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Poverty Alleviation and Deforestation in Brazil: Empirical Evidence from the Bolsa Escola/Familia Program

A Difference-in-Difference Analysis of how Increased Income Affects Deforestation in Brazilian Municipalities

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Soli Deo gloria.

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Abstract

In this thesis we estimate the effect of poverty alleviation on local deforestation in Brazil. We identify impacts of increased income among low-income families by studying the world's largest conditional cash transfer program, Bolsa Escola/Familia. We use municipality-level panel data on deforestation and program beneficiaries for the first years of the program (2001-2004). Through a difference-in-difference approach we estimate the average treatment effect on the treated (ATT). The results show that deforestation fell by 7,6% in municipalities with many beneficiaries, amounting to an estimated 1 million hectares of preserved forest in these locations. A back-of-the-envelope calculation suggest that these benefits are valued at approximately USD 4 650 million over these four years, which is almost three times the program costs. Furthermore, we estimate that increasing the share of beneficiary families by 10% on average leads to a reduction in deforestation by 1,7%. These findings suggest that the Bolsa program have reduced the local pressure on forests by providing low-income Brazilian families with greater financial stability. The thesis thus contributes to existing literature by providing new empirical evidence that poverty alleviation can be beneficial for the environment.

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Acronyms

ATT = Average Treatment Effect on the Treated

ATE = Average Treatment Effect

BE = Bolsa Escola

BF = Bolsa Familia

CCT = Conditional Cash Transfers

CO2 = Carbon dioxide

DID = Difference-in-Difference

FE = Fixed Effects

GDID = Generalized Difference-in-Difference

IBGE = Instituto Brasileiro de Geografia e Estatística (The Brazilian Institute of Geography and Statistics)

ILO = International Labour Organization

PNAD = Pesquisa Nacional por Amostra de Domicílios (Brazil National Household Sample Survery)

MT = Metric Tons

UN = United Nations

1 Introduction

Over the whole world, people are uniting around a vision to end poverty and save the planet. The UN sustainability goals (United Nations, n.d.-b) emphasize the need for taking care of the natural ecosystem, while also allowing the poor to prosper. It is not clear, however, to what extent these two goals support or conflict with each other. Poverty alleviation may raise demand for harmful consumption of natural resources, but can also help poor families to rely less on harmful environmental practices. Whether increased income will decrease or increase the environmental degradation therefore remains a central debate in the economics literature (Dasgupta, 1993; Grossman & Krueger, 1991; Swinton et al., 2003)

Many of the world's poor live in rural areas close to woodlands, and rely on the resources from the forest (Chomitz, 2006). At the same time, global deforestation continues at an alarming rate. The loss of tropical forests is a serious threat to biodiversity and has been calculated to be responsible for nearly 20% of the human generated CO2 emissions. This year, Brazil has gained the attention of the world through great fires in the Amazon. The country contains 40% of the world's rainforest (Kirby et al., 2006), but the local politicians now show reduced willingness to forego economic opportunity to conserve natural areas. While much of government regulations have targeted the large and wealthy farmers, the smallholder-dominated areas were the single largest contributors to deforestation in the Legal Amazon in 2010 (Godar et al., 2014). Discovering sustainable paths of development will therefore be an important challenge for the world. A central question is thus: *How can the population prosper, and the nature be conserved at the same time?*

This thesis contributes to answering this question by investigating the relationship between deforestation and increased income to the poor in Brazil. Specifically, we study effects from the world's largest conditional cash transfer program (CCT), the Bolsa Familia (BF). The program was implemented in 2003 and reaches over 50 million people (Erdoğdu & Akar, 2018). It has been praised as a source of poverty alleviation and reduced inequality and is unique in the way it reaches every municipality in Brazil. It has been shown to be very well targeted and covered 80% of the country's poor in 2006 (Lindert et al., 2007). The conditions for eligibility are that the family income is below half the minimum wage and that children attend school. The program leads to a significant income change for the poor families, and provides a good opportunity to explore the effect of poverty alleviation on deforestation through a difference-in-difference (DID) framework. Furthermore, while the impacts of the program have been evaluated on a number of different outcomes, no previous study have looked at the environmental effects.

The agricultural sector is by far the most important source of income for the BF beneficiaries, employing 49% of the recipients in 2004 (Machado et al., 2011). At the same time, most of the deforestation in the country is driven by farming activities. We therefore hypothesize that the CCT may have had significant consequences to yearly transitions from forest to land cover. This is supported by findings from other countries that poverty can push people to expand unproductive land (Kerr et al., 2004) and that a positive income shock can reduce the reliance on forests for consumption smoothing (Fisher & Shively, 2005).

While there are several evaluations of cash transfer programs that are conditional on reduced deforestation (J. M. Alix-Garcia et al., 2019; Simonet et al., 2019; Wong et al., 2018), there exist very few studies of transfers that did not explicitly require a change in environmental outcomes. According to our knowledge, only two previous studies have used CCTs that were only conditional on schooling and income. However, the setting of a CCT is very advantageous to study the income-deforestation link as they make it possible to evaluate the effect of exogenous income on deforestation. The two previous studies provide conflicting results, which makes it even more interesting to see what effects the Bolsa program had.

An evaluation of Oportunidades in Mexico used a discontinuity approach on communities just poor enough to participate in the program(J. Alix-Garcia et al., 2013). They found increased deforestation in recipient communities, but that the impact was mediated by market connectivity. Consumption of land-intensive goods such as beef and milk went up among participating households regardless of market access, but the link to increased local production was stronger in road-poor areas. However, Malerba (2020) found the opposite results from Familias en Accion in Colombia, using a difference-in-difference approach on a municipality level. While consumption of beef and milk went up among recipients, he found approximately 0,5% reduced deforestation in municipalities enrolled in the program. Furthermore, market access was statistically insignificant when interacted with enrollment, and the data showed that the consumption of beef was directly mediated by market access.

The link between income and environmental pressure may thus be heavily dependent on the institutions and conditions of each country. Consumption and market access can differ across countries in Latin America in a way that is significant to deforestation outcomes. This thesis therefore fills an important gap in literature as it specifically addresses the Brazilian context. The size of the BF program and the vital role the country has in the global combat against deforestation makes it especially interesting as a subject for examination.

Our thesis utilizes nation-wide dataset on forest transitions, while most other studies on deforestation only includes the Brazilian Legal Amazon (BLA) (Godar et al., 2014; Simonet et al., 2019; Wong et al., 2018). While this area contains 75% of the country`s forests, it only includes 13% of the total population[2]. We are able to expand the analysis through using recently published data from the MapBiomas Project (2019), which makes it possible to study all types of forests over the whole country. This dataset has been generated from satellite images, and provides detailed information on yearly land use and transitions. In our analysis we focus specifically on the transition between forest and farming areas to measure deforestation.

We combine the deforestation data with information on the number of beneficiary families of the Bolsa program to create a panel dataset. We focus on the roll-out of Bolsa Escola (BE), the predecessor of BF, as well as the first two years of BF. BE reached 5 million beneficiary families already in its implementation year in 2001, which represented the majority of families included in the expanded BF program in 2003. The two programs will hereafter often be jointly referred to as Bolsa.

The panel dataset allows us to use quasi-experimental techniques to establish causal inference between the program and deforestation. Specifically, we use a DID approach with a fixed effects estimation to control for time-invariant differences between municipalities. Through the use of year dummies, we control for time-variant shocks. We separate municipalities that had higher exposure to the program in terms of beneficiaries from those with less exposure.

[2] This number is calculated from our dataset (IBGE, 2020c).

We cannot compare with municipalities without the program since BE was quickly implemented in the whole country.

Since the amount of money that each family received varied on the number of enrolled children in the family, we use the share of beneficiary children in a population to define the treatment group. In the density plot over beneficiary children in the population (Figure 10), we observe a natural separation of two groups with different means. More specifically, the municipalities where beneficiary children constituted less than 8% of the total population, seem normally distributed around a mean of 5%, while the others seem normally distributed around 11%. We therefore define the treatment group as municipalities with more than 8% of beneficiary children in the total population. We use the years 1997-2000 as pre-program years and the years 2001-2004 as post-program period. As the municipalities in the treatment group initially had higher average levels of deforestation than the control, our estimations are defined as an Average Treatment effect on the Treated municipalities (ATT).

We begin our analysis with a simple DID approach where we interact treatment with the post-program period and estimate a 7,6% reduction in the deforestation in the treatment group. Further, we perform an event study and find that estimations of the yearly coefficients show that the impact of the program increased from a 6,5% decrease in deforestation in the first two years to an approximate decrease of 9% after 2003. This is likely due to the expansion of the program which happened in the transition from BE to BF. Finally, we expand our analysis to a generalized DID framework, where we allow the intensity of treatment to vary according to the share of families that were beneficiaries in each municipality each year. We estimate that an increase of 10% in the share of beneficiary families on average lead to a decrease in deforestation of about 1,7%.

We thereby conclude that there is evidence that the Bolsa programs had a positive effect on environmental preservation in Brazil and that increasing the income for the poor can be beneficial for the forests. These findings are in line with the theory that poverty pushes people towards environmentally harmful behavior (Brundtland, 1987; S. . D. Mink, 1993; Reardon & Vosti, 1995). This can happen because they cannot afford productivity improvements or to search for alternative sources for income, and therefore rely on expanding unproductive land. It is also possible that increases in income make cheap labor supply less attractive, which can increase the costs of deforestation. However, we only estimate effects on deforestation within the municipalities. If the consumption of land-intensive goods increased similarly to Mexico and Colombia, it is possible that market mediation lead to increased deforestation in other locations than our units of study (J. Alix-Garcia et al., 2013; Malerba, 2020). Because of the scope of this thesis we were not able to study consumption data in order to address this question, but encourage further research in this area.

The rest of this thesis is organized as follows. In Chapter 2 we present a review of existing literature on the relationship between deforestation and income, as well as previous evaluations of Bolsa. Chapter 3 provide historical information on deforestation, describe the Bolsa programs and present poverty in Brazil. We describe the panel data set in chapter 4 and outline our empirical strategy in chapter 5. The results of the analysis with a robustness test are presented in chapter 6. In chapter 7, we discuss our results and investigate possible limitations of our research. Finally, we conclude the thesis in chapter 8.

2 Previous Literature

This chapter presents two important strands of literature related to the topic of our thesis. First, we summarize contrasting views in the debate on the relationship between income and deforestation and discuss limitations in current empirical research. Second, previous evaluations on the impact of the Bolsa programs on social and economic factors are presented, which are important to have in mind in the discussion our findings.

2.1 Income and deforestation

There is a range of literature examining the link between forest degradation and poverty (Chomitz, 2006; Reardon & Vosti, 1995; Vosti et al., 2003; Wunder, 2001). Relating resource sustainability with human management is an idea that dates at least back to Thomas Malthus' prediction of increased means leading to population growth and resource pressure (Malthus, 1798). Many researchers have since then taken an interest in the role of income and poverty as an explanatory factor for environmental outcomes, but no consensus has emerged from the debate about the direction and magnitude of the causal link (Stern, 2017).

On one side of the debate are theories of Malthusian inspiration. These suggest that negative environmental impact is a result of population pressures and economic activities. As income rises, it will lead to more investment in activities that lead to environmental degradation. The IPAT identity presented by Ehrlich and Holden (Ehrlich & Holdren, 1974) has been widely used. This states that Impact = Population * Affluence* Technology, in which the impact is environmental degradation. The theory is criticized for treating technology as exogenous and portraying a closed system without flexibility in its limits (Lambin et al., 2001).

Toward the end of the 80s, the focus shifted towards the possibilities of seeing social and environmental outcomes in combination. The widely influential Brundtland report (Brundtland, 1987) presented the term sustainable development, which has recently gained renewed attention through the UN Sustainable Development Goals (United Nations, n.d.-b). The Brundtland report focused on how forest degradation leads to an erosion of the resources of the poor, and that protecting the woodlands is therefore in their interest. This view is reflected in the UN sustainability goal 15, stating that deforestation and degradation of drylands “pose major challenges to sustainable development and have affected the lives and livelihoods of millions of people” (United Nations, n.d.-a).

In literature, this is described as the poverty-environment nexus (Khan & Khan, 2009) or the environment-poverty trap (Barbier, 2010). According to this view, environmental degradation not only leads to poverty, but poverty subsequently pushes the poor towards resource-dependency and environmentally damaging behavior . Kerr et al. (2004) confirmed that people in the poorest areas in Costa Rica work on less productive, and thus less profitable land, motivating expansion on unproductive land and increasing deforestation. Alix-Garcia et al (2019) show that extremely poor families in Mexico have few alternative income opportunities, thus facing a high cost of giving up deforestation. Therefore, they do not easily accept smaller compensation in exchange for preservation. Poorer households are also expected to rely on forests for consumption smoothing (Dasgupta, 1993), and Fisher & Shively (2005) confirmed that a positive income shock can lead to reduced deforestation . Reardon and Vosti (1995) modify the theory by stating that one must separate between being poor in welfare or poor in investment capacity. Even if a household can cover some basic welfare needs, they may still not be able to invest in the necessary improvements in natural resources.

Empirical findings suggest that neither neo-Malthusian theories or the environment-poverty trap sufficiently address the complexity of drivers behind deforestation (Lambin et al., 2001; Stern, 2017). The relationship might be non-linear, like the Kuznets curve found in relation to pollution (Grossman & Krueger, 1991), but also highly dependent on other contextual and mediating factors (Khan & Khan, 2009; Wunder, 2001). Geist and Lambin (Geist & Lambin, 2002) found that only 42% of deforestation rates across 152 subnational case studies from developing countries could be explained by typical poverty indicators, and these are often linked to other social, economic, technological or cultural factors of higher importance. Swinton, Escobar and Reardon (Swinton et al., 2003) concluded on the basis of several studies that both poor and non-poor were responsible for deforestation in Latin America due to distorted incentives and poorly defined property rights.

Furthermore, it is not easy to estimate the causal relationship between poverty and the environment (Stern, 2017). Many studies rely on cross-sectional comparisons of poor and non-poor that are unlikely to capture underlying differences between these groups. There is also the danger of reverse causality, since poverty might be as likely to drive deforestation rates as the opposite. The evaluation of conditional cash transfers (CCT) which are unrelated to environmental policies is advantageous in this context because it introduces exogenous variation to income. To our knowledge, only two studies have made use of quasi-experimental methods to investigate environmental impacts from such programs. They offer almost opposite conclusions, underlining the importance of mediating effects.

Alix-Garcia et al (2013) studied effects of the Mexico Oportunidades program through a discontinuity approach. They found that the deforestation rate increased by 15-33 percentage points among communities that did deforest and who were just poor enough for program participation. The increase was higher in more isolated locations. Household data showed that recipient households used more land-intensive goods such as beef and milk. From this they concluded that increased consumption lead to more deforestation, but that the effect was to some extent mediated by markets.

However, Malerba (2020) showed that these findings might be context-specific. He performed a similar study of the Familias en Accion program in Colombia, using a difference-in-difference framework combined with propensity score matching. The results contrast those from Mexico, as enrolled municipalities were found to have about 0,5% lower deforestation rates than the control group. Furthermore, the distance to markets did not prove significant on deforestation. Rather, it was found that market proximity mediated the consumption of beef directly. However, the overall increase in the consumption of beef and milk suggests that there may be negative impacts that are not sufficiently accounted for at a municipality level, or that are offset by other mechanisms. Local and mediating factors thus play an important role in determining the environmental impact a CCT may have in a country. The findings of decreased deforestation may be explained by reduced reliance on forests for consumption smoothing (Fisher & Shively, 2005), or by a labor market mechanism outlined in Barbier (2010), in which increased income makes cheap labor supply less attractive. This makes deforestation activities more costly and thereby reduces the forest pressure.

No similar study has been performed for BF in Brazil, in spite of the size of the cash transfer program and the amount of tropical forest in the country. This thesis benefit from detailed satellite data to focus specifically on deforestation related to farming activity. Furthermore, we improve on existing studies by estimating impacts of heterogenous treatment intensity.

2.2 Former evaluations of Bolsa

Previous evaluations show that BF has successfully reduced poverty, inequality and hunger, while improving health and education (Erdoğdu & Akar, 2018; Soares, 2012). It is one of the largest and most comprehensive CCT programs in the world, benefitting almost 50 million people throughout in Brazil by 2018. In spite of this, no evaluation has been done of the environmental impact. In the following, we present findings on schooling, labor market and poverty. Considering that many of the beneficiaries of Bolsa are working in the agricultural sector, this would also be likely to impact deforestation rates, a point we return to in the discussion of our findings in 7.1.

One of the goals of Bolsa Escola was to increase school attendance, and there is empirical evidence to support that the goal was reached. Glewwe and Kassouf (Glewwe & Kassouf, 2012) found that BE and subsequently BF, increased enrollment rates by 5,5 - 6,5 percentage points. Additionally, it decreased dropout rates slightly and raised grade promotion rates by between 0,3 - 0,9 percentage points. Similar results are also found by De Brauw et al. (De Brauw et al., 2015) showing significant impact on school enrollment among children aged 6-17 years, with larger and more precise effect on girls and in rural areas. However, an estimated 82% of the participants would have enrolled in school without the program, meaning that most of the program cost did not directly improve enrollment outcomes (Glewwe & Kassouf, 2012).

While one could expect the increase in school attendance to reduce the time spent in child labor, empirical findings in this aspect are more mixed.

Although cash transfer programs have globally been claimed to reduce incidents of child labor (de Hoop & Rosati, 2014), Pais et al (Pais et al., 2017) found evidence that BF in fact had no effect, or even increased the number of children working. Costa et al. (Costa et al., 2020) also found that the probability of child labor increased in the North and Northeast region, but that on the intensive margin weekly hours decreased. Unfortunately, the numbers may be inaccurate since most studies rely on self-declarations. The evidence indicates that education and child labor are not perfect substitutes and that time allocated to education is taken primarily from the leisure time of the child. Most school days are only 4-5 hours long in Latin America, and can therefore be combined with working part-time (Holland, 2012). Furthermore, the monthly grants from both of the programs were only R$15 per child, while Kassouf, Dorman & Nunes

(Kassouf et al., 2005) estimated that average wages paid to children in rural areas averaged to R$77. The opportunity costs foregone by the families are therefore significantly higher than the grant provided.

A common concern with CCTs is that beneficiaries would shift away from labor and increase leisure hours due to the income effect. However, empirical results from evaluations of BF show either small or insignificant decreases in overall household labor supply (De Brauw et al., 2015; Ferro et al., 2009). In urban households, labor shifted away from the formal sector and towards informal work (De Brauw et al., 2015; Ribas & Soares, 2011). However, this effect was not found in rural households. A decrease of labor participation found among women appear to be compensated by an increase in weekly hours worked among men. Similarly, CCTs from Mexico and Ecuador had no effects on adult labor supply (Fiszbein & Schady, 2009). The reason may be that the beneficiaries are so poor that the income elasticity on leisure is very low.

Finally, several studies document the contribution BF has had on poverty and inequality in the country. The program has been found to have contributed to a reduction in Gini points, ranging between -0,20 and -0,86 in different studies (Soares, 2012). It is estimated to have reduced the percentage of poor by 1,6% and the poverty gap by 18%. Furthermore, it was responsible for about 15% of the reductions in regional inequality in the country (Silveira Neto & Azzoni, 2012).

Empirical studies thus show that while the program has reduced poverty and inequality in the country it is not clear how it has affected labor market mechanisms. Furthermore, the environmental impacts of Bolsa have not been studied. This thesis thus improves upon the understanding of the benefits and costs of the CCT.

3 Background

In this thesis we look closer at the link between deforestation and poverty, aiming to give more insight in how poverty alleviation is linked to environmental outcomes. In this chapter we first present historical and current trends in deforestation in Brazil, as well as describing the main features of the Bolsa Escola and Bolsa Familia program. Finally, the socio-economic situation in Brazil during the early 2000s is presented, as well as central characteristics on Bolsa beneficiaries, in order to understand the analysis and discussions of our findings.

3.1 Deforestation in Brazil

Tropical forests disappear at about 5 percent a decade, and contributes to emissions of 3 billion carbon dioxide (CO_2) every year (Chomitz, 2006). Deforestation threatens biodiversity and can trigger ecological collapse, with high local and global costs. Almost half of humanity lives in rural areas and depend on forest resources. While they contribute to and benefit from deforestation, they also suffer from the erosion of resources they rely on daily.

Brazil contains 40 % of the world's rainforest and is central in the global deforestation debate. Land and forestry use accounted for 61 per cent of total CO_2 emissions in the country in 1990-2005 (United Nations - ESCAP, n.d.). The drivers behind deforestation differ on the local, state, and national level (Sathler et al., 2018). While smallholders in Brazil use forests to improve their welfare in the face of credit, information, and other constraints, the forest loss on a national level is historically driven by expansion of infrastructure and increased demand for agricultural and food products (Barona et al., 2010). Mining, cattle farming, agriculture and urbanization are some of the most important sectors involved in deforestation.

Most of the focus on deforestation in the Brazilian context has been specified to The Brazilian Legal Amazon (BLA). This is a geographical subdivision, consisting of eight states in the North-, Northeast- and Center-West region (see Figure A 9 for illustration) (de Prado et al., 2005). The area contains 75% of the total forest cover in the country and is responsible for about 60% of the total deforestation[3]. Deforestation rates increased dramatically in the past decades, especially after the construction of the Transamazonian Highway in 1970 (Fearnside, 2005). The government encouraged colonization and economic activities in the period of military dictatorship. In 1985 negative international attention spurred the government to change their policy, but enforcement was weak in the beginning. After 2004 the government increased monitoring and fining, and along with economic and social factors this led to a significant decrease in the deforestation rates (Godar et al., 2014). Figure 1shows the differences in forest cover between the BLA and the rest of the country, and also illustrates the dramatic decrease in forest cover in the Amazon up until 2004, after which we see a stabilization.

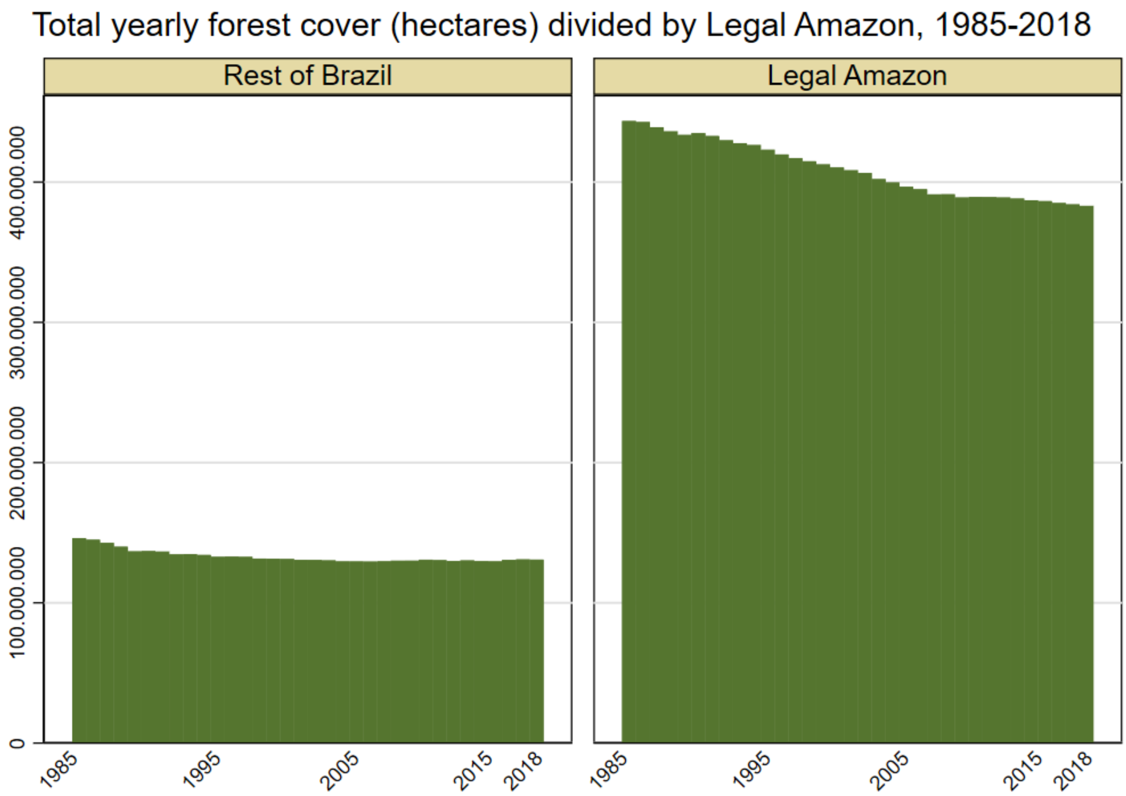

Figure 1: Historical changes in forest cover from 1985 to 2018

Notes: Bar graphs of total forest cover in Brazil. The x-axis represents years from1985 to 2018. The y-axis measures hectares forest per year. The graphs shows the amount of forest in Legal Amazon (right) and in the rest of Brazil (left).

[3] Numbers are calculated from our MapBiomas data set, over the years 1998-2004.

Government interventions disproportionally targeted larger properties, as these had been responsible for a high amount of legal violations (Chomitz, 2006). The government collected deforestation data from BLA which was made available to the public. In 2011 the government implemented the Bolsa Verde program in Priority Areas for conservation (Wong et al., 2018). This was a cash transfer program offered to poor households which was conditional on the commitment to engage in conservation and sustainable use of natural resources. The program thereby provided incentives to the poor to protect the forest areas. Wong et al found the program was very successful and reduced deforestation in the treated areas by 44-53 percentage points of the counterfactual. The overall Brazilian economy has also changed since the early 2000s, as agricultural employment has been shrinking and industry and service have gained higher importance (ILO, 2012).

As stated in the Introduction, the recently published MapBiomas data set (MapBiomas Project, 2019) makes it possible for us to expand the analysis beyond the Amazon to cover the whole country and all types of forested areas. This allows us to account for the entire national deforestation, rather than only 60%. Further, it provides more general findings for the interactions between human activities and forest cover in the country, and is especially beneficial since 87%[4] of the Brazilian population lives outside the BLA.

A closer illustration of the geographical location of deforestation is seen in Figure 2 and Figure 3. Deforestation is here more narrowly defined as transitions from forest areas to farming areas. This thesis focuses primarily on this indicator, a point we will explain in further detail in section 4.1. As can be seen by comparing the two maps, deforestation is particularly prevalent in the border areas between forest and agriculture in the North and North-East regions of Brazil. This is often described as the arc of deforestation. However, we also see evidence of deforestation happening in the entire Northeastern area. This is also known to be the poorest region in Brazil. There is also some deforestation happening in selected areas further South.

[4] The numbers is calculated from population estimates in our data set (IBGE, 2020c), over the years 1998-2004.

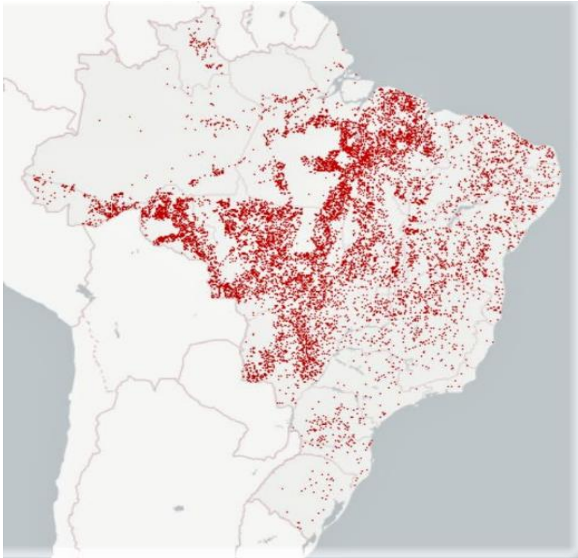

Figure 2 - Deforestation in Brazil from 1985-2018

Note: Map illustrating deforestation (red) in Brazil, defined as hectares of land that transitioned from forest to farming areas between year 2018 and 1985. Generated from MapBiomas (2019).

Figure 3 – Forest and farming cover in 2001

Note: Map of forest cover (green) and farming cover (yellow) in year 2001. Generated from MapBiomas (2019)

It has been found that both poor and non-poor are responsible for deforestation in the South America (Swinton et al., 2003). Owners of large properties (>500 ha) dominated in the early 2000s, and accounted for 48% of accumulated deforestation in the Brazilian Legal Amazon between 2004-2011 (Godar et al., 2014). Smallholders with less than 100 ha, were only responsible for 12%. Government regularization and monitoring have therefore mainly targeted the large landholders, and deforestation rates among the largest properties (≥2,500 ha) declined by 63% from the peak in 2005. This led to an increased deforestation share among the smaller farms, and these became the biggest contributor to annual deforestation in 2010. The question of what can help these farms to lower their deforestation is therefore likely to be crucial for the future of the forests of the world.

3.2 The Bolsa Escola/Familia program

Bolsa Familia is the largest CCT in the world, covering over 13 million Brazilian families, i.e. more than 25% of the population (Van Stolk & Patil, 2015). CCT programs became popular in

Latin America in the early 2000s. They provide transfers of cash to poorer household, conditional on some pre-specified investment in the human capital of their children (Fiszbein & Schady, 2009). The idea is to break the intergenerational cycle of poverty and combat underinvestment in children's health and education, while providing immediate relief to poor families. In Brazil, Bolsa Escola (BE) started in a few of the Brazilian municipalities in 1995, and by the beginning of 2001 it covered about 2% of all municipalities and 200 000 families (Lindert et al., 2007). That year it was launched on a national level by the Federal Government with a quick roll-out. By December 2001 it had been implemented in 5 470 municipalities, now covering nearly 5 000 000 families. 81 more municipalities joined in 2002, leading to nearly full coverage. Figure 4 shows graphically how many new municipalities were included each month.

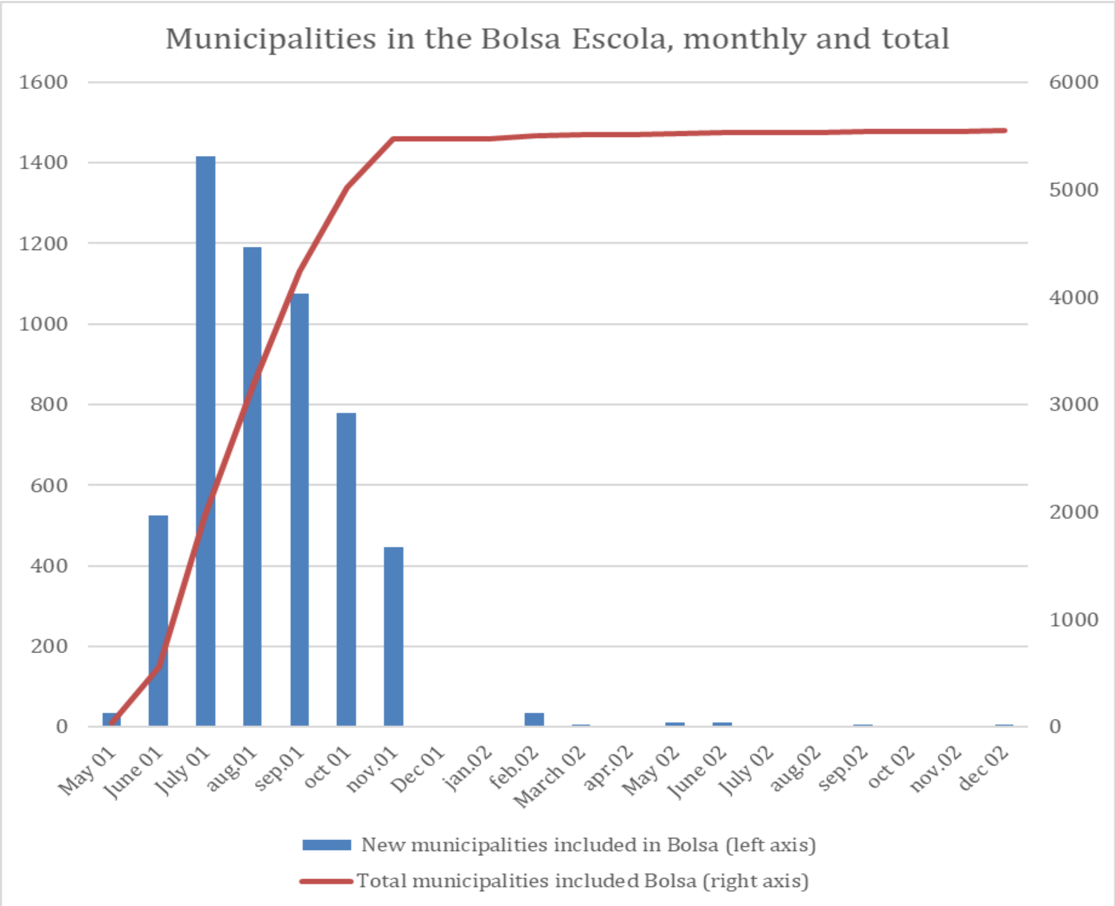

Figure 4: Roll-out of Bolsa Escola.

Note: Graphical illustration of the implementation of Bolsa Escola program in the municipalities in Brazil during the years 2001-2002. The blue bars represent new municipalities joining BE each month, while the orange line represent the total number of municipalities in the program.

The program gave monthly transfers of R$15 (US$7) per child to poor families, conditional upon three requirements specified by the federal government: (1) the child comes from a household that earns no more than R$90 per capita per month, (2), the child must be enrolled in primary or lower secondary school with 85% attendance, (3) the child must be between the ages of 6 to 15 (Janvry et al., 2005). In order to avoid fertility incentives, the maximum limit was 3 children per family. Based on an assessment of municipality needs, program financing was decided by the federal government. However, these quotas were insufficient to meet local demand and there was heterogeneity in the targeting strategies. Due to the limited funding, additional criteria were made in several municipalities and as a consequence, eligible families were left out of the program. Targeting was significantly improved during the implementation of BF in 2003, but still involved some administrative difficulties and limited budgets. According to Soares (Soares, 2012), 9,6% of eligible families were not beneficiaries in 2004.

Although one of the listed objectives were to reduce child labor, the program included no conditions directly related to keeping children out of work. For a family with 2 children, monthly transfers would amount to a 33% increase of the maximum income. For the country, however, total spending on CCTs only represented 0.18% of total GDP in year 2002, and 0.36% in 2005, portraying clearly the great inequalities of the Brazilian economy. In 2003, Bolsa Escola was merged together with several other CCTs into Bolsa Familia. The conditions and transfers were the same as before, but the income threshold was adjusted up to R$100 (US$48). BF also included the predecessor Bolsa Alimentação (BA) , which was given for children under 7 years, conditional on health check-ups and vaccinations. An unconditional part for extremely poor families was added, providing a fixed monthly transfer of R$50 for households that earned less than R$50 (De Brauw et al., 2015). If they had children, the BE and BF variable benefits were added on top. The program thus expanded the number of beneficiaries and the size of the benefits, and additionally improved the targeting and selection process. Most of the first recipients were beneficiaries of BE, but about 1.6 million new families were added in year 2004. Information on household income and characteristics was self-reported and listed in a registry called the Cadastro Único. While the lack of verification of the applicants' information could make it possible for ineligible families to benefit, Lindert et al. (Lindert et al., 2007) found that the program was generally well targeted, reaching over 80% of the poorest in Brazil in 2006. Figure 5 shows the total number of registered families of the Bolsa-programs every year, from 1997 to 2004. Under BE there were around 5 million beneficiary families in total. The data shows a significant decrease in beneficiary families during the implementation of BF in 2003, where the total number of registered families decreased from with 1.5 mill. This is likely due to missing numbers in our dataset, an issue we explain further in section 4.2.

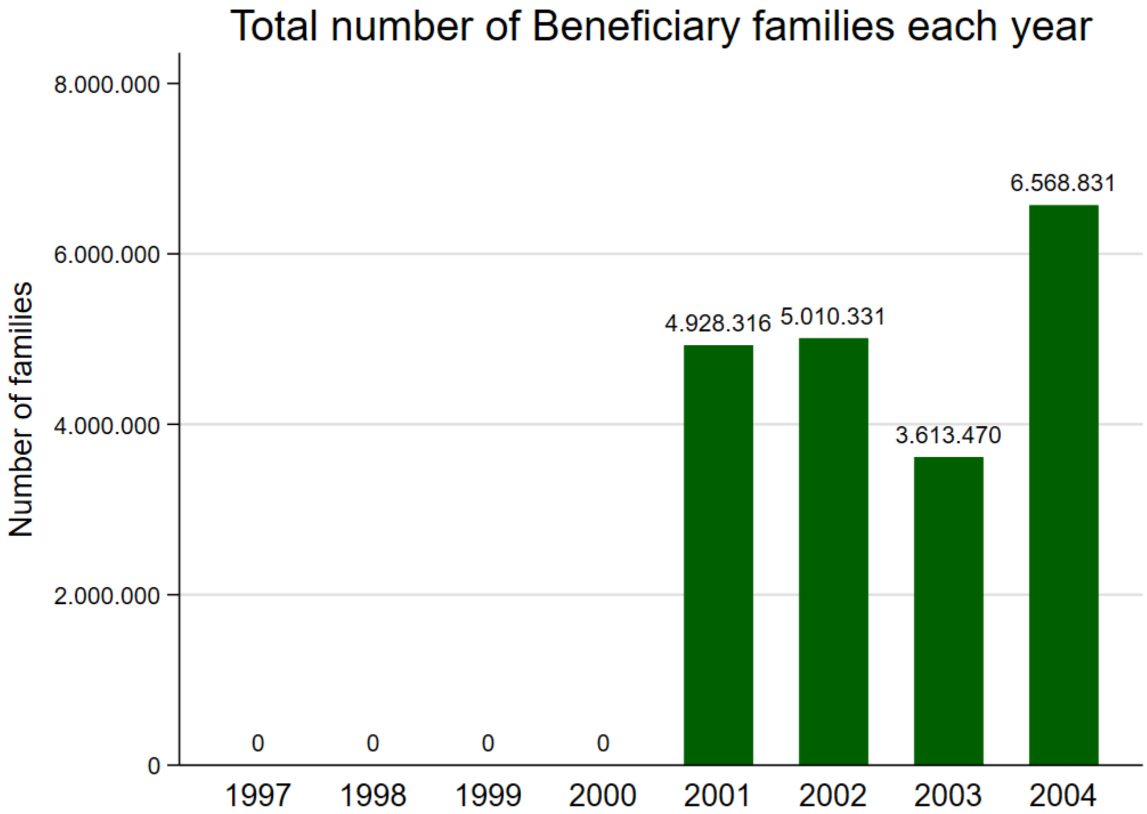

Figure 5: Total number of beneficiary families of Bolsa-programs

Note: The graph shows the number of families participating in the Bolsa programs (BE and BF) during the period 1997 – 2004. Implementation of BE on a federal level happened in year 2001, and transition to BF happened in year 2003. The number displayed above each bar represent the total number of families in the program that year.

3.3 Poverty in Brazil

In order to get a broader understanding on our findings, we will in this subsection describe more closely Brazil's socioeconomic conditions and the structure of the labor market. More specifically the importance of agriculture in the Brazilian economy, as this is relevant for deforestation. Further we relate these conditions to the Bolsa program, by giving some descriptive statistics of the beneficiaries, aiming to give a clearer picture of who they are and how they live.

With a GNI per capita of US$ 3 290 , Brazil was in 2001 defined by the World Bank as upper-middle income country (Prydz & Wadhwa, 2019). However, it is well recognized that this classification does not reflect a country's level of development and does not account for the large inequalities in income distribution in the country. In 2001, 11,6 % of Brazilian population lived below the international poverty line with less than US$ 1,9 per day (The World Bank Group, 2020b), and had a GINI measure of 58,4[5], ranking on top 10 countries with the highest level of inequality in the world (The World Bank Group, 2020a).

There are evidences that deforestation is closely linked to both poverty and agricultural activity (Barona et al., 2010) and household farming (Vosti et al., 2003). In Brazil, the poorest regions in the North and Northeast are also the ones who have most forest cover, as can be seen by comparing Figure 6 and Figure 7.

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[5] GINI is a commonly used measure of inequality, measuring the distribution of income among individuals or household in a population. The numbers range on a scale from 0 to 100 where 0 represents perfect equality.

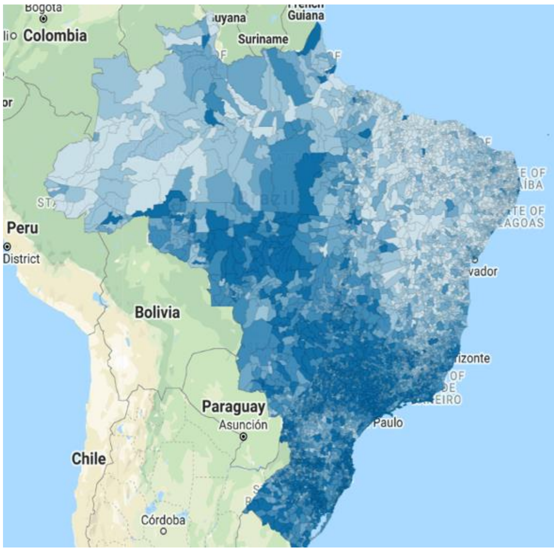

Figure 6 - Average per capita income in 2000.

Note: Map that shows the average per capita income in each municipality in Brazil in 2000. The darkest color represents the highest 20% quantile income level and lightest color represent lowest 20% quantile income level. Generated from (Atlas of Human Development in Brazil, 2020)

Figure 7: Total forest cover in Brazil in 2000

Note: Map that shows the total amount of forest in Brazil in 2000. The green areas represent forested areas. Generated from (MapBiomas Project, 2019)

According to ILO (ILO, 2012), agriculture is Brazil's largest employment sector, consisting of more than 21% of the country's total workforce in 2004. However, numbers were much higher among the BF beneficiaries, where 49% were employed in agriculture (Machado et al., 2011). This is over three times more than non-beneficiaries with only 12%. Considering the topic of this thesis it is interesting that many of the Bolsa beneficiaries are involved in the agricultural sector, an important driver behind deforestation in Brazil (Barona et al., 2010; Vosti et al., 2003; Wunder, 2001). Other beneficiaries are mostly employed in construction and service, representing 7% and 14% respectively, or in unemployment.

Brazil's agricultural labor force on average works longer hours and have lower wages compared to the overall Brazilian economy (ILO, 2012). Monthly earnings for agricultural workers were R$ 409 in 2003, compared to an average of R$ 885 real per month across the total economy. Lower wages might be explained by lack of regulations and social protection, but also as a consequence of high shares of child labor. When the BE program was implemented in 2001, 58% of children working, worked in agriculture. In the Brazilian context, child labor is defined as children aged 5-14 that are working, either as only occupation or working and studying (IPEC, 2001). On a national level the share of all children aged 5-14 years working, was 6,2%. Of the beneficiary children aged 10-17 years, 24% were by this definition in child labor, while the numbers were lower for the 5-9 group, with 4%. Child labor is closely linked to poverty, and 50% of children involved in child labor in 2004 were from families with a household income less than US$ 50 (Armand Pereira, 2010).

Beneficiary families are furthermore employed mainly in the informal sector, where the informality rate was 75% out of all beneficiary families, compared to 47% of Brazil's total employment(Machado et al., 2011). A general definition of informal employment is lack of decent regulations regarding workers' rights, including social protection and decent working conditions (ILO, 2018). This creates challenges for development and there are evidences of an "informality trap", indicating that chances of getting out of an informal job decline over time (Ulyssea & Szerman 2006).

In summary, Bolsa beneficiaries are mainly employed informally and in the agricultural sector. Children in poorer families are also vulnerable to child labor. As farming is also closely related to deforestation, it is interesting to estimate the effect Bolsa Escola and Bolsa Familia had on forest conservation. In the following chapters we will describe more closely the data and empirical approaches we use when answering this question.

4 Data

The following chapter describes the data utilized in order to investigate how the exogenous increase in income from Bolsa changes deforestation among the beneficiaries. Our analysis is mainly based on three data sets where we focus primarily on two variables: deforestation and Bolsa participation. We obtain panel data, reported on a municipal level with annual frequency. Data on deforestation is obtained from the MapBiomas Project (MapBiomas Project, 2019). Information on Bolsa beneficiaries are combined from two different programs, Bolsa Escola and its successor Bolsa Familia. Finally, we utilize population estimates and census from IBGE . From these data sets we obtain a balanced panel on 5 551 municipalities in Brazil[6], on annual frequency over a period from year 1997 to 2004. The years 1997 to 2000 are chosen as pre-program period to test for parallel trends, while we choose the years 2001-2004 as post-program period.

4.1 Data on land cover and transition

We obtain values for land cover and transition from the MapBiomas Collection 4 (MapBiomas Project, 2019). MapBiomas provide detailed data on land cover and land transitions for all 5 572 municipalities in Brazil on an annual frequency between 1985 and 2018. This data is generated from satellite images from the Landsat Data Archive, made available in the Google Earth Engine platform. Through the use of machine learning algorithms, the data is processed and classified according to 27 classes and sub-classes. The MapBiomas initiative is a collaboration between universities, NGOs and companies that released their first collection in 2016. Collection 4, released in 2019, includes a broader set of data than the early versions, and has been produced through the use of new approaches such as deep learning and sample collection for accuracy assessment.

The dataset is organized according to the six biomes: Amazon, Atlantic Forest, Caatinga, Cerrado, Pampa and Pantanal. There are three levels for classification of land cover and land use (LCLU). The five main classes included at the first level are (1) Forest, (2) Non-forest

[6] There were 5 561 municipalities in Brazil in 2001, but as 10 of these were not included in the BE dataset, we exclude them from the analysis.

natural formations, (3) Farming, (4) Non-vegetated areas and (5) Water bodies. See Figure A 8 for a full overview of the land cover classes in collection 4.

MapBiomas provides two different data sets, one for land cover and one for land transitions. The land cover data shows how many hectares of land is occupied by a certain class in a year, while the transition data maps transitions from and to the various classes between two years. For example, it will show specifically how many hectares of natural forest was replaced by pasture in a certain year. We assign these to the latter year, meaning that a transition between 1997-1998 is assigned to the year 1998.

We limit our data set to the years 1997-2004 and to the 5 551 municipalities that were consistent with the BE data set. From 2005, deforestation decreased drastically in Brazil due to government interventions, and comparing with this data may give misleading results (Godar, Gardner, Tizado, & Pacheco, 2014). From 1997 we only include forest cover, to be able to generate a lag for this variable in our analysis. Our tables and figures will not include deforestation estimates for this year.

In our analysis we use data on the classes Forest and Farming, and by this we include all categories of forest. We generate our deforestation variable from yearly transitions from level 1 Forest to level 1 Farming.[7] The reason we focus on transitions to farming is that there are multiple evidences of a close relationship between poverty and agricultural activity (Barona, Ramankutty, Hyman, & Coomes, 2010; Wunder, 2001). Another reason is that land used for agricultural purposes will not easily grow back to forest. As seen in Figure 8, farming also constitutes the largest share of total forest loss. Natural formation (grassland, wetland etc) represents the second largest share of deforestation. As it is not clear whether these arise from human activities or from natural causes, we do not include this in our analysis.

[7] Forest includes forest, savanna, mangrove and forest plantation. Farming includes pasture, agriculture and mosaic. See Figure A 8

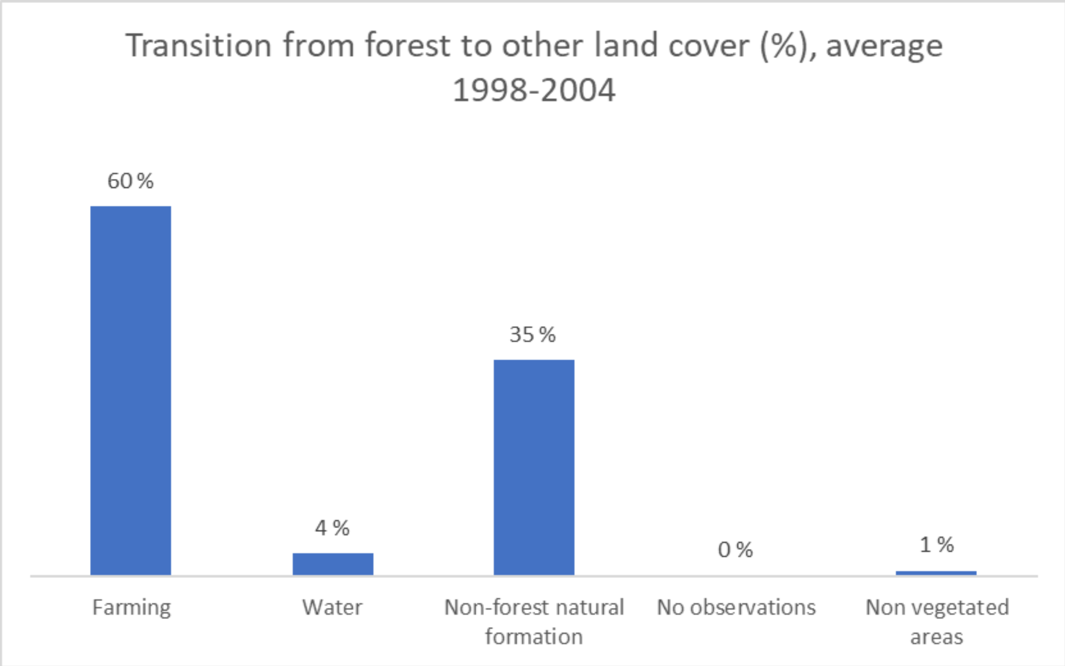

Figure 8: Average deforestation by categories, 1998-2004

Note: The figure shows the average percentage of total forest loss transitioned to each land use category during the years 1998-2004. The bars represent each of the categories in level 1 in MapBiomas classification 4 (see Figure A 8). Values are measured as average percentage of total forest loss transitioned to each category (MapBiomas, 2019).

Figure 9 **s**hows how the amount of land cleared for agricultural purposes remains at high levels although it has declined over the past decades. Most of the land is converted to pasture, which is closely related to the extensive cattle farming in the country, producing beef and milk. For the robustness check in section 6.4.2 we add two subcategories of farming, i.e. pasture and agriculture.

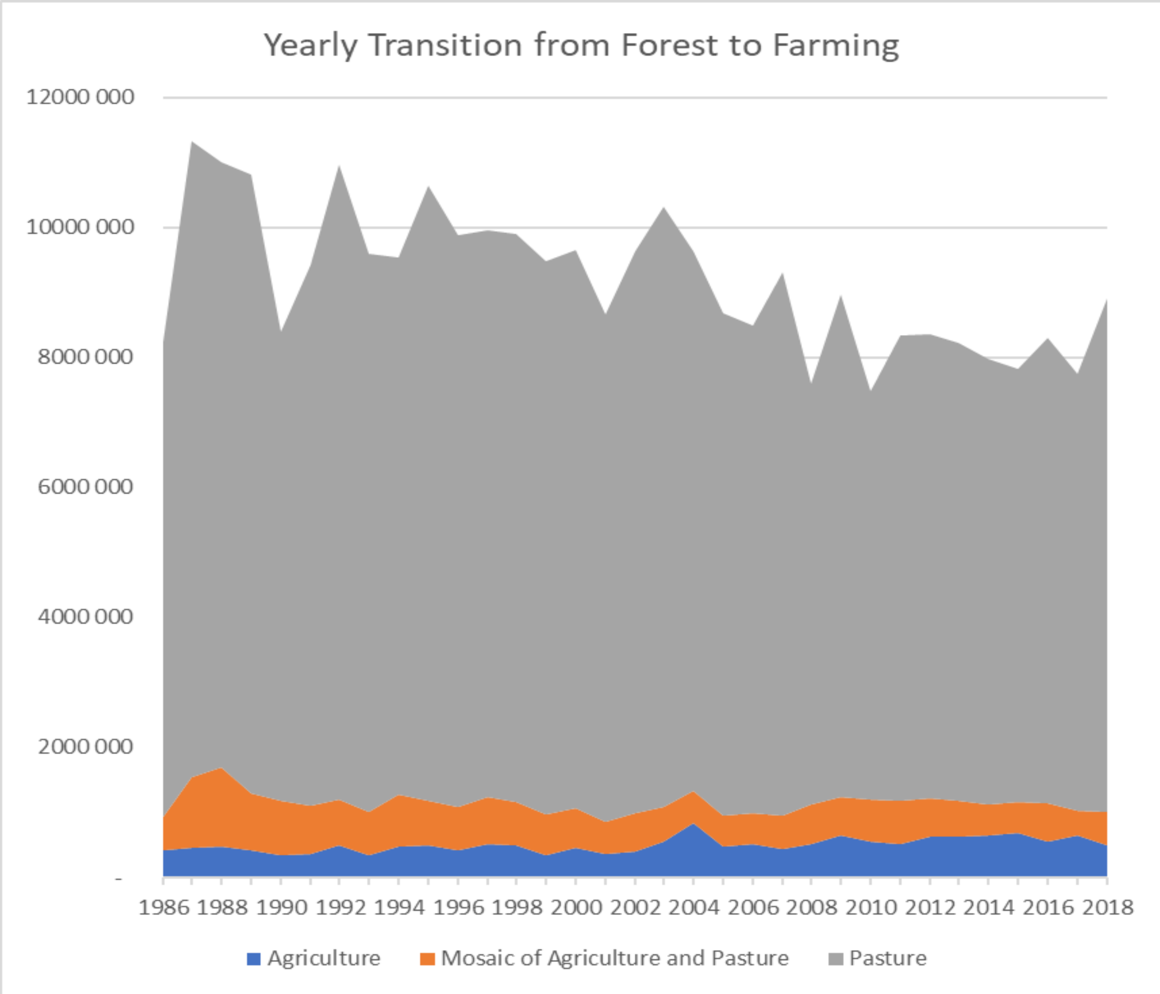

Figure 9: Historical trends in deforestation

Note: Graph of total land cover transitioned from level 1 Forest to Farming according to the three Level 2 subcategories of level 1 Farming in MapBiomas (See Figure A 8). Measured in hectares per year in the period 1986-2018.

4.2 Bolsa Escola/Familia data

In order to estimate the impact of the Bolsa program, we use data that shows the number of beneficiaries on a municipality level. It is consolidated from two different sources, one for the Bolsa Escola program for the year 2001-2002, and another for the Bolsa Familia program from 2003-2004. As explained in section 2, the BF program was an expanded version of BE. We received data on the beneficiaries from the BE program from professor Ana Lucia Kassouf[8]. These data were collected by the Ministério da Educação and covered the number of families and children receiving benefits within December 2002 in 5 551 municipalities. It also gives information on which date Bolsa Escola started in each municipality. If the date of implementation was in 2001, we assume that all families joined the program that year. This is according to the methodology of Glewwe and Kassouf (2012). The municipalities in which the program was implemented in 2002, we assigned zero recipients in 2001, as we also did for all municipalities in the years 1997-2000. We do not have information on the beneficiaries from the previous versions of BE that were implemented in a few municipalities before the federal reform, and therefore do not include this in our analysis. By December 2002, BE had been implemented in 5 551 of 5 561 municipalities. The remaining 10 were not included in the data set we received. Three of the municipalities participating in the program did not report date of implementation, and these were therefore included from the year 2002.

From October 2003 the BF program was implemented, and two years later, it had reached over 8 million households throughout Brazil (Janvry et al., 2005). Data for BF was received directly from the Departamento de Benefícios, and contained monthly data for beneficiaries in 5 570 municipalities from 2003 and 2004. Comparing to the data for Bolsa Escola program, this dataset only reports the number of families, not the number of children. Another difference is that the numbers were reported as total beneficiaries for each month. To make it compatible with our BE data, we therefore choose only the number of beneficiaries from December each year. We also excluded 19 municipalities that were not present in the BE dataset.

As seen in Figure 5 in section 5.2, the numbers of recipients of Bolsa Familia in 2003 were found to be lower than the numbers of Bolsa Escola from 2002. This is concerning, especially since Glewwe and Kassouf (2012) reported that the number of recipients increased from year 2002 to 2003. We suspect that there may be some recipients that were not registered in the 2003 database, but who continued to receive benefits from the previous database system. However, this need not be a problem for our analysis since our main DID estimates only rely

[8] These data were used by (Glewwe & Kassouf, 2012) to estimate the impact of the Bolsa Escola/Familia on school participation outcomes.

on the number of beneficiaries from 2002 for identification. In our generalized DID we also control the robustness for excluding 2003.

4.3 Population data

In order to obtain a measure of how big impact the Bolsa program had in each municipality, we included additional population estimates from IBGE (2020c). These are calculated using the Population Projections for Brazil and Federation Units and growth estimates from each municipality, based on the two last censuses. Censuses are performed once every 10 years. In the census from 2000 we also find average family sizes for each municipality (IBGE, 2020b). These are used to generate an estimation of the number of families to be found in each municipality in each year, in order to measure the percentage share of beneficiaries. It is not possible to gain these estimates on a municipality level between censuses. We therefore assume that the average from the year 2000 is representative for the time period of our study. Data on family sizes on a federal unit level shows that these only increased a little from 2000 to 2005 (see Figure A 10). An increase in family sizes after 2000 would mean that we might overestimate the total number of families in municipalities somewhat, and thereby underestimate the impact of Bolsa slightly.

We combine the aforementioned data in STATA in order to obtain a complete panel data set, and we use the municipality code as the identifier[9]. Further, we base our empirical strategy exclusively on the 5 551 municipalities reported in the BE data set. In 2002 there were a total of 5 561 municipalities in Brazil, which later changed to 5 570, meaning that our dataset covered 99,6 - 99,8% of the total number. We therefore do not expect the missing data to lead to a biased estimation.

[9] In order to make the municipality codes compatible for merging, we removed the last digit in the MapBiomas data.

5 Empirical Method

In this master thesis we use panel data on forest cover over the period from 1997-2004 to explore changes in local deforestation as a result of Bolsa Escola/Familia. In this section we explain in detail our choice of the DID-approach as a quasi-experimental empirical strategy. We take advantage of our panel data properties to control for individual heterogeneity between municipalities. We explain our treatment identification strategy, and present three models to estimate program impact on deforestation; (1) a simple DID-approach estimating the Average Treatment Effect on the Treated (ATT) (2) an event study and (3) a generalized DID with heterogeneity in treatment. In all models we are able to estimate the average treatment effect on the treated.

5.1 Difference in Difference Framework

The aim of our analysis is to determine the direction and magnitude of the causal effect of Bolsa on deforestation. However, a simple comparison of deforestation rates between municipalities would likely be subject to endogeneity issues. This is due to the fact that the Bolsa programs were not implemented randomly, but rather on the basis of monthly income and school enrollment criteria, described more detailed in section 3.2. Municipalities with poorer families and a higher number of children are likely to have different deforestation levels than others even without the implementation of the Bolsa program, i.e. the units in our study are heterogenous. Figure 12 and Table 1 in section 5.2 confirms that municipalities with higher share of Bolsa beneficiaries differed in deforestation levels and on other indicators. A cross-sectional ordinary least squares (OLS) estimation of the relationship between participation in Bolsa and deforestation would therefore suffer from a selection bias from unobserved characteristics like income, demography, resources, labor markets or the quality of the municipal administration (Wooldridge, 2014). In Equation (1) below, we show this more formally, where a_i represents these unobserved effects. The dependent variable is y_{it}, which in our study is the natural logarithm of deforestation. Failing to control for correlation between a_i and the treatment variable, x_{it}, will results in a correlation between the independent variable and the error term. This is also called an omitted variable bias, and violates the zero conditional mean assumption (Wooldridge, 2016).

$$y_{it} = \alpha + \beta_2 x_{it} + \underbrace{a_i + \varepsilon_{it}}_{error} \quad (1)$$

Having panel data allows us to apply a difference-in-difference framework to control for unobserved effects that are constant over time. This method is one of the most common methods within economics to evaluate the effects of public interventions or other treatments on some relevant outcome variable (Abadie, 2005). Through controlling for initial differences between municipalities, the selection bias is removed.

We use fixed effects (FE) estimation to control for the time-invariant differences between the municipalities. This is done through time-demeaning the variables. Equation (2) illustrates the FE transformation, which removes the omitted variable bias resulting from ignoring time-constant effects. The fixed effects, a_i, are removed through subtracting the average of each observation *i*. Equation (3) shows the new model with time-demeaned variables.

$$y_{it} - \bar{y}_{it} = \alpha + \beta_2 (x_{it} - \bar{x}_{it}) + a_i - a_i + \varepsilon_{it} - \bar{\varepsilon}_{it} \quad (2)$$

$$\ddot{y}_{it} = \alpha + \beta_2 (\ddot{x}_{it}) + \ddot{\varepsilon}_{it} \quad (3)$$

While we have controlled for unobserved individual effect, we also expect unobserved time effects in our data. National time trends in deforestation in Brazil may arise from variations in eg. product prices and policy implementation. Failing to control for this, could lead to spurious correlations, where the variation in deforestation levels and in Bolsa beneficiaries over time, creates a biased estimation. By adding year dummy variables, denoted by I_t, we remove any time-variable unobservable changes that affect all the municipalities. After controlling for both time-fixed effects and municipality-fixed effects through the use of dummies, we obtain the estimation in equation (4). β_2 is now the difference-in-difference estimator giving the ATT of the Bolsa program.

$$\ddot{y}_{it} = \alpha + \beta_2 (\ddot{x}_{it}) + I_t + \ddot{\varepsilon}_{it} \quad (4)$$

5.2 Treatment vs Control

Evaluations of public interventions usually include a control group that is not directly affected by the program. This non-treated group helps estimate the counterfactual outcome that would have happened without the program. However, in Brazil the BE program was quickly rolled out to the whole country. Already in the year the program was implemented, only 81 of the 5 551 municipalities in our data had no beneficiary families and in 2002 this number was reduced to zero[10]. Because deforestation is only registered at a municipal level, we cannot use the methodology of comparing beneficiary and non-beneficiary families either, as they do in de Brauw et al (2015) and Ribas and Soares (2011). However, the variety in the intensity level of treatment was large, which means that the amount of exogenous income in a municipality varied widely. While richer municipalities had few eligible families, the poorer municipalities had up to 86% of families enrolled. Where the total income increase caused by Bolsa was small, we would expect changes in deforestation due to changed demand or production patterns to be small. We therefore define the treatment group as municipalities where the impact of the Bolsa program was relatively large.

In order to determine which units had "a large impact" from the program, we consider the number of Bolsa beneficiary children within the municipality as a reasonable measure. More specifically we use the percentage share beneficiary children of the total population. The benefits each family received from the program varied with the number of children and this therefore gives us a more precise measure of the size of the program cash transfers to each municipality. We expect that the number of children per family, and thereby the amount of benefits per family, may have varied across municipalities. While the BF data only provides information on the number of beneficiary families, the BE data also describes the number of beneficiary children, and makes it possible to use this precise indicator for determining the treatment group. We use the year 2002, the first year of full BE coverage, to define the treatment group. To determine the threshold for high impact, we consider the density plot of the share of beneficiary children in the population, as seen in Figure 10. We find indications of a bimodal distribution in our data, where it seems like one group of observations had a higher

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[10] In our analysis, we leave out 10 municipalities as we do not have information on all 5 561 municipalities in Brazil in 2001-2002 the BE data set. It is possible that these were excluded because they had zero recipients in 2002.

share of beneficiary children than the other. Municipalities where more than approximately 8% of the population were beneficiary children in the year 2002 seem normally distributed around a mean of about 11%, while the rest seems distributed around 5%. We therefore define the treatment group as the municipalities where the percentage share of beneficiary children in the total population was equal to or greater than 8% in 2002.

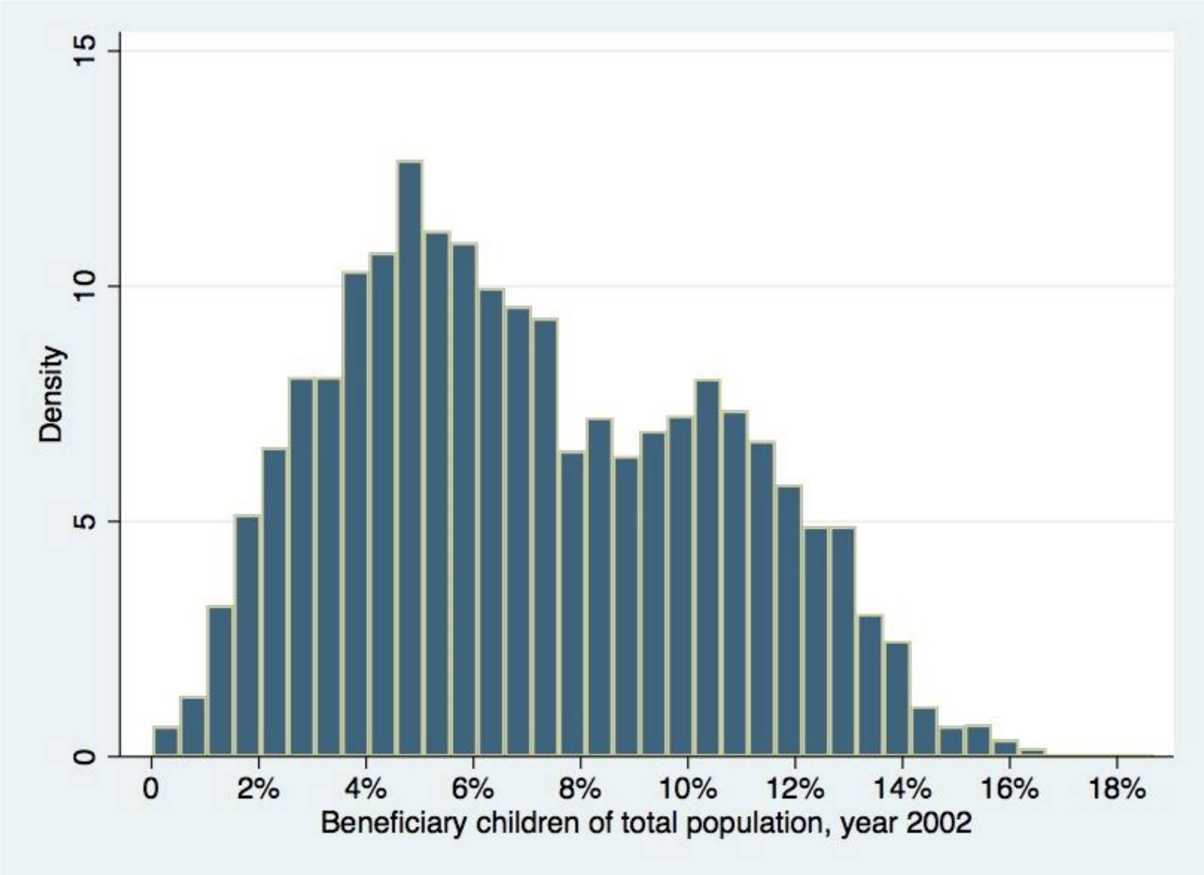


Figure 10 – Density plot of beneficiary children as a share of the total population

Note: The figure shows the density of observations in beneficiary children as a percentage share of the total population in the municipality, in the year 2002. The source of the population estimates is (IBGE, 2020c). The number of beneficiary children in each municipality is found in the BE data set from the Ministério da Educação.

For the simple DID we define treatment as constant over the program period. Because the program was continuous, the number of beneficiary families in each municipality could vary from one year to another. In order to confirm whether the definition of treatment is suitable for the whole period of our study, we examine whether the share of beneficiary families was higher in the treatment group in all years. We therefore regress the effect of treatment on the share of families that were Bolsa beneficiaries, to confirm that the groups differed from each other also after 2002. Figure 11 shows a visual representation, with 2000 as a baseline. The full regression results are found in Table A 1. The percentage share of beneficiary families is shown to be approximately 14% higher in the treatment group in the first two years of the program and increases somewhat after the transition to BF in the third year. We therefore conclude that the treatment group had a higher increase in income resulting from the CCT than the control group in all the program years in our dataset. In the robustness analysis in section 6.4.3 we will also test the results for using different boundaries to separate the two groups.

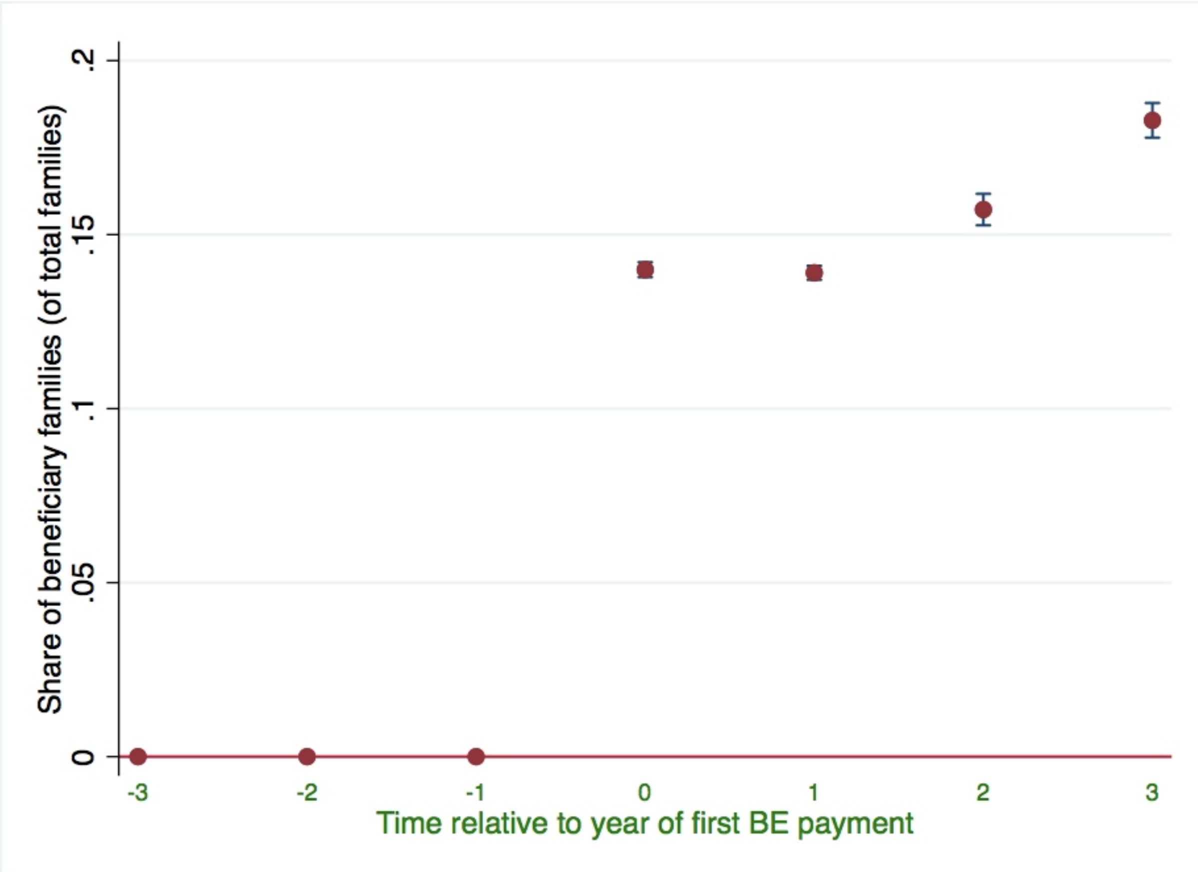


Figure 11 – Estimated share of beneficiary families in the treatment group, compared to the control group.

Notes: The plot shows the estimated coefficients and confidence intervals of the effect of treatment on the share of beneficiary families (of total families) prior to, during and after the first year of receiving BE payments. The year before the main roll-out of BE ("-1") is the omitted category. This is year 2000. Vertical bands represent 95 percent confidence intervals. Standard errors are clustered at the municipality level.

Of the 5 551 municipalities in our sample, 2 099 municipalities are defined as treatment group and 3 452 as control group, representing a share of 37,8% and 62,2% respectively. Table 1 presents summary statistics comparing averages of land cover characteristics and Bolsa participation in the municipalities in the treatment and control group. Average levels of deforestation initially appear similar between the two groups, but standard errors are very high, giving indication of extreme values. Transforming deforestation to natural logarithm reveals that the treatment group has a higher mean, which also implies a higher potential for reducing deforestation. The population number is on average higher in the control group, but standard errors show great variations within the groups. Consistent with Figure 11, we find that the treatment group has almost 14 percentage points higher average share of beneficiary families in year 2002. The t-test confirms that the population in the treatment group on average is more exposed to the Bolsa program than the control group. The difference in beneficiary children as a percentage share of the population is significant on a 0,01%-level.

Table 1 - Descriptive statistics on Treatment and Control group

	(1) Control (N=3.452)	(2) Treatment (N=2.099)	(3) Mean Difference (2) - (1)	(4) Total	(5) P-value of mean difference
Information on land cover and population, year 2000					
Deforestation to farming (hectares)	1 731 (4 656)	1 732 (3 630)	1,0	1 731 (4 297)	0,993
Log deforestation to farming	5,45 (2,06)	6,19 (1,71)	0,73***	5,73 (1,97)	0,000
Areal (hectares)	155 331 (601 077)	145 770 (485 102)	- 9 561,1	151 716 (560 027)	0,537
% deforestation to farming of total deforestation	84,5 % (21%)	81,3 % (24%)	-3,2 %***	83,3% (22%)	0,000
% forest of total areal	29,5 % (24%)	49,1 % (28%)	19,6 %***	37,0% (27%)	0,000
% farming of total areal	62,1 % (27%)	44,8 % (30%)	-17,3 %***	55,6% (30%)	0,000
Population	39 502 (228 198)	15 040 (17 001)	- 24 462,4***	30 190 (180 272)	0,000
Information on Bolsa participation, year 2002					
Number of beneficiary families	869 (3 284)	957 (1 051)	88	903 (2 669)	0,233
Number of beneficiary children	1 382 (4 959)	1 665 (1 781)	283*	1 489 (4 064)	0,012
Number of beneficiary children per family	1,62 (0,16)	1,76 (0,14)	0,14***	1,67 (0,08)	0,000
% of beneficiary children (of population)	4,78% (2%)	10,86% (2%)	6,08%***	7,1% (0,3)	0,000
% of beneficiary families (of total families)	10,5 % (4%)	24,4 % (5%)	13,9%***	15,8% (8%)	0,000

Note: Description of the municipalities in treatment and control group on some chosen characteristics. Treatment is defined as municipalities with a high percentage (>8%) of the population being Bolsa beneficiary children. The numbers are measured in mean values on municipality level. Column (3) shows the difference in means between the two groups. Column (4) shows the means of the whole sample of municipalities. Column (5) shows the P-value from the two-sided-t-test for the mean differences in (4) Standard errors reported in parentheses. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$

As described earlier, our DID approach takes advantage of comparing deforestation outcomes from a treated group to the counterfactual outcome. We thus need to ensure that the group that was not treated is relatively similar to the treated in two respects (Wooldridge, 2013). The first is the common trend assumption which require that we need to observe parallel trends in the outcome variable between the municipalities in the treatment and control group. The reasoning behind is that we cannot prove that the differences in deforestation between the two groups would have moved in tandem in the absence of the Bolsa program. However, if we can observe that they followed parallel trends in deforestation prior the program, we can make the assumption that it would also be the case if both groups continued as usual. The common trend assumption is only required to hold for the outcome variable of interest (Landaud, 2019), which we have defined as natural logarithm of deforestation from forest to farming. We use the year 1997-2000 as pre-program period to test for parallel trends. In Figure 12 we illustrate the outcome variable in the two groups during the analysis period and observe clear parallel trends prior to the implementation of BE in 2001. The figure also illustrates the findings from Table 1 of different initial values of log deforestation. In the year the program was rolled out it seems like the treatment group lowered their deforestation rates more than the control group. Figure 13 shows the same trend as a difference from each group's starting point in 1998. It shows clearly that deforestation fell more in the treatment group than the control group in 2001, an effect that seems to have lasted throughout the period in our study. In section 6.2 we test formally for the parallel trend assumption.

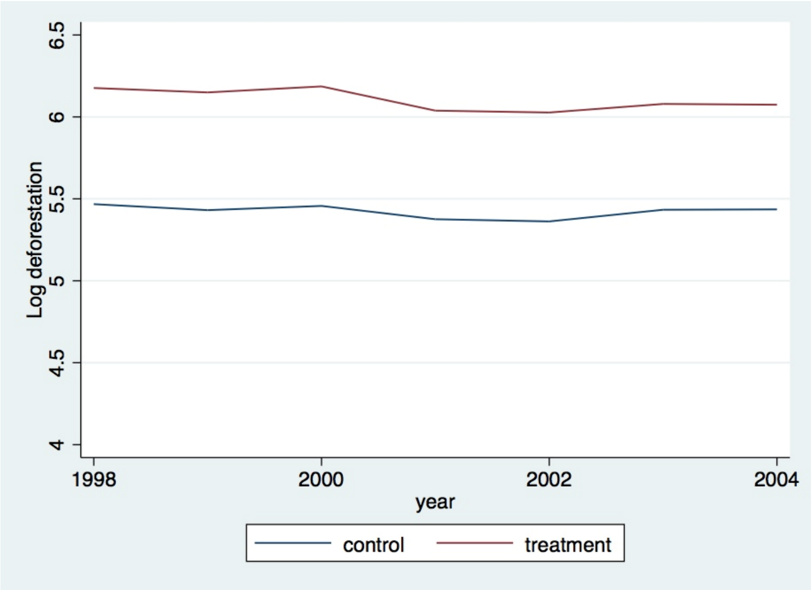


Figure 12 – Log deforestation in the control and treatment group

Notes: The figure plots averages of the natural logarithm of deforestation in the treatment and control group, year 1998 - 2004. Deforestation is defined as hectares of land that transitioned from forest to farming between year t and t-1. Treatment is defined as municipalities with a high percentage (>8%) of the population being Bolsa beneficiary children. The treatment areas always have higher deforestation than the control group. The trends are parallel before the implementation of BE in year 2001.

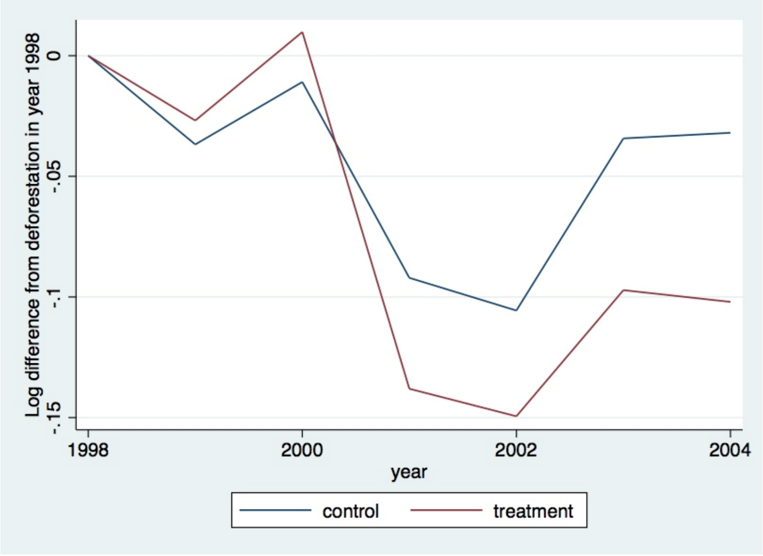


Figure 13 - Log deforestation, as change from year 1998

Notes: The figure plots averages of the natural logarithm of deforestation in the treatment and control group between 1998 and 2004, using 1998 as baseline. The y axis shows the difference in log points between the group's deforestation in year t compared to the value for the same group in 1998. Deforestation is defined as hectares of land that transitioned from forest to farming between year t and t-1. Treatment is defined as municipalities with a high percentage (>8%) of the population being Bolsa beneficiary children. There seems to be a larger decrease in deforestation in the treatment group average in 2001, which is the year of BE implementation.

The other important assumption is that there should be no anticipation, i.e. that municipalities should not be able to impact whether they were placed in the treatment group or not. The financing to each municipality was decided on national level based on the three main program criteria described in section 3.2 (Janvry et al., 2005). We can assume that the municipality administration did not have possibility to impact this decision, and therefore not affect the number of beneficiary children of the program. Time-invariant differences in administrative capacity that may have affected the efficiency of distribution are also controlled for by our FE estimator. Finally, the rapid roll-out of the program excludes most of our concerns of whether families would be likely to move, as eligible families would gain the same treatment in any municipality.

5.3 Empirical Model

We estimate the impact of Bolsa on deforestation by implementing the following empirical models, (1) a simple DID analysis, (2) an event study, (3) a generalized DID with heterogenous treatment intensity. In this section we describe each in further detail.

5.3.1 Empirical Model for Simple DID Analysis

To estimate the average treatment effect on treated of the Bolsa program, we use the following empirical specification:

$$ln(DF_{it}) = \alpha + \beta_1 Treatment_i * DPost_t + \delta\, FC_{it-1} + I_i + I_t + \varepsilon_{it} \tag{5}$$

where the dependent variable $ln(DF_{it})$ it the natural logarithm of deforestation in municipality *i* and year *t*. Deforestation is here defined as the total forest area (ha) that transitioned to farming land between year *t-1* and year *t* (see section 4.1.) We use natural logarithm to control for skewness in observations due to extreme values. As seen in Figure A 11, the distribution of annual deforestation is heavily skewed towards the left and show evidence of outlier observations with extreme values. By using the logarithmic form, the range of observed values of deforestation is narrowed and we obtain a more normal distribution (see Figure A 12). In A 13, we also see evidence of extreme values in scatter plots between deforestation and the number of Bolsa families that may render linear functions unable to capture the true relationship. Using the logarithmic model means that we assume that there is a constant percentage effect of Bolsa on deforestation on municipality level.[11] In the robustness analysis in section 6.4.1, we test whether the linear form is more appropriate and find that this does not give significant results.

β_1 shows the Average Treatment effect on Treated (ATT) of Bolsa on annual deforestation in the municipalities that received more income from the CCT. $Treatment_i$ is a dummy variable that equals one for municipality *i* if the percentage share of beneficiary children in the municipality was equal to or greater than 8% of the total population in 2002, and zero for municipalities with a smaller share of beneficiary children. $DPost_t$ takes one as value for the years that were post program implementation, i.e. year 2001 to 2004. The interaction variable thus takes one for municipalities in the treatment group in the years 2001-2004, and zero otherwise. This is done for all municipalities, although 9 of the 2 099 municipalities in the treatment group in fact did not implement the program before year 2002 (see Figure A 18). Later, we will however expand the framework to a generalized DID to allow treatment to vary between units and across years.

To increase the precision of our estimates, we include lagged forest cover as an independent control variable, denoted by FC_{it-1}. This variable includes information on the total forest cover in each municipality for the previous year. In time-series analysis, lagged independent variables are often used in policy analysis to account for historical factors of a municipality that cause current differences in the dependent variable, which are difficult to account for in other ways (Wooldridge, 2014). We reason that high levels of remaining forest cover in a municipality *i* in year *t-1*, can have an impact on deforestation levels in year *t*, since there are then many trees available to cut down. This is also supported by the forest transition theory, which suggests that share of forest is potentially endogenous to other factors that lead to deforestation (Angelson 2007, Robertsen 2012). For example, municipalities experiencing limited forest areas might more easily impose regulations regarding degradation of forest. Figure A 14 and Figure A 15 shows how annual deforestation to farming is negatively correlated with remaining forest cover in our data set.

[11] One limitation when using log form, is that deforestation cannot take the value zero or be negative. We have only seven municipalities with zero deforestation at some point, and we control for this by adding +1 and using ln(DF+1). Since 1 ha is still very little, and our data contains very few zero-values, results will not be much affected and can be interpreted as usual (Wooldridge, 2016).

Finally, we include municipality fixed effects, I_i, that capture time-invariant differences between the units, and year fixed effects, I_t that control for yearly shocks to deforestation across the country. When we have panel data of observations, clusters are very likely to be observed, meaning some municipalities might be identical or very similar within a cluster. Therefore, we use clustered standard errors at municipality level to control for serial correlation in our regressions.

5.3.2 Empirical Model for Event Study

We apply an event study model with leads and lags. This allows us to control whether the groups followed parallel trends before program intervention. In addition, it allows for changes in the effect over the years and shows whether the impact of the program was persistent. The empirical specification for the event study is seen in equation 6.

$$ln(DF_{it}) = \alpha + \sum_{k=-3}^{3} \beta_k \ Treatment_i + \delta \ FC_{it-1} + I_i + I_t + \ \varepsilon_{it} \qquad (6)$$

where $Treatment_i$ is a dummy variable that equals to one if the municipality is in the treatment group, and β_k is the average difference between the treatment and the control group compared to the the year before the first BE payments.

5.3.3 Generalized DID with heterogenous treatment intensity

Finally, we expand our analysis to estimate the impact of varying the number of Bolsa beneficiaries. We observe great variation in beneficiaries between municipalities and between years, and therefore expand the definition of treatment to mean any change in the percentage share of beneficiary families. This analysis can be seen as a dose-response estimation, where we vary the «dose» of how many families are included in the program and study the effect on deforestation. We use the share that beneficiary families constituted of the total number of families[12] as the independent variable, since this number is available for all years in our data set. The main empirical model for the generalized DID is described in equation 7.

$$ln(DF_{it}) = \alpha + \beta_1 \,\%\, Bolsa + \delta\, FC_{it-1} + I_i + I_t + \varepsilon_{it} \quad (7)$$

β_1 shows the impact of increasing the share of beneficiary families by one percentage point. The *%Bolsa* variable is equal to $\frac{Nr\ of\ Bolsa\ families}{Total\ nr\ of\ families}$, at municipality level. The results are useful for policy recommendations as it describes the impact of expanding the program to include more families.

[12] The total number of families is estimated by dividing population estimates in year *t* on the average household size in the municipality *i* in year 2000.

6 Results and Analysis

In this section we present the results of our estimations, according to the empirical strategy presented in the previous chapter. We begin with our simple DID estimation that shows the average treatment effect on the treated municipalities over the whole program period, before we expand the analysis with an event study. Our treatment group is defined as the municipalities with the highest impact from the program, i.e. those where at least 8% of the population were beneficiary children in 2002. We continue with an event study, where we include leads and lags to treatment and formally verify the assumption of a parallel trend. Finally, we allow for differences in treatment among municipalities and use a generalized DID framework to estimate the impact of increasing the share of beneficiary families with 1 %. After presenting the results, we do a robustness check, where we investigate the effect of changing the dependent, independent and control variables.

6.1 Results of the Simple DID estimation

We begin our analysis by estimating the ATT by the use of the treatment*Dpost variable as seen in equation (5) in section 5.3.1 above. Table 2 shows the results of the estimation and demonstrates that deforestation fell by 7,61 percentage points[13] in the municipalities with a high share of beneficiaries. The total deforestation in the treatment group was 13,6 million ha during the program years in our study (see Table A 7). We thus calculate that the decrease in deforestation translates to 1,2 million hectares less deforestation between 2001 and 2004. These results imply that the Bolsa CCT programs reduced the pressure on forests within municipalities in Brazil. For the DID analysis to be valid, the parallel trend assumption needs to hold. The next subsection therefore expands the study through the use of leads and lags in the estimation.

[13] $e^{0.0733}-1 = 0.0761$

Table 2 – Simple DID Estimation of Treatment Effect.

	Ln Deforestation
Treatment*Dpost	-0.0733***
	(0.0131)
Lag ln forest cover	0.00000609***
	(0.00000129)
Constant	5.141***
	(0.126)
N	38 828
R^2	0.016

Notes: The dependent variable is the natural logarithm of deforestation, defined as hectares of land that transitioned from forest to farming between year t and t-1. Treatment is a dummy variable that equals one in all years if the municipality has a high percentage (>8%) of children receiving Bolsa in the total population, and zero otherwise. Dpost is a dummy variable that equals one during and after the program implementation in year 2001. The specification includes municipality fixed effects and year fixed effects. Standard errors clustered at municipality level are in parentheses. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$

6.2 Results of the Event Study

We expand on the model by interacting treatment with year dummies. Figure 14 depicts the effect that treatment had on deforestation each year, with 2000 as a baseline. Total estimation results are found in table A.5 in the appendix. The results show that the effect of Bolsa was already profound in the first year of program implementation, and that it persisted during the time of the study. There is some indication that the deforestation was reduced further in 2003, two years after the implementation of BE. This would be consistent with the increase in the share of beneficiaries observed in the treatment group in Figure 11, section 5.2. The estimated treatment coefficient increased from approximately -6,5% in the first two program years to about -9% in the third and fourth year. The analysis furthermore confirms that the two groups followed parallel trends in the pre-program years, indicating that the data is suitable for establishing the counterfactual.

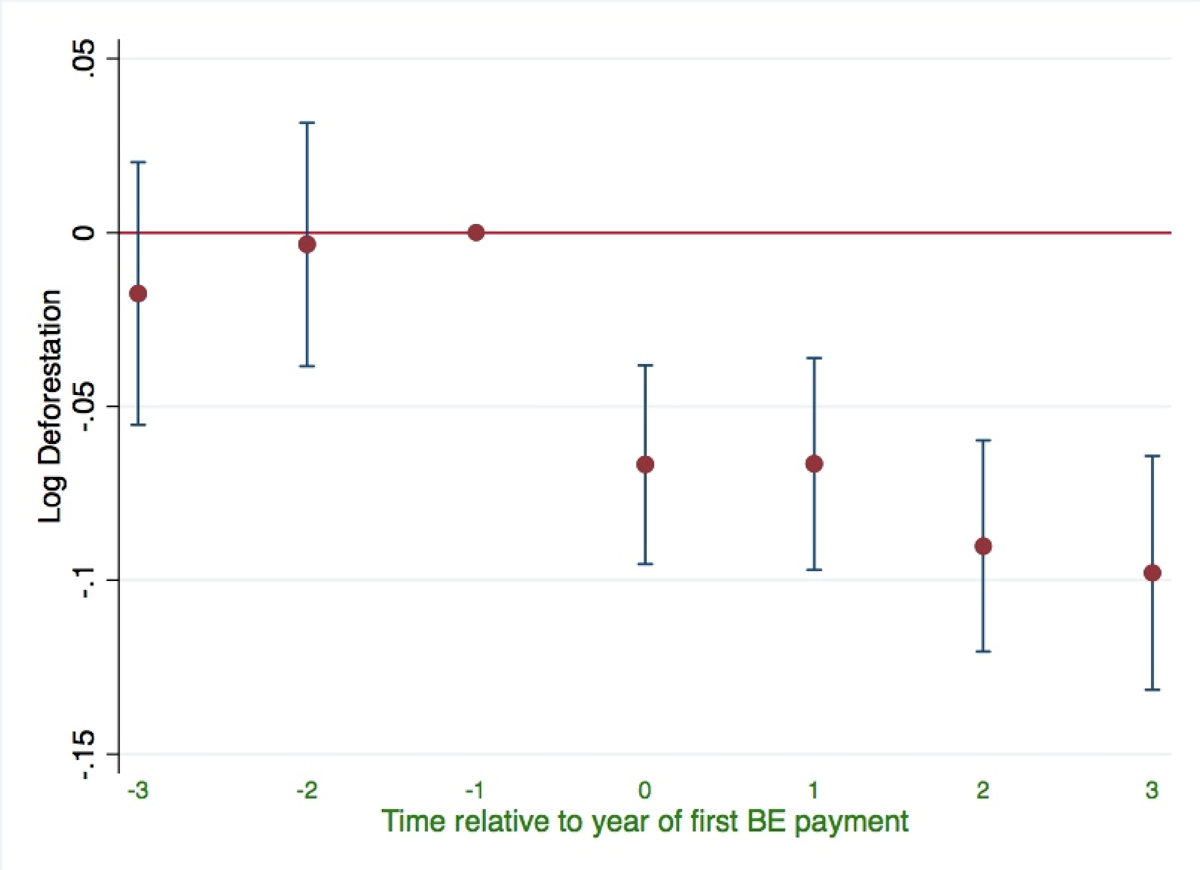


Figure 14 – Estimated effect of treatment on deforestation around implementation of BE

Notes: The plot shows the estimated coefficients and confidence intervals of the effect of treatment on the natural logarithm of deforestation. Deforestation is defined as hectares of land that transitioned from forest to farming between year t and t-1. Treatment is a dummy variable that equals one in all years in municipalities where the children receiving Bolsa constituted a high percentage (>8%) of the total population in year 2002, and zero otherwise. The figure shows the effect prior to, during and after the first year of receiving BE payments, i.e. year 2001. The year before the main roll-out of BE ("-1") is the omitted category. The specification includes municipality fixed effects, year fixed effects and lagged forest cover as a control variable. Vertical bands represent 95 percent confidence intervals. Standard errors are clustered at the municipality level.

6.3 Generalized DID with heterogenous treatment intensity

Finally, we use the whole variation in our dataset to estimate the impact of increasing the share of beneficiary families in a municipality by one percentage point. We estimate equation (7) as described in section 5.3.3. Results are shown in

Table 3. Column (1) shows the effect of increasing Bolsa beneficiaries as a share of population with one percentage point in our GDID model. Increasing the share of beneficiaries by 10% is

associated with a 1,73% decrease in deforestation[14]. Column (2) shows the same estimation excluding the data from year 2003 due to concerns of possible missing data in the BF data set, as explained in 4.2. Estimations do not change significantly, indicating that potential missing data does not affect the treatment effect. In column (3) we investigate the effect of including a square variable, in order to test whether a non-linear relationship is more suitable. We do not find that the square coefficient is significant, and the precision of our estimates is reduced. In column (4) we include two lags to study year effects on treatment. This shows that lagging the variable may give a larger effect of treatment, associating a 10% increase in beneficiaries with a 4% decrease in deforestation two years later. However, this result should be viewed with caution as we only have four program years in total.

Table 3 – Estimated effects of GDID with heterogenous treatment intensity

	Ln Deforestation			
	(1)	(2)	(3)	(4)
	All years	Excluding 2003	All years	All years
% Bolsa	-0.00173***	-0.00174**	-0.00269*	-0.000270
	(0.000518)	(0.000566)	(0.00125)	(0.000651)
% Bolsa ^2			0.0000221	
			(0.0000261)	
L. %Bolsa				0.00000300
				(0.000739)
L2. %Bolsa				-0.00408***
				(0.000888)
Constant	5.146***	5.147***	5.146***	4.851***
	(0.126)	(0.121)	(0.126)	(0.180)
N	38823	33276	38823	27729
R^2	0.015	0.017	0.015	0.024

Notes: The dependent variable for all estimates is deforestation, defined as hectares of land that transitioned from forest to farming between year t and t-1. The coefficient on % Bolsa represents the effect of an increase of 1% of beneficiary families in a municipality. All specifications include municipality fixed effects and year fixed effects. Standard errors clustered at municipality level are in parentheses. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$

[14] $(e^{0.00173}-1) *10=0,0173$

6.4 Robustness analysis

In this section we test the robustness of our analysis, by changing the dependent and independent variable and adding additional control variables.

6.4.1 Testing the assumption of a logarithmic relationship

First, we relax the assumption that the relationship between Bolsa and deforestation is logarithmic, and explore what happens to the three estimations if we use the deforestation variable in its linear form. Results are found in Table A 3 and show that the linear form of deforestation does not give significant results, except for three of the years in the event study. As discussed earlier, this is most likely due to extreme values in the deforestation variable.

6.4.2 Effects of changing the definition of deforestation

Furthermore, we wish to see if the effects we find through the event study are valid if we change the definition of deforestation. As explained in 3.1, we have defined deforestation as changes from forest to farming land in the most general term, by using level 1 in the MapBiomas classification (see Figure A 8). In Table A 4, we investigate what the estimated coefficients are for other forms of deforestation. First, we change our deforestation variable to a wider definition, by using transition from forest to all of the five land cover classifications, including non-forest natural formation, farming, water, non-vegetated area and no observations. We find indications of reduced deforestation, but the parallel trend assumption no longer holds. According to the discussion in 4.1, this may be due to loss of forest to other types of natural formation, which is less related to human activity. We also look at changes to two subcategories of farming land, namely transition from forest to pasture and agriculture. There is no common trend for the two groups within these subcategories, making causal inference challenging. Finally, we use the logarithms of overall forest cover and farming cover as outcome variables and find no plausible impact from the program.

6.4.3 Changing the definition of the treatment group

In our DID analysis we defined our treatment group as the municipalities where at least 8% of the population were Bolsa beneficiary children in 2002. In this section we test the robustness of our analysis if we replace the 8% threshold with quartile values of the same variable. In Table A 5 we show the results of the event study if we rather use the 25%, 50% and 75% quartile values in year 2002 to define the treatment group. The three estimates consistently show reduced deforestation after the program intervention, and the only matter of concern is some evidence of a pre-trend in 1998 which challenges the parallel trend assumption. Not surprisingly, the estimated coefficients show higher reduction in deforestation when the treatment group has a higher treatment intensity. This is consistent with findings from the GDID where we estimate that the impact on deforestation varies with the share of population which is being treated.

6.4.4 Including additional control variables

Finally, one concern might be that there are underlying changes in unobserved time-variant factors that are correlated with the implementation of the Bolsa programs or with deforestation in the municipalities. We therefore add two additional control variables to our analysis. The population estimates are added in order to control for changes to the pressure of forest that is related to how many people live in the municipality. We also add the share of children enrolled in school as a percentage of population for two reasons; (1) the proportion of children in a municipality might have an effect on the use of natural resources and (2) it can give information of the importance of the school enrollment condition of the program, and whether this condition is the main cause behind the changes in deforestation, rather than the income change. The results are seen in Table A 6. While both coefficients prove significant, they do not change the estimated impact of the program.

7 Discussion and Limitations

In this thesis we have investigated the causal link between income increases to poor families and annual deforestation on a municipal level, and found that the Bolsa programs decreased deforestation. However, our study does not give information on which mechanisms lies behind these findings. In this section we therefore discuss possible reasons for the obtained results in light of the existing literature reviewed in Section 2. We contrast our findings with those from similar CCTs in Colombia and Mexico. Finally, we discuss the external validity and present limitations to the methodology in this study.

7.1 Discussion of results

The results show that municipalities with a higher amount of Bolsa beneficiaries reduced annual deforestation compared to the counterfactual by about 7,6% overall, or between 6,5% and 9% each year of the study. The control group used to estimate the counterfactual was also treated with a lower number of beneficiaries, which suggest that the true impact may have been larger than our results show. Through expanding our analysis to study heterogenous treatment intensity, we find that increasing the share of beneficiaries with 10% leads to a 1,7% decrease[15] in our deforestation variable. It thus seems that the impact on the treatment group was greater than for other municipalities, considering that the implied difference between treatment and control group would have been smaller than our simple DID estimate. The difference in the average share of beneficiary families in treatment and control were about 15% on average Table 1, implying an expected difference of only 2,5% compared to the estimated 7,6%. Nonetheless, the analysis indicates an impressive reduction in deforestation, and a back-of-the-envelope calculation based on the estimation from the simple DID suggests that more than 1 million ha forest was preserved in total in the treatment group alone over the years 2001-2004. If we assume that emissions of CO2 are around 125 MT per ha[16] and estimate the value of each

[15] With a 95% confidence interval between -1,2% and -2,2%

[16] We follow Wong et al. (Wong et al., 2018). The estimate is specifically from the Brazilian Amazon, and as we measure all types of forest over the whole country, the number might not be accurate.

ton CO2 at USD31[17] (in 2007 U.S. dollars), this amounts to a total value of more than 4,6 billion USD. See Table A 7 for more detailed calculation and explanation. In comparison, we estimate the total program cost in the treatment group to be about 1,6 billion USD over the same period. This would imply that the social benefits of the program may have been three times the cost of the program, suggesting an immense environmental benefit.

The findings were robust across different levels of treatment intensity and the inclusion of additional control variables. However, more general and more specific definitions of deforestation showed some evidence of pre-trends between the two groups. We argue that these are likely subject to mechanisms that are less closely linked to the Bolsa beneficiaries, but encourage further studies to investigate this claim.

We provide evidence that cash transfers to the poor may give large benefits in relation to preserving forest area. These results contrast those from a similar program in Mexico (J. Alix-Garcia et al., 2013). They found that increased income led to a higher consumption of deforestation-related goods such as beef and milk. The program increased local deforestation, but less profoundly so in municipalities with better connected markets. There are several possible reasons why our findings differ. First, we do not know what the impact of Bolsa was on the demand of products such as beef and milk in Brazil. Consumption preferences may vary greatly across countries, and we do not have information on how the Bolsa beneficiaries spent their money. Second, even if the program led to increased consumption, it may be that beneficiaries were overall well connected to markets. It is thereby possible that the program lead to increased deforestation outside the local municipality, an effect that would not be captured by our data. Finally, it is likely that Brazil and Mexico differ in a variety of ways that would affect the income-deforestation link, for example in relation to labor markets, agricultural production and consumption preferences. Our study therefore supports the finding that local context and mediating factors need to be considered in determining the relationship between income and deforestation.

[17] The U.S. Environmental Protection Agency's estimated Social Cost of CO2 was 31 US$ (in 2007 dollars) per metric ton CO2 for the year 2010 (Interagency Working Group on Social Cost of Greenhouse Gases: United States Government, 2016). We were not able to find estimations from before 2010, and therefore use this value as our best estimate.

Our findings are supported by those from the Familias en Accion CCT program in Colombia (Malerba, 2020). However, we find larger effects on deforestation. A unique contribution in our study is that we are able to focus on transitions from forest to farming land specifically. This may be an advantage since the poor are primarily gaining their livelihood from agricultural activities. We find that the relationship between the program and overall transitions from forest is weaker, and thereby assume that effects can be offset by other changes in forest cover. This may be one reason why we find a stronger relationship. However, as mentioned previously it may also be primarily due to local mechanisms that vary across countries.

What are some of the mechanisms that may cause an income program to decrease deforestation? First, the idea that poverty alleviation can reduce people's reliance on expansion of unproductive land finds broad support within the sustainable development framework (Brundtland, 1987; S. D. Mink, 1993; United Nations, n.d.-a). An increased income makes it possible to increase the productivity of existing plots (Reardon & Vosti, 1995) or reduce the reliance on forests for consumption smoothing (Fisher & Shively, 2005). It is also in line with the labor market mechanisms outlined by Barbier (2010) and appropriated by Malerba (2020) which suggests that increases in income can make cheap labor supply less attractive, and thereby increase the costs related to deforestation. As discussed, deforestation and income are linked through a number of underlying mechanisms, and further research is therefore needed to establish the main drivers behind the observed impact.

An alternative hypothesis is that it is the conditions of the program, rather than the income, that caused the reduction in deforestation. Malerba (2020) suggests that the requirement for children to attend school may have reduced labor supply in relation to forest clearing, and a similar claim could be made if the increased income lead to general decreased labor market participation. However, as seen in section the empirical evidence for reduced labor participation is mixed. School attendance is unlikely to be a perfect substitute to child labor, and there is empirical evidence that children work alongside their studies. When we included the percentage of the population that attends school as a control variable in Table A 6, it did not lead to a significant change to our estimation. Besides, Glewwe and Kassouf (2012) estimates that most of the beneficiary children (82%) were in fact already enrolled in school. For many of the families the support was therefore in essence only conditional on income, which reduces the importance of the schooling condition. We thus find it unlikely that the specific schooling conditions of the program were the main drivers behind the effect. However, empirical evidence suggests that increased education may lead to decreased deforestation in the long term, signifying that there may be additional future benefits related to increased schooling (Ehrhardt-Martinez, 1998; Godoy & Contreras, 2001).

7.2 Discussion of external validity and limitations

While this study has confirmed that poverty alleviation can have a positive effect on the local environment, implications for policy will depend on the external validity of the findings. As discussed earlier, the link between income and deforestation is likely to be dependent on a number of local factors, including prices, labor market mechanisms and consumption preferences. This is underlined by the contrast between our findings and those of Alix-Garcia et al (2013) in Mexico. Furthermore, the effects of increasing income may depend on factors such as the initial poverty level and the size of the cash transfer. Until the mechanisms that drive the relationship between income and deforestation are better understood it is therefore hard to assess to what extent the same results may be found in other contexts.

The thesis focuses on the short-term impacts of Bolsa through studying only the four first years after the implementation of the program. We therefore do not know whether the program had other effects on the longer term. It is also possible that the effect of the program changed after the increased regulation of deforestation after 2004. We would therefore encourage further studies to estimate possible long-term impacts of the CCT.

There were also some limitations to our empirical approach. Since the Bolsa program was implemented quickly in the whole country, almost all municipalities were to some extent treated by the program. We were therefore not able to estimate a true counterfactual in terms of how deforestation trends would have evolved without any impact of the program. We do however test for different definitions of treatment and find that the general result of reduced deforestation rates holds for all estimations.

Another potential matter of concern is that the North-East region strongly dominates the treatment group, as can be seen in Figure A 16 and Figure A 17. This is due to big regional differences in income in Brazil, where the Northern part of the country generally has higher poverty rates. The fixed effects estimation controls for initial differences between municipalities (and thereby regions) and we have controlled for parallel pre-trends. However, policies or price changes that happened specifically in the Northeast region could still bias our results if they happened simultaneously with the implementation of Bolsa. It seems unlikely that this would be the main driver for the change we see in the program period, but it could affect the estimates.

We also faced some limitations to our data set, most significantly that we were not able to gather one coherent data set from 2001 to 2004. We therefore relied on merging together information on beneficiary families from Bolsa Escola with that from Bolsa Familia. However, it seems that these were not fully compatible, as the data set then showed a reduction of beneficiary families between 2002 and 2003. This opposes numbers in Glewwe and Kassouf (2012) and we have not seen such a decrease confirmed anywhere else. We therefore assume there is missing data related to the transition from BE to BF. However, our identification strategy of the treatment group minimizes this problem as we defined the treatment group based on the year 2002. Furthermore, excluding 2003 did not change estimates significantly in the GDID, as seen in section 5.3.3. There were also 10 municipalities that we did not include because they were not in our BE data, but since these only represent 0,2% of the total, we do not expect that this will lead to bias in our sample. Finally, we lack information on local versions of Bolsa Escola-programs that were implemented in 2% of Brazilian municipalities prior to the national level roll-out in 2001 (Lindert et al., 2007). 200 000 families already received benefits from pre-versions of the program in year 2000, which amounts to 4% of the 5 million BE beneficiaries in 2001. This could lead to an underestimation of the treatment effect.

Our analysis only measures local deforestation effects. This is an important limitation since Bolsa may have increased consumption of deforestation-related products that were bought through markets. It is therefore possible that the total effect on the forests in Brazil were affected in a negative way that are not measurable on a municipality level. Alix-Garcia (2013) showed that the relationship between cash transfers and deforestation in Mexico depended on the market connectivity in the areas, and it is possible that a similar mechanism is at work in Brazil. Furthermore, our study only considers one type of environmental impacts, and it is possible that the program had other negative environmental impacts through increasing the consumption of for instance electricity or other resources.

Our study focuses on deforestation from all types of forests, and we count all hectares of forest equally. There are however big differences between natural forest, mangrove, savannah and planted forest in terms of biodiversity and ability to capture CO2 (Chomitz, 2006). We therefore encourage further studies to consider whether there is heterogeneity on the effects between various subtypes. Finally, we see in the robustness analysis in section 6.4.2 that the relationship between the program and deforestation is less clear when we study the transition from forest to all other types of land use. Our assumption is that this variable is more affected by deforestation caused by natural causes, and therefore is less appropriate for the study. This needs to be confirmed by more information on the other types of transitions.

8 Conclusion

This thesis investigates the relationship between income and deforestation among low-income families in the Brazilian municipalities, during the period 2001-2004. We do this by examining the effects of an exogenous increase in income from one of the largest CCT programs in the world, Bolsa Familia and its predecessor Bolsa Escola, on local deforestation levels. We use detailed data on land cover transitions to measure deforestation from forest to farming land, obtained from MapBiomas Collection 4 (MapBiomas Project, 2019).

Through the use of a DID framework we estimate the ATT of the programs and find that yearly deforestation was decreased by 7,6% in the municipalities with a higher proportion of Bolsa beneficiaries. We expand our analysis to a generalized DID with heterogenous treatment intensity and estimate that increasing the beneficiary share of population by 10% leads to a 1,7% reduction in deforestation. A back-of-the-envelope calculation suggests that this may be worth more than 25 billion USD in avoided CO2 emissions. Our results contrast those from a CCT in Mexico (J. Alix-Garcia et al., 2013) but confirm the reduction in deforestation seen in municipalities in Colombia (Malerba, 2020).

Our findings provide further insight into the environmental impacts of increasing the income of the poor through monthly cash transfers. They suggest that poverty alleviation can have positive effects on the environment, through reduced deforestation. We provide evidence in favor of sustainable development, and complement a substantial literature that indicates that poverty puts pressure on the forests (Brundtland, 1987; Fisher & Shively, 2005; Reardon & Vosti, 1995). Further research is needed to explore what mechanisms are behind these findings, and to what extent they rely on specific circumstances of the Brazilian context. The evidence supports the theory of a poverty-environment trap, in that poor families in Brazil are likely to rely on natural resources for consumption smoothing, and providing a stable income may reduce the environmental pressure. Considering the great challenge that deforestation poses to the world, it is relevant for the whole international community to consider further how to provide the rural poor with sustainable alternatives for economic stability and prosperity.

A Appendix

Table A 1 - Estimated Impact of Treatment on Bolsa Families

	%Bolsa
Treatment*1998	6.93e-14
	(4.23e-10)
Treatment*1999	6.50e-14
	(2.05e-10)
Treatment*2000	0
	(.)
Treatment*2001	0.140***
	(0.00131)
Treatment*2002	0.139***
	(0.00123)
Treatment*2003	0.157***
	(0.00275)
Treatment*2004	0.183***
	(0.00303)
Constant	6.56e-08
	(0.000444)
N	38844
R^2	0.805

Notes: The dependent variable is %Bolsa, which is the share of beneficiary families of the total number of families in a municipality. The total number of families has been calculated by dividing population estimates with the average family size in the municipality. Treatment is a dummy variable that equals one if the municipality had a high percentage (>8%) of children receiving Bolsa in the total population in year 2002, and zero otherwise. The specification includes municipality fixed effects and year fixed effects, as well as leads and lags of participation in BE. The year before implementation of BE (2000) is the omitted category. The unit of observation is the municipality. Robust standard errors clustered on municipality level are reported in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A 2 - Event Study of the Estimated Impact of Bolsa Treatment on Deforestation

	Log deforestation
Treatment*1998	-0.0175
	(0.0230)
Treatment*1999	-0.00343
	(0.0213)
Treatment*2000	0
	(.)
Treatment*2001	-0.0667***
	(0.0174)
Treatment*2002	-0.0665***
	(0.0185)
Treatment*2003	-0.0902***
	(0.0185)
Treatment*2004	-0.0979***
	(0.0204)
Lag forest cover	0.00000611***
	(0.00000130)
Constant	5.146***
	(0.127)
N	38828
R^2	0.016

Notes: The dependent variable is deforestation, defined as the absolute number of hectares of land that transitioned from forest to farming between year t and t-1. Treatment is a dummy variable that equals one if the municipality had a high percentage (>8%) of children receiving Bolsa in the total population in year 2002, and zero otherwise. The specification includes municipality fixed effects and year fixed effects, as well as leads and lags of participation in BE. The year before implementation of BE (2000) is the omitted category. Robust standard errors clustered on municipality level are reported in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A 3: Robustness analysis: Testing a linear relationship

	Deforestation		
	(1)	(2)	(3)
	Simple DID	Event study	Generalized DID
Treatment*Dpost	-50.40		
	(39.81)		
Treatment*1998		-45.57	
		(78.86)	
Treatment*1999		-226.3**	
		(71.95)	
Treatment*2000		0	
		(.)	
Treatment*2001		13.22	
		(61.74)	
Treatment*2002		-140.1	
		(91.09)	
Treatment*2003		-247.6***	
		(66.68)	
Treatment*2004		-190.1**	
		(71.34)	
% Bolsa			-1.068
			(1.522)
Constant	1261.3	1268.7	1265.1
	(2733.3)	(2738.6)	(2733.6)
N	38843	38843	38838
R^2	0.002	0.002	0.002

Notes: The dependent variable is deforestation, defined as the absolute number of hectares of land that transitioned from forest to farming between year t and t-1. Treatment*Dpost in column (1) is the interaction between the treatment dummy and the dummy variable Dpost. Treatment is a dummy variable that equals one in all years if the municipality has a high percentage (>8%) of children receiving Bolsa in the total population, and zero otherwise. Dpost equals one during and after the program implementation in year 2001. Column (2) includes leads and lags of implementation of BE, with the year before implementation as the omitted category. % Bolsa in column (3) is the share of beneficiary families of the total number of families in a municipality. All specifications includes municipality fixed effects and year fixed effects. The unit of observation is the municipality. Robust standard errors clustered on municipality level are reported in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A 4 – Robustness analysis: Changing the definition of deforestation

	(1) Log deforestation to all land types	(2) Log deforestation to pasture	(3) Log deforestation to agriculture	(4) Log forest cover	(5) Log farming cover
Treatment*1998	0.0365	0.0702**	-0.129***	0.0213***	-0.0226***
	(0.0222)	(0.0218)	(0.0361)	(0.00281)	(0.00493)
Treatment*1999	0.0536**	0.0106	-0.0755*	0.00341	-0.0241***
	(0.0202)	(0.0197)	(0.0326)	(0.00216)	(0.00478)
Treatment*2000	0	0	0	0	0
Treatment*2001	-0.0627***	-0.0420*	-0.0236	0.00233	0.00370
	(0.0165)	(0.0164)	(0.0302)	(0.00179)	(0.00340)
Treatment*2002	-0.0203	-0.0996***	-0.135***	0.00305	-0.00401
	(0.0174)	(0.0178)	(0.0324)	(0.00238)	(0.00460)
Treatment*2003	-0.0513**	0.122***	-0.0496	-0.00679*	-0.00725
	(0.0182)	(0.0187)	(0.0323)	(0.00296)	(0.00412)
Treatment*2004	-0.0193	0.160***	-0.110**	0.00178	-0.00699
	(0.0192)	(0.0207)	(0.0334)	(0.00344)	(0.00535)
Lag forest cover		0.00000627***	-0.00000757***		
		(0.00000135)	(0.00000165)		
Constant	6.001***	3.481***	1.957***	9.414***	9.906***
	(0.00975)	(0.134)	(0.147)	(0.00167)	(0.00181)
N	38829	38192	30387	38836	38850
R^2	0.015	0.028	0.056	0.007	0.011

Notes: Deforestation is defined as hectares of land that transitioned from forest between t and t-1 to the specificated land uses. Forest cover is the total hectares of land defined as level 1 Forest in MapBiomas. Farming cover is the total hectares of land defined as level 1 Farming in MapBiomas. Treatment is a dummy variable that equals one in all years if the municipality has a high percentage (>8%) of children receiving Bolsa in the total population, and zero otherwise. All specifications includes municipality fixed effects and year fixed effects, as well as leads and lags to implementation of BE. The unit of observation is the municipality. Robust standard errors clustered on municipality level are reported in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A 5 – Robustness analysis: Defining the treatment group from quartiles

	Log deforestation		
	(1)	(2)	(3)
Definition of treatment	>25% quartile (4,3% BE children of total population)	>50% quartile (6,6% BE children of total population)	>75% quartile (9,9% BE children of total population)
Treatment*1998	-0.0781***	-0.0451*	-0.0176
	(0.0216)	(0.0207)	(0.0279)
Treatment*1999	-0.0162	0.0131	-0.0409
	(0.0217)	(0.0197)	(0.0245)
Treatment*2000	0	0	0
	(.)	(.)	(.)
Treatment*2001	-0.0413*	-0.0754***	-0.0712***
	(0.0191)	(0.0167)	(0.0195)
Treatment*2002	-0.0273	-0.0450*	-0.0726***
	(0.0204)	(0.0178)	(0.0208)
Treatment*2003	-0.0637**	-0.0689***	-0.0984***
	(0.0212)	(0.0181)	(0.0206)
Treatment*2004	-0.145***	-0.110***	-0.0829***
	(0.0225)	(0.0196)	(0.0234)
Lag forest cover	0.00000604***	0.00000609***	0.00000605***
	(0.00000128)	(0.00000129)	(0.00000129)
Constant	5.205***	5.163***	5.149***
	(0.125)	(0.126)	(0.126)
N	38828	38828	38828
R^2	0.016	0.017	0.016

Notes: The dependent variable is the natural logarithm of deforestation, defined as hectares of land that transitioned from forest to farming between year t and t-1. Treatment is a dummy variable that equals one in all years if the municipality has a high percentage of children receiving Bolsa in the total population, and zero otherwise. In column (1) this is all municipalities with more than the 25% quartile, in column (2) treatment >50% quartile and in column (3) treatment >75% quartile. All specifications include municipality fixed effects and year fixed effects, as well as leads and lags to implementation of BE. Robust standard errors clustered on municipality level are reported in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A 6 – Robustness analysis: Estimations with additional control variables

	Log Deforestation		
	(1)	(2)	(3)
	Simple DID	Event Study	Generalized DID
Treatment*Dpost	-0.0732***		
	(0.0132)		
Treatment*1998		-0.0141	
		(0.0231)	
Treatment*1999		-0.00203	
		(0.0213)	
Treatment*2000		0	
		(.)	
Treatment*2001		-0.0655***	
		(0.0174)	
Treatment*2002		-0.0656***	
		(0.0186)	
Treatment*2003		-0.0889***	
		(0.0186)	
Treatment*2004		-0.0945***	
		(0.0206)	
%Bolsa			-0.00172***
			(0.000521)
Population	-0.000000738**	-0.000000757**	-0.000000687**
	(0.000000262)	(0.000000267)	(0.000000250)
$\frac{\text{Enrolled children}}{\text{Population}}$	0.307***	0.315***	0.314***
	(0.0865)	(0.0861)	(0.0860)
Lag forest cover	0.00000609***	0.00000611***	0.00000605***
	(0.00000128)	(0.00000129)	(0.00000128)
Constant	5.091***	5.085***	5.089***
	(0.126)	(0.125)	(0.125)
N	38665	38665	38664
R^2	0.017	0.017	0.016

Notes: The dependent variable is the natural logarithm of deforestation, defined as hectares of land that transitioned from forest to farming between year t and t-1. Treatment*Dpost in column (1) is the interaction between the treatment dummy and the dummy variable Dpost. Treatment is a dummy variable that equals one in all years if the municipality has a high percentage (>8%) of children receiving Bolsa in the total population, and zero otherwise. Dpost equals one during and after the program implementation in year 2001. Column (2) includes leads and lags of implementation of BE, with the year before implementation as the omitted category. % Bolsa in column (3) is the share of beneficiary families of the total number of families in a municipality. All specifications includes municipality fixed effects and year fixed effects. Robust standard errors clustered on municipality level are reported in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A 7 - Back-of-the-envelope calculation of total deforestation avoided for years 2001-2004

Sum actual deforestation in treatment group	13,6 million ha
Counterfactual deforestation in treatment group	14, 8 million ha
Avoided deforestation (Counterfactual - Actual)	**1,2 million ha**
Avoided CO2 emissions	150 million MT
Benefit of avoided CO2 emissions in 2007 US$	**4 650 million $**
Approximate cost of BE in treatment (2001-2002)	349,4 million $
Approximate cost of BF in treatment (2003-2004)	1013,3 million $
Sum costs of Bolsa programs (appr year 2003)	**1 432,6 million $**
Costs of Bolsa programs converted to 2007 US$	**1 598 million $**

The calculation of costs and benefits is limited to the 2099 municipalities in our treatment group. The treatment group is defined as the municipalities with a high share of Bolsa recipient children, i.e. >8% of the total population. Deforestation is here as elsewhere defined as the transition from forest land to farming land.

The sum of actual deforestation is found from the MapBiomas data set, by summarizing the totals for all municipalities in our treatment group, in the years 2001-2004.

The counterfactual deforestation is calculated by dividing the actual deforestation with (1-0,0761), where 0,0761 is our estimation of the impact of Bolsa on deforestation in the treated municipalities, as found in section 6.1. The avoided deforestation is the difference between the counterfactual and actual deforestation.

To convert the effect to avoided CO2 emissions, we follow the estimate in Wong et al. (Wong et al., 2018) of assuming 125 metric tons (MT) CO2 per ha of forest. This might be somewhat unprecise since this estimate comes from the Brazilian Amazon while we use all types of forests in the whole country. To calculate the benefits of the avoided CO2 emissions we use the U.S. Environmental Protection Agency's estimated Social Cost of CO2 (Interagency Working Group on Social Cost of Greenhouse Gases: United States Government, 2016), which was 31 US$ (in 2007 dollars) per metric ton CO2 for the year 2010. We were not able to find earlier SCC estimations from before 2010, and therefore use this value as our best estimate.

The cost of Bolsa Escola was calculated by taking the total amount of beneficiary children in the treatment group in year 2002 (3494000 children) X 20 months X 15 BRL. 20 months is an upper-bound estimate, since BE was first implemented in municipalities in May 2001. We use a conversion rate of 3 BRL per 1 USD, based on an approximation of the rates between 2001 and 2004 (Trading Economics, n.d.).

As the Bolsa Familia data did not include information on the amounts paid to each family, we instead take the BF budget allocation from 2004 found in (Machado et al., 2011) and use the same estimate for the year 2003. In our dataset approximately 40% of beneficiary families were in the treatment group in 2004. We therefore take 3 800 million BRL X 2 X 0,4 and convert the sum to USD by dividing with 3.

We finally transform from 2003 USD to 2007 USD through using an inflation calculator with a total inflation rate of 11,55%(Inflation Tool, n.d.).

	COLLECTION 4 CLASSES	Level
1	**Forest**	**1**
1.1	Natural forest	2
1.1.1	Forest Formation	3
1.1.2	Savannah Formation	3
1.1.3	Mangrove	3
1.2	Forest Plantation	2
2	**Non-Forest Natural formation**	**1**
2.1	Wetland	2
2.2	Grassland	2
2.3	Salt flat	2
2.4	Rocky Outcrop	2
2.5	Other Non-Forest Natural Formation	2
3	**Farming**	**1**
3.1	Pasture	2
3.2	Agriculture	2
3.2.1	Annual and Perennial Crop	3
3.2.2	Semi-perennial Crop	3
3.3	Mosaic of Agriculture and Pasture	2
4	**Non-vegetated area**	**1**
4.1	Beach and dune	2
4.2	Urban Infrastructure	2
4.3	Mining	2
4.4	Other Non-Vegetated Area	2
5	**Water**	**1**
5.1	River, Lave, Ocean	2
5.2	Aquaculture	2
6	**Non-Observed**	**1**

Figure A 8 - Land cover categories

Note: Table over the five land cover categories in the landcover and land transition data. Each of the categories are divided in levels according to collection 4, 2018 (MapBiomas Project, 2019)

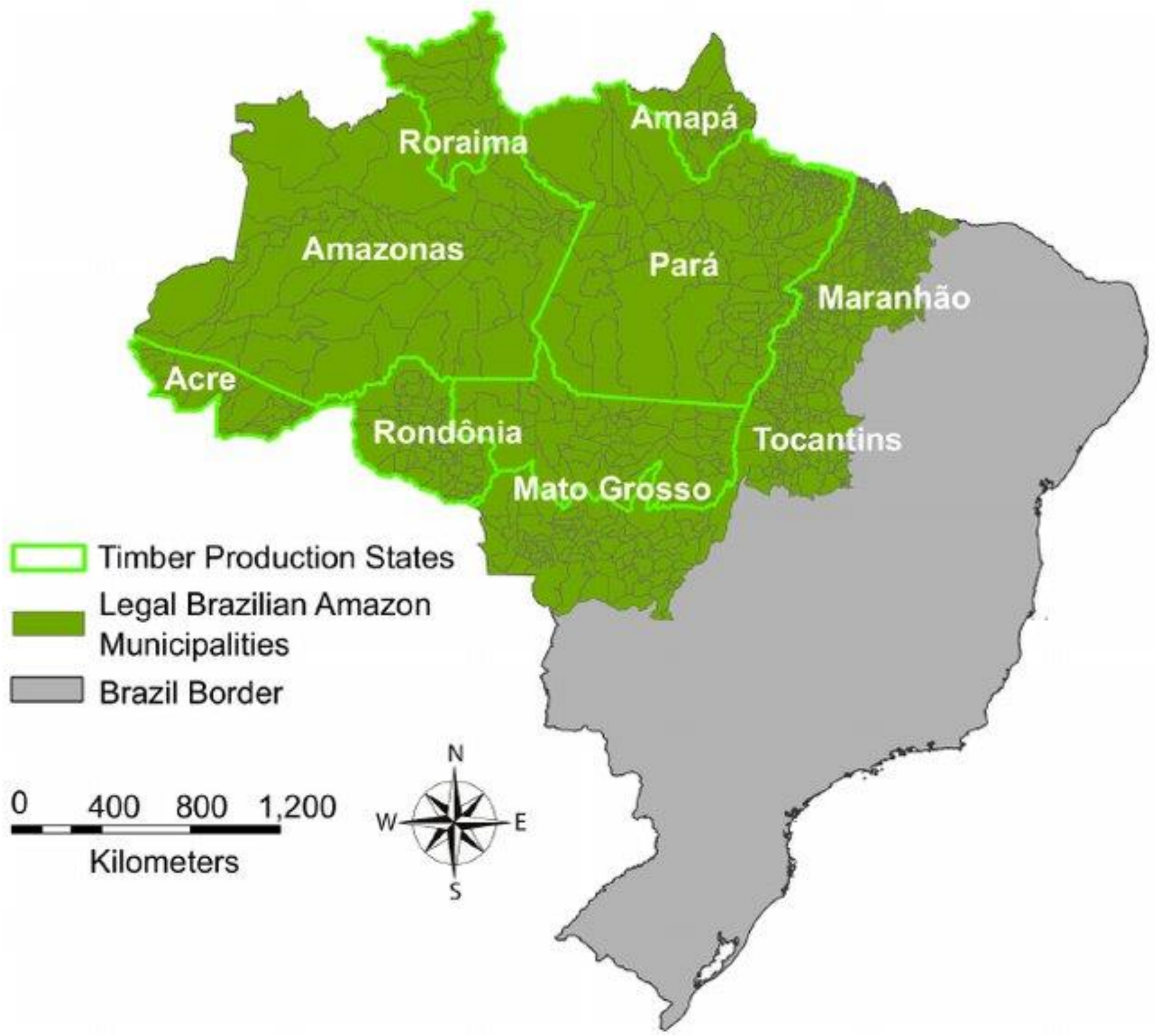


Figure A 9 - Map of the Brazilian Legal Amazon (BLA)

Note: Map of the municipalities that were defined within the borders of Brazilian Legal Amazon in year 2014 (dark green with grey borders). Obtained from (Hahn et al., 2014).

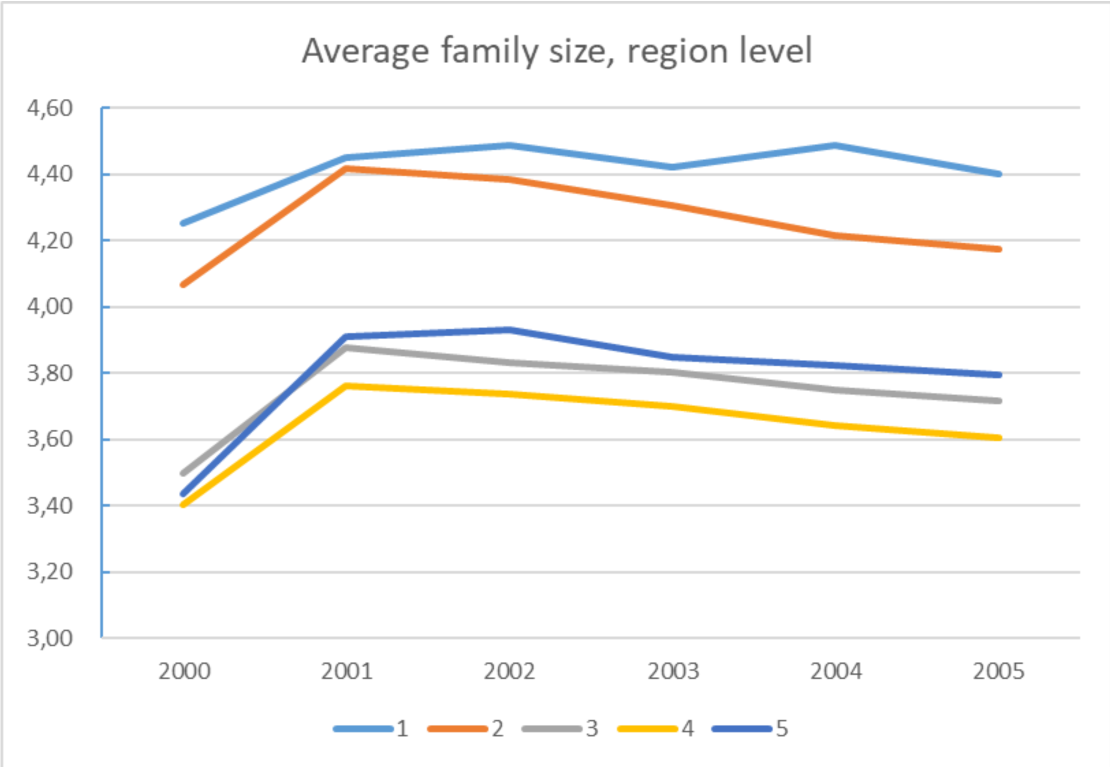


Figure A 10 - Historical trends in Average Family size

Note: the figure shows the mean family size, measured in average number of family in one average family one, each year, in each of the five regions One line in the figure represent the average family size in the region each year during the time period 2000-2005. Data obtained from (IBGE, 2020a)

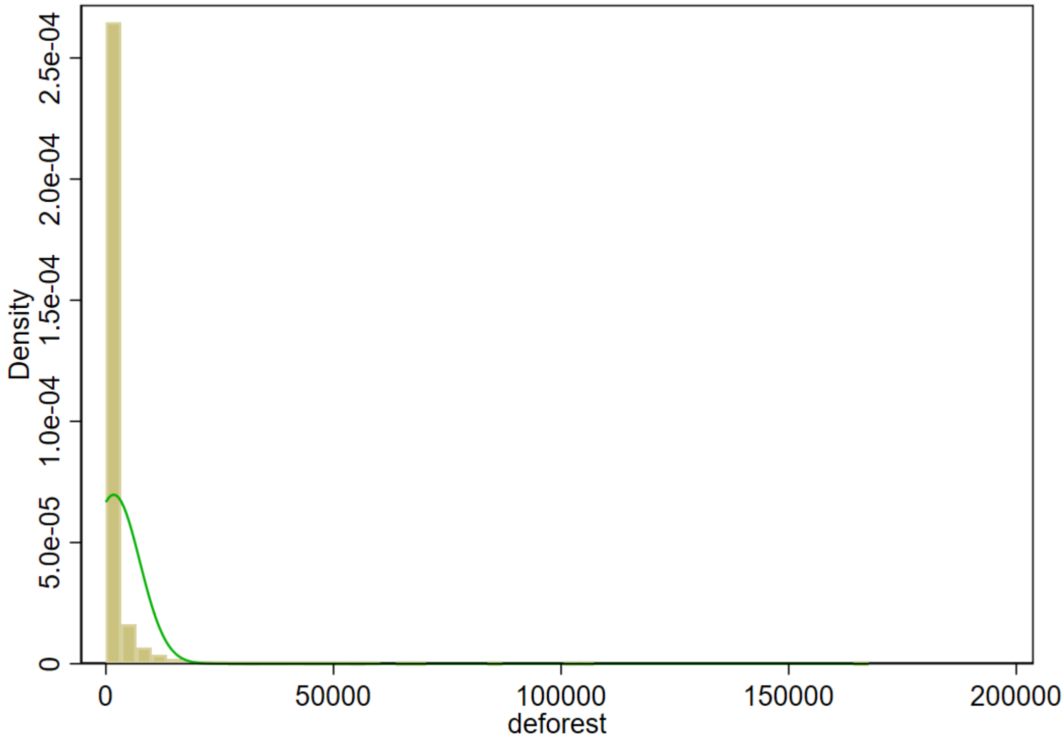


Figure A 11: Density plot of absolute deforestation

Note: Histogram showing the density plot of absolute levels of deforestation in Brazil year 2002. Deforestation is measured as the amount of hectares forest cover transitioned to farming from 2001 to 2002.

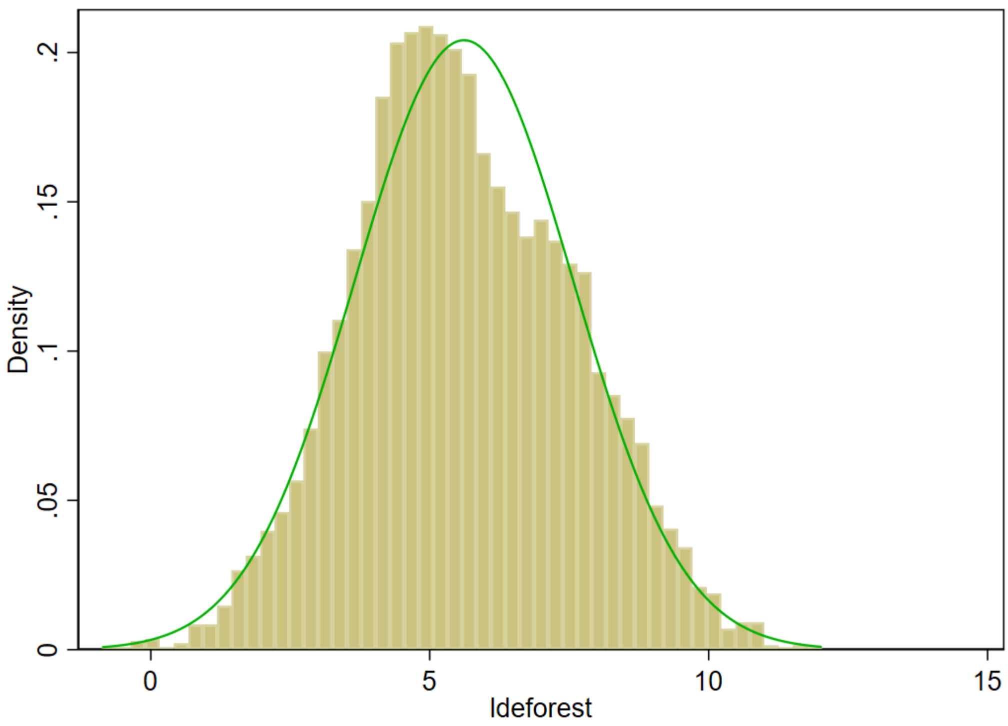
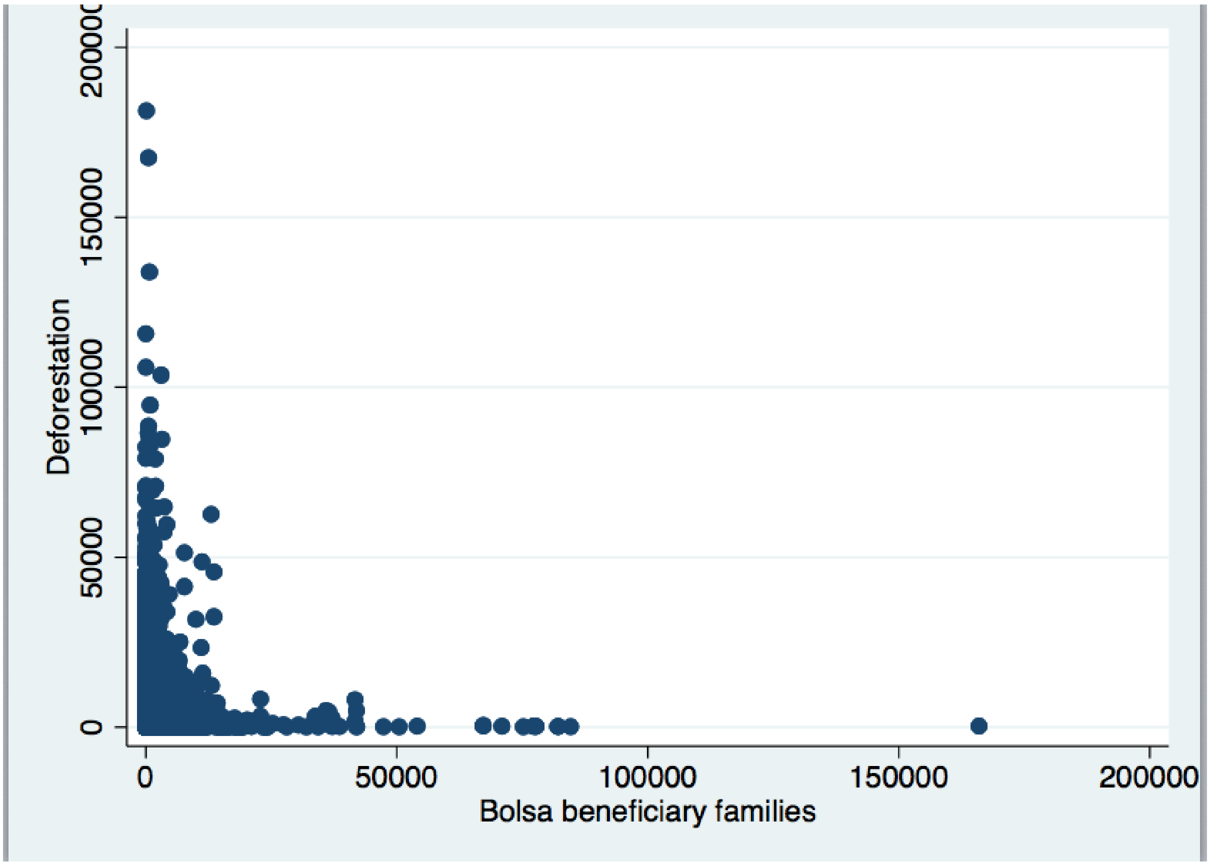


Figure A 12: Density plot of natural logarithm of deforestation.

Note: Histogram showing the density plot of the natural logarithm of deforestation in Brazil in year 2002. Deforestation is measured as the amount of hectares forest cover transitioned to farming from 2001 to 2002



A 13: Correlation between deforestation and beneficiary families

Note: Scatter plot illustrating the correlation between absolute deforestation and number of beneficiary families of BE and BF. The x-axis represents number of families and y-axis represent hectares deforestation. Values on municipality level. Observations over the period 2001 -2004.

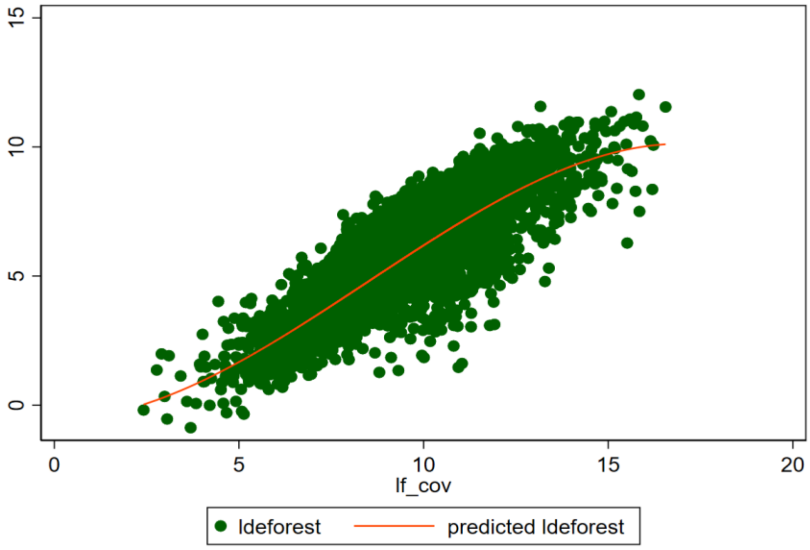


Figure A 14 - Correlation between log Deforestation and log Forest cover

Note: Scatter plot illustrating the correlation between the natural logarithm of deforestation (y-axis) and natural logarithm of forest cover (x axis). Values are measured as averages over the years 1998-2004. Deforestation measured as the amount of hectares forest cover transitioned to farming. Forest cover is measured in average hectares per year. The red line represents fitted values.

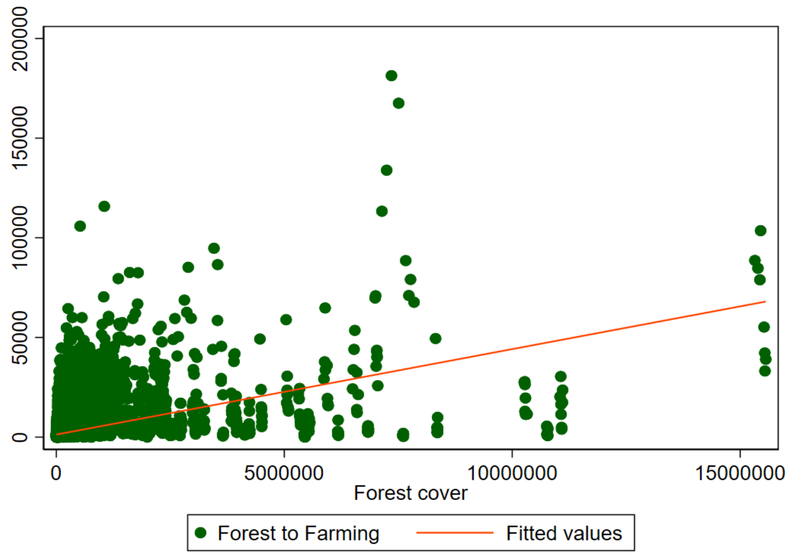


Figure A 15: Correlation between deforestation and forest cover

Note: Scatter plot illustrating the linear correlation between the absolute level of deforestation (y-axis) and absolute amount of forest cover (x axis). Values are measured as averages over the years 1998-2004. Deforestation measured as the amount of hectares forest cover transitioned to farming. Forest cover is measured in average hectares per year. The red line represents fitted values

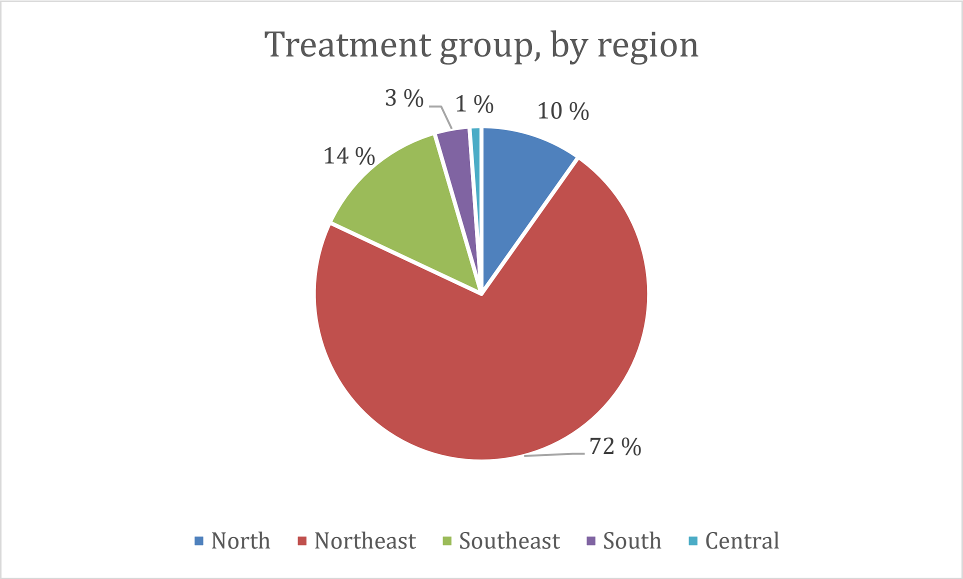


Figure A 16 Treatment group by region

Note: Graphical illustration of the distribution of the number of municipalities in the treatment group between the five regions in Brazil, in 2002. The treatment group is the group of municipalities where children receiving Bolsa in 2002 constituted a high percentage (>8%) of the total population. The figure shows that the Northeast region dominates the group.

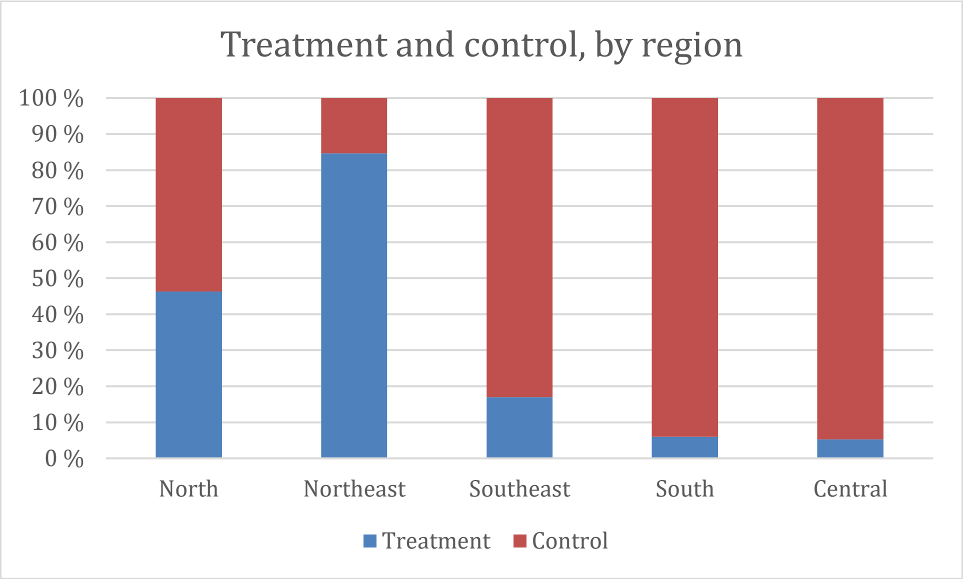


Figure A 17 - Treatment and control group by region

Note: Graphical illustration of the distribution of treatment and control in each of the five regions in Brazil in 2002, according to the number of municipalities. The treatment group is the group of municipalities where children receiving Bolsa in 2002 constituted a high percentage (>8%) of the total population. Each column is summarized to 100%. The figure shows that the share of municipalities in the treatment group is highest in the Northeast, and second highest in the North.

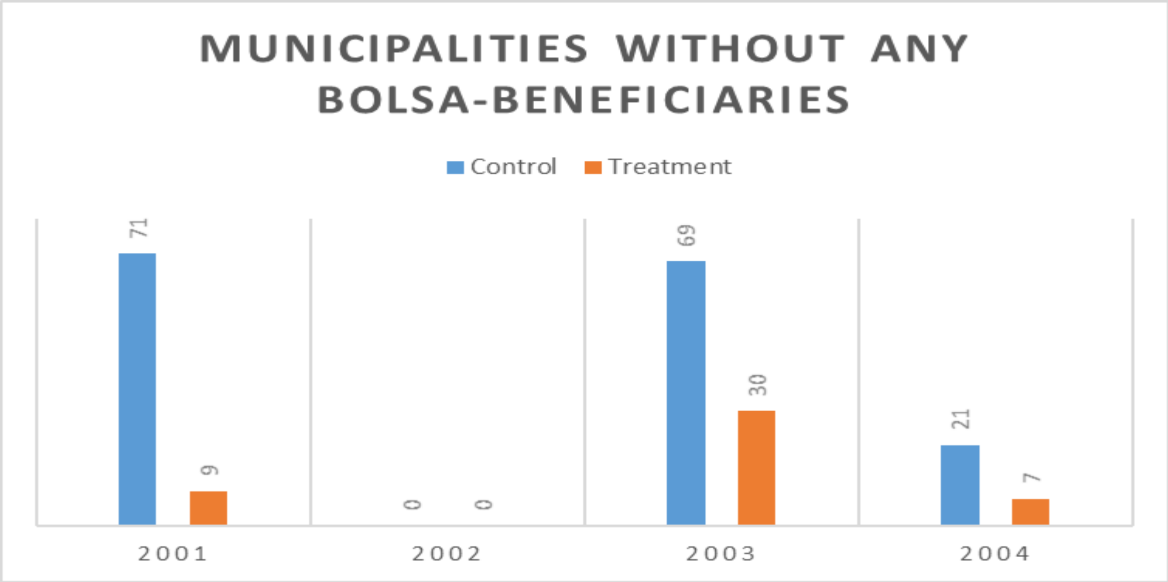


Figure A 18 – Number of municipalities with zero beneficiaries, by treatment

Note: The figure shows how many municipalities that did not have any beneficiaries each year. The two colors split municipalities on whether they were in control group (blue) or treatment group (orange). The exact number of municipalities without Bolsa beneficiaries at a given year, is specified above each bar

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