large reductions in the rate of deforestation with those who had little or no reduction in deforestation.

Our empirical approach is exposed to several threats, however. One of the most important of these is the introduction of new social programs that coincide with the adoption of the 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 herein suggests that the introduction of such programs have little effect on our estimates. In section 4, we discuss the major threats and how we address these threats.

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. Because Brazil is in the development stage, the deterioration of the environmental quality is increasing along with the economic development, which presents significant challenges (Grossman and Krueger, 1995). Third, deforestation contributes approximately 50% of the carbon dioxide (CO_2) emissions in Brazil (Ministério da Ciência e Tecnologia, 2013), suggesting that the emission of this gas could be a particularly important mechanism in the deforestation-health link. Finally, Brazil has detailed information and data about deforestation rates at the municipal level dating back to 2000, thus allowing us to study the effects of deforestation with a large panel data.

We find suggestive evidence that deforestation has a robust effect on infant health. Our preferred specifications suggest that the PPCDAM reduce the incidence of extreme preterm birth by 0.45% and very low birth-weight by 0.38%. Importantly, these findings are insensitive to a variety of robustness exercises. For example, we find 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, and section 6 discusses the results. Section 7 presents robustness checks, and the last section presents the paper’s conclusions.

2. Deforestation and Infant Health Linkages

We 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 temperature levels (IPCC, 2007; Kurukulasuriya, and Rosenthal, 2013; Serôa Da Motta, 2011; Dore, 2005; Nobre, and Assad, 2005). The Effect on rainfall occurs because deforestation reduces the natural recycling cycle through which vegetation absorbs moisture from the ground and emits it into the atmosphere, where it returns as rain. In turn, climate warming occurs through the connection between deforestation and greenhouse gases. As the forest plays an important role in the absorption of such gases, by reducing the size of the forests, increased pollution is emitted into the atmosphere and therefore the speed by which global warming spreads is increased.

These changes in climate may also have implications in children's health. Both water scarcity and a warmer climate may affect the household's demand for health inputs through reductions in agricultural production, which means less income. However, the effect of deforestation on child health through income is theoretically ambiguous. On the one hand, the restrictive policies of deforestation contribute to improving agricultural productivity by reducing fluctuations in rainfall and temperature. In turn, higher income implies an increase in the ability of mothers to invest in prenatal care (Trujillo, Carrillo, and Iglesias, 2014). If reduction in water scarcity means higher quality water, then the risk of diarrhea and respiratory infections also decrease (World Health Organization, 2010). On the other hand, such policies can impede the farmers' ability to expand their production levels. At least in the short term, these expansion constraints on farmers could result in less income for those households that are dependent on this activity. Therefore, the net effect of the restrictive policies of deforestation depends, in part, on the magnitude of these two impacts on production.

Changes in the ecosystem also influence the survival of vectors that induce malaria. Indeed, the survival of mosquitoes is mainly determined by temperature and humidity levels. Empirically, the relationship between deforestation and the risk of malaria has been documented by previous studies. Vittor et al. (2006) find that the risk of malaria is 278 times higher in deforested areas in the Amazon region of Peru. With respect to Brazil, Olson et al. (2010) find 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.

Other diseases are also associated with deforestation. Examples of these diseases include dengue, Lymey's pathology (leishmaniasis), SARS, Ebola, and those induced by the black fly and other viruses carried by bats (Wlson et al., 2002; Leroy et al., 2005; Looi, and Chua, 2007; Chaves et al., 2008; Field, 2009; Morin, Comrie, and Ernst, 2013). The transmission of these infectious diseases not only occurs because deforestation provides the optimal environment for the breeding of carrier insects but also because of 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 the 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 in Brazil.

While the interaction of these factors can exacerbate the effects of deforestation on birth outcomes, the overall effects are dependent on the rate at which deforestation affects temperature change and the magnitude of the impact of temperature changes on birth outcomes. In this regard, there are several studies in the literature that attempt to estimate the effects of exposure to extreme climates on the uterus. Deschênes, Greenstone and Guryan (2009), finding that exposure to extreme heat during pregnancy reduces birth-weight, predict that by the end of the XXI century, global climate change will have reduced the birth-weight of white children by 0.22% and that of African-American children by 0.36%. In addition, they find that the probability of low birth weight[3] will increase by approximately 5.9%. Lawlor, Leon, and George (2005) find heterogeneous effects based on period of gestation, contending that birth weight has a negative relationship with temperature exposure in the first trimester of pregnancy, whereas the exposure relationship in the third quarter is positive. The evidence regarding the effects of climate change, however, is concentrated on 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, both malaria and dengue are virtually non-existent in the developed economies. Moreover, the findings are compounded by the fact that higher-income families are better able to compensate for adverse impacts on the environment (Currie, and Vogl, 2013).

While the evidence on the link between temperature and birth-outcomes for developing countries is less, there is considerable literature that explores the link between water scarcity and child health (Kim, 2010; Kudamatsu et al., 2010; Aguilar, and Vicarelli, 2011; Skoufias et al., 2011;

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

Burgess et al., 2011; Rocha and Soares, 2012). The results of Kudamatsu et al. (2010), with respect to a set of African countries, indicate that fluctuations in precipitation levels have a negative impact on child mortality and malnutrition. With respect to Mexico, Aguilar and Vicarelli (2011), finding that the *Fenómeno del Niño* affects the height and weight of infants, present evidence to suggest that the decline 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 and find that negative shocks in rainfall levels imply higher rates of low birth weight and premature births. Accordingly, 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.

Greenhouse gas emissions can also affect birth outcomes independent of changes in climate. As is well known, forest areas play an important role in the absorption of pollutant gases in that deforestation reduces the natural ability of the forest to absorb such gases. Thus, increased deforestation equals increased air pollution. 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 due to the toxins carried in the blood of the mother that is then transmitted to the uterus, which increases the risk of health and developmental problems of the unborn child. 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 find negative effects on other child health indicators, are Beatty and Shimshack (2011), Knittel, Miller, and Sanders (2011), and Currie and Walker (2011).

While the above studies suggest that deforestation may be an environmental factor that contributes to poor birth outcomes, we are unable to find any studies that propose a link between these variables. Therefore, our study contributes to the literature regarding the effects of deforestation on birth weight and the length of the gestation period.

3. Policy Context - PPCDAM

One of the places in the world that best represents the consequences of deforestation is Brazil. This country is among the six countries that account for 60% of global deforestation (FAO, 2010).[4] It is estimated that by 1980, deforestation reached approximately 300 thousand square kilometers, which represents 6% of its total area. However, this pace became even more intense during the first years of the 2000s. According to figures from the *Instituto Nacional de Pesquisas*

[4] 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.

Espaciais (INPE), approximately 19,000 square kilometers of forest per year were lost, on average, between 1996 and 2005. Given this scenario, Brazilian conservation policies for the prevention and control of deforestation in the Amazon underwent an intensive review, and the Brazilian government adopted stringent measures to curb deforestation. As a result, 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 is based on a new way to combat deforestation. It integrates the efforts of federal, state and municipal governments and includes specialized agencies and civil society. The management and integrated action facilitates the implementation of innovative processes for monitoring environmental control and territorial management. The mutual collaboration among the stakeholders enables the increased intensity of the monitoring activities. This has improved with the implementation of the *Sistema de Detecção de Desmatamento em Tempo Real* (DETER) of the INPE and the creation of the *Centro de Monitoramento Ambiental* (CEMAM) within the *Instituto Brasileiro de Meio Ambiente e Recursos Naturais Renováveis* (IBAMA).

The PPCDAM is divided into three main areas. First, land and land use planning. Second, environmental monitoring and control. Finally, promotion of sustainable production activities. The implementation of these actions can be directed by the municipalities according to the prioritization of the criteria perceived as critical by each municipality. The intention is to reduce deforestation by 80% by 2020. Up to 2012, the figures have indicated that this goal is not far from being achieved. In fact, one of the lowest rates of deforestation since official data became available was recorded in 2011, with 78% less deforestation than in 2004.

Some studies in the literature have attempted to estimate the effects of the PPCDAM (Katos, 2010; Assunção et al., 2011; Assunção et al., 2012; Assunção, Gandour, and Rocha, 2013). In particular, Assunção et al. (2012) investigated the underlying causes of the decline in observed rates of deforestation in the Amazon since 2004. The authors take advantage of the heterogeneity in local politics to achieve transverse variation. Their results indicate that deforestation rates have been sensitive to the prices of agricultural production. Therefore, after controlling for the effects of the prices, they find that the conservation policies implemented have contributed significantly to the reduction of deforestation since approximately 2005. They further find that half of the decrease in deforestation between 2005 and 2009 is attributable to conservation policies introduced during that same period. The simulations suggest that the developed plans account for approximately 62,000 km2 of decreased deforestation. This amount represents approximately 52 % of the total area that would have been deforested in the absence of the policies.

To determine the associated PPCDAM policies that contributed to the reduction of deforestation in the Amazon, Assunção et al. (2012) and Assunção et al. (2013) evaluate the impact of certain changes in the plan, especially with respect to command and control. Assunção et al. (2012) analyze the new policy introduced in 2008 that provided rural credit[5] in the Amazon Biome. The authors find that approximately 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, a 15% decrease in deforestation for the period. Outstandingly, 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) estimate that policies of command and control based on the *Sistema de Detecção de Desmatamento em Tempo Real* (DETER) prevented the deforestation of over 59,500 km2 of the Amazon rainforest between 2007 and 2011. Their analysis also revealed that agricultural production in the region was not affected by such changes.

In summary, the evidence suggests that the PPCDAM is primarily responsible for the large reduction in deforestation observed after 2004. However, we do not know of any study that has evaluated the externalities of the PPCDAM on dimensions other than deforestation. In particular, the health dimension is important given its direct link with the welfare of the population. Our study contributes to the literature by estimating the effects of the PPCDAM on child health. Knowing the extent to which the PPCDAM affects child health will contribute better information for cost-benefit analysis of changes in forestation policies. For example, from 2012 to 2013, there was a 370% increase in deforestation, which 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 variations across Brazilian municipalities induced by the intervention of the PPCDAM. We estimate the following model for each outcome variable of child health:

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

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

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, the intervention period that witnessed a rapid escalation in controlling deforestation. $Deforestation_{i2004}$ is the rate of municipal deforestation in 2004. To facilitate interpretation, we normalize this variable by subtracting mean and standard deviation. The interaction between this variable and the linear trend *year* captures 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 termsμ y ω represent municipality and year fixed effects. Finally,ε_{it} is the idiosyncratic error term. Standard errors are robust and clustered at the municipality level. This allows us to perform statistical inference robust to heteroskedasticity and autocorrelation.

The coefficient of interest is β, which measures the impact of the deforestation policy. Our identification strategy is based on the pre-existing variation in deforestation due to geographic factors or unique natural conditions of the Brazilian Amazon. Therefore, one would expect that municipalities with high deforestation rates have received the greatest benefits. This is the same strategy implemented by Assunção, Gandour and Rocha (2011) to estimate the impact of PPCDAM on deforestation. Accordingly, 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 the most from the intervention.

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

Another potential threat is 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 environments. 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, municipalities with high deforestation are usually surrounded by municipalities with high deforestation. Therefore, to find a town with low deforestation levels would imply travelling many miles, which increases transaction costs. To improve the confidence level, 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 and teen pregnancy. If mothers choose not to systematically change their municipal location after surgery then the β coefficient should not be significantly different from zero. That is, there should be no systematic changes in the structural characteristics of mothers that are explained by the intervention.

An additional concern that arises is the fall in agricultural prices that coincide 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 the PPCDAM. 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 indirect control of the influence of any other confounding factor that varies in time and government level. As a robustness exercise, we include specific micro-region trends, a rather demanding task due to the computational load.

5. Data

In this study, we use data for the legal Amazon region of Brazil, which is comprised of 782 municipalities. The source of information on children's health comes from the Brazilian National System of Information on Birth Records (SINASC/Datasus)[6]. Information dating back to 1996

[6] 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

regarding infant and maternal characteristics, such as educational attainment, age and place of residence, is available in the system. However, we focus on the period 2000 to 2007 for infants who were born around the time of the introduction of the PPCDAM. Ideally, the unit of analysis regarding the effects of deforestation on health outcomes should be the individual. However, the SINASC only provides aggregate information on live births and mothers. Given this restriction, the unit of analysis in this study is the municipality. The municipality where the mother lives is used as the reference municipality for the panel. This is an important point because where the mother resides is not always the municipality 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 extremely 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 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 areas from year to year. Deforestation is given as the total deforested area in square kilometers for each of the municipalities. As previously mentioned herein, we use the rate of deforestation in 2004 to capture pre-existing variations in deforestation due to geographic or regional specific factors as a strategy to identify the impact of the 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 percentage of spending on education and health. The source of information of the first two variables is the Brazilian Institute of Geography and Statistics (IBGE, for its acronym in Portuguese), while the information for the latter two variables is obtained from the *Ministério da Fazenda*. In addition, an attempt to control for the influence of the *Bolsa Familia* program by including estimates to control for the percentage of beneficiaries. This information is obtained 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 to access basic sanitation. The information of these two variables is derived from the 2000 population census. Descriptive statistics for all variables used in this study are presented in Table 1.

[Table I]

6. Results

We begin by examining the distribution of the main variables before and after the intervention. To do so, 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 in the 75th percentile of the distribution) to those with high deforestation (those above the 75th percentile of the distribution). The table also reports the p-values obtained from testing mean differences among the municipalities with low and high rates of deforestation. The results indicate that a higher percentage of white infants are born in municipalities with high deforestation, but the educational level of the mothers is lower. The greatest difference between the two groups is observed in agricultural production, which is approximately 100% for both periods. This is consistent given that 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 is a statistically significant difference observed. With respect to the child health variables, significant differences are observed both in low birth-weights and preterm birth rates, with the highest incidence of both indicators in municipalities with less deforestation. The results in the table do not allow us to infer that there is any significant change in trend in child health variables, a finding that is possibly due to the influence of other confounding factors.

Regression models are implemented to control for several confounding factors and to 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 a different set of controls. The table is divided into four panels wherein the first panel presents the results for extremely low birth weight rates; the second presents low birth weight rates; the third presents extreme preterm rates and the fourth presents preterm rates.

The results for the first panel show that the incidence of extremely low birth weight decreased more relative to those municipalities where deforestation was more significantly reduced. Column 1 by controlling the interaction between deforestation in 2004, a linear trend and the fixed effects of year-municipality, yields a coefficient estimate of -0.000735 (with a standard error = 0.000349), which is significant at 5%. Column 2 adds the interaction between the 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, thereby 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 the PPCDAM had positive effects on the incidence of low birth weight, thus reducing it in the intervention period. While the parameter of interest is estimated at -0.00136 in column 1, it is statistically insignificant. When the influence of other social programs is indirectly controlled, the coefficient increases 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 the PPCDAM is estimated to be -0.00172 and significant at 10%.

The results for extreme prematurity (Panel C) suggest that the PPCDAM reduce the incidence of birth outcome. The coefficient of interest is relatively stable with 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 the PPCDAM does not significantly improve once this indicator is controlled by specific-state trends (Panel D).

To interpret the magnitude of the estimated coefficients, we estimate the reduction for each outcome variable if the rate of deforestation in 2004 were 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 extremely low birth-weight rate, of 0.09% in the incidence of low birth-weight rate, of 0.45% in the incidence of extreme preterm rate, and of 0.06% in the incidence of preterm rate. This analysis suggests that the effects of the PPCDAM on child health are modest.

[Table II]

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 the PPCDAM on child health presented above. Indeed, while the estimated coefficient of the impact of the PPCDAM on agricultural production is negative, it is only marginally significant in the most parsimonious specification.

[Table III]

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

7. Robustness of Findings

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, birth selection and serial autocorrelation. In general, the results from these robustness checks are reassuring.

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 rather, are influenced by the introduction of other social programs in 2004. The most important social program introduced in that year was the *Bolsa Familia* program. Our strategy to address this potential problem in our baseline estimates 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 for the degree of poverty of the municipalities or if the targeting of programs takes 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 the 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 to 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 housing[7]. Each of these interactions is added separately rather than all at once. Note that the inclusion of these interaction terms allows us to control indirectly the pre-existing differential trends in infant health. As evidenced, 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. 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 change only minimally with the inclusion of these variables.

Column 8 controls simultaneously for all variables used in the previous columns. While this can create problems of colinearity, 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 are no threat to our estimates, 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 significant at 5%, while those that were significant at 5% are significant at 1%.

[Table IV]

7.2. Pre-existing trends and Mean Reversion

The identifying assumption of our approach is that in the absence of the PPCDAM, municipalities with different levels of deforestation experienced the same proportional changes in infant health. We investigate the validity of this assumption in two related, but complementary, ways. First, we include micro-region specific linear trends. This results in the inclusion of approximately 100 additive terms given that, on average, a micro-region is comprised of seven municipalities. Assuming that variations in agricultural prices and the degree of dependence on the agricultural sector are homogeneous across municipalities within each micro-region, the inclusion of these micro-region specific trends allows us to control indirectly the influence of the dynamics in

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

the agricultural prices. Additionally, we include a lagged term of the dependent variable, which allows us to control for mean reversion.

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 micro-region has no noticeable effect on our main estimates. Column 3 adds the lag of the dependent variable as a control variable. The majority of our 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 that affect our results. Specifically, we exclude municipalities in states with extremely low rates of deforestation in 2004. This increases the comparability across municipalities and thus minimizes the likelihood of differential trends in child health. The specification in column 4 is the same as that in column 3, but now the number of observations is substantially reduced due to the restrictions that we impose. Despite this reduction in the number of observations, the coefficients of interest remain similar to our baseline results. Furthermore, 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 V]

7.3. Birth Selection

As previously mentioned, it could be argued that mothers can migrate to municipalities with a "healthy" environment after the implementation of the intervention. This could bias our results as migrating individuals generally have different characteristics than individuals who do not migrate. We are skeptical of this argument given the low mobility of women during pregnancy. Moreover, municipalities with a "bad" environmental setting are likely to be surrounded by municipalities with "bad" environmental surroundings. This implies that finding a municipality with a “good” surrounding environment requires a high cost of mobility. Accordingly, it is difficult to imagine that pregnant women during systematically relocate to municipalities with high deforestation reductions after the introduction of the PPCDAM.

Nonetheless, we perform a test of falsification whereby we evaluate the effect of the PPCDAM on the characteristics of mothers. The intuitive notion is that mothers who migrate are expected to have more education and to be single. Therefore, if there is no relocation, it should be reflected in statistically insignificant coefficients. Columns 1 to 3 of Table 6 present the results of this exercise. There are no changes in the characteristics of mothers (education, teen mother and marital status) that are associated with the implementation of the PPCDAM. Furthermore, the coefficients are far from being statistically significant, which offers additional confidence in our results.

It could also be argued that women may strategically postpone their fertility decisions due to the introduction of the PPCDAM, which could lead us to exaggerate the effect of the PPCDAM if women who make such a decision are those with greater investment in prenatal care. With this in mind, column 4 estimates the effect of the PPCDAM on the number of pregnancies per thousand inhabitants[8]. A positive and significant association between the implementation of the PPCDAM and the pregnancy rate would indicate that our baseline results could suffer from the aforementioned bias. The results in the table, however, do not suggest a statistically significant association between these two variables, with an estimated coefficient of 0.0878 and a standard error of 0.106.

[Table VI]

7.4. Serial Correlation and Standard Errors

A final concern with our baseline results deals with the estimation of standard errors. The estimates in Table 2 use standard errors clustered at the municipality level. Standard errors are therefore calculated taking into account any arbitrary correlation in the residuals across municipalities. A possible disadvantage of these standard-based cluster errors at the municipality level is that they do not allow for serial correlation across municipalities within the same state. This could be a problem in our research design. For example, deforestation in a municipality can cause changes in rainfall levels in neighboring municipalities, and thereby affect the health of infants. This would result in serial correlation at the municipal level within a greater unit of aggregation (e.g., micro-region or state).

To check the robustness, we calculate the standard errors allowing for any arbitrary serial correlation with levels of aggregation greater than the municipality. Column 2 of Table 2 investigates how our baseline results, presented in column 1, change when calculated using standard errors clustered at the level of the micro-region. The coefficients of interest are estimated more precisely as the standard errors are reduced. When using standard errors based on clustering at the meso-region (Column 3), the standard errors are smaller in most cases. In column 4, we use standard errors clustered at the state level. It is noted that the effect of the PPCDAM on the

[8] We use the number of births plus the number of fetal deaths as a proxy of total pregnancies.

incidence of extreme preterm birth is now slightly insignificant. However, we interpret this result with caution given that our sample consists of only nine states, which may bias the standard errors due to the relatively small number of clusters (Cameron, Gelbach, and Miller, 2008).

[Table VII]

8. Conclusions

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 extremely low birth-weight by 0.38% and extreme preterm birth rate by 0.45%. Our findings are robust to a variety of robustness exercises. We further check for possible mean reversion including the lag of each outcome variable, and the results are qualitatively and quantitatively similar. Furthermore, our results are insensitive to a variety of variables that capture the influence of local policy. In addition, we directly control for the influence of the *Bolsa Familia* program, the main intervention program for poverty alleviation introduced in 2004, and our findings remain consistent. Finally, our findings are not explained by pre-existing micro-regional trends.

The effects of deforestation on child health 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 are implied by reduced deforestation. On the one hand, less deforestation involves increased agricultural productivity due to less variability in temperature and rainfall. On the other hand, less deforestation implies lower productivity due to the reduced expansion of agricultural land. The combination of these two effects seems to explain the null effect of forest policy on agricultural production and, in turn, explain the modest impact of reduced deforestation on child health. The evaluation and validation of this argument is left for future studies.

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TABLES

Table I. 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		

Notes: 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 II. 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 Rate			
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 Rate			
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

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

Table III. 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

Notes: Robust standard errors clustered 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 IV. 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 Rate							
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 Rate							
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

Notes: Maternal Characteristics contains Married (%),Teen Mother (%), and Mother Education. Robust standard errors clustered 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 V. 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 Rate			
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 Rate			
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

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

Table VI. Effects of PPCDAm on characteristic of Mothers (Falsification test)

	(1)	(2)	(3)	(4)
	Mother Education	Teen Mother	Married	Pregnancy rate
Post 2004 x Deforestation 2004	-0.000506	-0.00294	-0.00143	0.0878
	(0.00233)	(0.00205)	(0.00322)	(0.106)
2004 GDP per capita x Post 2004	Yes	Yes	Yes	Yes
State-Specific trends	Yes	Yes	Yes	Yes
Year x 2004 Deforestation	Yes	Yes	Yes	Yes
Year and Municipality Fixed Effects	Yes	Yes	Yes	Yes
Observations	6152	6152	6152	6152

Robust standard errors clustered at municipality level are into parentheses. ** P<0.1; ** P<0.05; ***P<0.01.*

Table VII. Effects of PPCDAm on infant health (Serial correlation and Standard Errors)

	(1)	(2)	(3)	(4)
	Panel A: Dependent variable is Very Low Birth-Weight Rate			
Post 2004 x Deforestation 2004	-0.000714*	-0.000714*	-0.000714***	-0.000714**
	(0.000374)	(0.000374)	(0.000256)	(0.000346)
	Panel B: Dependent variable is Low Birth-Weight Rate			
Post 2004 x Deforestation 2004	-0.00170*	-0.00170*	-0.00170**	-0.00170**
	(0.000968)	(0.000968)	(0.000729)	(0.000670)
	Panel C: Dependent variable is Extreme Preterm Birth Rate			
Post 2004 x Deforestation 2004	-0.000361**	-0.000361**	-0.000361**	-0.000361
	(0.000170)	(0.000170)	(0.000181)	(0.000243)
	Panel D: Dependent variable is Preterm Birth Rate			
Post 2004 x Deforestation 2004	-0.00108	-0.00108	-0.00108	-0.00108
	(0.00189)	(0.00189)	(0.00195)	(0.00150)
State-Specific trends	Yes	Yes	Yes	Yes
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	6152	6152

Column 1 presents baseline results. Column 2 use standard errors clustered at the level of the micro-region. Column 3 use standard errors clustered at the level of the meso-region. Column 4 use standard errors clustered at the level of State. * *P<0.1; *** *P<0.05; ****P<0.01.*