LUND UNIVERSITY
School of Economics and Management

Master's Programme in Economic Growth, Population and Development

The Impact of Conditional Cash Transfer Programs on Educational Outcomes in Developing Countries

A Case Study: *Bolsa Família* in Brazil

by

Alisa Buchstab

alisa.buchstab@web.de

Abstract: Bolsa Família is one of the largest conditional cash transfer programs in the world. It provides cash transfers to poor households, conditional on human capital requirements such as minimum school attendance. The literature emphasizes that more schooling increases the human capital formation of children, which leads to improved employment outcomes and will break the inter-generational transmission of poverty. Despite the importance of schooling for poverty reduction, there is little evidence on *Bolsa Família's* impact on children's education. This thesis estimated the impact of *Bolsa Família* on school enrollment and literacy rates by using data from the Brazilian household survey PNAD 2014. A Regression Discontinuity Design was applied, and impacts were estimated by using logistic regressions. The results using the baseline sample suggest that *Bolsa Família* did not have any statistically significant effect on school enrollment for children between six and 17 years of age in 2014. However, when the initial assumptions were relaxed it was revealed that *Bolsa Família's* effects on education were stronger among the poorest. This was attributed to higher school enrollment rates within this group. In addition, a heterogeneous treatment effect was found: the impact of *Bolsa Família* on school enrollment was larger among boys than girls, as well as, among younger children. Furthermore, the models suggest a lower chance of being literate for *Bolsa Família* beneficiaries. However, those results were not statistically significant and therefore no clear effect could be identified.

Key words: Conditional Cash Transfer Program, Education, Bolsa Família, Brazil

EKHS22
Master's Thesis, Second Year (15 ECTS)
June 2021
Supervisor: Igor Baccin Martins
Examiner: Tobias Karlsson
Word Count: 16,856

Acknowledgements

I would like to thank my supervisor Igor Martins for all the discussions as well as his feedback and guidance throughout this thesis. I am grateful for his meticulous proofreading of this thesis and his expertise, which significantly contributed to the improvement of this research.

I also want to express my gratitude to my parents, Sibylle and Georg, and to my sister Isi who supported me throughout my masters and especially during this thesis writing process.

Thanks also goes to Clara, Anne, and Sebastian for proofreading this thesis.

Finally, I would like to thank Lisa for the gratuitous encouragement and support during the last two years.

This research would not have been possible without them. Thank you.

Table of Contents

List of Abbreviations

BF	Bolsa Família
CCT	Conditional Cash Transfer
CEDEPLAR	Center for Development and Regional Planning
CI	Confidence Interval
FUNDEB	Fund for the Maintenance and Development of Basic Education and Valuation of Education Professionals
FUNDEF	Fund for the Maintenance and Development of Primary Education and Valuation of Teachers
GDP	Gross Domestic Product
IBGE	Brazilian Bureau of Statistics
IPEA	Institute for Applied Economic Research
MDS	Ministry of Social Development and Fight Against Hunger
PNAD	Pesquisa Nacional por Amostra de Domicílios
RD	Regression Discontinuity
SRD	Sharp Regression Discontinuity

List of Tables

List of Figures

1 Introduction

Since the 1990s a growing number of developing countries are providing conditional cash transfers (CCT) to poor households. Especially in Latin America, CCTs have become a popular development policy tool (Sánchez-Ancochea & Mattei, 2011). CCTs gained popularity as they not only seek to provide short-term poverty alleviation by increasing basic consumption among the poor, but also aim to break the inter-generational transmission of poverty. To break the cycle of poverty and to promote childhood education, CCTs are conditioned on requirements such as a minimum school attendance (Lindert et al., 2007; Jones, 2016). The importance of education for poverty reduction is based on human capital theory: school attendance increases the human capital accumulation of children, which leads to improved employment outcomes and higher future earnings, and thereby provides a chance for breaking the inter-generational transmission of poverty (Jones, 2016).

Along with many other countries in Latin America, Brazil launched its CCT program *Bolsa Família* (BF) in 2003. Today, BF is one of the largest CCT programs in the developing world, covering approximately 24 percent of the Brazilian population in 2019 (Soares et al., 2007; ECLAC, 2020). To increase the human capital accumulation of children it is, among other things, conditioned on a minimum school attendance of 85 percent for children between six and 15 years of age and a minimum school attendance of 75 percent for children between 16 and 17 years of age (Sánchez-Ancochea & Mattei, 2011).

To evaluate the program's educational conditionality, and its impact on school enrollment and literacy rates, this study used data from the Brazilian household survey *Pesquisa Nacional por Amostra de Domícilios* (PNAD) 2014. The estimation strategy consisted of a Regression Discontinuity Design and logistic regressions. It was found from the baseline sample that BF did not have any statistically significant effect on school enrollment for children between six and 17 years of age in 2014. By relaxing the initial assumptions it was, however, revealed that *Bolsa Família's* effects on education were more pronounced among the poorest; this was ascribed to higher school enrollment rates within this group. In addition, BF had a larger impact on school enrollment rates among boys than girls, as well as, among younger children. Furthermore, BF had no statistically significant effect on literacy rates.

1.1 Research Problem

Most empirical studies have analyzed the impact of BF on inequality and poverty (Sánchez-Ancochea & Mattei, 2011; Soares, 2006; Barros et al., 2007; Hoffmann, 2006; Hoffmann, 2013; Rocha, 2008; IPEA, 2009; Soares et al., 2007). From these studies, a consensus was reached that BF contributes to declining inequality. Apart from that, the empirical evidence on poverty was less conclusive. Some authors claimed that even though BF reduced poverty, its contributions were insufficient to lift households out of poverty (Rocha, 2008). In any case, the effect on poverty and inequality is only a one-time effect. To sustain the positive impact on the income distribution BF has to improve the levels of the human capital of participating children. Hence, it depends on the impact of the program on educational outcomes (Sánchez-Ancochea & Mattei, 2011). Studies on the impact of BF on educational outcomes are rare and inconclusive. On the one hand, many studies have evaluated the impact of the preceding program *Bolsa Escola* on educational outcomes and not BF itself (Bourguignon et al., 2003; Janvry et al., 2006). On the other hand, some authors evaluating BF found a negative impact on educational outcomes (Nilsson & Sjöberg, 2013), while others found a positive effect (de Brauw et al., 2014; Oliveira, 2008; Amaral et al., 2014). However, the studies that found a positive impact are ambiguous. In those studies, the average effect showed significant heterogeneity across children in different grades and the effect of BF on school enrollment was quite small and often of low statistical significance (Oliveira, 2008; de Brauw et al., 2014).

1.2 Aim and Scope

This thesis aims to better understand the relationship between the CCT program BF and educational indicators in Brazil in 2014. Therefore, the study seeks to address the main research question:

How did Bolsa Família affect school enrollment rates of children in beneficiary households compared to non-beneficiary households in 2014?

The main hypothesis of this thesis is that BF had a positive effect on school enrollment.

Since the impact of CCTs on school enrollment may differ between girls and boys due to sex-based differences in opportunity costs of schooling and returns to education, a sub research question was added:

Was there a heterogeneous treatment effect of Bolsa Família on school enrollment rates between boys and girls in 2014?

Given that CCTs try to overcome low investments in girls' schooling in developing countries it is anticipated that BF had a larger effect on school enrollment rates for girls than for boys (Fiszbein & Schady, 2009).

To gain a deeper understanding of the relationship between BF and other educational indicators, a second research question was added:

How did Bolsa Família affect the literacy rates of children in beneficiary households compared to non-beneficiary households in 2014?

It is expected that BF had a positive effect on literacy.

To contribute to the body of literature, this study estimated the effect of BF on educational indicators in 2014, which has not been researched so far. Until now, most studies have pursued a short-term approach to the program. However, authors such as Paes-Sousa et al. (2013) point out that "CCTs are long-term interventions"; therefore, CCTs are likely to have an impact on educational indicators and human capital levels several years after their implementation. In line with Paes-Sousa et al. (2013), this thesis contributes to the discussion by analyzing the long-term consequences of BF. Given that BF was implemented in 2004, 2014 seems to be a suitable timeframe to study the long-term consequences of the program.

By exploring the research questions, this study contributes to the existing literature in several ways. Firstly, the study aims to shed light on the inconclusive literature of BF on educational outcomes. Secondly, by looking at education, the study goes beyond analyzing the one-time effect of the program. Thirdly, by looking at the year 2014 it extends the temporal dimension within which the program was previously analyzed. Fourthly, by investigating the impact of BF on school enrollment the study facilitates an evaluation of the program's educational conditionality. Fifthly, by researching the impact of BF on literacy, the study adds a new educational indicator to the existing body of literature. Lastly, understanding the impact of BF on educational outcomes can guide policymakers in the Global South. BF is the largest CCT program in the developing world and is often cited as a well-designed program even though evidence on its impact on children's human capital formation is lacking. Therefore, it is important to research its impact on educational indicators (Lindert, 2006).

1.3 Outline of the Thesis

This study is divided into eight sections. The first one consists of the present introduction. The second section establishes a theoretical framework for the relation between CCTs, education, and poverty reduction. Section three provides background information on Brazil. It presents a brief discussion of the economic situation in Brazil and provides a detailed presentation of the Brazilian CCT program BF. Section four reviews previous literature on CCTs with emphasis on educational outcomes and BF. The employed data, its limitations, and the variables used in this study are described in section five, followed by section six which establishes the methodological framework. Section seven consists of the empirical analysis, including the results, as well as a sensitivity analysis. Finally, section eight recapitulates the key findings of the analysis and links the research outcomes to the existing literature and research questions. The reference list and the appendices are presented separately at the end of this work.

2 Theoretical Framework

2.1 Conditional Cash Transfer Programs

The fundamental structure of CCT programs consists of transferring money to poor and extremely poor households with school-aged children (mostly in developing countries). The majority of these transfers are tied to conditions related to education, health, and nutrition. If households do not comply with these conditions, they do not receive the cash transfer. Nearly all conditions aim to increase the human capital of participating households. Education conditions usually include school enrollment and minimum school attendance of 80-85 percent of school days[1]. Health conditions often include periodic checkups, vaccinations of children, and prenatal care for mothers (Fiszbein & Schady, 2009). Several programs also include non-monetary transfers such as the provision of school equipment. A minority of these programs include households without school-aged children (Cecchini & Madariaga, 2011). Consequently, a major criticism of CCTs is the exclusion of segments of the society that do not match the program selection criteria, but might be equally in need of cash transfers, for instance, poor families without children (Baird et al., 2014). Another criticism arises as some scholars argue that the cash transfers are too low to lift households out of poverty (Rocha, 2008). Lastly, the operational costs of imposing conditionalities are controversial. For example, monitoring

[1] In Brazil a school year consists on average of 200 school days. Thus, in the case of Brazil, a minimum school attendance of 80 to 85 percent of school days represents a total of 160 to 170 school days per year (Brazileducation, 2021).

conditionality represents approximately 18 percent of the administrative costs and two percent of the total costs of the CCT program *Progresa* in Mexico (de Brauw & Hoddinott, 2011).

In general, CCTs target households and not individuals. Preferably, the transfers are paid to women within the household. Several studies found that women are more likely than men to spend their additional money on the education, health, and nutrition of their children (Lindert, 2006; Baird et al., 2014; Fiszbein & Schady, 2009). Mothers' objectives might also be more closely aligned with those of their daughters. Thus, CCTs try to overcome the low levels of investments in girls' schooling in many developing countries and aim to lower gender disparities (Fiszbein & Schady, 2009). Furthermore, it is argued that the impacts of CCTs are larger among groups with low initial outcomes. In this case, the effect might be larger for girls, since in many developing countries girls lag behind boys' school enrollment (de Brauw et al., 2014).

Despite the common structure, CCTs vary greatly among countries. For instance, in their eligibility criteria and their targeting mechanism (Cecchini & Madariaga, 2011). However, almost all CCT programs draw on the economic theory of consumers as well as on human capital theory.

2.2 The Economic Rationale for CCTs

The following part introduces the economic theory of consumers, which is used as a framework to understand the behavior of individuals regarding their educational investment decisions and to understand the role of CCTs within this model.

The economic theory of consumers assumes that consumers choose the best bundle of goods they can afford within their budget constraints. Suppose that there a two goods from which a consumer can choose: x_1 and x_2. To understand the role of CCTs within this model, let x_1 denote education and x_2 work. The consumption bundle (x_1, x_2) describes how much a consumer is consuming of good one, x_1, in this case, education, and good two, x_2, in this case work. Denoting the prices of the goods using (p_1, p_2) and the amount of money a consumer can spend by m, then the budget constraint can be written as

$$p_1 x_1 + p_2 x_2 \leq m \qquad (1)$$

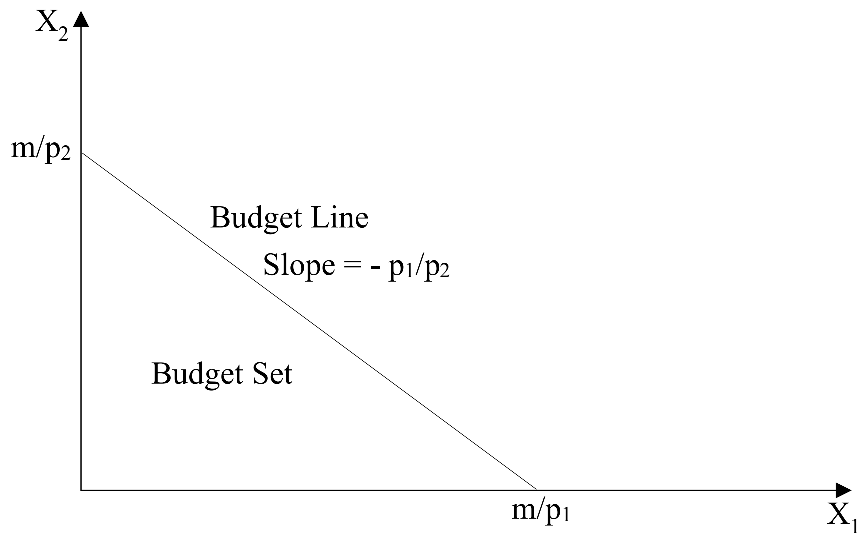
Here, p_1x_1 is the amount of money a consumer is spending on education and p_2x_2 represents the amount of money spent on work. The total amount spent on both goods has to be less than or equal to the budget of the consumer (Varian, 2010, pp. 20-26).

The budget line is the set of bundles that exactly cost m, which can be written as

$$p_1x_1 + p_2x_2 = m \qquad (2)$$

This is depicted in Figure 1.

Figure 1: *The Budget Set*



Source: based on Varian (2010)

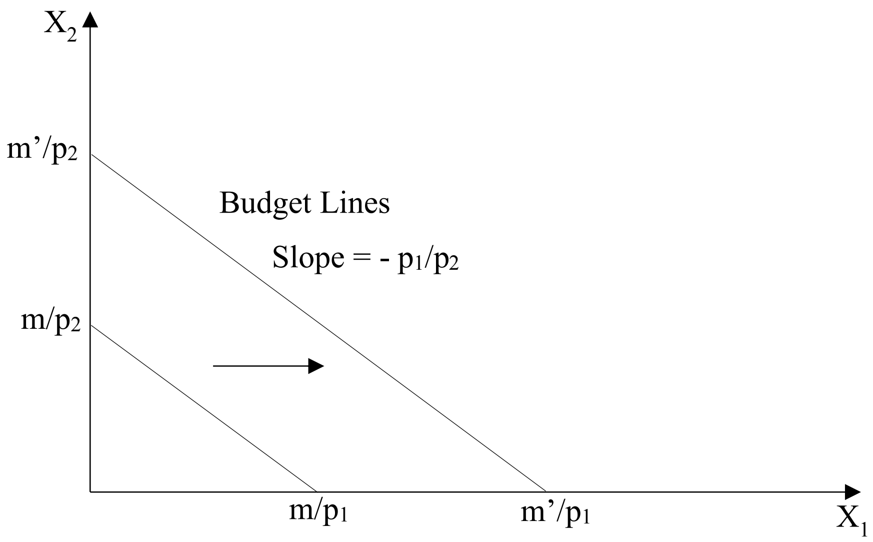
A consumer can afford all bundles below the budget line. To consume more from good one, in this case, education, one has to give up some of the consumption of good two, in this case, work. The slope of the budget line measures the opportunity cost of consuming good one (Varian, 2010, pp. 20-26). Hence, giving up the opportunity of going to work is the economic cost of going to school.

In this context, Ferreira, and Schady (2008) outlined a simple model of educational choice. In their model, the welfare of an individual depends on consumption in two periods – childhood and adulthood. During the first period, children can contribute to the household income by working. However, the time spent working comes at the expense of the available time for studying, and moreover, at the expense of earnings and consumption during adulthood.

Therefore, the optimal schooling choice depends on the child wage rate in the first period, the expected returns to education in the second period, the quality of schooling, and on household access to a functioning credit market. If credit markets are not functioning, the choice is influenced by the initial income of a household (Ferreira & Schady, 2008).

If the income of a consumer changes in period one, that is during childhood, the set of goods a consumer can afford changes as well. An increase in income will not affect the slope of the budget line, but will result in a parallel shift of the budget line in the positive X_1 direction, as depicted in Figure 2.

Figure 2: *Budget Lines and Increasing Income*



Source: based on Varian (2010)

Thus, if the income of a consumer increases, the consumer can afford a new consumption bundle and the opportunity cost of consuming more from one good decreases (Varian, 2010, pp. 20-26). In this case, if a household receives a CCT its income increases, which results in a parallel shift of the budget line. Hence, the consumption bundles a household can afford change, and most importantly, the opportunity cost of sending a child to school decreases.

2.3 The CCT Model for Long-Term Poverty Reduction

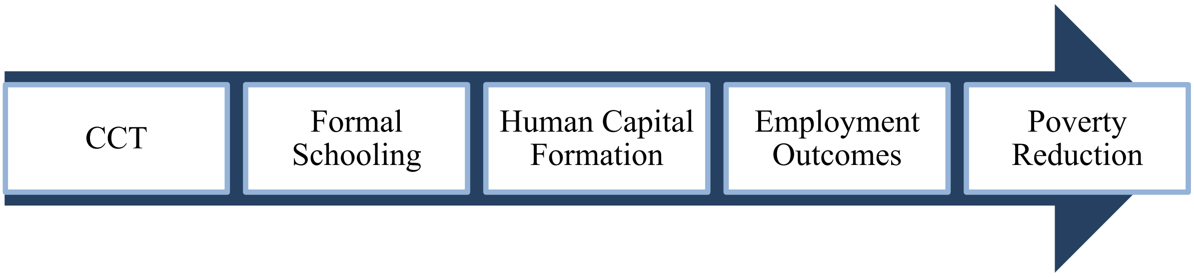
The CCT model draws from both the economic theory of consumers and the human capital theory. The latter postulates that access to employment and future earnings is a function of human capital attainment, which is at least partly acquired through schooling (Mincer, 1974; Schultz, 1961). The fundamental idea of the framework is that families choose to invest in the education of their children to increase their future productivity and earnings. The investment decision is affected by the balance between the current opportunity costs and the anticipated future earnings, which can be linked to the economic theory of consumers (Schultz, 2000; Oliveira, 2008).

In many developing countries credit markets are underdeveloped and poor households face constraints to invest in children's education due to budget as well as credit restrictions that prevent borrowing. Additionally, parents often have limited information on the returns of investments in education, contributing to under-investment (Cunha et al., 2005; Carneiro & Heckman, 2002, 2003). For example, parents might believe that earnings respond to education less elastically. In practice, there is evidence that this is the case in some developing countries such as Mexico and the Dominican Republic (Fiszbein & Schady, 2009). At the same time, the opportunity cost of going to school instead of working is high. As children contribute to the household income, the income decreases once they are sent to school, discouraging school enrollment.

Thus, low levels of human capital and the constraints to invest hinder poor families from escaping poverty across generations. CCT programs attempt to address this shortfall in human capital formation by transferring resources (cash) to poor families, which are linked to educational conditionalities (Jones, 2016). Hence, CCTs seek to encourage increased demand for schooling through an "income effect", by increasing the household income, and a "substitution effect", by decreasing the opportunity cost of schooling (Baird et al., 2014).

The broader logic of the CCTs is illustrated in Figure 3 below.

Figure 3: *The CCT Model for Long-Term Poverty Reduction*



Source: based on Jonas (2016)

Figure 3 shows that CCTs increase access to formal schooling through which students can obtain human capital. The creation of human capital will improve employment outcomes, increase earnings, and thus, lift individuals out of poverty (Jones, 2016).

Apart from that, returns to investments in education are not only private but also societal as education can boost economic growth (Gillies, 2015, p.1). Because of this, it is assumed to be beneficial for states to invest in education. Thus, CCTs can not only change household behavior towards a privately optimal investment in children's schooling, but also towards a socially optimal level. Even if investments in schooling are optimal from a private point of view, they might be below the socially desired level because of positive externalities arising from the education process. In the case of education, externalities might arise if there are increasing returns to skilled labor in production or if higher education lowers crime rates (Baird et al., 2014; Fiszbein & Schady, 2009).

Another argument in favor of CCTs is one of a political economy perspective. Redistributive policies might be more acceptable for taxpayers if they see that the transfers are tied to socially desirable behaviors rather than just being "handouts" (Baird et al., 2014). Moreover, CCT programs constitute a new form of a social contract between the state and recipients. The state does not undermine the role of households, but CCTs are based on the concept of shared responsibility. In this context, an analysis of Lindert and Vincensini (2008) found that conditions tied to cash transfers were important in generating broad-based support for BF in Brazil.

Critique of this theory arises as some scholars argue that the CCT model makes an inherent assumption about the quality of schooling. Thus, the model assumes that the quality of schooling that beneficiaries receive is high enough to supply the required human capital to increase future productivity and income, and hence, escape poverty. This also raises the problem that households that are aware of the low quality of the local education might not enroll their children in school. Consequently, households decide that it is more important for their children to contribute to the household income by working. Hence, those households might be deterred from taking up the benefit and exclude themselves from the program (Fiszbein & Schady, 2009). Aside from this, Jones (2016) criticized the linearity of CCT models, assuming that employment outcomes are directly related to human capital stocks. Jones (2016) argued that the linearity of CCT models fails to account for the demand side of the employment equation; that is, the availability of employment opportunities. Despite that, Jones (2016) claimed that other factors such as ethnic and gender discrimination, and individual networks, influence the relationship between schooling and future earnings, which the CCT model fails to address. An additional criticism is that the poorest households might find the conditions too costly to comply with and might therefore exclude themselves from the program. For example, the next school might be too far away, and despite the increased income, the opportunity costs might still be too high (Fiszbein & Schady, 2009).

Despite that critique, most scholars argue that CCTs are an important development policy tool to foster long-term, intergenerational poverty reduction (Baird et al., 2014).

3 Context

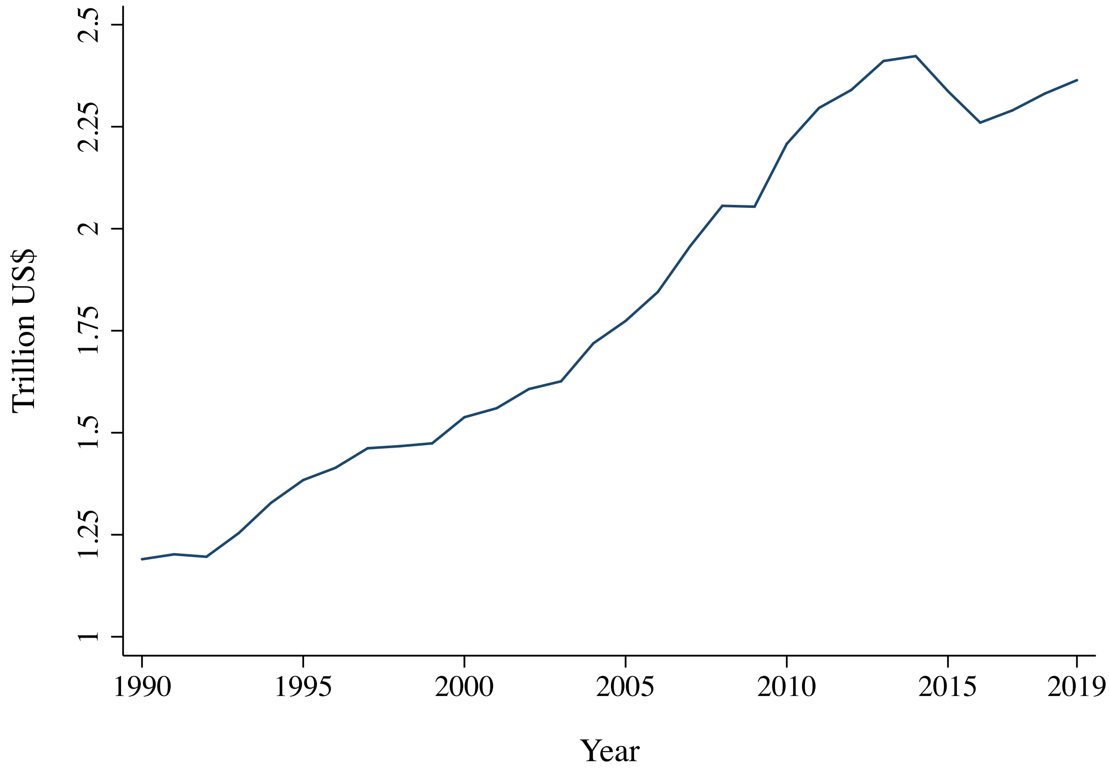
3.1 Country Overview: Brazil

The research of this thesis is assessed in the context of Brazil; the biggest country in Latin America in terms of population, area, and gross domestic product (GDP). Since the 1970s, Brazil has been known as one of the most unequal countries in the world (Neri, 2019; BMZ, 2020). Historically, the country has been highly segmented and large parts of the society, including the poor, have not been incorporated into the social system. For the first time, the government of Getulio Vargas (1930-45) took a real effort to create a social protection system (Lewis & Llyod-Sherlock, 2009). However, large parts of the workers in rural and informal sectors were not included and social policies remained subordinated to the country's economic strategy. Between 1946 and the 1980s efforts were made to expand social insurance to the rural sector, but to a minimal extent. Throughout the 1980s and 1990s Brazil struggled with political and economic crises. Even though the Federal Constitution of 1988 included a chapter on social security reforms, the implementation of social guarantees was slow during the 1990s. As a result, segmentation remained high (Sánchez-Ancochea & Mattei, 2011).

Until today, Brazil is characterized by high levels of inequality and poverty despite encouraging figures of growth in the last decades. Some descriptive statistics are presented in the following to understand the context of Brazil regarding poverty, inequality, and economic development.

Figure 4 below illustrates that within the period of interest, 2004 to 2014, Brazil experienced a consistent upward trend in economic growth.

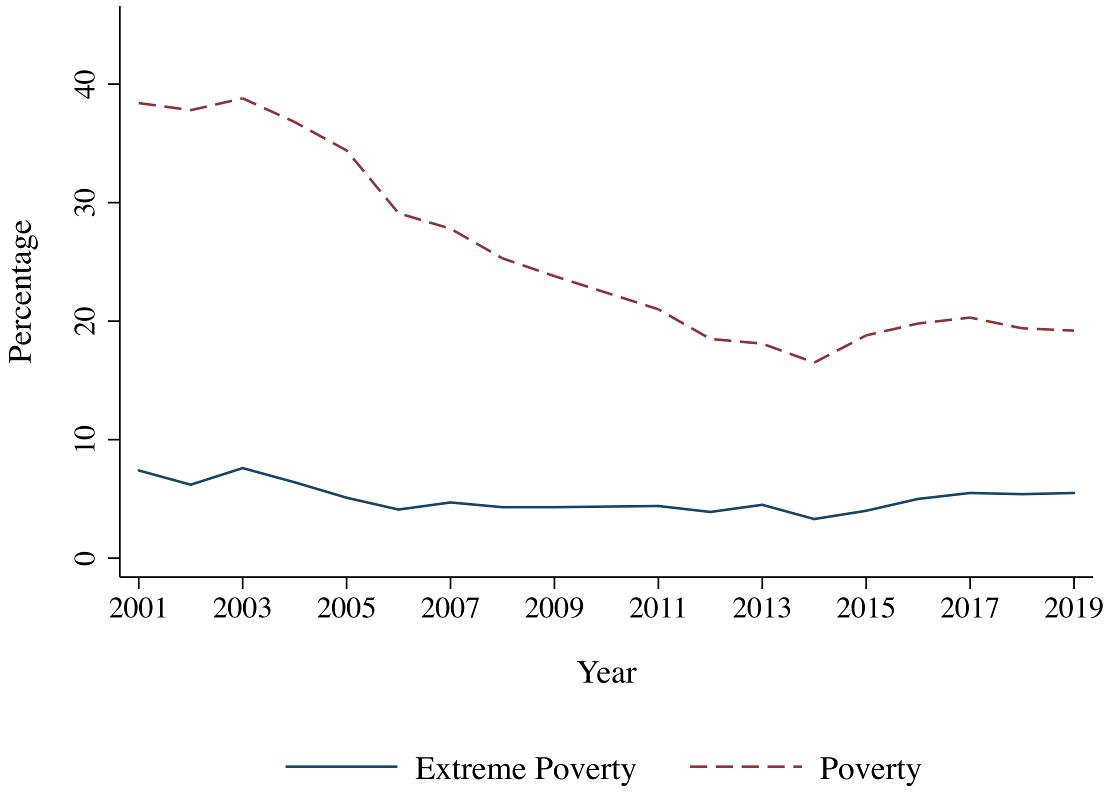
***Figure 4**: GDP (Constant 2010 US$), 1990-2019*



Source: based on CEPAL (2020c)

Between 2004 and 2014, GDP at constant 2010 US$ rose from US$1.72 trillion to US$2.42 trillion. That great economic performance can partly be attributed to the commodity boom that had a positive impact on the Brazilian trade balance and produced consistent surpluses (Adler & Sosa, 2011). Other variables that capture improvements in social indicators have also shown a positive trend, such as a reduction in poverty, which is depicted in Figure 5.

Figure 5: *Proportion of Individuals Considered Poor and Extreme Poor within the Brazilian Population, 2001-2019*[2]



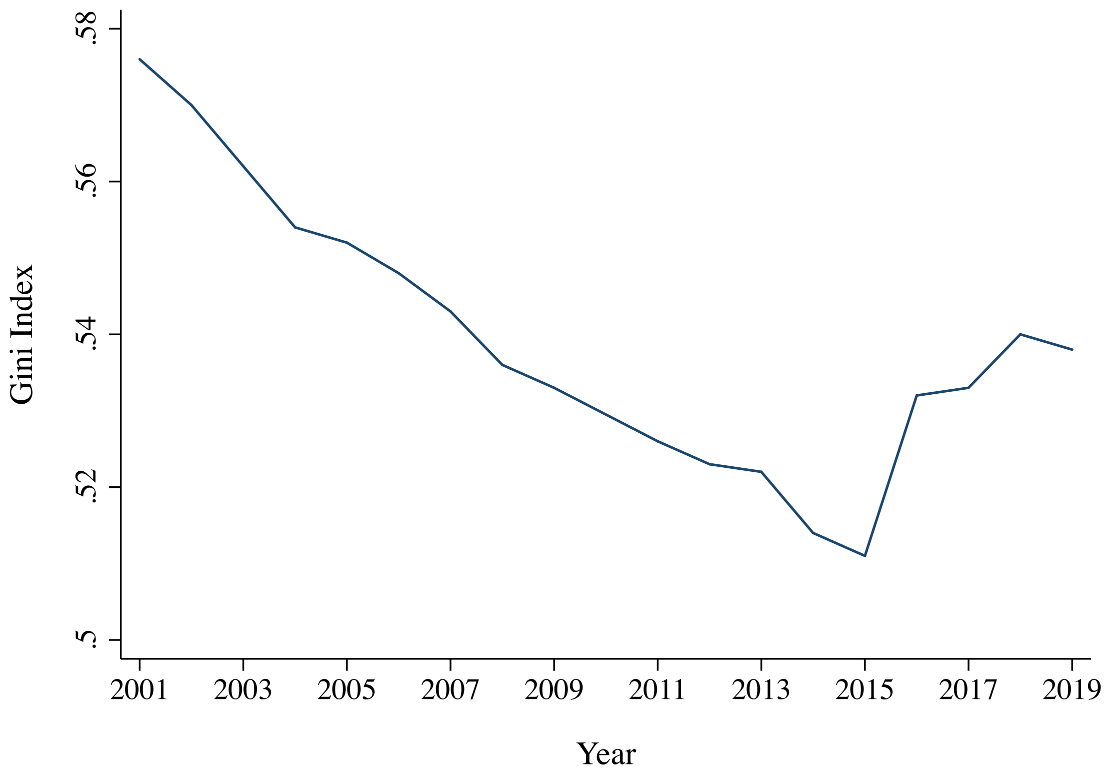
Source: based on CEPAL (2020b)

As shown in Figure 5, there was little change in the percentage of the population considered poor until the early 2000s. However, since 2003 a consistent downward trend in poverty can be observed, while extreme poverty remained stable. Besides that, Figure 6 shows that the Gini index fell slightly between 2004 and 2014 from 0.55 to 0.51, respectively. The reduction of

[2] The definition of extreme poor is based on the International Poverty Line, which is set at US$1.90 (2011PPP) per day per capita. The definition of poor is based on the Upper Middle Income Class Poverty Line, which is set at US$5.50 (2011PPP) per day per capita.

inequality was partly due to better redistributive policies, which benefited from the economic growth process (Barreto, 2005).

Figure 6: *Evolution of the Gini Index, 2001-2019*



Source: based on CEPAL (2020a)

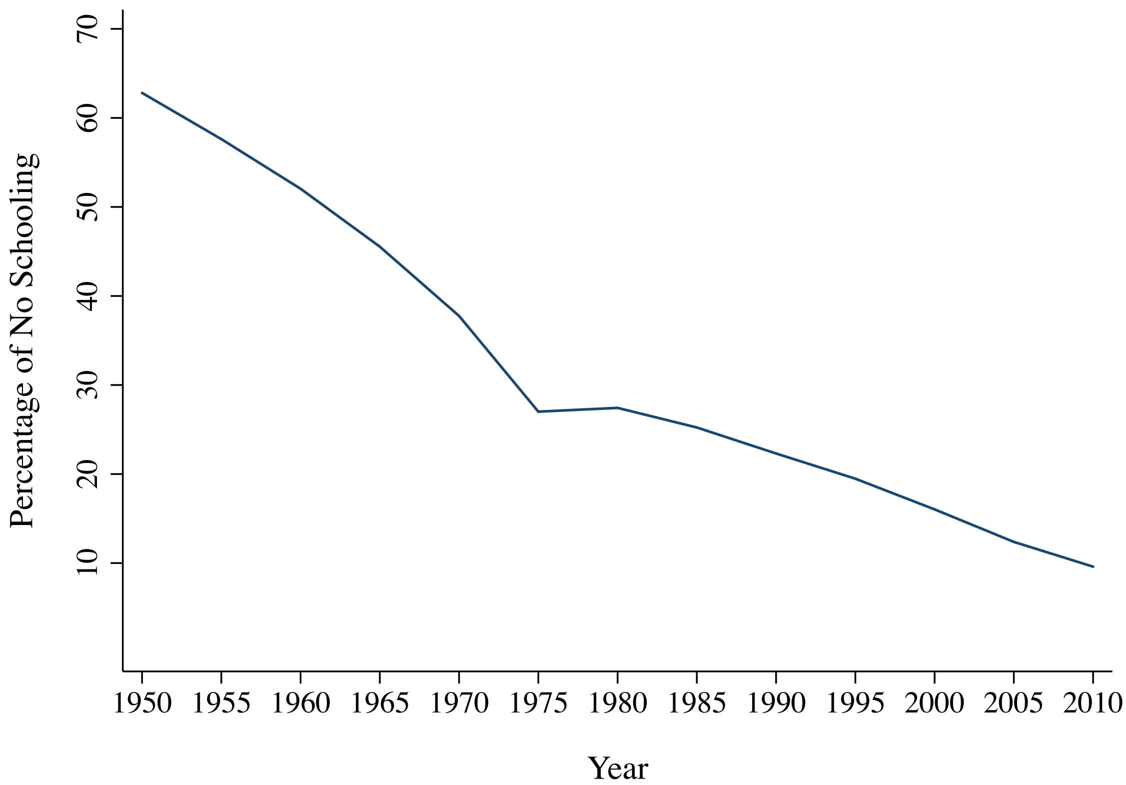
Even though the percentage of the Brazilian population living in poverty was cut by almost half and inequality declined, the levels remain high. One reason is the unequal distribution of access to education, which is important to enabling people to escape poverty and to lower inequality (Neri, 2019). Thus, the remainder of this section concentrates on the development of educational indicators.

The educational system in Brazil has experienced significant improvements since the 1990s. The Fund for the Maintenance and Development of Primary Education and Valuation of Teachers (FUNDEF) was created in 1996 to reduce inequalities in the supply of primary education. Its activities led to increasing coverage rates, higher wages for teachers, and redistribution of spending on primary education among states. Under President Lula (2003-

2011) FUNDEF was replaced with the Fund for the Maintenance and Development of Basic Education and Valuation of Education Professionals (FUNDEB). It extended the previous fund by incorporating secondary education. However, FUNDEB was accused of not being able to improve the quality of education (Burton, 2009; Sánchez-Ancochea & Mattei, 2011).

Nevertheless, school attendance increased and primary education became almost universal (Sánchez-Ancochea & Mattei, 2011). Figure 7 underlines the improvements in the educational sector in Brazil. In 1950, 62.81 percent of the population aged 15 years and older were without schooling, while the rate decreased to 9.6 percent in 2010.

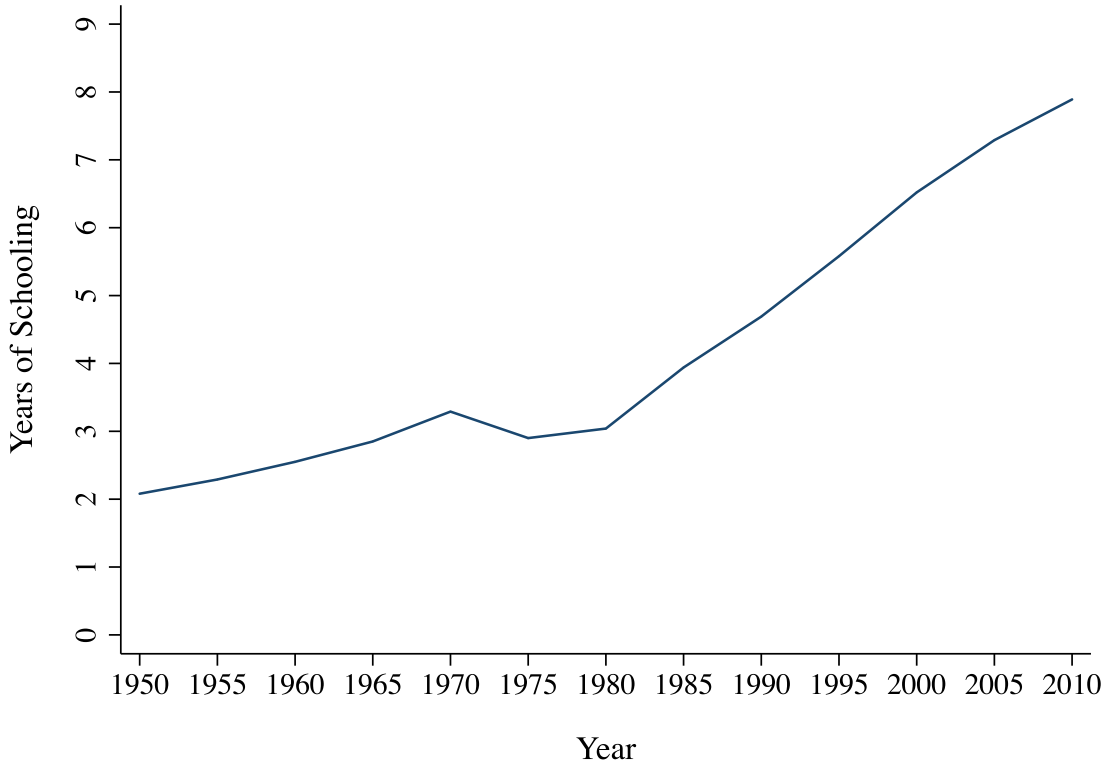
Figure 7: Proportion of Brazilian Population Without Schooling, 1950-2010



Source: based on Barro & Lee (2013)

Alongside the reduced percentage of the population without schooling, the average years of schooling of the Brazilian population have increased, which is illustrated in Figure 8.

Figure 8*: Average Years of Schooling of Total Population, 1950-2010*



Source: based on Barro & Lee (2013)[3]

Despite those advances, education in Brazil remains subpar. In 2010, the average schooling of a Brazilian adult aged 15 or older was 7.8 years, which was below the Latin American average. Moreover, regional discrepancies appear as the poorer Northern and Northeastern regions are those with the lowest school enrollment rates (Barro & Lee, 2013).

---

[3] The best-known database containing information on education performance. However, it does not provide data for the most recent years, which weakens the analysis. But the lack of quantitative data on the evolution of Brazilian education in the 20th century is a major obstacle to overcome this limitation.

Given the high economic growth rates alongside falling poverty, falling inequality, and some improvements in educational indicators between 2004 and 2014, it is of particular interest to examine if BF contributed to better educational outcomes in 2014. As poverty and inequality remain high, and the level of education low for some segments of the society, BF could influence those indicators through its potential impact on human capital formation.

3.2 Bolsa Família

The CCT program BF was implemented in 2003 through the merger of four previously existing cash transfer programs, which are discussed below.

During the time of political and social instability throughout the 1980s and early 1990s, experimentation and innovation in social policy in Brazil emerged. The first experiments with CCTs happened in the Federal District of Brasilia and were impacted by the debate on "Basic Citizen's Income" (Sánchez-Ancochea & Mattei, 2011). During that time, there was increasing consensus that poverty reduction strategies have to go beyond tackling the symptoms of poverty. Thus, the strategies have to confront the structural sources of poverty. Education was seen as the key to break the intergenerational cycle of poverty. The idea was based on demand-side constraints. For instance, poor children cannot attend school due to direct and indirect opportunity costs even though there are schools available (Lindert et al., 2007). In this context, the program *Bolsa Escola* was introduced in 1995 in the Distrito Federal[4] (Sánchez-Ancochea & Mattei, 2011). By 2001, many states and municipalities were covered by the program, and President Fernando Henrique Cardoso (1995-2003) introduced the program at the federal level in the same year. Poor families whose income was below R$90[5] received R$15 per month per child, up to a maximum of three children, if they had a minimum school attendance of 85 percent (Lindert et al., 2007). In addition, three other cash transfer programs were introduced (Sánchez-Ancochea & Mattei, 2011). The program *Bolsa Alimentação* was implemented to counteract malnutrition. Families with a monthly per capita income below R$90 received R$15 per child, up to three children. To receive those transfers, several conditions had to be fulfilled. Pre- and post-maternal checks had to be attended, the growth of children had to be monitored, vaccinations had to be kept up to date, and participation in nutritional educational seminars was required. In 2002, *Auxillo Gas* was introduced, a cash transfer program for cooking gas subsidies. Households received an unconditional transfer of R$7.50 per month and families whose income was less than half of the minimum wage received R$15 per month. At last, President Lula (2003-2011) introduced the Program *Cartão Alimentação* in 2003 to fight hunger. Families whose income was less than half of the minimum wage received R$50 per month for food purchases (Lindert et al., 2007).

All the programs, despite different goals, targeted poor families. President Lula's administration, therefore, consolidated the programs in 2003 to reduce administrative inefficiencies such as double coverages (Lindert, 2006). Ultimately, BF resulted from the merger of the four existing cash transfer programs and was built upon three principles: (1) expansion of healthcare, education, and nutritional services; (2) integration of conditional cash

---

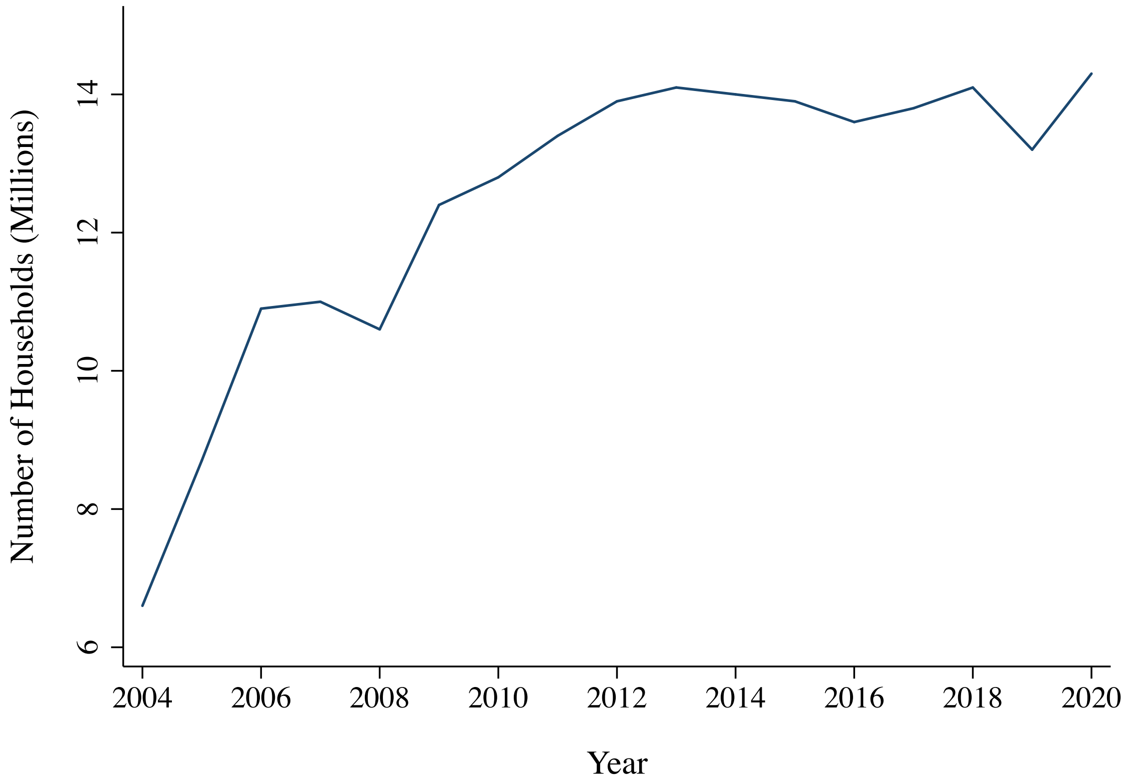
[4] The Distrito Federal is not a state but one of the 27 federative units of Brazil. When the capital of Brazil was moved to Brasília in 1960, the current Federal District was founded. Hence, the capital of Brazil, Brasília, is located in its territory (Meyer, 2010).

[5] 1 BRL = 0.56 2010 USD

transfer programs in the rest of the social protection system; (3) reduction of poverty through cash transfers. The Federal Law 10.836 made BF official on January 9, 2004, and the new *Ministério de Desenvolvimento Social e Combate à Fome* (Ministry of Social Development and Fight Against Hunger; MDS) was formed to administrate the program (Lindert et al., 2007; Sánchez-Ancochea & Mattei, 2011).

Today BF is the largest CCT program in developing countries in terms of beneficiaries (Soares et al., 2007; Lindert, 2006). Figure 9 shows that the number of families benefiting from BF increased from 6.5 million in 2004 to 14 million in 2014. While in 2004, 15.92 percent of the Brazilian population was covered by the program, the percentage increased up to 27.44 percent in 2014 (ECLAC, 2020).

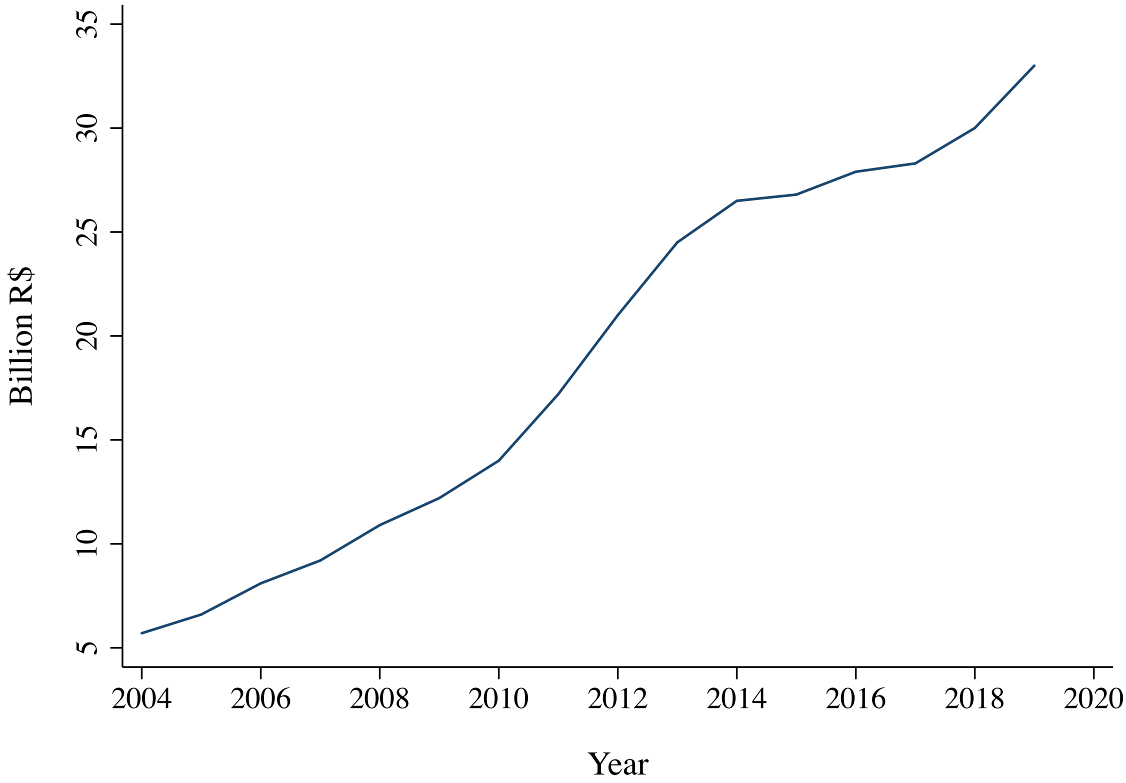
Figure 9: *Number of Beneficiary Households of Bolsa Família, 2004-2020*



Source: based on Ministério da Cidadania (2021)

At the same time, the annual expenditure on the program had risen from R$5.7 billion in 2004 to R$26.5 billion in 2014 and up to R$33 billion in 2019; this is depicted in Figure 10 below.

Figure 10: *Total Expenditure on Bolsa Família, 2004–2019, (R$)*



Source: ECLAC (2020)

The main objective of BF is to "reduce current poverty and inequality, by providing a minimum level of income to poor families and to break the intergenerational transmission of poverty by conditioning the transfers on compliance with human capital requirements" (Lindert et al., 2007). The conditions which have to be complied with to receive the program are presented in Table 1 below.

Table 1: *Conditionalities in Order to Receive Bolsa Família*

Children	*Mothers*
- Minimum school attendance of 85% for children between six and 15 years old - Minimum school attendance of 75% for children between 16 and 17 years old - Compliance with the vaccination schedule - Control of growth and development of children under seven	- Pre-natal controls - Monitoring of breastfeeding mothers between 14 and 44 years of age - Participation in nutritional seminars

Source: ECLAC (2020); Lindert et al. (2007)

To control if, for instance, school attendance is fulfilled, data on daily school attendance for all children are collected by teachers and merged by the school directors. Every school receives a list of the students who are BF beneficiaries from the municipality who in turn obtain their information from the federal bank CAIXA. Every two months, the information on attendance is sent to the Ministry of Education through the municipality and CAIXA. On this basis the Ministry prepares reports for the MDS, which enables linking school attendance to registry and payment information.

To be eligible for the program, households have to be registered in Brazil's National Registry for Social Programmes *Cadastro Único* and have to have a household income below a defined extreme poverty threshold (monthly household income ≤ R$77 in 2014) or the poverty threshold (monthly household income ≤ R$154 in 2014). Since 2004, many changes in the income threshold for eligibility took place, which is depicted in Table 2 below.

Table 2: Eligibility Criteria for Bolsa Família Receipt between 2004 and 2014[6]

Year	*Extreme Poverty Eligibility Criteria*	*Poverty Eligibility Criteria*
2004	≤ R$50 (US$12.5)	≤ R$100 (US$26)
2007	≤ R$60 (US$15)	≤ R$120 (US$30)
2009	≤ R$70 (US$17.5)	≤ R$140 (US$35)
2014	≤ R$77 (US$19.3)	≤ R$154 (US$38.5)

Source: Pescarini et al. (2020)

When the program started extremely poor households received a basic grant of R$50 per month, independent of their household characteristics. They received an additional R$15 per child below the age of 15, up to a maximum of three children, when complying with the conditionalities presented above. Poor households with an income between R$50 and R$100 received only the conditional benefit from the children-based allowance, but not the fixed benefit (Sánchez-Ancochea & Mattei, 2011). Table 3 provides information on the monthly basic grant and the variable bonus from BF in 2014 to underpin the difference between the grants received by poor and extremely poor households.

[6] The values are set at per capita per month.

Table 3: *Monthly Grant from Bolsa Família in 2014*

	Monthly Household Income per Capita	*Basic Grant*	*Variable Bonus for Children under 15 Years (Max. 3 Children)*	*Variable Bonus for Adolescents between 16-17 Years (Max. 2 Children)*	*Variable Bonus for Pregnant Women*	*Variable Bonus for Breastfeeding Mothers*
Extremely Poor	0 - 77	77	35	42	35	35
Poor	77.01 - 154	0	35	42	35	35

Source: ECLAC (2020)

Extremely poor families received a basic grant of R$89 per month, independent of household characteristics. Poor families only received the variable bonus for children, adolescents, pregnant women, and breastfeeding mothers if the conditions were fulfilled. Extremely poor families also obtained bonuses if they complied with these conditions. Preferentially, BF is paid to women, since a substantial body of research has shown that women are more likely to spend the money on their children's education, nutrition, and health (Lindert, 2006).

At last, BF has been under criticism for a high unmet demand. Studies based on information from the Brazilian Institute of Geography and Statistics (IBGE) found a high percentage of exclusion; that is, eligible families that do not receive the transfer (Soares et al., 2007; Rocha, 2008). Some scholars explain this by the fact that the program depends on self-reporting and that poor households might be afraid of stigmatizing effects of receiving such a program (Kerstenetzky, 2009). Moreover, cases of corruption and political favoritism at the local level have been criticized (Sánchez-Ancochea & Mattei, 2011).

4 Previous Research

With the expansion of CCT programs in Latin America since the 1990s, a large body of literature has assessed the relevance of CCTs as a policy tool. Most of these studies have focused on the impact of these interventions on poverty, inequality, health, and education (Millán et al., 2019). The preferred methods to evaluate CCTs were experimental or quasi-experimental (Cecchini & Madariaga, 2011).

When assessing the educational component of CCTs, most studies found that the effects were concentrated in the increase in school enrollment (Schady, 2006). Aside from this, the increase was found to be bigger in countries with lower levels of school enrollment as well as for the poorest households (Cecchini & Madariaga, 2011; Fiszbein & Schady, 2009).

Fiszbein and Schady (2009) found that CCTs had a positive effect on school enrollment in Chile, Colombia, Ecuador, Honduras, Jamaica, Mexico, and Nicaragua. Although, the authors found the impact of CCTs on other educational outcomes to be less conclusive. For example, in Mexico adults receiving the CCT had on average two years more of schooling. However, the increase in wages because of this added schooling was small. Fiszbein and Schady (2009) claimed that this might be due to the low quality of services and concluded that increased use alone does not yield large benefits.

Closely related to this, de Brauw and Hoddinott (2011) found that conditionality led to a significant difference in the probability of school attendance in their study on the CCT program *Progresa* in Mexico. Particularly, the authors found that the average effect showed significant heterogeneity across children in different grades. While the effect of receiving the transfer on school enrollment was low for children in primary school, it was quite large for children in secondary school. Analyzing the same program, Parker (2003) found that it closed the gender gap in school enrollment rates in secondary schools, especially in rural areas.

Similarly, Levy and Ohls (2010) estimated that the *Program of Advancement Through Education and Health* in Jamaica increased school attendance by 0.5 days per month for children between six and 17 years of age. Comparably, the *Programa Solidaridad* in the

Dominican Republic increased the likelihood of attending school by 14 percentage points for students between 14 and 16 years (Programa Solidaridad, 2008). Likewise, Soares et al. (2008) estimated that the *Tekopara* Program in Paraguay increased school enrollment rates by 2.5 percent for children while the school attendance rate rose by eight percentage points.

Lastly, using data from 75 reports that cover 35 studies, Baird et al. (2014) found that the odds of being enrolled in school were 36 percent higher among children in households which received a CCT compared to children who did not received a CCT.

Thus, several studies have assessed the impact of CCTs on education. However, literature on the impact of BF on education is scarce. Most studies have investigated the impact of BF on inequality and a consent has emerged that BF contributed to the decline of inequality in Brazil (Sánchez-Ancochea & Mattei, 2011; IPEA, 2009; Soares, 2006; Barros et al., 2007; Soares et al., 2007; Hoffmann, 2013). For instance, the IPEA (2009) estimated that BF was responsible for ten percent of the overall reduction in inequality between 2001 and 2008 (Sánchez-Ancochea & Mattei, 2011). Using a similar methodology, Soares (2006) arrived at comparable results. By subtracting the effects of social security transfers and rents, Soares (2006) concluded that BF contributed with twelve percent to the improvements in the income distribution between 2001 and 2004. Confirming these studies, Barros et al. (2007) found that BF contributed to the fall of inequality by eleven percent. Hoffmann (2013) confirmed those findings for the 2001-2011 period. Authors such as Barros et al. (2007) explained the positive effect of BF on inequality by the fact that the transfers were concentrated on households at the bottom of the income distribution (Barros et al., 2007).

As discussed above, there is a broad consensus within academia that BF contributes to declining inequality. Most studies found an even larger impact of BF on poverty than on inequality; however, the results were less conclusive (Sánchez-Ancochea & Mattei, 2011). On the one hand, Hoffmann (2006) estimated that BF was responsible for 30 percent of the poverty reduction between 2002 and 2004. Similarly, Soares et al. (2007) argued that BF reduced poverty by twelve percent, while the poverty severity measure showed that BF led to a 19 percent reduction in poverty. On the other hand, authors such as Rocha (2008) stated that the impact of BF on poverty depends on the location of the poor. For instance, the relative effect of the transfers on urban poor was estimated to be smaller than on rural poor and the author claimed that the contributions were often insufficient to lift the households out of poverty.

Hence, several studies have assessed the effect of BF on inequality and poverty. Even though a positive impact was found, the effect on poverty and inequality was determined to be a one-time effect. To sustain the positive impact, BF has to improve the level of the human capital of participating children. However, literature on the impact of BF on education is scarce and most studies have evaluated its predecessor program *Bolsa Escola.* The lack of information is partly due to the lack of impact evaluations in the program's design. Apart from that, no randomized evaluation was designed for Brazil and no longitudinal household survey data is available (de Brauw et al., 2014). Consequently, much less is known about the effect of BF on poverty and education compared to other programs (Fiszbein & Schady, 2009).

In this context, Bourguignon et al. (2003) assessed the *Bolsa Escola* Program using an ex-ante methodology. Their results suggested that 60 percent of children between ten and 15 years of age of poor households, who were not enrolled in school, would enroll in response to the program. In general, 40 percent of ten to 15-year-olds would enroll in school. Less positive were the results concerning poverty and inequality. The authors found that the program reduced the incidence of poverty by only one percentage point, whereas the Gini coefficient fell by just half a point.

Similarly, a study by Janvry et al. (2006) assessed the impact of *Bolsa Escola* on dropout rates and grade retention using school records of 293,800 children between 1999 and 2003. The findings suggested that *Bolsa Escola* had a strong positive impact on reducing child dropouts during the school year. The program led to a 7.8 percentage point improvement in complete year attendance. Despite that, the grade failure rate increased by 0.8 percentage points. Janvry et al. (2006) pointed out that the program might have helped less able children to stay in school who otherwise would have dropped out.

Despite the lack of information on BF some studies have assessed its impact on educational indicators. The minority of them found a negative effect of BF on the human capital formation of children. Evaluating the impact of BF on school enrollment in 2011 by using a Regression Discontinuity Design, Nilsson and Sjöberg (2013) found that BF led to lower school enrollment rates for children born between 1993 and 2004.

On the contrary, the majority of studies found a positive impact of BF on educational indicators (Oliveira, 2008; Amaral et al., 2014; de Brauw et al., 2014).

Oliveira (2008) used propensity score matching to determine the effect of BF on beneficiaries' lives. The author found that the allocation of time spent on schooling instead of working has increased among BF recipients. Depending on the region, school results have improved as well. However, by evaluating other programs such as the *Programa de Erradicação do Trabalho Infantil* (Eradication of Child Labor), Oliveira (2008) found that those programs had a larger positive impact on school attendance than BF.

In line with the results from Oliveira (2008), a report by CEDEPLAR (Center for Development and Regional Planning) from 2005 found a positive impact of BF on school attendance. The probability of absence of children participating in BF was 3.6 percentage points lower, while the probability of dropping out was 1.6 percentage points lower than for children of not-participating households. Despite that, the study found that the program had a small impact on class performance as children who benefited from BF were less likely to pass their classes (Soares et al., 2007; Sánchez-Ancochea & Mattei, 2011).

Closely related, Amaral et al. (2014) used data from the 2010 Brazilian Demographic Census and logistical models to estimate the effect of BF on school enrollment, age-grade discrepancy, and child labor. Their results suggested that beneficiaries had a higher chance of being enrolled in school and that there was a lower age-grade discrepancy among children who received BF. However, the models also suggested higher chances of child labor among BF recipients.

Lastly, de Brauw et al. (2014) evaluated the impact of BF on school participation, grade progression, grade repetition, and dropout rates by constructing a household survey panel using the years 2005 and 2009. By using a propensity-score-weighted regression, the authors estimated that BF increased school participation of children between six and 17 years of age by 4.5 percent. On average, BF had no impact on grade promotion. However, for girls BF led to an increase in school participation of 8.2 percent and rates of progression of 10.4 percent. Overall, the authors found that the impacts were larger among older children, in rural areas, and in the Northeast.

5 Data

5.1 Source Material

The data used in this analysis comes from the Brazilian household survey *Pesquisa Nacional por Amostra de Domícilios* (PNAD) provided by the Brazilian Bureau of Statistics. The IBGE conducts the PNAD yearly, and, for this analysis, the PNAD 2014 was used.

The survey collects annual information on the socioeconomic status and demographic characteristics of the Brazilian population. Variables like age, gender, income, and education are collected at the individual as well as at the household level. Overall, each survey includes more than 300,000 individuals and contains more than 300 variables (IBGE, 2014).

The individuals in the sample were randomly selected and were obtained through three different stages: (1) municipalities, (2) census areas, and (3) residential units. Silva et al. (2002) provided a thorough description of the sampling process using PNAD 1998. The authors pointed out that weighting or stratification during the sampling process could weaken the representativeness of the data and hence, could bias the estimates and could lead to interpretation problems.

To avoid that issue, the IBGE provides a weighted database. By using these weights, the IBGE aims to correct for biases during the sampling process. At the same time, it aims to secure the representativeness of the database by taking fertility, mortality, and migration patterns in Brazil into account. For further information and explanation on the weighting process see IBGE (2013).

5.2 Data Limitations

Despite the efforts to minimize sampling issues and estimation biases, some questions about the quality of the survey remain. Ferreira et al. (2003) raised some of those concerns. Firstly, the authors criticized that the questions on income sources other than wage employment are insufficiently disaggregated and detailed. The authors claimed that the absence of such questions is likely to lead to income under-reporting of workers. Because of the short-term income questionnaire, incomes are not only underestimated, but poverty levels are also overestimated. Secondly, Ferreira et al. (2003) are skeptical about the PNAD’s representativeness in Northern rural areas. Similarly, Soares et al. (2006) argued that the surveys do not capture phenomena well that are concentrated in specific geographical areas. In addition, they criticized that the surveys do not capture government transfers on an individual’s income.

Nevertheless, the National Household Survey PNAD is the most comprehensive data set which is publicly available and allows the effect of BF on educational indicators to be studied. Because of its comprehensiveness alongside its potential explanatory power, PNAD is seen as a reliable data source that can be used for this type of study.

Having covered the general aspects of the survey, the variables used in this study are introduced in the following section.

5.3 Variables

To conduct the analysis, two empirical models were estimated, which only differ in their outcome variable. The first model aims to answer the main research question[7]. The outcome variable is school enrollment, which is based on the question "Are you enrolled in school?" The variable was coded as a dummy variable where one equals enrolled in school and zero equals not enrolled in school. In the second empirical model, literacy was used as an outcome variable to answer the second research question[8]. This is based on the question "Can you read and write?" The variable was coded as a dummy variable where one equals yes and zero equals no. Both outcome variables were used as they are considered to be a good measure of the level of enhancement of human capital (Nilsson & Sjöberg, 2013). In addition, most studies assessing the impact of CCTs on education use school enrollment as an outcome variable (Baird et al., 2014; Cecchini & Madariaga, 2011; de Brauw & Hoddinott, 2011; de Brauw et al., 2014; Levy & Ohls, 2010; Bourguignon et al., 2007; Amaral et al., 2010). The main explanatory variable in both models is whether a household received BF or not. This is a binary coded treatment variable (1 = *Bolsa Família*; 0 = *No Bolsa Família*), which is based on the question "What is your monthly household income?" As the household surveys lack a direct identification of BF recipients, information on monthly household income was used to construct the variable. This was possible due to the monetary threshold which makes households eligible for BF. Hence, the assumption was made that in 2014 households with a monthly household income between zero and R$154 received BF. This method was also used by the *Insituto de Pesquisa Econômica Aplicada*, IPEA (Institute for Applied Economic Research), as well as by Nilsson and Sjöberg

---

[7] Main research question: "*How did Bolsa Família affect school enrollment rates of children in beneficiary households compared to non-beneficiary households in 2014?*"

[8] Second research question: "*How did Bolsa Família affect the literacy rates of children in beneficiary households compared to non-beneficiary households in 2014?*"

(2013) and suggested by Foguel and Barros (2008) and Soares et al. (2006). These authors concluded that the identification of BF recipients through the report of their monthly household income is a valid method.

The control variables used in this study include gender (1=Male; 0=Female) and whether a mother was present in the household (1=Yes; 0=No). Other control variables include the number of household members (continuous), the monthly household income (continuous), the race of the recipient (1=White; 0=Non-White), the geographical location of the family home (1=Urban; 0=Rural), and the age of the beneficiary in years (continuous). As the study is interested in the effect of BF on educational indicators, the sample was restricted to individuals between six and 17 years of age since BF is conditioned on school attendance of children in this age range. Lastly, following Weiss (2014), the standard errors were clustered at the state level, using the state variable which indicates in which state the individual was living. Summary statistics are presented in Table 4 below.

Table 4: *Summary Statistics*

Variable	*Obs.*	*Mean*	*Std. Dev.*	*Min*	*Max*
School enrollment (1=Enrolled; 0=Not enrolled)	66,471	0.95	0.23	0	1
Literacy (1=Literate; 0=Illiterate)	66,471	0.92	0.26	0	1
Bolsa Família (1=Beneficiary; 0=Non-beneficiary)	66,471	0.01	0.11	0	1
Monthly household income (R$)	66,471	2,732.97	3,747.34	0	200,000
Gender (1=Male; 0=Female)	66,471	0.51	0.50	0	1
Age (Years)	66,471	11.72	3.44	6	17
Race (1=White; 0=Non-white)	66,471	0.38	0.48	0	1
Mother present in household (1=Yes; 0=No)	66,471	0.87	0.33	0	1
Number of household members	66,471	4.59	1.65	1	17
Geographical location (1=Urban; 0=Rural)	66,471	0.83	0.38	0	1

6 Methodology

6.1 The Model

To estimate the effect of BF on school enrollment and literacy, a logistic regression was applied. It consists of a logistic function to model a binary dependent variable (Kleinbaum & Klein, 2010). Since both dependent variables in this study are binary coded variables, this design seemed most suitable.

Naturally, the best way to evaluate the impact of BF would have been a natural experiment. However, BF was not randomly implemented and therefore a natural experiment could not be carried out. Most studies evaluating the effect of CCTs on education outcomes deal with this issue by using a difference in difference method. However, this method could not be applied when evaluating BF. Given that the Brazilian program was not gradually rolled out, data before and after the treatment for the treatment and the control group was not available. Therefore, the regression was performed as a Sharp Regression Discontinuity (SRD) analysis. This method has been applied in other studies that evaluated CCTs (e.g. Nilsson & Sjöberg, 2013), and is a good alternative as it allows the estimate of the average causal treatment effect.

A SRD design takes advantage of the income threshold of households to be eligible for BF. In this case, once the income of a household is below a certain threshold, the treatment, BF, is "switched on". A certain bandwidth around that threshold was used to identify the treatment group, just below the threshold, and the control group, just above the threshold. Within that bandwidth, individuals were assumed to have on average the same characteristics and the only difference was whether they received BF or not. Thus, the average causal treatment effect could be measured (Imbens & Lemiux, 2008).

The econometric specification follows Imbens and Lemiux (2008). Let $Y_i(0)$ denote the outcome without exposure to treatment and $Y_i(1)$ the outcome with exposure to treatment. The main interest of this study is then the difference $Y_i(1) - Y_i(0)$. In this setting, $W_i \in \{0,1\}$ denotes the treatment received with $W_i = 1$ if unit i was exposed to treatment, and $W_i = 0$ if otherwise. The outcome can be written as

$$Y_i = (1 - W_i)\, Y_i(0) + W_i\, Y_i(1) = \begin{cases} Y_i(0)\ if\ W_i = 0, \\ Y_i(1)\ if\ W_i = 1. \end{cases} \qquad (3)$$

Here, Y_i denotes school enrollment or literacy and W_i whether an individual received BF or not.

In a SRD setting, the assignment to treatment, W_i, is determined by the forcing variable X_i. In this case, the treatment, BF, is determined by the covariate X_i, the monthly household income in R$.

$$W_i = 1\{X_i \leq c\} \qquad (4)$$

Here, X_i denotes the monthly household income and c the threshold. This threshold was set at R$154 in 2014 (Pescarini et al., 2020). All units with a covariate value below or equal to c were assigned to treatment, in this case, the households received BF. All other units with a covariate value above c were not assigned to treatment.

In an SRD design, given the value of the covariate, the conditional expectation of the outcome variable is looked at near the discontinuity to find the average causal treatment effect. Thus, this study analyzes the discontinuity in the expected value of Y, school enrollment and literacy, given a household received BF. This is given by the following relation

$$\lim_{x \uparrow c} \mathbb{E}[Y_i | X_i = x] - \lim_{x \downarrow c} \mathbb{E}[Y_i | X_i = x] \qquad (5)$$

This can be interpreted as the average causal treatment effect at the discontinuity point

$$\tau_{SRD} = \mathbb{E}[Y_i(1) - Y_i(0) | X_i = c] \qquad (6)$$

This equation gives the average causal treatment effect as it shows the conditional expectation of the difference in school enrollment or literacy between individuals that received BF and individuals that did not receive BF when their monthly household income equaled R$154 in 2014.

However, in the model, there are no individuals in the control group whose monthly household income equals c. If directly implemented, the overlap assumption, which requires that there is a treatment and control group for all values of the covariate, would be violated. According to

Imbens and Lemiux (2008), this implies a need for extrapolation. However, extrapolation increases the uncertainty of the results. Nevertheless, the sample size is large enough that this uncertainty can be avoided by using the average treatment effect at $X = c$ instead of the extrapolation.

$$\tau_{SRD} = \mathbb{E}[Y(1) - Y(0)|\mathrm{X} = c] = \mathbb{E}[Y(1)|\mathrm{X} = c] - \mathbb{E}[Y(0)|\mathrm{X} = c] \qquad (7)$$

Here, the treatment effect is observed when the monthly household income is close to c. Thus, individuals with a covariate value close to the threshold were exploited. To justify this, a smoothness assumption had to be made which ensured the continuity of the conditional regression functions as well as the conditional distribution functions. Hence, it was assumed that unobserved and observed variables that also influence school enrollment and literacy were likely to be smooth across the threshold of R$154. Thus, changes in school enrollment and literacy around the threshold can be attributed to BF.

As mentioned above, it was assumed that individuals close to the threshold had on average the same characteristics. Therefore, the logistic regressions only ran within a distance of h on either side of the discontinuity point.

For the treatment group the function is

$$\min_{a_1\beta_1} \sum_{i:c-h<X_i<c} (Y_i - a_1 - \beta_1 (X_i - c))^2 \qquad (8)$$

For the control group the function is given by

$$\min_{a_r\beta_r} \sum_{i:c\leq X_i<c+h} (Y_i - a_r - \beta_r (X_i - c))^2 \qquad (9)$$

The average causal treatment effect can then be estimated by solving

$$\min_{a,\beta,\tau,y} \sum_{i=1}^{N} 1\{c - h \leq X_i \leq c + h\} (Y_i - a - \beta (X_i - c) - \tau W_i - y (X_i - c) W_i)^2 \qquad (10)$$

Following Nilsson and Sjöberg (2013) the smallest possible bandwidth h was calculated by $h = c \times N^{-\frac{1}{5}}$. Estimating the bandwidth for 2014 by solving $154 \times 66471^{-\frac{1}{5}}$ resulted in a bandwidth h of $\pm$16.71.

Concerning the bandwidth, there is always a tradeoff between proportionality, sample size, and comparability. By choosing a bandwidth of ± 16.71, which is the smallest bandwidth possible for the restricted dataset, individuals around the threshold likely have similar characteristics. However, at the same time, the sample size was reduced to 321 individuals and the size of the treatment and control group was not balanced: 73.83 percent of the sample were beneficiaries while 26.17 percent of the sample were non-beneficiaries. Nevertheless, the proportionality of the treatment and control group is not considered important as long as the number of observations in each group is large enough. Consequently, the model still has statistical power. To test if the results are robust using a different bandwidth, the bandwidth was increased to the largest bandwidth possible in the sensitivity analysis. Using h of ± 154[9] increased the sample size to 2,156 individuals and the sample became more balanced: 38.78 percent of the sample were beneficiaries while 61.22 percent of the sample were non-beneficiaries. Moreover, a larger sample size makes it easier to establish statistical significance. However, more observations at each side of the threshold bear the risk that the individuals are less similar in their characteristics.

Lastly, the logistic regression used in this study can be written as

$$Y_{X_i} = a + \beta_1 D_{X_i} + \Gamma Z_{X_i} + u_{X_i} \tag{11}$$

Here, Y_{X_i} in model one is the binary distributed outcome variable indicating if an individual is enrolled in school ($Y_{X_i} = 1$) or not ($Y_{X_i} = 0$) at a certain monthly household income. In model two, the binary distributed outcome variable Y_{X_i} indicates if an individual is literate ($Y_{X_i} = 1$) or not ($Y_{X_i} = 0$) at a certain monthly household income.

[9] Using a bandwidth of $h = \pm 154$ implies that on the left side of the cutoff point, $c = 154$, all individuals were included in the analysis. Thus, at least on the left side of the cutoff point, it is the largest possible bandwidth.

BF ($D_{X_i} = 1\, if\ BF;\ D_{X_i} = 0\, if\ no\ BF$) is the binary coded treatment variable which is a deterministic function of the running variable X_i, here the monthly household income. The vector Z_{X_i} represents a set of control variables. In principle, there is no need for additional controls other than the running variable, here the monthly household income, because there should not be important differences in other covariates right around the cutoff point. Nevertheless, including covariates is useful to see if the results stay robust. In addition to monthly household income, the model was controlled for gender, number of household members, geographical location of the household, race, age of the individual, and whether a mother was present in the household. The error term is represented by u_{X_i} and was assumed to be uncorrelated with D_{X_i} and Z_{X_i}. The parameters a, β_1, and Γ estimate the effect of the included independent variables. The coefficient of interest is β_1. It captures the effect of BF on school enrollment in model one and on literacy in model two.

As stated in the hypothesis, it is expected that BF had a positive effect on school enrollment and literacy as it seeks to contribute to the formation of the human capital of children (Sánchez-Ancochea & Mattei, 2011). Concerning the control variables, it is expected that the higher the monthly household income the higher the chance that children were enrolled in school and that they were literate. This is based on the assumption that households with higher incomes face fewer financial constraints. Therefore, the opportunity costs of sending children to school are lower (Baird et al., 2014). Furthermore, it is expected that being male was associated with a higher probability of being enrolled in school and being literate, since in many developing countries families rather send their male than female children to school (Fiszbein & Schady, 2009). It is also assumed that age negatively correlates with school enrollment due to the early labor force participation of children in developing countries (Dubois et al., 2012). However, it is assumed that age had a positive effect on literacy, because as children grow older they are likely to learn how to read and write. Concerning race, it is assumed that white people were more likely to be enrolled in school. This is likely to be the case as white people are, on average, wealthier than people of color, which decreases the opportunity costs of sending their children to school (Jones, 2016). It is expected that if a mother was present in the household the probability of being enrolled in school and being literate increased. This relates to the theory that mothers are more likely than men to spend their additional income on their children, and thus, might have a positive impact on school enrollment as well (Baird et al., 2014). It is also expected that the more individuals were living in the household, the higher the chance that not all children could attend school. Lastly, given the higher supply of schools in urban areas, it is anticipated that living in urban areas had a positive effect on school enrollment (Barro & Lee, 2013).

6.2 Limitations of the Model

In regard to the methodology, some limitations have to be kept in mind. As this study used a quasi-experimental design it relied to some extent on an imperfect identification strategy, which could lead to more uncertainty regarding the measurement of the treatment effect. De Brauw et al. (2014) argued that it is likely that there is some dimension of self-selection into the program as it depends on self-registration. Thus, not every household whose income was below R$154 in 2014 might have received BF. However, by conducting household interviews, Nilsson and Sjöberg (2013) found that most families that were eligible for BF signed up to receive the benefit. On the contrary, Sánchez-Ancochea and Mattei (2011) argued that the exclusion error is high.

Additionally, certain assumptions have been made to calculate the size of the effect; for example, that individuals close to the threshold within the selected bandwidth had, on average, the same characteristics. If that assumption is violated, the effect on school enrollment cannot be attributed to BF alone, but can be influenced by different characteristics among the individuals in the sample. Furthermore, the SRD design provides estimates of the average treatment effect for a subpopulation with a covariate value close to $X_i = c$. Therefore, the design has only a limited degree of external validity, and thus, the findings cannot be generalized to different contexts. Despite low external validity, the advantage of the SRD design is a high degree of internal validity (Imbens & Lemiux, 2008). The robustness of the results was checked by varying the selected bandwidth. However, threats to internal validity such as an omitted variable bias cannot fully be ruled out. For instance, other events than the treatment event that occur between the pre-and post-intervention could impact the outcome variable and such events are too complex to be captured by the model.

Despite the limited transferability of the results to the cases of other countries, the SRD design outlined above seems most suitable to answer the research questions. Moreover, the results of this thesis have a high internal validity for the case of Brazil.

7 Empirical Analysis

Following the methodological framework, this section presents the models' estimates and tests the robustness of the findings.

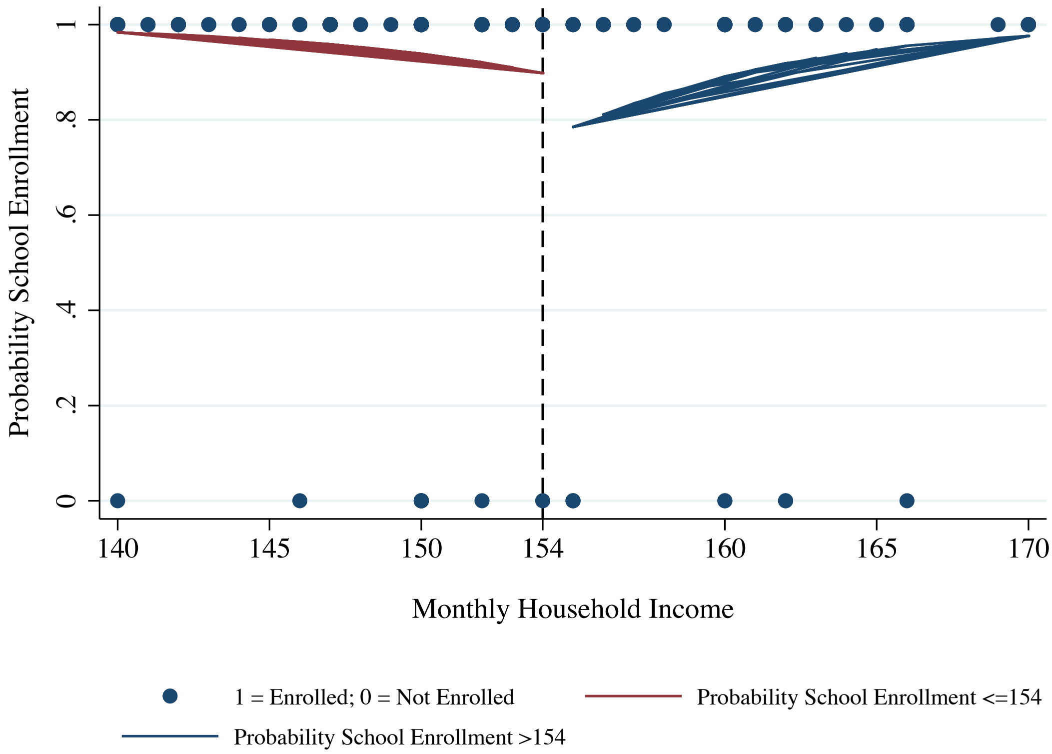
A graphical analysis was conducted to test the validity of the SRD design, followed by descriptive statistics to provide an overview of the whole sample, the treatment, as well as the control group. The model estimates are presented in section 7.3 and lastly, a sensitivity analysis was carried out to test the robustness of the results.

7.1 Graphical Analysis

The graphical analysis examines how the forcing variable relates to both outcome variables and tests if a Regression Discontinuity (RD) is a valid design to answer the research questions.

Figure 11 shows a clear jump in the probability of being enrolled in school at the cutoff point of R$154, indicating that there is a case for an RD design. It seems that beneficiaries around the cutoff have a higher probability of being enrolled in school compared to non-beneficiaries.

Figure 11: *RD Plot for School Enrollment*[10]

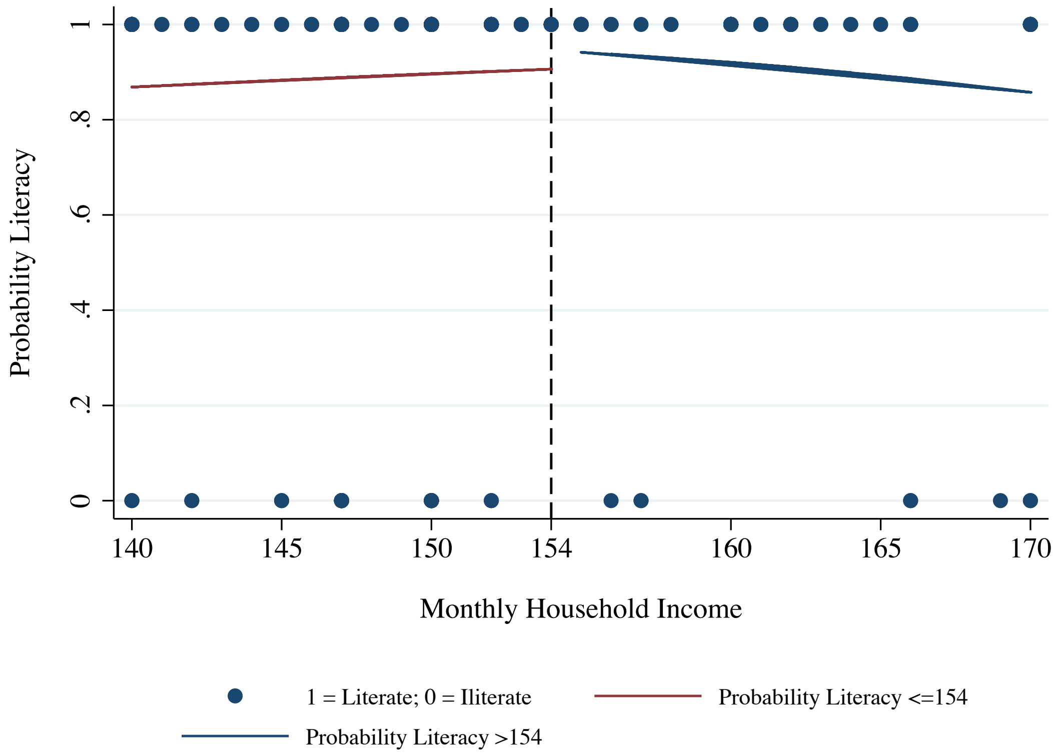


Similarly, Figure 12 displays a clear jump in the probability of being literate at the cutoff point. The graph suggests that beneficiaries have a slightly lower probability of being literate compared to non-beneficiaries around the cutoff.

---

[10] The results of Figure 11 and 12 were robust to the inclusion of covariates. To not mistaken nonlinearity in the running variable for discontinuity, a quadratic as well as a cubic, instead of a linear term of monthly household income, were used. Yet, the results stayed robust. A clear jump in the probability of being enrolled in school was still visible if the bandwidth was increased to 154. For literacy, the jump became small. It seems that an RD design is still a valid design, but more suitable for school enrollment as an outcome variable.

Figure 12: *RD Plot for Literacy*



All in all, both plots show a discontinuity in the outcome variable around the cutoff and an RD design seems suitable. Within the RD setting, an SRD design seems most appropriate, which is depicted in Figure 13 below.

__Figure 13__: BF and Monthly Household Income

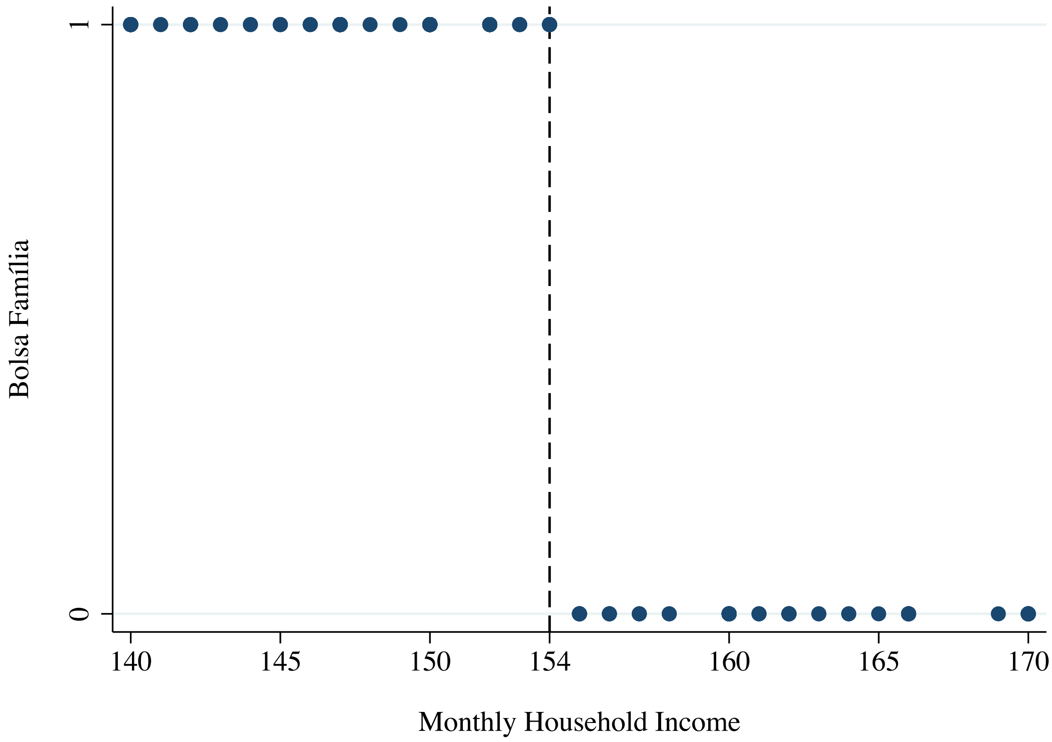


Figure 13 underpins that the threshold predicts the treatment status. Once the monthly household income passes the cutoff point of R$154, a clear jump in assignment to treatment is visible. Below R$154 individuals receive BF whereas above R$154 individuals are not eligible for BF.

Overall, a SRD seems to be a valid design to research the impact of BF on school enrollment rates and literacy.

7.2 Descriptive Statistics

Next, descriptive statistics are provided to analyze differences between BF beneficiaries and non-beneficiaries.

The analysis was restricted to individuals between six and 17 years of age. Additionally, monthly household income was restricted to an income between R$137.29 and R$170.71, which was due to the bandwidth selection of $h = \pm 16.71$ and the cutoff c of R$154.

Table 5 below presents descriptive statistics for the whole sample.

Table 5: *Descriptive Statistics of the Total Sample*

	2014				
Variable	*Obs.*	*Mean*	*Std. Dev.*	*Min*	*Max*
School enrollment	321	0.94	0.24	0	1
Literacy	321	0.89	0.31	0	1
Bolsa Família	321	0.74	0.44	0	1
Monthly household income	321	151.56	7.70	140	170
Gender	321	0.53	0.50	0	1
Age	321	11.35	3.45	6	17
Race	321	0.29	0.45	0	1
Mother present in household	321	0.89	0.31	0	1
Number of household members	321	3.79	1.34	1	10
Geographical location	321	0.70	0.46	0	1

According to descriptive statistics, 94 percent of the individuals in the sample are enrolled in school and 89 percent of the individuals are literate. 74 percent of the individuals are BF recipients while the average monthly household income is R$151.56. Table 6 presents descriptive statistics for the treatment group; that is, for BF beneficiaries. Table 7 presents descriptive statistics for the control group; namely, for non-beneficiaries.

Table 6: *Descriptive Statistics of the Treatment Group*

	2014				
Variable	*Obs.*	*Mean*	*Std. Dev.*	*Min*	*Max*
School enrollment	237	0.95	0.22	0	1
Literacy	237	0.89	0.31	0	1
Bolsa Família	237	1	0	1	1
Monthly household income	237	147.72	3.87	140	154
Gender	237	0.55	0.50	0	1
Age	237	11.45	3.40	6	17
Race	237	0.28	0.45	0	1
Mother present in household	237	0.91	0.28	0	1
Number of household members	237	3.70	0.99	1	7
Geographical location	237	0.71	0.45	0	1

Table 7: *Descriptive Statistics of the Control Group*

	2014				
Variable	*Obs.*	*Mean*	*Std. Dev.*	*Min*	*Max*
School enrollment	84	0.90	0.30	0	1
Literacy	84	0.90	0.30	0	1
Bolsa Família	84	0	0	0	0
Monthly household income	84	162.39	4.99	155	170
Gender	84	0.48	0.50	0	1
Age	84	11.07	3.58	6	17
Race	84	0.31	0.47	0	1
Mother present in household	84	0.85	0.36	0	1
Number of household members	84	4.04	2.00	2	10
Geographical location	84	0.65	0.48	0	1

Comparing the treatment and control group, 95 percent of BF recipients are enrolled in school whereas 90 percent of the non-beneficiaries are enrolled in school. 89 percent of BF recipients are literate while 90 percent of non-beneficiaries are literate. Despite a difference in the average monthly household income, which is due to the design of the study, the treatment and control groups have similar characteristics. This is an important condition for an RD design to be valid.

Overall, the descriptive statistics suggest that BF beneficiaries tend to have slightly higher school enrollment rates and slightly lower literacy rates than non-beneficiaries. In the following section, it is discussed whether these results change when utilizing a logistic regression rather than simple descriptive statistics.

7.3 Results

Extending the analysis, a series of logistic regressions with robust standard errors were estimated. To perform the analysis, three models for each outcome variable were estimated: the first one included the treatment and the running variable, the second one included additional control variables[11], and the third one tested if the results changed if a quadratic term of the running variable was assumed. State clusters adjusted the standard error of the regression models.

To interpret the output, coefficients that were not statistically significant were also analyzed. Even when p-values are not statistically significant, they might still hold economic significance, since small p-values might be caused, for instance, by small sample sizes. Therefore, a focus on the interpretation of statistically significant coefficients could lead to wrong interpretations and could overlook important developments (Bernardi et al., 2016).

---

[11] The results should not change when including other covariates, since there should not be important differences in other covariates around the cutoff point.

7.3.1 Impact of Bolsa Família on School Enrollment

To answer the main research question, the impact of BF on school enrollment was analyzed by running three logistic regressions. The results are presented in Table 8 below.

Table 8: *Odds Ratios for the Dependent Variable School Enrollment*

	Dependent Variable is School Enrollment		
Variables	(1)	(2)	(3)
Bolsa Família	2.41	2.10	2.55
	(2.33)	(1.88)	(2.23)
Monthly household income	1.01	1.00	0.28
	(0.04)	(0.06)	(0.50)
Monthly household income squared			1.00
			(0.01)
Gender		2.27	2.20
		(1.17)	(1.11)
Age		0.76**	0.77**
		(0.09)	(0.09)
Race		2.07	2.06
		(1.58)	(1.53)
Mother present in household		2.78	2.79
		(1.74)	(1.75)
Number of household members		1.58	1.48
		(0.51)	(0.51)
Geographical location		1.43	1.40
		(0.67)	(0.67)
Pseudo R^2	0.013	0.24	0.25
Observations	321	321	321

Notes: Robust standard errors in parentheses; State clusters adjusted these standard errors; *** p<0.01, ** p<0.05, * p<0.1

Examining the models, the majority of the household characteristics, except age, are not statistically significantly related to the likelihood that a child is enrolled in school. Despite that, covariates controlling for household characteristics, except age, increase the likelihood of being enrolled in school, which reflects the expected outcomes of the model. Only the number of household members deviates from the expected outcomes as it is associated with an increase in the likelihood of school enrollment.

Turning to the relationship of interest, the models show that BF increases the odds of being enrolled in school; however, this is not statistically significant. Apart from that, the effect is similar in magnitude for all models. Thus, including covariates did not change the impact of BF on school enrollment. In model two, a BF beneficiary has a higher chance of going to school than a non-beneficiary. Particularly, being a BF recipient increases the odds of being enrolled in school by a factor of 2.10, compared to a non-beneficiary, holding all other variables constant.

Since odds ratios offer little substantive information other than the sign, marginal effects are provided to understand the effect of BF on the probability of being enrolled in school. The results in Table 9 show that the marginal effect of BF on school enrollment is 0.02. This implies that being a BF beneficiary increases the probability of being enrolled in school by two percentage points compared to a non-beneficiary, when all independent variables are at their mean values[12]. However, the results are not statistically significant.

Table 9: *Marginal Effect of BF on School Enrollment*

Variable	Dependent Variable is School Enrollment
Bolsa Família	0.02
	(0.03)[13]

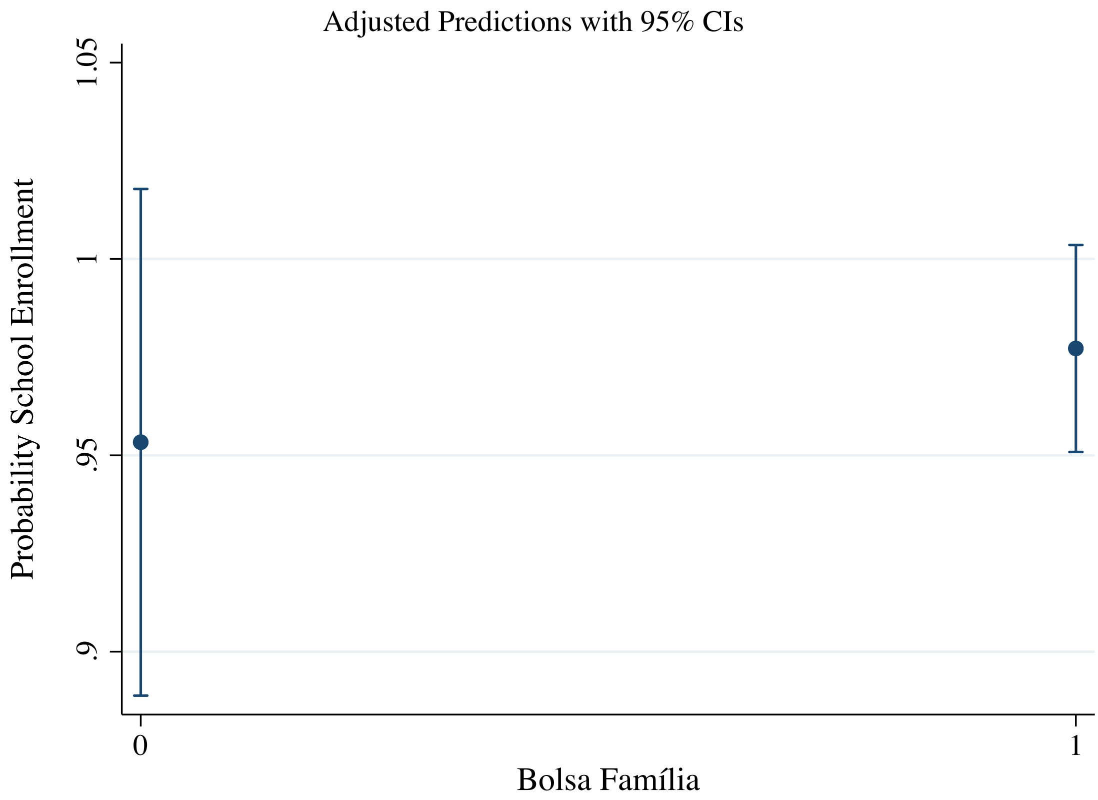
Notes: Standard deviation in parentheses; *** p<0.01, ** p<0.05, * p<0.1

[12] The sample means of the covariates for the whole sample are presented in Table A.1 in Appendix A.

[13] The lack of statistical significance can be explained by the standard deviation, which is higher than the effect itself.

In line with the results above, the following margins plot depicts a predicted probability of 98 percent of being enrolled in school for a BF beneficiary whereas the predicted probability is 95 percent for a non-beneficiary[14]. The overlapping confidence intervals (CI) are the reason for which the difference between the two groups is not statistically significant. However, it has to be considered that the CIs are point estimates and that there is a covariance between the differences. This has to be considered when making statements about those differences.

Figure 14: *Margins Plot School Enrollment*



---

[14] These effects are specified to a predicted probability determined by the means of the independent variables. This holds for all margin plots and marginal effects in the results section.

Overall, the results suggest that BF increases the odds of being enrolled in school. However, the effect is not statistically significant. Therefore, no systematic effect of BF on school enrollment is found. Nevertheless, that a beneficiary is more likely to be enrolled in school than a non-beneficiary is in line with the descriptive examination, which found that 95 percent of BF beneficiaries are enrolled in school while 90 percent of non-beneficiaries are enrolled in school. The small differences in the percentage of children being enrolled in school between the results of the descriptive examination and the logistic regressions are likely to stem from the inclusion of covariates in the regression models. If the covariates were excluded, the regression results matched closely with the results of the descriptive examination.

7.3.1.1. Impact of BF on School Enrollment by Gender

To deepen the analysis and to answer the sub research question[15], it was investigated if there was a heterogeneous treatment effect among male and female children. Fiszbein and Schady (2009) pointed out that CCTs try to overcome the low levels of investments in girls' schooling in many developing countries and aim to lower gender disparities. Consequently, it was analyzed if BF had a larger effect on school enrollment rates among girls than boys. For the analysis, the treatment variable BF*,* and the control variable gender were interacted.

[15] Sub research question: "*Was there a heterogeneous treatment effect of Bolsa Família on school enrollment rates between boys and girls in 2014?*"

Table 10: *Odds Ratios for the Dependent Variable School Enrollment; By Gender*

Variables	Dependent Variable is School Enrollment
Interaction effects	
Female & Bolsa Família	ref
Male & Bolsa Família	3.87
	(4.52)
Female & No Bolsa Família	0.78
	(0.44)
Male & No Bolsa Família	1.25
	(1.11)
Monthly household income	1.00
	(0.06)
Age	0.76**
	(0.09)
Race	1.94
	(1.44)
Mother present in household	3.00*
	(1.83)
Number of household members	1.58
	(0.50)
Geographical location	1.44
	(0.69)
Pseudo R^2	0.25
Observations	321

Notes: Robust standard errors in parentheses; State clusters adjusted these standard errors; *** p<0.01, ** p<0.05, * p<0.1

Table 10 shows that the odds of being enrolled in school increase by a factor of 3.87 for a male BF beneficiary, compared to a female BF recipient. Moreover, being a female non-recipient is associated with a lower likelihood of school enrollment compared to a female BF recipient. Aside from that, being a male non-beneficiary is still associated with a higher likelihood of being enrolled in school compared to a female BF recipient. However, the effects are not statistically significant and therefore no clear conclusions can be drawn.

Examining the marginal effects, a male BF beneficiary has a three percentage point higher probability of being enrolled in school compared to a male non-beneficiary, if all independent variables are at their mean values. In comparison, a female BF recipient has a two percentage points higher probability of school enrollment compared to a female non-recipient, if all independent variables are at their mean values[16]. In this instance, the results are not statistically significant.

Table 11: *Marginal Effect of BF on School Enrollment; By Gender*

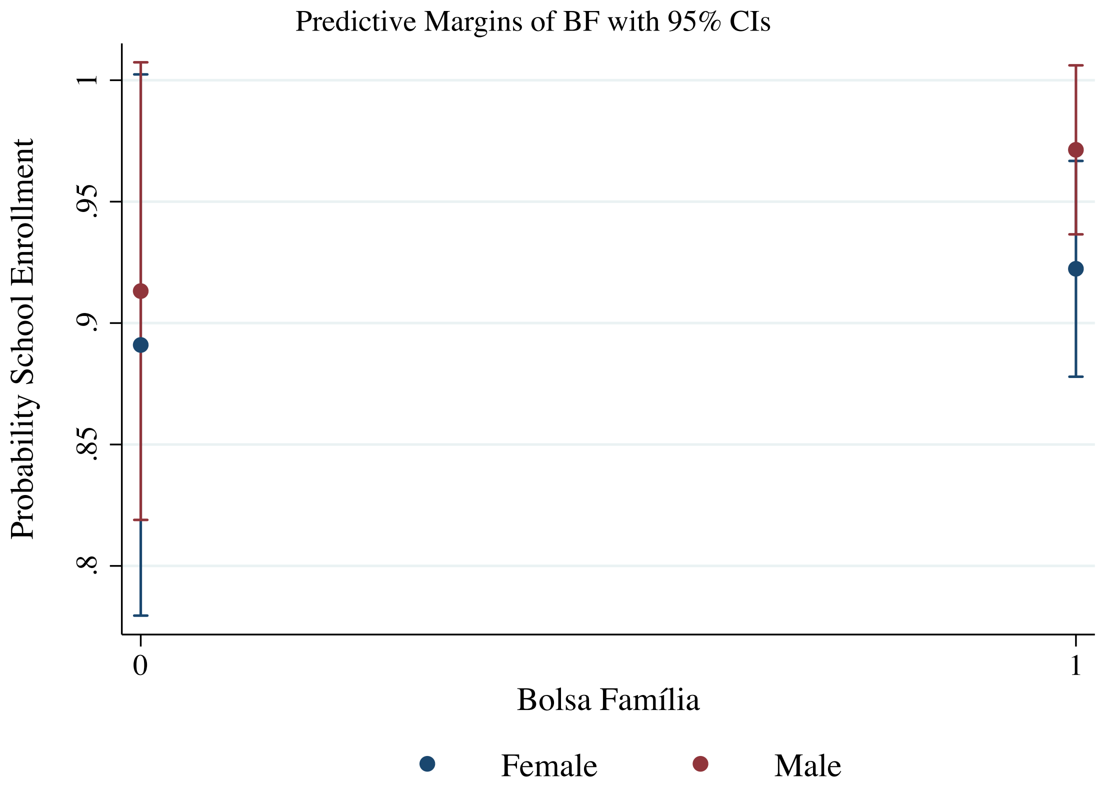
	Dependent Variable is School Enrollment	
Variable	Male	Female
Bolsa Família	0.03	0.02
	(0.04)	(0.05)

Notes: Standard deviation in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Comparing the marginal effects at the means, a male BF beneficiary has a predicted probability of 97 percent of being enrolled in school whereas a male non-beneficiary has a predicted probability of 91 percent. On the contrary, a female non-beneficiary has a predicted probability of 89 percent of going to school, while a female beneficiary has a predicted probability of 92 percent. Again, the CIs for men as well as for women are overlapping, which is a sign that the differences between the groups of comparison are not statistically significant. Apart from that, Figure 15 shows that the difference in the likelihood of school enrollment are lower between men and women who are not eligible for BF. Thus, the difference in the likelihood of school enrollment is larger between male and female BF beneficiaries.

[16] The corresponding sample means of the covariates for women and men are presented in Table A.1 in Appendix A.

Figure 15: *Margins Plot School Enrollment; By Gender*



Those results imply that there was a heterogeneous treatment effect among male and female children and that there was a larger effect of BF on school enrollment among boys in 2014. However, the results are not backed up by statistical significance and therefore, no clear effect can be identified.

7.3.2 Impact of Bolsa Família on Literacy

The results to answer the second research question "*How did Bolsa Família affect the literacy rates of children in beneficiary households compared to non-beneficiary households in 2014?",* are presented in Table 12 below.

Table 12: *Odds Ratios for the Dependent Variable Literacy*

	Dependent Variable is Literacy		
Variables	(1)	(2)	(3)
Bolsa Família	0.80	0.24	0.21
	(0.60)	(0.23)	(2.20)
Monthly household income	1.01	1.00	1.52
	(0.04)	(0.05)	(1.34)
Monthly household income squared			1.00
			(0.00)
Gender		0.68	0.66
		(0.33)	(0.34)
Age		2.09***	2.09***
		(0.29)	(0.29)
Race		0.91	0.90
		(0.58)	(0.58)
Mother present in household		0.31	0.31
		(0.31)	(0.32)
Number of household members		1.46	1.48
		(0.41)	(0.40)
Geographical location		2.39*	2.39*
		(1.11)	(1.10)
Pseudo R^2	0.00	0.35	0.35
Observations	321	321	321

Notes: Robust standard errors in parentheses; State clusters adjusted these standard errors; *** p<0.01, ** p<0.05, * p<0.1

The majority of the control variables, except age and geographical location, are not statistically significantly related to the likelihood that a child is literate. The variables age, geographical location, and monthly household income reflect the expected outcomes of the model, while all other variables stand in contrast to the expected outcomes.

Analyzing the relationship of interest, all models indicate that BF is associated with a decrease in the odds of being literate; however, without statistical significance. Despite that, the effect changed when covariates were included, which weakened the assumption that the RD design is a valid method to research the impact of BF on literacy rates[17]. Nevertheless, the results in model two indicate that receiving BF is associated with a 76 percent lower likelihood (OR = 0.24) of being enrolled in school compared to a non-beneficiary, holding all other variables constant.

Exploring the marginal effects, the results suggest that, if all independent variables are at their mean values[18], a BF recipient has a two percentage point lower probability of being literate compared to a non-beneficiary. In this instance, the effect is not statistically significant.

Table 13: *Marginal Effect of BF on Literacy*

Variable	Dependent Variable is Literacy
Bolsa Família	- 0.02
	(0.01)

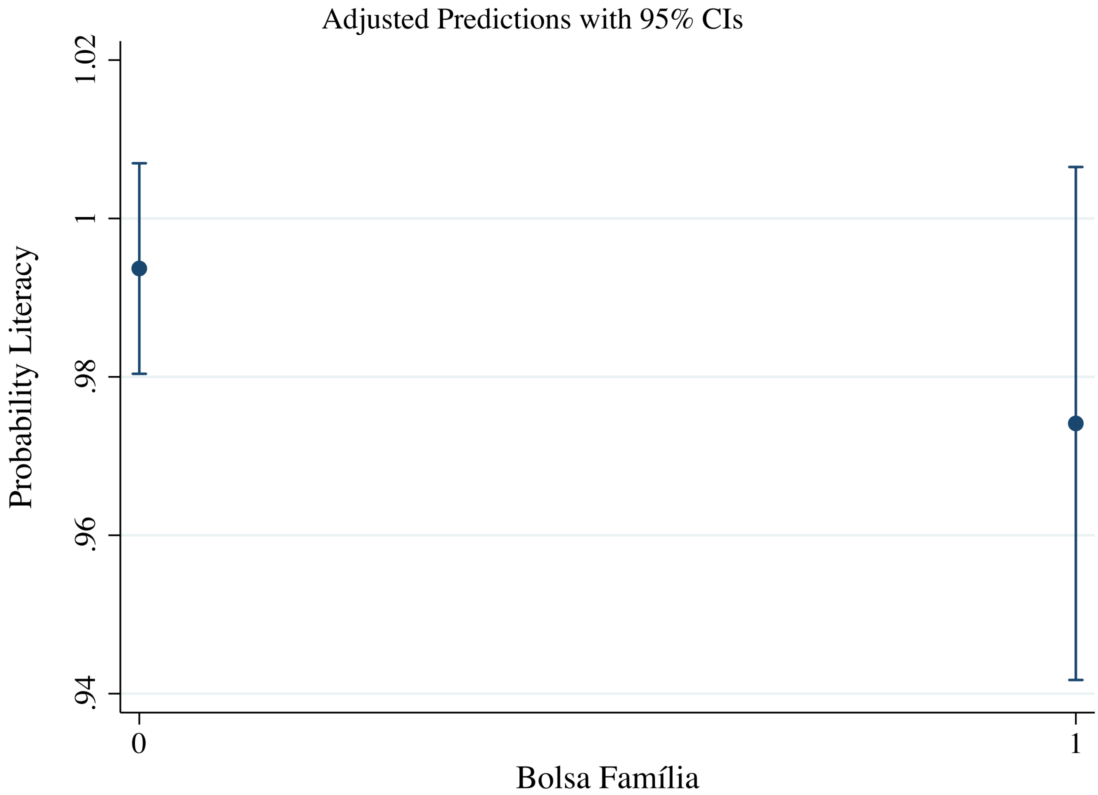
Notes: Standard deviation in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Lastly, the margins plot below shows that a BF recipient has on average a probability of 97 percent of being literate whereas a non-recipient has a probability of 99 percent of being literate.

[17] Assumption: there should not be important differences in other covariates right around the cutoff point, so the estimates of the main dependent variable should not change to a large extent by including covariates in the model.

[18] The sample means of the covariates for the whole sample are presented in Table A.1 in Appendix A.

Figure 16: *Margins Plot Literacy*



All in all, the results suggest that receiving BF is associated with a decrease in the odds of being literate. Although, the correlation is not statistically significant. The results differ to a small extent from the results of the descriptive statistics. The descriptive examination found almost no difference in literacy rates among beneficiaries and non-beneficiaries, while the results of the logistic regressions suggest a lower predicted probability of being literate for BF beneficiaries. That small difference in the percentage of children being literate between the descriptive statistics and the results of the logistic regressions likely stems from the inclusion of covariates in the latter.

7.4 Sensitivity Analysis

To test the robustness of the main findings[19] the main model for each outcome variable was estimated for the largest bandwidth possible; thus, for $h = \pm 154$. The robustness check for school enrollment is presented in section 7.4.1, while in section 7.4.1.1 it is discussed whether the effect differs among different age groups. Lastly, the robustness check for literacy using a different bandwidth is presented in section 7.4.2.

7.4.1 Increased Bandwidth and School Enrollment

The results for school enrollment are reported in Table 14 below.

[19] See Table 8 for school enrollment and Table 12 for literacy.

Table 14: *Odds Ratios for the Dependent Variable School Enrollment with Larger Bandwidth*

	Dependent Variable is School Enrollment		
Variables	(1)	(2)	(3)
Bolsa Família	2.60***	2.48***	2.53***
	(0.68)	(0.84)	(0.90)
Monthly household income	1.01***	1.00***	1.01**
	(0.00)	(0.00)	(0.00)
Monthly household income squared			1.00
			(0.00)
Gender		1.52**	1.51**
		(0.3)	(0.3)
Age		0.73***	0.73**
		(0.03)	(0.03)
Race		1.94***	1.97***
		(0.51)	(0.51)
Mother present in household		3.70***	3.65***
		(0.79)	(0.78)
Number of household members		0.98	0.98
		(0.06)	(0.06)
Geographical location		0.82	0.82
		(0.17)	(0.17)
Pseudo R^2	0.01	0.21	0.21
Observations	2,156	2,156	2,156

Notes: Robust standard errors in parentheses; State clusters adjusted these standard errors; *** p<0.01, ** p<0.05, * p<0.1

The control variables: gender, age, race, and mother present in the household, are now statistically significantly correlated with school enrollment. The magnitude of the effect of age on school enrollment remains robust. The magnitude of the effect of gender and race decreased to a small extent, while the effect of a mother present in the household increased. The number of household members is still not statistically significantly correlated with school enrollment. However, the effect became negative and now reflects the expected outcome of the model. Lastly, the effect of the geographical location on school enrollment became negative. Despite that, the effect remains statistically insignificant.

Turning to the relationship of interest, the results show that the relationship between BF and school enrollment as well as the magnitude of the effect did not change to a great extent by increasing the bandwidth. However, the results became statistically significant. This may be partially explained by the increased sample size, which makes it easier to establish significance and to observe a treatment effect as more people receive treatment. However, by increasing the bandwidth, it is likely that individuals became less similar in their characteristics and that the results of the estimation are impacted by other, so-called, confounding factors.

In model two, receiving BF increases the odds of being enrolled in school by a factor of 2.48 compared to a non-beneficiary, which is significant at the one percent level. Examining the conditional marginal effects, someone receiving BF has a three percentage point higher probability of being enrolled in school compared to someone who is not eligible for BF, if all independent variables are at their mean values[20]. This is statistically significant at the one percent level.

Table 15: *Marginal Effect of BF on School Enrollment; Larger Bandwidth*

Variable	Dependent Variable is School Enrollment
Bolsa Família	0.03***
	(0.01)

Notes: Standard deviation in parentheses; *** p<0.01, ** p<0.05, * p<0.1

This estimate is close to the estimated probability of two percent when using a bandwidth of $h = \pm 16.71$. In line with the main findings, the results of the sensitivity analysis confirm that a BF beneficiary has on average a probability of 98 percent of being enrolled in school whereas

[20] The sample means of the covariates for the whole sample and the bandwidth $h = \pm 154$ are presented in Table A.2 in Appendix A.

a non-beneficiary has a probability of 95 percent of being enrolled in school, if all independent variables are at their mean values.

Altogether, the positive effect of BF on school enrollment stayed robust in its magnitude when the bandwidth was increased. The only difference is that the results are now backed up by statistical significance.

The robustness check for the impact of BF on school enrollment by gender, using a larger bandwidth, can be found in Appendix B, Table B.1. The results suggest that being a male BF beneficiary increases the odds of being enrolled in school by a factor of 3.35, compared to a female BF recipient, statistically significant at the one percent level. Hence, the magnitude of the effect, and the larger effect among boys, remains robust, while it is now backed up by statistical significance.

7.4.1.1. School Enrollment among Different Age Groups

Using a bandwidth of $h = \pm 154$ also allowed to research the impact of BF on school enrollment for different age groups. To test if the effect of BF on school enrollment varied among age groups, two groups were formed. One includes children between six and 15 years of age, while the other group includes children between 16 and 17 years of age[21]. The results are presented in Table 16 below.

[21] This classification was chosen based on the design of the program: BF is conditioned on minimum school attendance of 85 percent for individuals between six and 15 years of age and on a minimum school attendance of 75 percent for individuals between 16 and 17 years of age. By dividing the initial sample (N=321) into these age groups, the sample size of each group, especially the control group, became small and lost statistical power. Therefore, the analysis could only be carried out by using a larger bandwidth. By doing so, the groups were large enough to still have statistical power.

Table 16: *Odds Ratios for the Dependent Variable School Enrollment with Larger Bandwidth; By Age Groups*

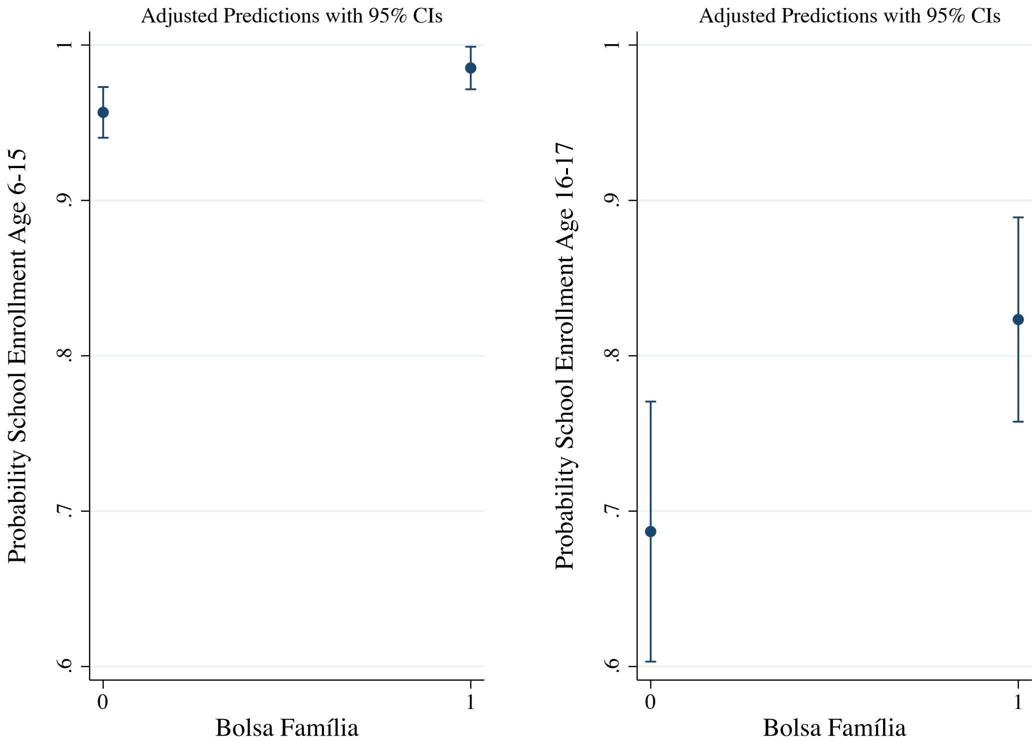
	Dependent Variable is School Enrollment	
	(1)	(2)
Variables	Age 6-15	Age 16-17
Bolsa Família	3.02*	2.13**
	(1.73)	(0.81)
Monthly household income	1.01**	1.00*
	(0.00)	(0.00)
Age	0.82***	0.55**
	(0.05)	(0.11)
Race	2.07***	1.76
	(0.54)	(0.83)
Mother present in household	3.29***	3.75***
	(1.03)	(0.90)
Number of household members	0.96	0.99
	(0.09)	(0.12)
Geographical location	0.72	0.90
	(0.19)	(0.37)
Pseudo R^2	0.10	0.12
Observations	1,833	323

Notes: Robust standard errors in parentheses; State clusters adjusted these standard errors; *** p<0.01, ** p<0.05, * p<0.1

Analyzing the relationship of interest, the effect of BF on the likelihood of school enrollment is larger among younger children. The models suggest that BF increases the odds of being enrolled in school by a factor of 3.02 for children between six and 15 years of age and by a factor of 2.13 for children between 16 and 17 years of age. The former is statistically significant at the ten percent level whereas the latter is statistically significant at the five percent level.

These results are reflected in the margins plot below. Regardless of being a BF recipient or not, younger children have a higher probability of school enrollment compared to older children. Within the age group of six to 15 years of age, a BF beneficiary has on average a probability of 99 percent of being enrolled in school; conversely, a non-beneficiary has a probability of 96 percent of being enrolled in school if all independent variables are at their mean values[22]. For children between 16 and 17 years of age[23], a BF recipient has a predicted probability of 82 percent of being enrolled in school whereas a non-beneficiary has a predicted probability of 69 percent.

Figure 17: *Margins Plot School Enrollment; By Age Groups*



---

[22] The sample means of the covariates for the sample restricted to children between six and 15 years of age using a bandwidth of $h = \pm 154$ are presented in Table A.2 in Appendix A.

[23] The sample means of the covariates for the sample restricted to children between 16 and 17 years of age using a bandwidth of $h = \pm 154$ are presented in Table A.3 in Appendix A.

Overall, these results suggest that BF has a larger impact on school enrollment among younger children.

7.4.2 Increased Bandwidth and Literacy

Lastly, it was tested if the results for literacy stay robust when the bandwidth was increased to $h = \pm 154$.

***Table 17**: Odds Ratios for the Dependent Variable Literacy with Larger Bandwidth*

	Dependent Variable is Literacy		
Variables	(1)	(2)	(3)
Bolsa Família	0.96	0.82	0.82
	(0.16)	(0.18)	(0.18)
Monthly household income	1.00	1.00	1.00
	(0.00)	(0.00)	(0.00)
Monthly household income squared			1.00
			(0.00)
Gender		0.74**	0.74**
		(0.11)	(0.11)
Age		1.89***	1.89***
		(0.10)	(0.03)
Race		1.27	1.25
		(0.23)	(0.22)
Mother present in household		1.94***	3.65***
		(0.46)	(0.78)
Number of household members		0.95	0.98
		(0.05)	(0.06)
Geographical location		1.95***	1.95***
		(0.26)	(0.27)
Pseudo R^2	0.00	0.32	0.32
Observations	2,156	2,156	2,156

Notes: Robust standard errors in parentheses; State clusters adjusted these standard errors;
*** p<0.01, ** p<0.05, * p<0.1

Compared to the main findings, the control variables gender and mother present in the household are now statistically significantly correlated with literacy. A mother present in the household and being white is now associated with an increase in the odds of being literate, which reflects the expected outcome of the model. The geographical location and age are still statistical significantly correlated with literacy. However, the effects decreased slightly. Lastly, the number of household members now decreases the likelihood of being literate, which reflects the expected outcome of the model. In this instance, the results are not statistically significant.

Analyzing the correlation between BF and literacy, the results became more robust to the inclusion of covariates. However, the results show that the magnitude of the effect of BF on literacy changed by increasing the bandwidth. Apart from that, the results remain statistically insignificant; this establishes that there was no clear effect of BF on literacy in 2014.

In model two, receiving BF is associated with an 18 percentage point (OR = 0.82) decrease in the likelihood of being literate, compared to a non-beneficiary. Examining the marginal effects indicates that a BF beneficiary has a one percentage point lower probability of being literate than a non-beneficiary, if all independent variables are at their mean values[24]. However, the results are not statistically significant.

Table 18: *Marginal Effect of BF on Literacy; Larger Bandwidth*

Variable	Dependent Variable is School Enrollment
Bolsa Família	-0.01
	(0.01)

Notes: Standard deviation in parentheses; *** p<0.01, ** p<0.05, * p<0.1

[24] The sample means of the covariates for the whole sample and the bandwidth $h = \pm 154$ are presented in Table A.4 in Appendix A.

This estimate is close to the estimated probability of minus two percentage points when using a bandwidth of $h = \pm 16.71$. Lastly, it is predicted that both, beneficiaries and non-beneficiaries, have a probability of 96 percent of being literate. This stands in contrast to the main results, which predicted that a BF recipient has a probability of 97 percent of being literate; in contrast, a non-recipient has a probability of 99 percent of being literate.

Summing up the main results of the sensitivity analysis, the positive effect of BF on the likelihood of being enrolled in school remains robust when increasing the bandwidth. This holds for the odds ratio as well as the marginal effects at the means. The only difference is that the results are now backed up by statistical significance and therefore, a clear effect can be identified. Concerning literacy, the results are less conclusive. While the results remain statistically insignificant, the odds of being literate for a BF beneficiary increase with the new bandwidth, but remain lower compared to a non-beneficiary. Lastly, the marginal effect remains robust, while the predicted probability of being literate decreases for BF beneficiaries as well as non-beneficiaries.

8 Discussion and Conclusion

8.1 Research Outcomes and Existing Literature

This section discusses the results of the study and relates the findings to the existing body of literature.

Concerning the main research question:

How did Bolsa Família affect school enrollment rates of children in beneficiary households compared to non-beneficiary households in 2014?

The study concludes that in 2014, a BF beneficiary had a higher chance of going to school than a non-beneficiary. Particularly, the results suggest that being a BF beneficiary increased the odds of being enrolled in school by a factor of 2.10, compared to a non-beneficiary. However, the results were not statistically significant. By increasing the bandwidth, the effect became statistically significant and BF was associated with an increase in the likelihood of school enrollment by a factor of 2.48. Examining the marginal effects, a BF beneficiary had a two percentage points higher probability of going to school than a non-beneficiary. By increasing the bandwidth, the effect increased to three percentage points and became statistically significant. The fact that the results became statistically significant and remained similar in magnitude could point out that the initial bandwidth selection was too narrow to observe an effect. By increasing the bandwidth, the sample size increased, which made it easier to establish statistical significance as more individuals received BF. Given that the effect became statistically significant by increasing the bandwidth, thus by including poorer people in the sample, could point out that BF had a larger effect among the poorest. The initial bandwidth only included poor people close to the threshold to be eligible for BF. Thus, only individuals that were not considered extremely poor were included. Those individuals might have already been able to send their children to school, even without a BF benefit. This could be a reason why no clear effect of BF on school enrollment was visible. On the contrary, the poorest individuals might not have been able to send their children to school, but needed them to work at home. Hence, BF could have had a larger effect among the poorest households. BF decreases the opportunity costs of sending children to school and therefore, enables poor households to enroll their children in school. By increasing the bandwidth, not only poorer households but also richer households were included in the sample. That the effect still became statistically significant underpins the fact that BF had a larger effect among the poorest, even when richer individuals were included. That the effects of CCTs are larger among the poorest households is also reported in several studies (Cecchini & Madariaga, 2011; Fiszbein & Schady, 2009).

Overall, the results confirm the hypothesis that BF had a positive effect on school enrollment in 2014.

Relative to the existing body of literature, the results are in line with previous conclusions. Most studies assessing the impact of CCTs on school enrollment found that receiving a CCT increased the odds of being enrolled in school (Schady, 2006; Cecchini & Madariaga, 2011; Fiszbein & Schady, 2009). In line with the results of this thesis, Amaral et al. (2014) found that BF increased the odds of being enrolled in school by a factor of 1.96 in 2010. Given that Amaral et al. (2014) found a lower increase in the odds of being enrolled in school for 2010 than this thesis for 2014, it might be possible to argue that the impact of BF on school enrollment increases over time[25]. This would be in accordance with Paes-Sousa et al. (2013), claiming that

[25] That CCTs have an impact on educational indicators several years after their implementation was confirmed by running the model of this thesis for all years between 2004 and 2014. It was found that in the early years of the program (2004-2008), the recipients of BF were less likely to be enrolled in school. But since 2008, the recipients became more likely to be enrolled in school. This evidence suggests that as the program was rolled out, beneficiaries were accruing more human capital.

CCTs are long-term interventions and therefore, are likely to have an impact on educational indicators several years after their implementation. Despite that, the results of the present study align closely with the findings of Amaral et al. (2014); namely, that a BF beneficiary has a predicted probability of 98 percent of being enrolled in school whereas a non-beneficiary has a probability of 95 percent[26] (Amaral et al., 2014).

On the contrary, the results of this thesis contradict the findings of Nilsson and Sjöberg (2013). The authors found that BF had a very small, but negative effect on school enrollment in 2011. Part of that deviation could stem from the use of a different methodology. While the present study used logistic regression, Nilsson and Sjöberg (2013) used a multiple linear regression estimation. Since in both studies the outcome variable was binary coded, using logistic regressions seems to be the better design for the impact evaluation. In addition, Nilsson and Sjöberg (2013) did not provide a coherent explanation for their findings. The authors argued that households might not spend their additional income on education and that poor households have a low preference for education. Therefore, BF can negatively impact school enrollment. However, this explanation is controversial in several ways. Firstly, it is unlikely that households do not spend their additional income on education, since it is conditioned on sending children to school. Secondly, poorer households might have a lower preference for education, since the opportunity costs of sending their children to school are high. However, if those households receive BF, the opportunity costs of going to school decrease, and those households can send their children to school. Thirdly, the authors claimed, that the negative results might be caused by the Regression Discontinuity Design. According to them, one is comparing too similar groups with low income, which indicates low school enrollment. Despite that, BF can still have a positive impact on schooling, especially among households with low income. Among those, the effect might be larger due to decreasing opportunity costs. Lastly, the results of the quantitative estimation contradict the qualitative estimation by Nilsson and Sjöberg (2013). By

[26] This result holds for both bandwidths.

conducting household interviews, the authors found that BF had a positive impact on children's schooling.

Concerning the sub research question:

Was there a heterogeneous treatment effect of Bolsa Família on school enrollment rates between boys and girls in 2014?

It is concluded that BF had a larger impact on school enrollment rates among boys than girls. In particular, the odds of being enrolled in school increased by a factor of 3.87 for a male beneficiary, compared to a female beneficiary. However, the results were not statistically significant. By increasing the bandwidth, the odds of being enrolled in school increased by a factor of 3.35 for a male recipient compared to a female recipient. Additionally, the results became statistically significant and the heterogeneous treatment effect was backed up by statistical significance. However, the effect is contrary to what was anticipated, as BF had a larger impact on school enrollment rates among boys than girls.

Those results are inconsistent with previous research conducted by de Brauw et al. (2014). The authors found that BF increased school enrollment of girls by 8.2 percentage points but had no impact on the school enrollment of boys. One explanation for this discrepancy is again the use of a different methodology. De Brauw et al. (2014) did not only investigate one year but constructed a household survey panel survey from 2005 to 2009 and estimated impacts using a propensity-score-weighted regression. Despite that, the overall results of de Brauw et al. (2014) align with the findings of this thesis, namely that BF increases school enrollment of children age six to 17 years.

Moreover, the findings of this thesis question if BF is a useful policy tool to lower gender disparities. The results estimated in this study do not support the theory that mother's presence in a household is more beneficial for children's education, especially for girls, as suggested by Lindert (2006), Baird et al. (2014), and Fiszbein and Schady (2009). Within academia, the factors that contribute to differences in impacts by gender are not well understood (de Brauw et al., 2014). Therefore, it is difficult to identify the impact pathways behind the results of the present thesis. Nevertheless, the results could point out that the targeting mechanism of BF can be improved. Other CCT programs, for instance, *Progresa* in Mexico, provide larger transfers to households with girls to reduce the gender gap in school enrollment (de Brauw et al., 2014).

Moving on, the sensitivity analysis also showed a heterogeneous treatment effect among children in different age groups. For children between six and 15 years of age, BF increased the odds of being enrolled in school by a factor of 3.02, which was statistically significant at the ten percent level. For children between 16 and 17 years of age, BF increased the odds by a factor of 2.13; statistically significant at the five percent level. Again, those findings are inconsistent with the evidence by de Brauw et al. (2014). The authors found that the effects were larger for older than for younger children, which is in line with evidence for other CCT programs. However, the authors divided the groups into ages six to 14 and 15 to 17 years. Some deviations in the results could be explained by that different classification. Moreover, the results of this thesis seem to reflect the design of the BF program. In particular, BF is conditioned on higher minimum school attendance for younger children. Therefore, it seems plausible that BF has a larger impact among younger children. Despite that, it could be argued that when children are younger, the opportunity costs of going to school are lower. Once children grow older, they can contribute more to work at home or in other sectors of an economy. Thus, it might be costlier for older children to go to school instead of working. Therefore, school enrollment rates among older children might be lower.

With regards to the second research question:

How did Bolsa Família affect the literacy rates of children in beneficiary households compared to non-beneficiary households in 2014?

This thesis concludes that in 2014, being a BF beneficiary decreased the odds of being literate, compared to a non-beneficiary. However, the results were not statistically significant. In addition, the SRD design seems less suitable for literacy than for school enrollment as an outcome variable. More precisely, including covariates changed the impact of BF on literacy. By using a larger bandwidth, the results were less sensitive to the inclusion of covariates and the design seems more suitable. Apart from that, the negative effect of BF on the likelihood of being literate remained but decreased. However, the results still lacked statistical significance. Therefore, no clear conclusions can be drawn, and it seems that there was no effect of BF on literacy rates. Overall, these results contradict the hypothesis that BF was associated with an increase in literacy rates in 2014.

Those results could point towards differences in the educational levels between beneficiary and non-beneficiary households before the start of the program. Hence, the results do not necessarily imply that BF decreased the likelihood of being literate. Poorer households have on average lower literacy rates, which could remain for a longer time period, despite increasing school enrollment rates (Ratcliffe, 2015). In light of those results, it would be interesting to research if children of beneficiary households still lag behind in other educational indicators, which might hinder them from accruing human capital.

Lastly, the existing body of literature on the effect of CCTs on literacy is limited. Since this thesis has not found a statistically significant effect of BF on literacy, one could argue that other papers on the topic have not been published because of the so-called "publication bias" in academia. This bias occurs since papers that find statistically significant results are more likely to get published than the ones that do not find an effect. As a result, papers that find no effect might not be submitted or published, and researchers are also motivated to tailor their research to ensure that a statistically significant result is reported (Song et al., 2013). To some extent, this can also be linked to the results of this thesis for school enrollment, since no statistically significant effect was found using the small bandwidth.

8.2 Practical Implications

Based on the results obtained, central implications for the future can be derived; spurring the human capital formation of children in Brazil.

The empirical analysis showed that the educational conditionalities of BF are working. However, BF was only associated with a small increase in the likelihood of school enrollment in 2014. This impact on schooling was also found to be lower compared to other CCTs programs. In relation to human capital theory, this gives rise to the concern that the increase in schooling is too small to contribute to the formation of human capital and long-term poverty reduction. Based on that, policymakers should discuss the design of BF. One implication would be to provide larger transfers to households with girls to increase school enrollment rates. Another implication would be to increase the monetary transfer to households. By doing so, opportunity costs would decrease, and more households could afford to send their children to school.

In this context, policymakers need to ensure the quality of schooling. An effective increase in the human capital formation of children and the desired break with the intergenerational transmission of poverty will not be achieved by simply ensuring that more children are enrolled in school. The present results for literacy are already a sign that other educational indicators are not improving for BF beneficiaries. One implication is therefore that policymakers have to ensure that the existing policies are accompanied by investments in quality public education, especially at the basic level.

Those implications can also guide policymakers in other countries in the Global South. However, it has to be kept in mind that the results of this study count with a high internal validity while external validity is low. Therefore, it is difficult to transfer the results of this study one by one to different country settings.

8.3 Future Research

The results of this thesis suggest that BF contributes to better schooling outcomes and could break the intergenerational transmission of poverty. Future research should analyze if the same trajectory is sustained even in light of the Brazilian economic stagnation that characterized the period post-2014. It would be revealing to understand if and how lower state revenues influence state spending on BF and therefore, could limit the future success of the program. Taking into account the increasing inequality since 2015, BF could counteract those trends through its impact on human capital formation. Therefore, it is important to sustain state spending on BF.

For obtaining more profound insights, it is also important to research the impact of BF on employment outcomes. This aligns with the fundamental idea of the human capital framework that future earnings are a function of human capital attainment, acquired through schooling. Only if employment outcomes are improved, one can break the intergenerational cycle of poverty. Again, it would be revealing to link this research to the labor market situation in Brazil in light of the economic stagnation. Another interesting supplement would be to analyze the quality of schooling in Brazil to ensure the success of BF. Given that presidential terms after Dilma Rousseff (2011-2016) sought to decrease social spending, it would be important to research how those trends influence state spending on education and the quality of education.

References

Adler, G. & Sosa, S. (2011). Commodity Price Cycles: The Perils of Mismanaging the Boom, IMF Working Paper, no.11/283, Washington D.C.: International Monetary Fund.

Amaral, E. F. L., Gonçalves, G. Q. & Weiss, C. (2014). The Impact of Brazil's Bolsa Família Program on School Attendance, Age-Grade Discrepancy, and Child Labor, 2010, *Journal of Social Science for Policy Implications*, vol. 2, no. 1, pp.101-125.

Baird, S., Ferreira, F. H. G., Özler, B. & Woolcock, M. (2014). Conditional, Unconditional and Everything in between: A Systematic Review of the Effects of Cash Transfer Programmes on Schooling Outcomes, *Journal of Development Effectiveness*, vol. 6, no. 1, pp.1–43.

Barreto, F. (2005). Crescimento Econômico, Pobreza e Desigualdade de Renda: O Que Sabemos Sobre Eles?, LEP Ensaio Sobre Pobreza, no.1, Fortaleza: Laboratório de Estudos Da Pobreza/CAEN - UFC.

Barro, R. & Lee, J.W. (2013). A New Data Set of Educational Attainment in the World, 1950-2010, *Journal of Development Economics*, vol. 104, pp.184–198.

Barros, R. P., Carvalho, M., Franco, S. & Mendonça, R. (2007). A Queda Recente da Desigualdade de Renda no Brasil, IPEA Texto Para Discussão, no.1258, Rio de Janeiro: Instituto de Pesquisa Econômica Aplicada.

Bernardi, F., Chakhaia, L. & Leopold, L. (2016). 'Sing Me a Song with Social Significance': The (Mis)Use of Statistical Significance Testing in European Sociological Research, *European Sociological Review*, vol. 33, no.1, pp.1-15.

BMZ, Bundesministerium für wirtschaftliche Zusammenarbeit und Entwicklung. (2020). Brazil, Available Online: https://www.bmz.de/en/countries_regions/lateinamerika/brasilien/index.html#section-30648792 [Accessed 14 January 2021].

Bourguignon, F., Ferreira, F. H. G. & Leite, P. G. (2003). Conditional Cash Transfers, Schooling and Child Labor: Micro-Simulating Brazil's Bolsa Escola Program, *The World Bank Economic Review*, vol. 17, no. 2, pp.229–254.

Brazileducation. (2021). Academic Year and Language of Instruction in Brazil, Available Online: https://www.brazileducation.info/education-system/academic-year-and-language-of-instruction-in-brazil.html [Accessed 23 April 2021].

Burton, G. J. S. (2009). Social Democracy in Latin America: Policymakers and Education Reform in Brazil and Chile, PhD Thesis, Department of Government, London School of Economics and Political Science.

Carneiro, P. & Heckman, J. (2002). The Evidence on Credit Constraints in Post-Secondary Schooling, *The Economic Journal*, vol. 112, no. 482, pp.705–7034.

Carneiro, P. & Heckman, J. (2003). Human Capital Policy, NBER Working Paper, no. 9495, Cambridge, MA: National Bureau of Economic Research.

Cecchini, S. & Madariaga, A. (2011). Conditional Cash Transfer Programmes: The Recent Experience in Latin America and the Caribbean, *Cuadernos de la CEPAL*, no. 95.

CEPAL. (2020a). Índice de Concentración de Gini, Available Online: https://estadisticas.cepal.org/cepalstat/tabulador/ConsultaIntegrada.asp?idIndicador=3289&idioma=e [Accessed 14 January 2021].

CEPAL. (2020b). Población En Situación de Pobreza Extrema y Pobreza Según Área Geográfica, Available Online: https://estadisticas.cepal.org/cepalstat/tabulador/ConsultaIntegrada.asp?idIndicador=3328&idioma=e [Accessed 14 January 2021].

CEPAL. (2020c). Producto Interno Bruto (PIB) Total Anual a Precios Constantes En Dólares, Available Online: https://estadisticas.cepal.org/cepalstat/tabulador/ConsultaIntegrada.asp?IdAplicacion=6&idTema=131&idIndicador=2204&idioma=e [Accessed 14 January 2021].

Cunha, F., Heckman, J., Lochner, L. & Masterov, D. (2005). Interpreting the Evidence on Life Cycle Skill Formation, NBER Working Paper, no. 11331, Cambridge, MA: National Bureau of Economic Research.

De Brauw, A., Gilligan, D. O., Hoddinott, J. & Roy, S. (2014). The Impact of Bolsa Família on Schooling, Girls' Advantage Increases and Older Children Gain, IFPRI Discussion Paper, no. 01319, Washington D.C.: International Food Policy Research Institute.

De Brauw, A. & Hoddinott, J. (2011). Must Conditional Cash Transfer Programs Be Conditioned to Be Effective? The Impact of Conditioning Transfers on School Enrollment in Mexico, *Journal of Development Economics*, vol. 96, no. 2, pp.359–370.

Dubois, P., de Janvry, A. & Sadoulet, E. (2012). Effects on School Enrollment and Performance of a Conditional Cash Transfer Program in Mexico, *Journal of Labor Economics*, vol. 30, no. 3, pp.555–589.

ECLAC. (2020). Non-Contributory Social Protection Programmes Database, Latin America and the Caribbean, Bolsa Familia (2003-), Data on Expenditure, Coverage, and Amount of the Monetary Transfers, Available Online: https://dds.cepal.org/bpsnc/programme?id=6 [Accessed 8 January 2021].

Ferreira, F. H. G., Lanjouw, P. & Neri, M. (2003). A Robust Poverty Profile for Brazil Using Multiple Data Sources, *Revista Brasileira de Economia*, vol. 57, no. 1, pp.59–92.

Ferreira, F. H. G. & Schady, N. (2008). Aggregate Economic Shocks, Child Schooling, and Child Health, *The World Bank Research Observer*, vol. 24, no. 2, pp.147–181.

Fiszbein, A. & Schady, N. R. (2009). Conditional Cash Transfers: Reducing Present and Future Poverty, A World Bank Policy Research Report, no. 47603, Washington D.C: The World Bank.

Foguel, M. N. & Barros, R. P. de. (2008). The Effects of Conditional Cash Transfer Programmes on Adult Labour Supply: An Empirical Analysis Using a Time-Series-Cross-Section Sample of Brazilian Municipalities, *Estudos Econômicos (São Paulo)*, vol. 40, no. 2, pp.259–293.

Gillies, D. (2015). Human Capital Theory in Education, in M. Peters (ed.), *Encyclopedia of Educational Philosophy and Theory*, Singapore: Springer Singapore.

Hoffmann, R. (2006). Transferências de Renda e a Redução da Desigualdade No Brasil e Cinco Regiões Entre 1997 e 2004, *Revista Econômica*, vol. 8, no. 1, pp.55-81.

Hoffmann, R. (2013). Transferências de Renda e Desigualdade No Brasil (1995-2011), in T. Campello & M. Neri (eds), *Programa Bolsa Família: Uma Década de Inclusão e Cidadania*, Brasília: Instituto de Pesquisa Econômica Aplicada, pp.207–216.

IBGE. (2013). Projecões Da Populacão: Brasil e Unidades Federativas, Série de Relatórios Metodológicos, Rio de Janeiro: Instituto Brasileiro de Geografia e Estatística.

IBGE. (2014). PNAD 2014, Available Online: https://ftp.ibge.gov.br/Trabalho_e_Rendimento/Pesquisa_Nacional_por_Amostra_de_Domicilios_anual/microdados/2014/ [Accessed 8 January 2021].

Imbens, G. W. & Lemieux, T. (2008). Regression Discontinuity Designs: A Guide to Practice, *Journal of Econometrics*, vol. 142, no. 2, pp.615–635.

Janvry, A., Finan, F. & Sadoulet, E. (2006). Evaluating Brazil's Bolsa Escola Program: Impact on Schooling and Municipal Roles, University of California at Berkeley.

Jones, H. (2016). More Education, Better Jobs? A Critical Review of CCTs and Brazil's Bolsa Família Programme for Long-Term Poverty Reduction, *Social Policy & Society*, vol. 15, no. 3, pp.465–478.

Kerstenetzky, C. L. (2009). Redistribuição e Desenvolvimento? A Economia Política Do Programa Bolsa Família, *Revista de Ciências Sociais*, vol. 52, no. 1, pp.53–83.

Kleinbaum, D. G. & Klein, M. (2010). Logistic Regression, New York, NY: Springer New York.

Levy, D. & Ohls, J. (2010). Evaluation of Jamaica's PATH Conditional Cash Transfer Programme, *Journal of Development Effectiveness*, vol. 2, no. 4, pp.421–441.

Lewis, C. & Lloyd-Sherlock, P. (2009). Social Policy and Economic Development in South America: An Historical Approach to Social Insurance, *Economy and Society*, vol. 38, no. 1, pp.109–131.

Lindert, K. (2006). Brazil: Bolsa Familia Program – Scaling-up Cash Transfers for the Poor, MfDR Principles in Action: Sourcebook on Emerging Good Practices, Part 3, Examples of MfDR in Sector Programs and Projects, Washington, D.C.: The World Bank.

Lindert, K., Linder, A., Hobbs, J. & Brière, B. (2007). The Nuts and Bolts of Brazil's Bolsa Família Program: Implementing Conditional Cash Transfers in a Decentralized Context, SP Discussion Paper, no. 0709, Washington, D.C.: The World Bank.

Meyer, A. (2010). Distrito Federal, Available Online: https://www.brazil.org.za/distrito-federal.html [Accessed 14 April 2021].

Millán, T. M., Barham, T., Macours, K., Maluccio, J. A. & Stampini, M. (2019). Long-Term Impacts of Conditional Cash Transfers: Review of the Evidence, *The World Bank Research Observer*, vol. 34, no. 1, pp.119–159.

Mincer, J. (1974). Schooling, Experience, and Earnings, New York: Columbia University Press.

Ministério da Cidadania. (2021). Famílias Beneficiárias Do Programa Bolsa Família, Secretaria de Avaliação e Gestão Da Informação, VIS DATA 3, Available Online: https://aplicacoes.mds.gov.br/sagi/vis/data3/v.php?q[]=5ItjcmGJnfSh1aLB1MiFcoeVhX5hhoNzgIuIhJl2dHukfYXnybKys9%2B%2BsqilzpK4yca6q7DVybrMibllqHyigKm%2FudC0iLe6osWKpucSF63jsN11k66z2d3NurM2Asm3ycZTpqB5verfwKSm1K1zhMbNy69Qn7SvCAbEu8nFtIQ%3D [Accessed 19 February 2021].

Neri, M. (2019). What Are the Main Drivers of Brazilian Income Distribution Changes in the New Millennium?, WIDER Working Paper, no. 2018/186, Helsinki: World Institute for Development Economics Research.

Nilsson, H. & Sjöberg, K. (2013). An Evaluation of the Impacts of Bolsa Família on Schooling, Master Thesis, Department of Economics, Lund University School of Economics and Management.

Oliveira, A. M. H. C. (2008). An Evaluation of the Bolsa Familia Program in Brazil: Expenditures, Education and Labor Outcomes, Belo Horizonte: CEDEPLAR/UFMG.

Paes-Sousa, R., Regalia, F. & Stampini, M. (2013). Conditions f or Success in Implementing CCT Programs: Lessons for Asia from Latin America and the Caribbean, IDB Policy Brief, no.IDB-PB-192, Washington D.C.: Inter-American Development Bank.

Parker, S. (2003). Evaluación Del Impacto de Oportunidades Sobre La Inscripción Escolar: Primaria, Secundaria y Media Superior, Evaluación de Resultados de Impacto del Programa de Desarrollo Humano Oportunidades, Mexico City: Instituto Nacional de Salud Publica.

Pescarini, J. M., Craig, P., Allik, M., Amorim, L., Ali, S., Smeeth, L., Barreto, M. L., Leyland, A. H., Aquino, E. M. L. & Katikireddi, S. V. (2020). Evaluating the Impact of the Bolsa Familia

Conditional Cash Transfer Program on Premature Cardiovascular and All-Cause Mortality Using the 100 Million Brazilian Cohort: A Natural Experiment Study Protocol, *BMJ Open*, vol. 10, no. 11.

Programa Solidaridad. (2008). Impacto Del Programa Solidaridad En Asistencia Escolar y Niveles Nutricionales: Un Enfoque Empírico, Government of the Dominican Republic.

Ratcliffe, R. (2015). Poorer Children Fall behind in Literacy and Earn Less in Later Life, Available Online: https://www.theguardian.com/education/2015/apr/09/poorer-children-literacy-nurses [Accessed 29 April 2021].

Rocha, S. (2008). Transferências de Renda Federais: Focalização e Impactos Sobre Pobreza e Desigualdade, *Revista de Economia Contemporânea*, vol. 12, no. 1, pp.67–96.

Sánchez-Ancochea, D. & Mattei, L. (2011). Bolsa Família, Poverty and Inequality: Political and Economic Effects in the Short and Long Run, *Global Social Policy: An Interdisciplinary Journal of Public Policy and Social Development*, vol. 11, no. 2–3, pp.299–318.

Schady, N. R. (2006). Early Childhood Development in Latin America and the Caribbean, *Economía*, vol. 6, no. 2, pp.185–225.

Schultz, T. P. (1961). Investment in Human Capital, *American Economic Review*, vol. 51, pp.1–17.

Schultz, T. P. (2000). The Impact of Progresa on School Enrollments, IFPRI Final Report on Progresa, Washington D.C.: International Food Policy Research Institute.

Silva, P. L. do N., Pessoa, D. G. C. & Lila, M. F. (2002). Análise Estatística de Dados Da PNAD: Incorporando a Estrutura Do Plano Amostral, *Ciência & Saúde Coletiva*, vol. 7, no. 4, pp.659–670.

Soares, F.V., Ribas, R. P. & Hirata, G. (2008). Achievements and Shortfalls of Conditional Cash Transfers: Impact Evaluation of Paraguay’s Tekoporã Programme, IPC Evaluation Note, no.3, Brasilia: International Poverty Centre.

Soares, F. V., Ribas, R. P. & Osorio, R. G. (2007). Evaluating the Impact of Brazil’s Bolsa Família: Cash Transfer Programs in Comparative Perspective, IPC Evaluation Note, no.1, Brasilia: International Poverty Centre.

Soares, F. V., Soares, S., Medeiros, M. & Guerreiro Osório, R. (2006). Cash Transfer Programmes in Brazil: Impacts on Inequality and Poverty, IPC Working Paper, no. 21, Brasilia: International Poverty Centre.

Soares, S. (2006). Distribuição Da Renda No Brasil de 1976 a 2004 Com Ênfase No Período Entre 2001 e 2004, IPEA Texto Para Discussão, no. 1166, Brasília: Instituto de Pesquisa Econômica Aplicada.

Song, F., Hooper & Loke, Y. (2013). Publication Bias: What Is It? How Do We Measure It? How Do We Avoid It?, *Open Access Journal of Clinical Trials*, vol. 5, pp.71–81.

Varian, H. R. (2010). Intermediate Microeconomics: A Modern Approach, 8th ed., New York: W.W. Norton & Co.

Appendix A

Table A.1: *Sample Means of Covariates; Whole Sample*

Variable	*Mean*
Bolsa Família = 1	0.74
Bolsa Família = 0	0.26
Male = 1	0.53
Male = 0	0.48
Mother present in household = 1	0.89
Mother present in household = 0	0.11
Urban = 1	0.70
Urban = 0	0.30
Race = 1	0.29
Race = 0	0.71
Number of household members	3.8
Monthly household income	151.56
Age	11.35

Table A.2: *Sample Means of Covariates; Whole Sample & Lager Bandwidth*

Variable	*Mean*
Bolsa Família = 1	0.39
Bolsa Família = 0	0.61
Gender = 1	0.50
Gender = 0	0.50
Mother present in household = 1	0.86
Mother present in household = 0	0.14
Urban = 1	0.67
Urban = 0	0.33
Race = 1	0.28
Race = 0	0.72
Number of household members	4.02
Monthly household income	178.31
Age	11.32

Table A.3: *Sample Means of Covariates; Age 6-15*

Variable	*Mean*
Bolsa Família = 1	0.38
Bolsa Família = 0	0.62
Gender = 1	0.50
Gender = 0	0.50
Mother present in household = 1	0.89
Mother present in household = 0	0.11
Urban = 1	0.67
Urban = 0	0.33
Race = 1	0.29
Race = 0	0.71
Number of household members	4.1
Monthly household income	179.59
Age	10.4

Table A.4: *Sample Means of Covariates; Age 16-17*

Variable	*Mean*
Bolsa Família = 1	0.41
Bolsa Família = 0	0.59
Gender = 1	0.49
Gender = 0	0.51
Mother present in household = 1	0.68
Mother present in household = 0	0.32
Urban = 1	0.67
Urban = 0	0.33
Race = 1	0.22
Race = 0	0.78
Number of household members	3.67
Monthly household income	170.99
Age	16.48

Appendix B

Table B.1: *Odds Ratios for Dependent Variable School Enrollment; By Gender with Larger Bandwidth*

Variables	Dependent Variable is School Enrollment
Interaction effects	
Female & Bolsa Família	ref
Male & Bolsa Família	3.35***
	(1.34)
Female & No Bolsa Família	0.80
	(0.16)
Male & No Bolsa Família	1.56
	(0.55)
Monthly household income	1.00***
	(0.00)
Age	0.73***
	(0.03)
Race	1.95***
	(0.51)
Mother present in household	3.73***
	(0.81)
Number of household members	0.98
	(0.06)
Geographical location	0.81
	(0.17)
Pseudo R^2	0.21
Observations	2,156

Notes: Robust standard errors in parentheses; State clusters adjusted these standard errors; *** p<0.01, ** p<0.05, * p<0.1