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Striving for Educational Improvement: Essays on Intergenerational Mobility and Teacher Bonus Programs in Contemporary Brazil

Tharcisio Leone

Dissertation

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Tharcisio Leone
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List of Abbreviations

2SLS	**T**wo **S**tage **L**east **S**quares
3PL	**T**hree **P**arameter **L**ogistic
APRs	**A**djusted **P**redictions (at) **R**epresentative **V**alues
BRL	**B**razilian **R**eais
CTT	**C**lassical **T**est **T**heory
DiD	**D**ifference **in** **D**ifference
ENEM	**E**xame **N**acional (do) **E**nsino **M**édio
GERES	(Estudo Longitudinal da) **Ger**ação **Es**colar 2005
GMM	**G**eneralized **M**ethod (of) **M**oments
IBGE	**I**nstituto **B**rasileiro (de) **G**eografia (e) **E**statistica
ICM	**Í**ndice (de) **C**umprimento (de) **M**etas
IDEB	**Í**ndice (de) **D**esenvolvimento (da) **E**ducação **B**ásica
IDESP	**Í**ndice (de) **D**esenvolvimento (da) **E**ducação (do Estado de) **S**ão **P**aulo
INPC	**Í**ndice **N**acional (de) **P**reços (ao) **C**onsumidor
INSE	**I**ndicador (do) **N**ível **S**ocio-**E**conômico (das Escolas de Educação Básica)
IP	**I**ndicator (of) **P**erformance
IRT	**I**tem **R**esponse **T**heory
IV	**I**nstrumental **V**ariables
LDB	**L**ei (de) **D**iretrizes (e) **B**ases (da Educação)
LPM	**L**inear **P**robability **M**odel
LSDV	**L**east **S**quares **D**ummy **V**ariable
NEGD	**N**on-**E**quivalent **G**roups **D**esign
OECD	**O**rganisation (for) **E**conomic **C**o-operation (and) **D**evelopment
OLS	**O**rdinary **L**east **S**quares
PFP	**P**ay **f**or **P**erformance
PISA	**P**rogramme (for) **I**nternational **S**tudent **A**ssessment
PNAD	**P**esquisa **N**acional (por) **A**mostra (de) **D**omicílios
PR	**P**assing **R**ate
RCT	**R**andomized **C**ontrolled **T**rial
SARESP	**S**istema (de) **A**valiação (de) **R**endimento **E**scolar (do Estado de) **S**ão **P**aulo
SD	**S**tandard **D**eviation
SEE-SP	**S**ecretaria **E**stadual (de) **E**ducação (do Estado de) **S**ão **P**aulo
SQP	**S**chool **Q**uality **P**rogram

CHAPTER 1

Introduction

1.1 Motivation

Intergenerational mobility refers to movements in the socioeconomic status of family members that takes place from one generation to the next; it has been, from both a theoretical and empirical perspective, an intense area of research in the Social Sciences (Black and Devereux, 2010; Blanden and Macmillan, 2016). In this case the focus of the research is on the persistence between parents' and children's outcomes. This can be measured based on income, earnings, professional occupation, or educational attainment (Chetty et al., 2014a; Hertz et al., 2007a; Torche, 2015).

Intergenerational persistence in economic outcomes contributes to the perpetuation and aggravation of the resource gap between rich and poor (Mazumder, 2015). For this reason, political and scientific interest in intergenerational mobility has grown sharply during the last few years (see e.g. Blanden and Macmillan, 2014; Corak, 2013c; Corak et al., 2014). Increasing access to data about the economic status of children and their parents, together with the development of new methodological tools for estimating mobility, have provided society with worrying empirical evidence: a person's chances of economic success are highly dependent on their family background (Chetty et al., 2014a; Corak, 2006). This dependence has grown in recent decades in many countries (Lee and Solon, 2009; Mazumder, 2012).

The mobility question was first addressed from a philosophical approach. The Rawls' philosophical principle of fair equality of opportunity is frequently used in the literature as a starting point for the discussion of intergenerational mobility chances. According to Rawls (1971), equality of opportunity requires that social mobility shall be possible for all and that all individuals shall be eligible to compete on equal terms vis-à-vis moving up the social ladder. Then, the acceptance and full implementation of this principle would mean that individuals with the same ability and strength of will must have the same chance of achieving their desired economic status, irrespective of their social, ethnic, or racial background.

More recently examined issues relating to equality of opportunity have been strongly influenced by the work of the American economist and political scientist John Roemer (see e.g. Roemer, 1998a,b, 2009; Roemer and Trannoy, 2015). His basic idea is that two different types of factors, namely circumstance and effort, are responsible for individual outcomes and there are morally acceptable and morally unacceptable inequalities. The term "circumstance" refers to variables that are exogenous to the person (such as gender, race, handicaps, birthplace, mother's and father's education, and parental income). Hence, according to Roemer, inequalities can be only justified when they are derived from (a lack of) personal efforts. Should circumstances have an effect on individual outcomes, however, then this inequality becomes morally unacceptable, and must—at least in part—be compensated for by the action of the state.

These theoretical considerations lead to the assumption that public institutions need to be committed to improving equality of opportunity by circumstance, such that personal outcomes depend only on individual effort and life choices and not on interdynastic resources derived from the "accident of birth" (Strauss, 1992). Because the investment in human capital is a key driver for social mobility, the school system plays a crucial role by promoting equality of opportunity (Abbott et al., 2019). Therefore, the improving of graduation rates and academic achievements among students—especially for those from socially disadvantaged households—is often considered a necessary condition for the promoting of intergenerational mobility (De Hoyos et al., 2019).

Since teacher qualifications are a crucial element of students' academic development (Woessmann, 2011), we find a broad consensus in the literature about the importance of school staff in the implementation of a meritocratic and inclusive education system (Canales and Maldonado, 2018; Dee and Wyckoff, 2015). Hence, there is growing interest in addressing teaching activities in the political reforms aiming to increase equality of opportunity in the education system (Yuan et al., 2013). International development organizations increasingly suggest implementing pay-for-performance (PFP) programs in schools as a mechanism to increase the professional engagement in classrooms, and, consequently, the academic performance of students (Barrera-Osorio and Raju, 2017). Attracting and retaining high-performing teachers and motivating them to work for the success of schools are nowadays promising policies to improve student outcomes (Woessmann, 2011).

Against this background, this dissertation set outs to explore the topics of intergenerational educational mobility and teacher bonus programs using empirical data from Brazil. As in other developing countries, the average level of educational attainment in Brazilian society has grown steadily over the last five decades.[1] In the mid-1970s, the share of school-age children in primary education was still below 70 percent; it would continuously increase in the years that followed, yet achieve a level above 95 percent only in 1999 however (Leone, 2021). Therefore, it is of scientific importance and political relevance to provide evidence showing the impact of this increasing educational attainment on the chances of intergenerational mobility.

Despite the almost-universal net enrollment rate in primary education achieved in the last few years in Brazil (see Table 2.1), the country still faces enormous challenges in terms of school quality. Cross-national comparative studies designed to evaluate educational achievement, such as the Programme for International Student Assessment (PISA), indicate that the average performance of Brazilian students is significantly lower as compared with the levels of those from Organisation for Economic Co-operation and Development (OECD) countries, and this situation has not changed in recent years. PISA also highlights that the performance gap cannot be explained only by educational expenditure: low-spending countries such as Colombia, Mexico, and Uruguay are able to achieve better PISA scores with even less education spending per student than Brazil, suggesting that the low performance of the latter's students is not solely a problem of investment (Schleicher, 2019). For this reason, many school districts in the country are using merit-pay programs to better align teacher incentives with student learning (Scorzafave et al., 2015)—but the genuine effectiveness of these programs remains a topic of intense discussion, in part due to the lack of rigorous empirical evaluations. Hence this dissertation offers new insights into the main effects of bonus schemes on the education system, thus shedding necessary light on the Brazilian public debate about the effectiveness of these PFP programs.

1.2 Contribution

This cumulative dissertation contains three self-contained research papers related to the topic of education economics in Brazil, with each chapter consisting of a single paper. While chapter 2 addresses the variation in intergenerational education mobility across Brazilian states, the following chapters 3 and 4 deal with the impact evaluation of the teacher bonus program of the state of São Paulo. Table 1.1 gives a brief overview

[1] See Leone (2019) for a description of the global evolution of educational attainment over the last few decades.

of the research questions, data sources, methodological approaches, and main findings of each of the three papers.[2]

The main feature of this dissertation is the use of multiple research methods to ensure the reliability and credibility of the empirical findings under the reality of restricted data availability—in the Brazilian case. For this reason, the empirical analyses of this work are carried out using (secondary) cross-sectional and panel data as well as own quantitative and qualitative data collection. Moreover, besides the use of sophisticated econometric estimations, such as value-added and probit models, qualitative methods are also integrated to supplement the quantitative findings.

Table 1.1. Overview of Chapters

	Chapter 2	**Chapter 3**	**Chapter 4**
Title	The Geography of Intergenerational Mobility	Does a Productivity Bonus Pay Off?	Addressing Changes in Professional Behavior by Bonus
Geographical Focus	Brazil (national level)	Campinas (municipality level)	Campinas (municipality level)
Research Questions	(i) Does the "Great Gatsby curve" hold true within a single country? (ii) Why can income inequality lead to less mobility?	Did the implementation of the teacher bonus program lead to changes in student performance in Mathematics and Portuguese?	Did the implementation of the teacher bonus program lead to changes in the professional practices and behaviors of teachers?
Database	PNAD	GERES	Own Data Collection
Data Structure	Cross-Sectional Data	Panel Data	Questionnaire Survey and Interviews
Method	Quantitative	Quantitative	Mixed Methods
Empirical Strategy	(i) Intergenerational Transition Matrix; (ii) Linear Regression Model; (iii) Probit Model.	(i) Quasi-Experimental Design; (ii) Difference in Difference; (iii) Value-Added Model.	(i) Structured Questionnaire; (ii) Open-Ended Interviews; (iii) Data Triangulation.
Main Results	(i) Confirmation of the "Great Gatsby curve." (ii) Children from less-educated families are more likely to drop out of school if they live in states with higher income inequality.	(i) The bonus had no statistically significant impact on student performance. (ii) Alternative specifications, placebo tests, and robustness checks also support this finding.	(i) The bonus program of São Paulo state reduced work absenteeism but increased cheating in schools. (ii) No positive impact on teaching activities or career plan was found.

Source: Author's own elaboration.

Chapter 2, entitled "The Geography of Intergenerational Mobility," applies the most recently published mobility data for Brazil to present a comprehensive and up-to-date analysis of mobility chances in Brazilian society.[3] The study aims at expanding the literature on the "Great Gatsby curve"—started by Krueger (2012)—by incorporating a national investigation of the relationship between income inequality and intergenerational mobility. In addition, the chapter applies the theoretical approach proposed by Kearney and Levine (2016) to investigate a specific mechanism behind the "Great Gatsby curve," namely whether income inequality does affect the (final) education outcomes of children from socially vulnerable families. Using cross-sectional data from the nationally representative Brazilian household surveys and econometric models, this paper provides two main empirical findings to the literature. First, the "Great Gatsby curve" also holds true within a single country; or, in other words, the Brazilian states with the highest levels of income disparity present

[2] All the empirical evidence presented in this dissertation was estimated using the statistic program Stata (version 12.0).

[3] The microdata of the PNAD-2014 used in this study for the estimation of mobility were only made freely available for research in November 2016.

also the lowest values for intergenerational education mobility. And, second, a possible reason for this association is the negative impact of inequality on educational outcomes: each additional point in the 75/10 ratio of income inequality decreases the chances of achieving secondary education by 5.4 percent for children from low-educated parents.

The other two papers (chapters 2 and 3) provide a comprehensive analysis of a PFP program for teachers implemented in the state of São Paulo in 2008. Both studies have in common that they investigate the effectiveness of this program, but each paper addresses different research questions and they each also apply very diverse empirical strategies. As will be discussed in both chapters, teacher bonus programs have been introduced in many Brazilian school districts as an instrument to improve the quality of the education system, but the absence of an appropriate monitoring and assessment framework has hampered the empirical evaluation of these programs (Bresolin, 2014). Hence, the main innovation of the next two papers is to go beyond the existing data limitations for Brazil and develop empirical strategies capable of generating robust empirical evidence for the impact of the merit-pay program in the education system of São Paulo state.

Investigation of the teacher bonus program begins with the data analysis of the GERES, which was the first longitudinal data survey on student academic achievement carried out successfully in the Brazilian education system (Brooke and Bomamino, 2011). Applying this database and limiting the investigation to the city of Campinas, I use in chapter 3 a quasi-experimental design and a series of econometric methods to evaluate ex post the impact of the implementation of the bonus program on the academic-test scores of pupils. Since neither the GERES—nor the other available data on educational attainment for Brazil—provide sufficient information on teaching practices with regard to the learning process, I carry out for chapter 4 an own data collection with teachers from state schools in Campinas and apply a mixed-methods research approach to investigate the effects of the teacher bonus program on the professional practices and behaviors of educators in the classroom.

In chapter 3, entitled "Does a Productivity Bonus Pay Off?," I explore the panel nature of the GERES database and apply value-added models for the investigation of the bonus scheme's impact in order to control the estimation strategy for the students' previous knowledge and ability. Using a difference-in-difference approach in which students from state schools are the treatment and their peers from municipal schools the comparison group, the article concludes that the implementation of performance-based bonuses for teachers in the state schools of São Paulo has led to no statistically significant impact on the performance of students in Math and Portuguese. In the first year of the bonus program, the test scores in treatment schools were slightly lower than those in comparison schools. But none of this variation was statistically significant. The results from alternative specifications, placebo tests, and robustness checks also support these core findings.

The final chapter, entitled "Addressing Changes in Professional Behavior by Teacher bonuses," applies an explanatory sequential design by combining data from a questionnaire survey and qualitative interviews. The main motivation behind this analysis was addressing the lack of empirical evidence in the literature showing the mechanisms through which the teacher bonus program can lead to an increase in the academic achievements of students. Then, the paper focuses on the individual perceptions and viewpoints of teachers to investigate a possible causal link between the implementation of the merit-pay program in the education system and the improvement of professional practices and behaviors in schools. According to the opinions of the teachers themselves, the bonus scheme created no additional incentives for working in the state schools of São Paulo or for the improvement of teaching activities; it had furthermore a negative side effect, namely an increase in dishonest behavior in the schools. The only positive impact of the bonus program felt by the teachers was the reduction of work absenteeism.

In sum, the empirical evidence from chapters 3 and 4 points to the ineffectiveness of the teacher bonus program of São Paulo state in relation to the improvement of student performance and teaching activities. These results highlight the urgent need to rethink the structure of the bonus program, since it has not been efficient in attaining the targets that spurred its implementation.

CHAPTER 2

The Geography of Inter-generational Mobility

2.1 Introduction

Empirical evidence from cross-country comparisons has revealed a negative correlation between intergenerational mobility and income inequality: Countries with greater income disparity tend to have lower levels of economic mobility between generations (Björklund and Jäntti, 2009; Blanden, 2013; Corak, 2006; Ermisch et al., 2012). The so-called Great Gatsby curve illustrates the transmission of income inequality across generations and underlines the fact that the higher the level of inequality in one generation, the more children's chances of economic success depend on whether they have poor or rich parents (Boudreaux, 2014; Chetty et al., 2014b; Corak, 2013a; Jerrim and Macmillan, 2015; Mazumder, 2015).

The original Great Gatsby curve was based on research conducted at the international level, using cross-country comparisons. However, some authors have questioned the results, owing to the poor comparability of the data across countries (see e.g. Andrews and Leigh, 2009; Güell et al., 2018; Jantti and Jenkins, 2013; Jerrim and Macmillan, 2015). The demonstration of equivalence (lack of bias) is an important criteria for any cross-regional comparison in order to provide empirical findings free from differences in data construction across countries. For this purpose, studies that address the lack of suitable data represent an important and beneficial contribution to international research (Andrews and Leigh, 2009; Boudreaux, 2014).

This paper is intended primarily to expand the available literature by providing a Great Gatsby curve free of comparability bias, in which the correlation between income inequality and intergenerational mobility is analyzed across different regions within a single country, using observations recorded and consolidated in a single database.[4] Given the lack of intergenerational income data for Brazil, the investigation of the Great Gatsby curve in this study is based on education mobility, and applies the data of educational attainment from children and their parents that have been published in the Mobility Supplement from the nationally representative Brazilian household survey (PNAD-2014). The case of Brazil, with its continental dimensions and widespread regional and social inequalities, is a very promising area for research. The country has one of the highest levels of income inequality in the world and at the same time a significant variation in inequality across its 27 states.[5] The income inequality—as measured by the Gini coefficient—varied in the year 2014 from 0.416 in Santa Catarina to 0.577 in Distrito Federal.

I focus on state-level variation because in Brazil the responsibility for the provision of primary and secondary education lies with the states. According to the Law of Directives and Bases of National Education, the current legislation that regulates the education system in Brazil, the tasks of the federal government in relation to primary and secondary public education are restricted to providing technical and financial support to the states and municipalities, thereby guaranteeing the equalization of opportunities and a minimum level of quality.[6]

Despite the increasing scientific interest in the Great Gatsby curve, far too little is known about the causal link between inequality and intergenerational mobility,

[4]This approach has already been adopted by Güell et al. (2018) for Italy, and Bradbury and Triest (2016), Chetty et al. (2014a), and Kearney and Levine (2016) for the United States. They analyzed single data sets and found that the correlation between intergenerational mobility and inequality also holds true across provinces in these countries.

[5]To be more precise, Brazil comprises 26 states plus a federal district (Distrito Federal), where the federal capital is located. See Figure 2.1 for a clear picture of the variation in income inequality across Brazilian states.

[6]The appendix of this paper provides a more comprehensive and detailed overview of Brazilian educational system.

because only limited research has been undertaken on the determinants of this correlation (Jerrim and Macmillan, 2015). In the final part of this paper, I seek to fill this research gap by focusing on a possible mechanism through which inequality might affect intergenerational mobility—namely, curtailed investment in education. Kearney and Levine (2016) propose that a greater level of inequality could lead to an underestimation of the return on investment in human capital for children from socially vulnerable families, which would increase their school drop-out rates, thereby decreasing their chances of mobility.

The findings of this study indicate that the case of Brazil provides two main findings to the existing literature. First, the relationship between income inequality and intergenerational mobility illustrated in the Great Gatsby curve remains persist within a single country; and second, a possible reason for this association is the link between educational outcomes and inequality: in states with a higher gap between the bottom and the top of the income distribution, children from socially vulnerable families have a higher chance of dropping out of the education system.

The remainder of this chapter is structured as follows. The next section describes the theoretical basis for the later empirical investigation. Section 2.3 reviews the related literature and section 2.4 presents the database. In the following, I describe the three methodological approaches applied in the paper. Section 2.6 deals with the empirical findings. I first estimate the level of intergenerational educational mobility in the 27 Brazilian states, then I correlate the results from mobility with income inequality. Finally, I apply an econometric model to investigate whether (socially) vulnerable children living in states with a higher gap between the top and the bottom of the income distribution have a greater probability of leaving school without a certificate. Section 2.7 concludes with a summary of the key findings.[7]

2.2 The State of the Art

The term "intergenerational mobility" describes the ability of individuals to move beyond their social origins and achieve a socioeconomic status that is not dictated by that of their parents (Fox et al., 2016; Ribeiro, 2007). In the mobility literature, the focus of the empirical investigations lies on the measurement of the correlation between parents' and children's economic outcomes, in terms of income, earnings, education, or professional occupation (Blanden and Macmillan, 2014; Corak et al., 2014; Hills et al., 2015). The greater this association, the greater the economic advantages and disadvantages inherited from one's family background (Schneebaum et al., 2016).

The scientific community has been working for a long time on a framework for understanding the transmission of economic outcomes from parents to their offspring (Black and Devereux, 2010; Blanden et al., 2014), and the studies of Solon (1992) and Zimmerman (1992) were the precursors to the modern empirical estimations of intergenerational correlation in outcomes (Björklund and Jäntti, 2009; Blanden et al., 2014; Ichino et al., 2011). In subsequent years, motivated mainly by the theoretical contribution of Solon (2004), several researchers around the world began to investigate the persistence of income, wealth, consumption, and education between parents and their children (see e.g. Ayala and Sastre, 2008; Blanden, 2013; Bratsberg et al., 2007; Chen, 2009; Corak et al., 2014; Dunn, 2007b; Roemer, 2004; Ueda, 2009). In a second

[7]This paper is supplemented by a comprehensive appendix with relevant information concerning the educational system in Brazil, the data harmonization, the codification process for the variables, the formal description of the underlying theoretical models, tables and figures.

stage of the literature, researchers have focused on the variation in intergenerational mobility over time (see e.g. Aaronson and Mazumder, 2008; Björklund et al., 2009; Hertz et al., 2007a; Hout and Guest, 2013; Lee and Solon, 2009; Mazumder, 2012) and across countries (see e.g. Aaberge et al., 2002; Ayala and Sastre, 2008; Blanden, 2013; Blanden et al., 2014; Corak, 2006; Jantti et al., 2006).[8]

An analysis of these works shows that two different research methodologies have primarily been used to measure intergenerational mobility in the economic literature: the first approach focuses on income and the second on educational attainment (Torche, 2015).[9] Given the limited availability of lifetime income data—specially in developing countries (Azam and Bhatt, 2015; Ferreira and Veloso, 2006b)—an increasing number of authors have used the strong positive correlation between education and income to measure mobility across generations. This approach is justified by the solid set of studies and empirical evidence which indicate that educational inequality plays a determining role in the transmission of inequalities across generations, making it a robust indicator for future trends in income inequality (Blanden and Macmillan, 2014; Psacharopoulos and Patrinos, 2018).

Specially, from the turn of the century onward, the economic literature started also to deal with the mechanisms behind the intergenerational persistence in outcomes (Black and Devereux, 2010; Rothwell and Massey, 2015). Corak (2006) was the first to provide empirical evidence of a negative correlation between intergenerational mobility and income inequality (Kearney and Levine, 2016). Based on cross-country comparisons and the theoretical approach of Solon (2004), Corak (2006) showed that countries with greater income disparity tend to exhibit lower levels of income mobility between generations. It did not take long for the finding of Corak (2006) to enter into the political debate. In his speech as chairman of President Barack Obama's Council of Economic Advisers, economics professor Alan Krueger (2012) introduced the Great Gatsby curve, and within a short space of time this curve gained a prominent position in the international economic community (Jerrim and Macmillan, 2015). It has been mentioned by Nobel Prize winners (see e.g. Heckman, 2013) and has been extensively addressed by the mainstream press (see e.g. Economist, 2013; The Guardian, 2012) and high-ranking policymakers (see e.g. Obama, 2013; White House, 2013). Furthermore, the Great Gatsby curve has also been addressed in a long list of recent publications in peer-reviewed journals (see e.g. Boudreaux, 2014; Brahim and McLeod, 2016; Chetty et al., 2014b; Corak, 2013a,b; Fan et al., 2015; Güell et al., 2018; Jerrim and Macmillan, 2015; Lefgren et al., 2015; Mazumder, 2015; Neidhöfer, 2019).

The negative relationship between inequality and intergenerational mobility illustrated by the Great Gatsby curve is also supported by economic theory. Becker and Tomes (1986), Breen and Jonsson (2005), Corak (2013a), Duncan and Murnane (2011), and Solon (2004) are just some examples of authors who have argued that the disparities in the investment in children's human capital across families increase with the growth of income inequality. Solon (2004), for example, adapted the classical model of Becker and Tomes (1979, 1986) in a detailed theoretical model presenting the intergenerational transmission of inequality and demonstrated on the basis of

[8]Fox et al. (2016), Torche (2015), Hills et al. (2015), Jantti and Jenkins (2013), and Black and Devereux (2010) offer a detailed discussion of recent developments in the literature on intergenerational mobility.

[9]A third approach, found especially in sociological studies, measures the degree of intergenerational mobility using the professional occupations of parents and their children (see e.g. Pastore and Valle Silva, 2000; Reddy, 2015; Xie and Killewald, 2013).

a mathematical approach that higher-income parents have a higher capacity to invest more in the human capital of their children, and they are also more inclined to make this investment if the expected earnings return on human capital increases over time.[10]

However, the model of Solon (2004) has been used in the economic literature only as a starting point for understanding the variation in the intergenerational persistence of outcomes across countries and time. The Great Gatsby curve does not present a causal link between inequality and mobility, but rather a summary of all mechanisms reflecting the outcome of a host of ways that income inequality affects children's development (Corak, 2013a; Kearney and Levine, 2016).

Recent research has offered significant evidence that childhood development has direct effects on adult economic productivity (Cunha et al., 2006; Knudsen et al., 2006; Phillips, Shonkoff, et al., 2000). Socially vulnerable families lack the socioeconomic resources to provide effective early development for their children. Therefore, these children are exposed from a very young age to adverse environments, leading to skill and ability deficits that result in low productivity in the future (Shonkoff and Meisels, 2000). Also during adult life, children continue to benefit from the resources of their family. Social connections, for example, play an important role in mobility chances. Children from wealthy families can use the extensive network of their parents to climb the economic ladder, which means they have an advantage relative to children from low-income households (Corak, 2013a).

Then, the Great Gatsby curve calls for us to reflect on the reasons for the association between social mobility and inequality, and how the current earning disparities can influence the economic outcomes of the new generations. To address these questions, it is important to bear in mind the three main institutions that play a crucial role in children's chances of mobility: the family, the labor market, and the state (Corak, 2013a; Neidhöfer, 2019). As described in the model of Solon (2004), the income inequality resulting from the labor market impacts the financial capacity and the incentives for investment in the human capital of children across families. The individual capabilities of children are also strongly influenced by nonmonetary resources, such as the behavioral patterns, motivations, and social connections which are transmitted in the family environment and play an important role for mobility chances. Finally, the importance of public policy for intergenerational mobility relates to all key aspects that affect the interaction between families and the labor market, such as taxation and structure of education system (Björklund and Jäntti, 2009; Corak, 2013a).

Based on the theoretical considerations of Corak (2013a), the most recent empirical studies concerning the Great Gatsby curve have investigated the association between intergenerational mobility and an increasing number of socioeconomic indicators referring to these three institutions. Using income data, Chetty et al. (2014a), for example, estimated the intergenerational mobility for 741 "Commuting Zones" in the United States, providing empirical evidence for a strong variation in the mobility across these regions. In second step, they explored the spatial variation in mobility correlating the results with observable sociopolitical variables. According to the authors, the level of (income) mobility across the Commuting Zones are positively associated with: (1) less residential segregation; (2) less income inequality; (3) better primary schools; (4) greater social capital; and (5) greater family stability. In a more

[10]The appendix provides a formal description for the model of Solon (2004), which shows how income inequality can affect the chances of intergenerational mobility.

recent study, Güell et al. (2018) followed Chetty et al. (2014a) to produce comparable measures of intergenerational mobility for 103 Italian provinces and correlate the findings with a serie of indicators for economic and social development. The empirical evidence has suggested two main findings: First, there is a positive correlation of mobility with “good” economic outcomes, such as value added per capita, wealth, income, employment rates, and participation rates, and, second, the correlation changes direction when “bad” economic outcomes are analyzed. Intergeneration mobility is negatively associated with income inequality, unemployment rates, and shares of less-educated young individuals.

Assuming that the investigation of the causal effects of mobility is viewed with increasing mistrust in the academic community—due to the methodological difficulties of measuring causation within the intergenerational persistence framework (see e.g. Björklund and Jäntti, 2009; Chetty et al., 2014a; Fessler and Schneebaum, 2012)—this paper is not, in principle, looking for causal relationships, but rather aims to generate stylized facts and trends, thereby improving our understanding of the mechanisms behind the correlation between income inequality and the persistence of economic outcomes across generations illustrated by the Great Gatsby curve. Consequently, the empirical approach applied in the last part of this paper resembles the study of Kearney and Levine (2016). These authors proposed curtailed investment in human capital as an important channel via which an increase in income inequality may adversely affect the mobility chances of the younger generations. According to the authors, an increase in the gap between the bottom and the top of the income distribution could change the expected return on human capital investment for children from socially disadvantaged families. In this case, children born into poverty generally do not believe that a school-leaving qualification will help them move up the economic ladder, which thus reinforces their economic marginalization.[11] Based on a formal econometric model and five sources of individual-level data for the US, Kearney and Levine (2016) confirmed the hypothesis that low-income youths are more likely to drop out of school if they live in a place with greater income inequality.

2.3 Literature Review

Although the empirical evidence for intergenerational educational mobility remains highly concentrated in the industrialized world, it is possible to detect in recent years increasing academic interest in estimating education mobility chances for developing countries. Recent papers on this topic have been published by Dacuycuy and Bayudan-Dacuycuy (2019) for the Philippines, Assaad and Saleh (2018) for Jordan, Leone (2021) and Mahlmeister et al. (2019) for Brazil, Fan et al. (2015), Li and Zhong (2017), and Magnani and Zhu (2015) for China, Azam and Bhatt (2015) and Emran and Shilpi (2015) for India, and Cheema and Naseer (2013) for Pakistan. In the same way, the literature already offers cross-national comparative studies conducted exclusively with developing countries, such as the cases of Daude and Robano (2015), Neidhöfer (2019), and Neidhöfer et al. (2018) for Latin America, and Azomahou and Yitbarek (2016) for sub-Saharan Africa.[12]

The research of intergenerational mobility in Brazil is characterized by data limitations, since, as in the other Latin American countries, no Brazilian database collects income data over time for different generations (Torche, 2014). Consequently, authors

[11] See appendix for a formal description of the model of Kearney and Levine (2016) concerning the decision to drop out of school.

[12] See Torche (2019) for a comprehensive review of the recent literature relating to educational mobility in developing countries.

have applied cross-sectional retrospective surveys for the analysis of mobility across generations. These household surveys normally contain the earnings the respondents, but no retrospective information on parental income is provided, thus making it difficult to conduct empirical analyses for earnings mobility.[13] Given this income data limitation, the studies that aim to investigate the intergenerational mobility of the (whole) Brazilian population are based on surveys in which offspring are asked about the (professional) occupation and educational level of their parents. From this point of departure, Brazilian research on the intergenerational persistence of outcomes has used either the educational attainments (see e.g. Leone, 2021; Mahlmeister et al., 2019; Ribeiro, 2017a; Ribeiro et al., 2019) or the professional occupations (see e.g. Pastore and Silva, 2000; Torche and Ribeiro, 2012) of parents and children for the empirical investigation.[14]

The vast majority of these empirical studies made use of the Brazilian National Household Survey (PNAD) for the empirical estimations, and have reached similar conclusions. In Brazil, there is a strong intergenerational persistence of inequality; in other words: offspring' economic outcomes correlate strongly with the outcomes of their parents (see e.g. Mahlmeister et al., 2019; Ribeiro, 2017b). Not by coincidence, Brazil does not fare well in the international rankings of intergenerational mobility.[15]

Despite this strong persistence in economic outcomes across generations, previous studies have shown that in Brazil the chances of climbing the economic ladder have increased more recently. Applying the PNADs from 1996 and 2014, Mahlmeister et al. (2019) found that the grade of intergenerational persistence in education has decreased since the 1990s, given that the years of schooling of children from less-educated parents has grown considerably in this period and the schooling of their peers remained relatively stable. Estimating the educational mobility based on household survey data from 1996 and 2008, Ribeiro (2017a) also confirmed a reduction in the impact of a father's schooling on his son's education. Based on the PNADs from the years of 1973, 1982, 1988, and 1996, Torche and Ribeiro (2010) also show a substantial increase in social fluidity over time, which was mainly caused by the decline in the intergenerational association in educational attainments, during the 1970s and 1980s.

The empirical analyses of Hertz et al. (2007b), Mahlmeister et al. (2019), and Neidhöfer et al. (2018) are excellent companions to this paper. These works also apply correlation coefficients from a linear regression of children's on parents' schooling to estimate intergenerational educational mobility in Brazil. The papers of Mahlmeister et al. (2019) and Neidhöfer et al. (2018) also use transition matrices to measure time-dependence mobility and the same database (PNAD-2014) that is applied in this paper. While Mahlmeister et al. (2019) examine differences in mobility across individuals by regions, race, locality of residence, and cohort, Neidhöfer et al. (2018) apply a set of harmonized household survey data for 18 Latin American countries to

[13] An interesting alternative to address this income data limitation, utilized by Marchon (2014) for example, was to restrict the investigation of intergenerational mobility in earnings to adult sons aged 22–27 still living with their parents, since the PNAD contains, in this case, the income for both generations.

[14] For Brazil we can also find empirical investigations of mobility that have combined the educational attainments and the occupational categories of parents to estimate proxies of their previous income, and then compared these values with the current income of their offspring (see e.g. Dunn, 2007a; Ferreira and Veloso, 2006a; Pero and Szerman, 2008).

[15] Across the 42 individual countries reported by Hertz et al. (2007b), Brazil had the fifth-largest educational persistence between parents and children. Based on a recent set of harmonized household survey data for 18 Latin American countries, Neidhöfer et al. (2018) found that Brazil occupies an intermediate position in the degree of intergenerational education mobility.

identify (at the national level) key macroeconomic variables related to higher levels of educational mobility.

This paper aims at extending these empirical analyses, presenting an in-depth investigation of the intergeneration educational mobility across Brazilian states and the role of income inequality for mobility chances. Despite the political reforms in the structure of the education system in Brazil over time (see Table 2.5) and the consequent increase in the average years of schooling (see Figure 2.2), studies investigating the drivers of mobility remain unexplored in the Brazilian literature. For other countries, the association between inequality and intergenerational mobility illustrated by the Great Gatsby curve was already explored, whereby only a handful of these studies have concentrated on developing countries and used education data for the measure of mobility. The resultant findings indicated that education mobility is positively correlated with several macroeconomic indicators, such as economic development, public education spending, and the strength of financial markets (Torche, 2019). Azam and Bhatt (2015), for example, investigated the variation of intergenerational educational persistence across states in India and come to the conclusion that states with a higher per capita expenditure on primary education achieved higher levels of mobility across generations.

Similar empirical evidence was also found in comparative studies using only developing countries. Applying harmonized data for 18 Latin American nations, Neidhöfer (2019) could confirm a positive impact of public spending on education and economic growth on the chances of intergenerational educational mobility. Using a sample for 16 Latin American countries, Behrman et al. (2001) found that public spending on primary and secondary education have a positive impact for mobility, while a relatively greater share of educational budgets to higher education tends to reinforce the importance of family background, reducing in this way the chances of mobility. In the same study, the authors indicated also that better-developed financial markets increase social mobility given that they can help to reduce the dependence of family income on the educational outcomes of children. Working with a sample of 26 African countries, Alesina et al. (2019) pointed to the importance of economic development for education mobility. In regions with more vibrant economies—normally in areas close to the coast and national capitals, and less affected by contagious diseases—the chances of upward mobility are higher.

2.4 Data

The data for this study stem from the Brazilian National Household Sample Survey (PNAD) from the year 2014. The PNAD is a representative household survey conducted annually from 1967 to 2015 by the Brazilian Institute of Geography and Statistics (IBGE) to collect socioeconomic and demographic information about the Brazilian population, including household composition, education, labor, income, migration, and fertility. To investigate intergenerational mobility, I use the data from PNAD's Socio-Occupational Mobility Survey. Every year the PNAD investigates an additional topic on the basis of the "Supplementary Survey," and in year 2014 its focus was socio-occupational mobility. This supplement was conducted in a retrospective way, asking the respondents older than 16 years of age to provide information about the professional occupation and educational level of their parents.[16]

[16] The information about the education and occupation of parents refers to the level when respondents were 15 years old.

In 2014 the PNAD's sample consisted of 151,291 households with 362,627 individuals. Despite this high number of observations, some data limitations are necessary to keep in mind in the analysis of the empirical results presented in this paper. First, the construction of the sample was based on demographic forecasts which are always uncertain and capable of being misleading since the estimate of population growth is understandably difficult to predict (Cunha and Jakob, 2011). Second, the supplement for social mobility covered only 50 percent of all households selected by PNAD-2014, therefore the sample size limits the investigation of time trends by state level given that the number of observations in some states with a thinly spread population—specially states from the North region—becomes very low when divided by birth cohorts (see Table 2.2). And last but not least, around 13 percent of respondents provided no information on the educational attainment of their parents. Since these missing values are not distributed proportionally across birth cohorts and socioeconomic levels, estimation bias cannot be ruled out.

The two main outcomes of interest in this paper are years of schooling and levels of education, for both children and parents.[17] The educational levels are classified into four identical categories: no school certificate and primary, secondary, and tertiary education, with primary education referring to the compulsory schooling.[18] Given that the PNAD does not provide the number of years of schooling for the parents, I calculated this variable according to the information about the highest level of education attained.[19] In addition, information about gender, year of birth, location of residence (rural or urban areas), and whether the respondent grew up in a two-parent family are used as control variables. Finally, I use (total) personal income to estimate the Gini coefficient and the 75/10 ratio of income inequality.

I excluded individuals under 25 years old from the sample, given that approximately 42 percent of them were still attending school, training, or university in 2014. Similarly, I excluded persons over 75 years of age due to the positive correlation between education and life expectancy.[20] Consequently, this paper considers people born between 1940 and 1989 in its empirical analysis and works with a sample of 46,051 individuals.

For the empirical investigation in section 2.6.3, I created a dummy variable for "economic marginalization," which refers to children of parents with no school certificate. Moreover, the observations were categorized into 10-year birth cohorts (1940–1949, 1950–1959, 1960–1969, 1970–1979, and 1980–1989) in order to minimize the lifecycle bias resulting from the variation in average years of schooling and in education dispersion over time (see Figures 2.2 and 2.3). For the indicator of income inequality, I created the continuous variable "75/10 ratio," which represents the relation between the income of the richest 25 percent and the poorest 10 percent of the income distribution. This paper argues that this ratio is the most relevant inequality metric for educational mobility in Brazil, since it identifies the distance between the bottom and the top of income distribution that will serve as key motivator for the

[17] In those cases where the educational level of the father and mother is known, this paper will use the educational attainment of the most educated parent in the empirical estimations, since Leone (2021) has shown that in Brazil the educational attainment of children is stronger associated with the education of their most educated parent.

[18] In practical terms, primary education means the minimum years of schooling required by law when the children and parents were of school age.

[19] Please see the appendix for a detailed description of the codification process.

[20] According to the IBGE, life expectancy in Brazil in 2014 was 75.2 years.

investment in human capital.[21] Given that the measures of inequality were determined retrospectively for the year in which the individuals (should) have completed compulsory education, I used the earlier PNAD sample surveys for the calculations.[22]

For the sake of a comprehensive analysis, Table 2.1 reports the summary statistics on population, income distribution, net enrollment ratio, and educational attainment divided by the states and macro regions of Brazil. Figure 2.2 visually displays the development of average schooling across birth cohorts, and Figure 2.3 presents the same development for the inequality in schooling. Finally, Charts 2.4 and 2.5 report for the year 2014 the variation in years of schooling and in the levels of education across Brazilian states respectively.

In light of Table 2.1, it is possible to observe the average educational attainment of children and parents. Note that in all states the average schooling of offspring is higher than that of their forebears and that the mothers are almost always more educated than their spouses.[23] Columns (7) to (9) list the proportions of school-age students who were enrolled in the education system in 2014. According to data from PNAD-2014, all states in Brazil are close to the objective of achieving universal primary education for children between 7 and 14 years old.[24] However, beyond the age of compulsory schooling, the deviation in the net enrollment ratio across states increases significantly. The proportion of children aged 15–17 enrolled in school is lowest in Roraima (0.758) and highest in the Distrito Federal (0.895) and in the southeastern states, such as São Paulo (0.864), Minas Gerais (0.867), and Rio de Janeiro (0.874). Moreover, the variation in the share of adults between 18 and 24 years old who are still attending school, training, or university is even greater. This ratio ranges from 0.263 in Pernambuco to 0.414 in Distrito Federal.

Figure 2.4 indicates significant differences in average educational attainment across Brazilian states. In southern states such as São Paulo, Rio de Janeiro, and Santa Catarina, children have higher average years of schooling relative to those in the states in the northeast. Finally, Chart 2.5 illustrates the main reason for these differences in average education: the share of individuals with no school-leaving certificate in the northeastern states is greater than in the other macro regions of Brazil.

2.5 Conceptual Framework

This paper employs a two-step empirical framework. I start by measuring intergenerational persistence in education, using linear regression models (e.g. Checchi et al., 2013) and transition matrices (e.g. Jantti et al., 2006). I then follow Kearney and Levine (2016) and apply an econometric method to investigate whether children from disadvantaged families have a lower chance of completing secondary education.

[21] This paper assumes that in Brazil the 75/10 ratio of income inequality works better than the 90/10 for the individual estimation of educational returns, given that the PNAD data show that inherited wealth and capital income play a greater role for the achievement of the top 10 percent of the income distribution than the educational level.

[22] Please see Section 2.5.2 for the empirical background and the appendix for a full description of the harmonization process that needed to be undertaken in order to fit the data over time.

[23] The exceptions are: Amapá, Espírito Santo, Rio de Janeiro, São Paulo, Paraná, Santa Catarina, Rio Grande do Sul, and Mato Grosso do Sul, where the average education of fathers is higher than that of mothers.

[24] The estimated values varied between 0.965 in Acre and 0.994 in São Paulo.

2.5.1 Intergenerational Educational Mobility

A. Mobility Matrices

Following Daouli et al. (2010), this section classifies the educational outcomes of children (generation t) and parents (generation $t-1$) into four categories: no school certificate, and primary, secondary, and tertiary education. Thereafter, I estimate the intergenerational transition matrices $\mathbb{P}$ with the number of states S, such that:

$$p_{ij} = \mathbb{P}(X_{t-1} = j \mid X_t = i) \quad \text{for} \quad i, j \in S \tag{2.1}$$

The estimated transition matrices present two important properties:

$$\forall \quad i, j \in \mathbb{R}, \quad P(i, j) \geq 0, \quad \text{and} \tag{2.2}$$

$$\sum_{j=1}^{N} p_{ij} = \sum_{j=1}^{N} \mathbb{P}(X_{t-1} = j \mid X_t = i) = \sum_{j=1}^{N} \mathbb{P}_{\{X_t = i\}}(X_{t-1} = j) = 1. \tag{2.3}$$

In transition matrix $\mathbb{P}$, the value of $p_{i,j}$ denotes the proportion of children from parents with the educational attainment j who achieved the education level i. Given that the estimations are based on identical education levels for children and their parents, the diagonal cells from the square matrices $\mathbb{P}$ represent immobility or inheritance in the intergenerational transition from state j to state i (Altham and Ferrie, 2007; Reddy, 2015; Xie and Killewald, 2013). Consequently, the "immobility ratio" (ImR) can be calculated as a percentage of the sum total of all entries on the main diagonal of the matrix $\mathbb{P}$ and its number of states S (Heineck and Riphahn, 2007):

$$ImR = \frac{\mathrm{Tr}(\mathbb{P})}{S} = \frac{\sum_{i=1}^{N} \rho_{ij}}{S} \tag{2.4}$$

Following Corak et al. (2014), I describe upward and downward mobility—UpM and DoM respectively—as the probability that the children's level of education exceeds or is less than the parents' educational level l.[25]

$$UpM = Pr\left(X_t > l \mid X_{t-1} = l\right) \qquad \text{and} \qquad DoM = Pr\left(X_t < l \mid X_{t-1} = l\right) \tag{2.5}$$

In order to summarize the degree of mobility intrinsic in transition matrix $\mathbb{P}$, allowing for a ranking of the Brazilian states according to mobility levels, I follow Checchi et al. (1999) and Daouli et al. (2010) and calculate the Prais–Shorrocks indicator based on the trace ($Tr(\mathbb{P})$) and the number of states in the transition matrix.

$$M_{PS}(\mathbb{P}) = \frac{S - Tr(\mathbb{P})}{S - 1} \qquad \text{with} \qquad M_{PS} \in [0, 1] \tag{2.6}$$

The $M_{PS}(\mathbb{P})$ provides a measure of the normalized distance between the identity matrix and the independent matrix. It ranges from 0 to 1, with values closer to 1 indicating a higher level of intergenerational educational mobility.[26]

[25] From a graphical point of view, the downward (upward) mobility is derived from the values of the elements below (above) the main diagonal of the square matrix $\mathbb{P}$ (Heineck and Riphahn, 2007).

[26] A $M_{PS}(\mathbb{P}) = 1$ would mean that the probability that children will end up with education level i is independent of the parents' educational attainment j (full "equality of opportunity"). In contrast, a $M_{PS}(\mathbb{P}) = 0$ corresponds to an "identity matrix" in which all the main diagonal elements are 1 and all the remaining elements are 0, indicating a perfectly immobile society (Chevalier et al., 2003).

B. Linear Regression Model

Following the standard empirical model presented in the economic literature on intergenerational mobility (see e.g. Black and Devereux, 2010; Blanden, 2013; Hertz et al., 2007a), this paper estimates the educational persistence between parents and children with the regression equation:

$$educ_{is}^{c} = \alpha + \beta\, educ_{is}^{p} + \epsilon_i \quad \text{for} \quad i = 1, 2, ...N \tag{2.7}$$

where $educ_{is}^{c}$ is the years of schooling of an individual i resident in the state s, and $educ_{is}^{p}$ denotes the same variable for his or her parents. The error term ϵ_i reflects the combined effects on a child's education of factors orthogonal to parental education, and the slope coefficient β is the parameter of interest, representing the elasticity of children's education with respect to their parents' education. The coefficient β is commonly known in the economic literature as the "regression coefficient" and gives the value of each 1 percent difference in parental education across families that will be transmitted as an educational difference to their children (Blanden, 2013).

Given the changes in the mandatory education over time in Brazil (see Table 2.5), and their resultant effects on average schooling and standard deviations (see Figures 2.2 and 2.3), I follow Azam (2016) and Checchi et al. (2013) and normalize the years of schooling in equation (2.7) by the corresponding standard deviation. The OLS estimate of β is given by:

$$\hat{\beta} = \rho_s^{cp}\, \frac{\sigma_s^c}{\sigma_s^p}, \qquad \text{with} \qquad \sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_1 - \mu)^2} \tag{2.8}$$

where σ_s^c and σ_s^p correspond to the standard deviation in education for children and parents in state s, while the coefficient ρ_s^{cp} captures the association between children's and parents' education respectively. Based on equations (2.7) and (2.8), the resulting empirical model can be summarized as:

$$\frac{educ_{is}^{c}}{\sigma_s^c} = \delta \,+\, \rho \left(\frac{educ_{is}^{p}}{\sigma_s^p} \right) \,+\, \epsilon_i \qquad \text{with} \qquad \rho \in [0, 1] \tag{2.9}$$

In this regard, the coefficient ρ is defined in the economic literature as the "relative" measure of intergenerational mobility or the "correlation coefficient." The higher its value, the stronger the correlation between the educational attainment of children and parents. To allow the estimation of the "correlation coefficient" for all states in a single run estimation, I include in equation (2.9) a vector of dummy variables UF with the state of residence of the individual i and interaction terms. Finally, the vector X comprises control variables for gender, race, and year of birth. Thus, the resulting fully interacted model takes the following form:

$$\frac{educ_{is}^{c}}{\sigma_s^c} \;=\; \delta \,+\, \rho\, \frac{educ_{is}^{p}}{\sigma_s^p} \,+\, \eta \left(\frac{educ_{is}^{p}}{\sigma_s^p} \times UF_i \right) \,+\, \lambda\, UF_i \,+\, \gamma\, (X_i \times UF_i) \,+\, \epsilon_{is} \tag{2.10}$$

2.5.2 Linking Inequality and School Dropouts

In this section, I follow Kearney and Levine (2016) and apply a probit model aimed at investigating whether children from marginalized socioeconomic backgrounds living in states with greater income inequality levels have a lower chance of completing secondary education. In this underlying latent model, the observed binary response ($ComSec_{i,t}$) assumes the value 1 if the individual i born in year t has completed secondary education and this is a function of socioeconomic background, income inequality in the state of residence, and individual characteristics. Thus, the empirical probit model can be written as:

$$\begin{aligned} ComSec_{i,t} = \pi_0 \,+\, \pi_1\,(MSB_i \times Ineq_{s,t+14}) \,+\, \pi_2\,MSB_i \,+\, \pi_3\,Ineq_{s,t+14} \\ +\,\gamma_1\,male_i \,+\, \gamma_2\,rural_i \,+\, \gamma_3\,bothP_i \,+\, \gamma_4\,race_i \,+\, \gamma_5\,birth_i \,+\, \epsilon_i \end{aligned} \tag{2.11}$$

The (marginalized) socioeconomic background is summarized in the variable MSB_i, which represents individuals from (two) parents with no school certificate. The variable $Ineq$ refers to income inequality, measured by the 75/10 ratio, in the individual's state of residence (s) 14 years after their birth ($t + 14$).[27] The model also includes controls for gender ($male$), location of residence ($rural$), self-declared race/ethnicity ($race$), and birth year ($birth$), as well as a dummy indicating whether the children lived with both parents in the same household at age 15 ($bothP$). These control variables tend to exclude from the results the effects of circumstances that are beyond the individual's control, but affect his/her decision regarding (further) education.

The parameter π_1 estimated from the interaction term between the continuous variable $Ineq_{s,t+14}$ and the discrete (binary) variable MSB_i is the main coefficient of interest and indicates whether individuals with a lower family-education background living in states with high income inequality have a lower probability of completing secondary education. In order to present a more informative view of the expected changes in the educational outcome of children as a function of changes in the explanatory variables (economic background and income inequality), the marginal effects are estimated from equation (2.11) as:

$$\left.\frac{\partial E(ComSec|\boldsymbol{x})}{\partial \boldsymbol{x}}\right|_{\boldsymbol{x}=\tilde{\boldsymbol{x}}} = \left.\frac{\partial F(\boldsymbol{x}\boldsymbol{\beta})}{\partial \boldsymbol{x}}\right|_{\boldsymbol{x}=\tilde{\boldsymbol{x}}} = f(\tilde{\boldsymbol{x}}\boldsymbol{\beta})\boldsymbol{\beta} \tag{2.12}$$

For the categorical variables, the marginal effects indicate how $ComSec_{i,t}$ is predicted as MSB_i changes from 0 to 1, holding all the other covariates constant at their average values, while for the continuous variable $Ineq_{s,t+14}$, the results from the marginal effects indicate how much the increase in the inequality ratio will change children's probability of achieving a secondary education.

2.6 Empirical Results

This section presents the study's empirical findings. I start with the estimation of intergenerational educational mobility based on the transition matrix and the linear regression model. This is followed by the results on whether mobility at the state level is correlated with income inequality. Then, section 2.6.3 deals with one important mechanism behind the relationship between inequality and mobility illustrated by the Great Gatsby curve, namely, whether greater income inequality contributes to a higher school-dropout rate for economically marginalized children.

[27] Following the theoretical model of Solon (2004), what is particularly relevant for the accumulation of human capital is the level of income inequality when children have completed their compulsory education and are facing a decision about whether or not to pursue more years of schooling. Given that until the year 2009 education in Brazil was compulsory for children aged 7 to 14 years old, equation (2.11) uses the 75/10 ratio from the year in which the individual turned 14 as measure of inequality.

2.6.1 Intergenerational Educational Mobility

Mobility matrices and linear regression models have been widely used in the economic literature to measure the extent of intergenerational educational mobility. These two empirical approaches complement each other and together provide a more detailed picture of mobility. The regression model takes into account the variation in standard deviation across both generations and presents a degree of mobility free from bias that can be caused by an increase in average education over time. The transition matrix approach, in comparison, has the advantage of providing a more comprehensive overview of the direction of the mobility (Corak and Heisz, 1999; Dearden et al., 1997; Fields, 2002).

A. Mobility Matrices

Figure 2.8 measures children's probability of attaining a certain educational level as a function of parents' education. If we analyze the four charts together, we see only minimal changes over time in the intergenerational persistence of education in Brazil. Note that regardless of birth year, the chance of attaining higher education is strongly correlated with parents' educational background. In summary, it is possible to state that the children of more highly educated parents tend to become more highly educated adults, while the children of less-educated parents tend to become adults with less education. However, the data clearly show that the probability of attaining the compulsory level of education has increased considerably over time. As can be seen in Figure 2.8, the proportion of people with no school certificate and only primary education is becoming increasingly smaller.

Following on from this brief description of the development of mobility over time, I now turn to the variation in the intergenerational persistence of education across Brazilian states. Figure 2.6 presents the direction of mobility, displaying the results of equations (2.4) and (2.5). Figure 2.7 places the states in increasing order, according to the degree of mobility estimated from equation (2.6).

Figure 2.6 illustrates the two different directions in mobility. Individuals who achieve a higher educational level than their parents move upward on the educational scale, while downward mobility refers to the cases where the children's level of schooling remains lower than that of their parents. In Brazil 38.8 percent of children have achieved a higher level of education than their parents, while only around 15 percent have experienced downward mobility. However, these values vary strongly across the states. Paraiba is the state in Brazil with the highest level of intergenerational immobility in education (49.1%), approximately 12 percentage points more than the results obtained in Rio Grande do Norte, the state with the lowest level of persistence in education across generations (37.3%). The levels of upward mobility exhibit even greater variation across the states, from 30.4 percent in Pará to 52.1 percent in Distrito Federal.

If we look more closely into the mobility rates of the most mobile state, we can observe that the high level of mobility was mainly due to the larger downward mobility: Almost one-third of the population in Rio Grande do Norte (30.3%) reached a lower level of education than their parents. Therefore, Rio Grande do Norte presents the greatest level of downward mobility across the 27 Brazilian states, this value being nearly five times larger than in Distrito Federal (6.2%) and three times higher than in São Paulo (10.7%)—the states with the lowest level of downward mobility.

Figure 2.7 ranks the Brazilian states on the basis of the Prais-Shorrocks indicator from equation (2.6) and provides more detailed information on the movement of children within the education distribution. The red circles indicate the ratio of children from parents with no school-leaving certificate who have successfully completed tertiary education, representing the maximum possible degree of upward mobility. The indicator "top persistence" displays the proportion of children from parents with tertiary education who have achieved the same educational level as their parents. The "bottom persistence" shows the lack of mobility at the lowest extreme of the transition matrix, displaying the share of individuals from parents with no school certificate that remain without education.

In Brazil, the top persistence achieves a value higher than 70 percent, and nearly half of children (49.2%) from parents without a school certificate have not completed (primary) education, highlighting once again the strong intergenerational persistence in educational levels. This strong persistence at both extremes of educational distribution is compatible with previous results obtained by Neidhöfer et al. (2018) and Mahlmeister et al. (2019). The latter focuses the investigation on the mobility of men aged 25–64 and concludes that the probability that sons will achieve the same educational level as their fathers is much higher when the fathers have more than 11 years of schooling. Neidhöfer et al. (2018), applying a transition matrix with three levels of education (low, middle, and high), estimated a value of 55 percent for the top persistence and 56 percent for the bottom persistence.

With a Prais-Schorrocks index equal to 0.836, Rio Grande do Norte leads the Brazilian rankings for intergenerational mobility in Figure 2.7. The main reason for this is that Rio Grande do Norte exhibits very low persistence at the top of distribution. Only 15.1 percent of children from parents with a tertiary education achieved a college degree. By way of comparison, this value is 92.4 percent in Distrito Federal, 82.3 percent in Roraima, and 78.5 percent in São Paulo.

Figure 2.7 confirms also a strong variation in the bottom persistence across the Brazilian states, which rages from 32.2 percent in Distrito Federal to 69.7 percent in Piauí. Note that the lack of mobility at the bottom of the education distribution is especially low for individuals living in the north-eastern states.[28] Figure 2.7 illustrates also how extremely difficult it is to climb the educational ladder in Brazil. In only four of the 27 states do the chances of moving from the bottom to the top of the educational distribution exceed 10 percent: Mato Grosso (10.9%), Amapá (11.0%), Roraima (16.4%) and Distrito Federal (16.6%).

B. Linear Regression Model

Table 2.2 presents the educational persistence between children and parents for each state based on equation (2.10). For the sample as a whole, the correlation coefficient generated a value of 0.475. This value is close to the result of 0.59 found by Hertz et al. (2007b) using a similar empirical strategy and a dataset from 1996 to estimate the parent-child schooling correlation for individuals aged 20–69 in Brazil. Using the PNAD-2014, Mahlmeister et al. (2019) came to a result of 0.60 for the grade of persistence between sons and fathers.

The variation in intergenerational educational persistence across Brazilian states reached a maximum of 0.257, which represents the difference between Rio de Janeiro (0.510), and Roraima (0.253). Among the top five in educational mobility apart from Roraima, we find the states of Amapá (0.351), Goiás (0.356), Tocantins (0.370),

[28] The seven states with the greatest educational persistence at the bottom of the distribution, are all located in northeastern Brazil: Rio Grande do Norte (57.8%), Bahia (58.2%), Paraíba (60.3%), Maranhão (60.6%), Alagoas (61.1%), Sergipe (62.6%), and Piauí (69.7%).

and Maranhão (0.377). Bahia (0.488), Distrito Federal (0.492), Alagoas (0.497), Acre (0.502), and Rio de Janeiro (0.510) are located at the other end of the scale meanwhile.

As already indicated in Figure 2.8, children's chances of attaining primary education have increased significantly over time in Brazil. Accordingly, Figures 2.2 and 2.3 report a strong variation in average years of schooling and standard deviation across the birth cohorts. These findings are strong indications that the degree of intergenerational mobility may have changed in recent decades. In order to test this hypothesis, I divided the full sample into five birth cohorts, each of which covered 10 consecutive birth years, and subsequently estimated the predictive margins from equation (2.10) with a two-way interaction (education by birth cohort) to investigate how children's chances of mobility change according to their year of birth.

The results of this exercise are plotted in Figure 2.9 and confirm a decrease in the association between parents' and children's education over time. Note that for all birth cohorts, as parents' schooling increases, the linear prediction for children's education also increases. However, the increase (slope) is greater for children born between 1940–1949 than for the 1980–1989 cohort. At low levels of parental education, there is virtually no difference across birth cohorts (the children of parents with a low educational level do not achieve a high level of education no matter when they were born). As parents' educational level increases, the education gap between children becomes increasingly larger, because children born between 1940 and 1949 benefit more from the greater human capital of their parents than the younger generations. Given this variation of correlation coefficients over time, Table 2.2 displays the levels of mobility (separately) across birth cohorts.

2.6.2 The Great Gatsby Curve

As discussed in section 2.2, Solon (2004) concluded that the current level of income inequality between families can affect the investment in their children's human capital and, consequently, these children's chances of intergenerational mobility. It can therefore be expected that the variation in mobility presented in Table 2.2 can be explained by the variation in inequality across Brazilian states (see Chart 2.1).

According to the theoretical model of Solon (2004), what is particularly relevant for the accumulation of human capital is the level of inequality when children have completed their compulsory education and face a decision about whether or not to pursue further schooling. Therefore, this paper has used—as a measure of inequality—the Gini coefficients for the years in which the individuals should have concluded their compulsory schooling.[29] Given the variation over time in mobility shown in Table 2.2, I focused the investigation on one single birth cohort containing individuals born between 1970 and 1979 to minimize the life-cycle bias.[30] Then, the measures of inequality are based on the PNAD samples between 1984 and 1993, and in order to eliminate possible short-term fluctuations in inequality across these years, I average the Gini coefficients throughout the period under consideration.

Figure 2.10 plots the Great Gatsby curve for the Brazilian states. On the y-axis we find the level of intergenerational persistence in education estimated from equation

[29] A child born in 1970, for example, started school at age 7 in 1977 and presumably concluded their compulsory (primary) education in 1984.

[30] The youngest cohort (1980–1989) has not been chosen for the investigation because approximately 9.2 percent of the individuals in this group were enrolled in the educational system in 2014. The oldest birth cohorts (1940–1949 and 1950–1959) needed to be excluded from the analysis because there is no data available for the measure of the Gini coefficient for the years before 1976.

(2.10), while income inequality is plotted on the x-axis.[31] The findings confirm the statistically significant relationship between the Gini coefficient and intergenerational mobility:[32] States with a higher level of income disparity, such as Paraíba (PB) and Ceará (CE), present higher values of persistence in education (or low levels of mobility), while the correlation coefficients tend to be lower in states with a more equal distribution of income, such as Santa Catarina (SC) and Amazonas (AM). However, the negative correlation between income inequality and mobility does not hold true for all states. Amapá (AP) can be considered a "point outside the curve," because the state has the most equal distribution of income in Brazil, but presented a relatively high persistence in education across generations. In addition some states with similar Gini coefficients, such as Bahia (BA), Goiás (GO), and Rio Grande do Norte (RN), present very different indices of intergenerational mobility.

2.6.3 Linking Inequality and School Dropouts

In this section, I move away from the analysis of intergenerational persistence in education via the correlation hypothesis toward an investigation of the determinants that could better explain the association between inequality and mobility illustrated by the Great Gatsby Curve. At this point, it is important to introduce the concept of "economic marginalization" presented by Kearney and Levine (2016), which can be described as the process of a person setting aside participation in the educational system given their very low expected-earnings premium. In this case, young individuals do not believe that an investment in human capital can increase their chances of mobility, which leads them to leave school early.[33]

According to the human capital approach developed by Kearney and Levine (2016), marginality arises as a consequence of higher income inequality. An increase in the 75/10 ratio of income distribution might lead to direct social exclusion, particularly for children from socially vulnerable families that do not see the possibility of climbing up the social ladder via education. The marginalized population often lives in disadvantaged areas with negative neighborhood behavioral patterns and notably restricted access to high-quality schools, thus reducing their belief in personal advancement through schooling, and consequently making social mobility more difficult (Rothwell and Massey, 2015).[34] With this problem in mind, the empirical objective of this section is to investigate whether children from socially disadvantaged households living in states with greater income inequality have a lower chance of completing (secondary) education.

Figures 2.11 and 2.12 introduce the two main variables used in the identification strategy. Chart 2.11 illustrates the variation across Brazilian states in the ratio of the income of the upper-bound value of the third quartile (i.e. the 25 percent of individuals with the highest income) to that of the first decile. For this exercise the

[31] The original Great Gatsby curve used the intergenerational elasticity (regression coefficient) on the y-axis instead of the correlation coefficient. However, in the context of developing countries where the access to formal education was considerably expanded in recent decades, the relative measure of mobility will make more sense to the investigation of mobility (Torche, 2019). Leone (2021) confirmed for Brazil a significant increase in the intergenerational educational mobility over time; however he showed that this increase was principally caused by the general increase over time in the years of schooling ("elevator effect") and not by changes in parents-children transmission.

[32] The Pearson correlation coefficient (r) achieves a value of 0.4245 and indicates a moderate positive linear relationship between persistence in education and income inequality.

[33] The appendix provides a formal description of the model of Kearney and Levine (2016).

[34] See Rothwell and Massey (2015) for a large and rich literature overview concerning the channels through which neighborhood can affect future earnings.

27 administrative units making up the Federation have been classified into three inequality groups (low, middle, and high) according to the 75/10 ratio for the year 2014. The resulting visual presents an almost perfect geographic distribution of inequality and a significant variation across states: In Rio de Janeiro the income of the richest 25 percent corresponds to 2.76 times the income of the poorest 10 percent, while this ratio is 8.32 in Piauí. Figure 2.12 provides the first empirical evidence for the subsequently applied econometric model. It presents the proportion of the population with secondary-school education, divided by the inequality groups introduced in the previous figure and the educational achievement of parents, which is used as a proxy for "economic marginalization." The findings highlight the effect of marginalization on the decision to leave school early. Note that independent of the inequality level, less than 20 percent of children from illiterate parents have completed secondary education. In contrast, more than 80 percent of children of parents with a graduate degree have a secondary school-leaving qualification. In addition, Figure 2.12 confirms that for vulnerable children, dropping out of school is associated with income inequality: the children of illiterate parents and parents with no (primary) education living in states with lower income inequality have a higher chance of completing secondary education than vulnerable children from high-inequality states.

Probit Latent Variable Model

In order to empirically test the assumption regarding economic marginalization, I run equation (2.11) and present the results in Table 2.3.[35] The first column contains the results for the whole sample, and the subsequent columns the values for the five-year birth cohorts.[36]

Parental educational level, gender, location of residence, race, year of birth, and whether a child has been living with both parents have a statistically significant effect on the chance of completing secondary education. Being male, for example, decreases the probability of achieving a (secondary) school-leaving certificate by 20.3 percentage points. As expected, children of parents with no school certificate have a lower chance of completing secondary education (40.5%), compared to offspring of parents with at least a primary education.

The interaction term between the categorical variable "socioeconomic marginalization" and the continuous variable "income inequality" is the focus of this investigation and confirms the statistically significant effect of income disparity on educational attainment. The negative coefficient indicates that children of parents with no school-leaving certificate are more disadvantaged by an increase in income inequality. Specifically, each additional point in the 75/10 ratio decreases the likelihood of achieving secondary education by 5.4 percent for children of parents without education.

For a better overview of the interaction between income inequality and economic marginalization, I estimate the marginal effects from equation (2.11) and display the predicted probabilities for all the 10^{th} values of the ratio 75/10 (from 3 to 12) in Figure 2.13.[37] Note that independent of the level of inequality, children of parents with no

[35] The parameters in the probit model were estimated using maximum likelihood methods.

[36] Because there is no nationally representative database for the period prior to 1981 that could be harmonized in a reliable way with the most recent samples of PNAD, this section limited the estimates to individuals born from the year 1965 onward, thereby using the income inequality after the year 1981. See the appendix for a detailed description of the data harmonization.

[37] In effect, the adjusted predictions at representative values (APRs) are comparing two hypothetical populations—children of parents with and without a (primary) education—that have exactly the same values for all the other independent variables in the model, with the exception of the income inequality level in the state of residence (75/10 ratio). Since the only difference between these two

education have an even lower chance of completing secondary school. Moreover, both curves have different shapes and slopes: The slope of the no-education curve is higher, indicating that the effects of an increase in income inequality are disproportionately higher for children of parents with no education. As a consequence, at a low level of income inequality, there is a relatively small difference in the probability of achieving a secondary school certificate between children from educated and uneducated parents. However as the 75/10 ratio increases, the gap between these two groups becomes increasingly bigger.[38]

Robustness Checks

As described in detail by Neumayer and Plümper (2017), econometric results become more credible and effective if they are sufficiently independent from the model specification. For that reason, this section tests the same economic-marginalization hypothesis using alternative model specifications and alternative econometric approaches to improve the validity of the evidence presented in the previous section.

A. Alternative Econometric Approaches

As previously described, the objective of section 2.6.3 was to identify whether children from (socioeconomically) marginalized households living in states with greater income inequality are more disadvantaged in their school careers. As a proxy for socioeconomic marginalization, I used above a dummy variable indicating children from parents with no primary education ($NoEducP_i$) in equation (2.11).

As usual in such circumstances, the empirical model assumed that the correlations between the residual and the predictors are zero. But now, based on the theoretical approach of Wooldridge (2010), I relax this assumption and consider the case where the probit model contains a binary explanatory variable that is endogenous. The "feeling of marginalization" varies according to the parents' economic situation, and having both parents in the household can shift the family's budget constraints, providing higher socioeconomic status for the family, similarly to a higher level of parental education. I therefore use for the variable responsible for the socioeconomic marginalization ($NoEduP_i$) the instrumental variable "both parents" ($bothP_i$) which is a binary variable equal to 1 if the individual lived with both parents in the household at the age of 15.

In this section, I continue to use equation (2.11) to study the effects of economic marginalization on the chances of completing secondary education, but the empirical investigations have been conducted on the basis of three different empirical approaches: ordinary least squares (OLS) estimations of a linear probability model (LPM), two-stage least squares (2SLS) estimations of the LPM, and a bivariate probit that drops the variable "both parents" ($bothP_i$) from the probit for MSB_i.[39]

Table 2.4 provides the results of the robustness checks using the whole sample and confirms that the estimates from section 2.6.3 are also robust to alternative econometric approaches. For brevity's sake, the table reports only the coefficients π_1 from the interaction term between income inequality ($Ineq_s$) and the proxy for socioeconomic marginalization (MSB_i). Next, I have used margins to obtain the predicted

populations is the income inequality, inequality must be the cause of the differences in their likelihood of achieving a secondary education (Williams et al., 2012).

[38] Figure 2.13 shows that both curves have non-overlapping confidence intervals, demonstrating a statistically significant difference between the estimations.

[39] To facilitate comparison, Table 2.4 also contains the estimation results from the probit model in section 2.6.3, in which the variable $bothP_i$ was treated as exogenous.

probabilities for this interaction and have also displayed the adjusted predictions of educational chances at representative values of income inequality (APRs), meaning for every 10*th* value for the distribution of the 75/10 ratio.

As in the main model specification, all three expanded models present negative and statistically significant values for the interaction term indicating that the higher the inequality level in the state, the lower the share of students with a secondary school-leaving qualification. The nonlinear models (columns 1 and 4) give larger estimated coefficients for this interaction than the linear model (columns 2 and 3): -0.0540 and -0.0487 versus -0.0179 and -0.0175 respectively, suggesting that the nonlinearity in the probit models plays a decisive role in determining the chances of formal educational achievement.

With the estimations of marginal effects for different inequality levels, it is possible to observe that the effects of economic marginalization differ greatly according to the level of inequality. When MSB_i is assumed to be exogenous, the probit and LPM models provide very similar average partial effects by increasing income disparity. Children of parents with no formal education in the lowest inequality decile have, for example, a 22 percent lower chance of achieving a secondary-education certificate than pupils from parents with at least a primary education. The same difference in the top decile is approximately 40 percent. This empirical evidence remains practically unchanged when $bothP$ is used as IV in the LPM estimation.

Lastly, but by no means least importantly, the use of the bivariate probit, assuming that MSB_i and $bothP_i$ are correlated, presents substantially lower estimated APRs than the (normal) probit model.[40] However, the estimates continue to indicate the same direction and statistical significance.

B. Alternative Model Specifications

In the following, I explore the dependence of parameter π_1, estimated from equation (2.11), on four specific changes in model specification: In column 5, the estimations were limited to individuals who have never lived in another Brazilian state or another country. Column 6 used the ratio 90/10 as an indicator of income inequality, instead of the 75/10 ratio. In column 7, I changed the variable responsible for socioeconomic marginalization, substituting parents with no (primary) education for illiterate parents. Finally, in column 8 the dummy variable representing children with illiterate parents has been added to the empirical model and estimated in combination with $NoEducP_i$.[41]

All four expanded models generated robust results, demonstrating the significantly negative impact of income inequality on educational attainment, as already indicated in Section 2.6.3. In this context, it is hardly surprising that the results for column 5, with only individuals who have never lived in another state, indicated a higher effect of inequality on educational outcomes than the other specifications. As already noted by Kearney and Levine (2016), boys and girls who have been born into a region with an extremely uneven distribution of wealth and have never seen another reality tend to underestimate the returns on schooling given their lower belief in social mobility through education.

[40] The adjusted predications range from 0.223 to 0.401 for the probit model, while in the bivariate probit the APRs vary between 0.175 and 0.323.

[41] For specification 8, the empirical model assumes the following form:
$ComSec_{i,t} = \pi_0 + \pi_1 (NoEducP_i \times Ineq_{s,t+14}) + \pi_2 (IlliteP_i \times Ineq_{s,t+14}) + \pi_3\, NoEducP_i + \pi_4\, IlliteP_s + \pi_5\, Ineq_{s,t+14} + \gamma_1\, male_i + \gamma_2\, rural_i + \gamma_3\, bothP_i + \gamma_4\, race_i + \gamma_5\, birthc_i + \epsilon_i.$

Once again, the estimations of marginal effects for different inequality levels pointed to an increase in the gap in educational attainment by the aggravation of income disparity. According to the model with only the local population, for example, the advantage of having parents with a primary education is 21.0 percent at the bottom of the distribution and 42.3 percent at the other extreme of the inequality scale. These results are consistent with the findings presented in Figure 2.13 and show that—keeping all other variables constant—the adverse effect of socioeconomic marginalization on the chance of completing secondary education tends to be stronger in states with greater income disparity.

2.7 Conclusions

The estimates presented in this paper are based on data from the mobility supplement from the PNAD-2014, which is a nationally representative survey from Brazil detailing the educational attainments for two generations within the same family. The empirical findings provided here have shown for the first time that intergenerational persistence in education varies substantially across Brazilian states. For example, the probability that a child born to parents without a school certificate will achieve a university degree is 3.2 percent in Pará, but 16.6 percent in Roraima. Together with findings from other countries (Azam and Bhatt, 2015; Chetty et al., 2014a; Güell et al., 2018) this work strengthens the assumption that mobility levels can vary considerably within a single country.

This paper has also examined the spatial variation in intergenerational educational mobility across Brazilian states, and for that purpose correlated mobility with income inequality at state level. Hence, this study contributes to the literature that is presenting new findings on the Great Gatsby curve. I have presented empirical evidence for a statistically significant association between intergenerational mobility and income inequality, thus confirming the existence of the Great Gatsby curve at the national level as well: persistence in educational levels across generations tends to be stronger in states with a more unequal distribution of income.

In addition, this work was novel in illuminating the mechanisms underlying the link between inequality and mobility presented in the Great Gatsby curve—currently the biggest gap in this field of research. Thanks to the empirical approach proposed by Kearney and Levine (2016), it was possible to study the effects of an increase in income inequality on the chances of education for children from socially vulnerable families. I have found compelling evidence that offspring born into families with no education are more likely to leave school early if they live in states where the gap between the bottom and the middle of the income distribution is wider. These findings are particularly relevant for the literature because they are independent of the econometric model and remain robust to different model specifications and alternative econometric approaches.

The results obtained here have key implications for policy-making and highlight the need to promote and develop policies and initiatives to support the educational trajectories of students with less educated family background. In order to increase the chances of intergenerational mobility in Brazilian society, public interventions should focus on programs that increase the expected return on human capital investment in those children. To do this, two improvements appear to be fundamental: the improvement of the real return associated with education, but also its perception among students. To increase social fluidity, public institutions in Brazil should combat the feeling of "social exclusion" by economically disadvantaged children, making them believe in the transformative power of education.

Appendix

2.A Tables

Table 2.1. Weighted Descriptive Statistics (PNAD-2014)

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
State		**Population**			**Income distribution (BRL)**			**Net enrollment ratio (age)**				**Average years of schooling**			**Standard deviation**		
Name	**Abbrev.**	**Total**	**Average age**	**Ratio in rural**	**Bottom**	**Middle**	**Top**	**7–14**	**15–17**	**16–24**	**Obs.**	**Children**	**Fathers**	**Mothers**	**Children**	**Fathers**	**Mothers**
Rondônia	RO	1,748,531	30.65	0.2369	204	593	1,666	0.9921	0.7948	0.2972	541	8.4842	2.9488	3.2734	4.5993	3.5316	3.9711
Acre	AC	790,101	27.27	0.2591	128	400	1,500	0.9653	0.7616	0.3191	415	7.3954	2.9512	3.7874	5.3104	4.2085	4.7970
Amazonas	AM	3,873,743	28.49	0.1634	150	438	1,500	0.9776	0.8294	0.3482	1,045	8.2446	3.8986	4.1803	4.7067	4.2232	4.2799
Roraima	RR	496,936	28.37	0.1680	191	530	1,862	0.9865	0.7576	0.3238	160	10.0415	4.1797	4.5257	4.2826	4.2936	4.3761
Pará	PA	8,073,924	29.82	0.2992	133	399	1,185	0.9824	0.8454	0.3268	2,019	7.3653	3.3370	3.6478	4.4826	3.7415	4.0299
Amapá	AP	750,912	27.46	0.1039	200	499	1,860	0.9917	0.8541	0.3197	217	9.3247	4.5997	4.2800	4.8566	4.6337	4.4242
Tocantins	TO	1,496,880	31.59	0.2148	164	500	1,674	0.9910	0.8205	0.3233	545	7.6599	2.3349	2.9175	4.7665	3.3784	3.9490
North		**17,231,027**	**29.50**	**0.2408**	**146**	**437**	**1,433**	**0.9826**	**0.829**	**0.3277**	**4,942**	**7.8259**	**3.3986**	**3.7343**	**4.6621**	**3.9186**	**4.1553**
Maranhão	MA	6,850,884	30.14	0.4083	89	333	1,015	0.9825	0.8508	0.2747	864	6.2833	1.9498	2.6083	4.9003	3.3379	3.8792
Piauí	PI	3,194,718	32.26	0.3247	117	400	1,114	0.9879	0.8552	0.3149	628	6.0786	1.7586	2.2864	5.1269	3.2388	3.8753
Ceará	CE	8,842,791	33.38	0.2648	120	400	1,134	0.9824	0.8346	0.2742	2,018	6.7593	2.3395	2.8007	4.9012	3.7040	3.9939
Rio Grande do Norte	RN	3,408,510	32.90	0.2352	150	434	1,314	0.9936	0.8235	0.2861	560	6.9774	2.3294	3.1026	4.8696	3.5646	4.0347
Paraíba	PB	3,943,885	33.08	0.1839	145	436	1,400	0.9752	0.7962	0.2943	672	6.7942	2.7729	3.0116	5.1071	4.1112	4.1259
Pernambuco	PE	9,277,727	33.50	0.1894	140	437	1,308	0.9831	0.8162	0.2627	2,541	7.4292	3.4088	3.5120	4.9493	4.3138	4.3208
Alagoas	AL	3,321,730	30.91	0.2833	95	348	1,005	0.9706	0.7744	0.2814	563	6.3830	2.9068	3.0360	5.1566	4.1516	4.2944
Sergipe	SE	2,219,574	32.09	0.2812	156	431	1,200	0.9770	0.8352	0.3242	652	6.5579	1.9785	2.4805	4.8874	3.4009	3.5932
Bahia	BA	15,126,371	33.11	0.2488	139	431	1,400	0.9850	0.8461	0.3171	3,359	7.1842	2.8426	3.0643	4.9479	3.9217	4.1399
Northeast		**56,186,190**	**32.62**	**0.2632**	**126**	**403**	**1,250**	**0.9827**	**0.8315**	**0.2904**	**11,857**	**6.8927**	**2.6340**	**2.9858**	**4.9778**	**3.8801**	**4.1025**
Minas Gerais	MG	20,734,097	34.77	0.1544	236	706	1,933	0.9876	0.8674	0.2785	4,111	7.8235	3.4013	3.4944	4.7173	3.7202	3.8092
Espírito Santo	ES	3,885,049	34.25	0.1553	225	700	2,066	0.9728	0.8133	0.3240	772	8.3036	3.3526	3.2428	4.5309	3.6945	3.6406
Rio de Janeiro	RJ	16,461,173	36.80	0.0268	266	750	2,566	0.9899	0.8736	0.3319	3,085	9.5006	6.0272	5.4156	4.3063	4.7137	4.2991
São Paulo	SP	44,035,304	35.29	0.0344	326	860	2,650	0.9938	0.8645	0.2907	4,339	9.9718	5.1388	4.7980	4.3038	4.4431	4.3142
Southeast		**85,115,623**	**35.41**	**0.0676**	**277**	**766**	**2,405**	**0.9905**	**0.8645**	**0.2968**	**12,307**	**9.2358**	**4.7551**	**4.4993**	**4.5212**	**4.3904**	**4.2187**
Paraná	PR	11,081,692	34.52	0.1252	315	817	2,325	0.9881	0.8231	0.2923	2,301	8.3716	3.8072	3.6635	4.6968	3.8634	3.9054
Santa Catarina	SC	6,727,148	35.59	0.1589	390	1000	2,500	0.9914	0.8207	0.2948	1,117	8.7443	4.3552	4.1688	4.6119	3.7287	3.6662
Rio Grande do Sul	RS	11,207,274	36.90	0.1501	300	850	2,500	0.9869	0.8370	0.3084	3,702	8.4965	4.0837	3.9188	4.4833	4.0926	3.9434
South		**29,016,114**	**35.69**	**0.1426**	**320**	**870**	**2,444**	**0.9884**	**0.8278**	**0.2989**	**7,120**	**8.5022**	**4.0360**	**3.8726**	**4.5912**	**3.9347**	**3.8773**
Mato Grosso do Sul	MS	2,619,657	33.19	0.1078	300	766	2,232	0.9849	0.7832	0.2918	615	8.5436	4.1849	4.0337	4.7883	4.5221	4.5129
Mato Grosso	MT	3,224,357	32.12	0.1720	285	733	2,000	0.9911	0.7919	0.2840	627	8.7704	4.2925	4.7669	4.8419	4.6268	4.7849
Goiás	GO	6,523,222	33.35	0.0776	268	724	1,912	0.9923	0.8126	0.3153	1,361	8.0773	3.0697	3.4046	4.7121	3.7236	4.0061
Distrito Federal	DF	2,852,372	32.69	0.0442	301	1000	5,000	0.9931	0.8955	0.4140	408	11.7179	7.1630	7.2125	3.8968	5.2292	5.3176
West Central		**15,219,608**	**32.94**	**0.0965**	**285**	**750**	**2,500**	**0.9909**	**0.8193**	**0.3237**	**3,011**	**8.7258**	**4.0041**	**4.2698**	**4.7976**	**4.4461**	**4.6084**
Brazil		**202,768,562**	**33.55**	**0.1494**	**200**	**662**	**2,000**	**0.9870**	**0.8427**	**0.3002**	**39,237**	**8.3237**	**3.9598**	**3.9380**	**4.7947**	**4.2511**	**4.1976**

Notes: Column 1 refers to the IBGE estimation based on the PNAD-2014 data. Columns 2 to 9 are the author's own estimates based on all the observations from PNAD-2014. The values in columns 10 to 16 have been determined on the basis of the PNAD-2014 mobility supplement. The income distribution is based on monthly per capita domiciliary income. Bottom, middle, and top represent the poorest 10 percent, the middle 50 percent, and the richest 10 percent respectively of the income distribution.

Table 2.2. Correlation Coefficients, by Birth Cohort

State		Cohort: 1940—1989		Cohort: 1940–1949		Cohort: 1950–1959		Cohort: 1960–1969		Cohort: 1970–1979		Cohort: 1980–1989	
Name	**Abbrev.**	**Obs.**	**Correlation**	**Obs.**	**Correlation**	**Obs.**	**Correlation**	**Obs.**	**Correlation**	**Obs.**	**Correlation**	**Obs.**	**Correlation**
Rondônia	RO	669	0.379***	56	0.115	84	0.611***	121	0.260**	191	0.304***	217	0.512***
Acre	AC	325	0.502***	19	0.254	39	0.655***	45	0.491**	92	0.524***	130	0.526***
Amazonas	AM	915	0.419***	64	0.822***	105	0.463***	152	0.395***	264	0.361***	330	0.424***
Roraima	RR	190	0.253***	7	0.118	32	-0.012	21	0.373	55	0.232	75	0.401***
Pará	PA	1,673	0.439***	139	0.518***	230	0.561***	315	0.465***	430	0.442***	559	0.428***
Amapá	AP	198	0.351***	12	0.441	25	0.223	35	0.321	48	0.511***	78	0.361**
Tocantins	TO	484	0.370***	56	0.301*	73	0.354**	98	0.213	121	0.476***	136	0.414***
North		**4,454**	**0.425*****	**353**	**0.511*****	**588**	**0.503*****	**787**	**0.401*****	**1,201**	**0.419*****	**1,525**	**0.460*****
Maranhão	MA	620	0.377***	60	0.176	87	0.321**	111	0.384***	156	0.336***	206	0.462***
Piauí	PI	562	0.480***	63	0.696***	86	0.552***	89	0.458***	163	0.426***	161	0.529***
Ceará	CE	1,464	0.440***	147	0.458***	212	0.456***	305	0.469***	344	0.493***	456	0.469***
Rio Grande do Norte	RN	486	0.410***	51	0.631***	51	0.491***	122	0.437***	124	0.369***	138	0.468***
Paraíba	PB	598	0.461***	56	0.400**	74	0.594***	137	0.481***	153	0.559***	178	0.388***
Pernambuco	PE	1,965	0.472***	228	0.437***	291	0.500***	409	0.531***	483	0.545***	554	0.419***
Alagoas	AL	371	0.497***	37	0.710***	59	0.649***	67	0.358**	93	0.500***	115	0.518***
Sergipe	SE	530	0.471***	58	0.634***	70	0.449***	94	0.549***	143	0.484***	165	0.485***
Bahia	BA	2,744	0.488***	263	0.628***	378	0.529***	602	0.469***	644	0.501***	857	0.533***
Northeast		**9,340**	**0.466*****	**963**	**0.517*****	**1,308**	**0.519*****	**1,936**	**0.474*****	**2,303**	**0.484*****	**2,830**	**0.493*****
Minas Gerais	MG	3,746	0.454***	415	0.637***	608	0.433***	759	0.459***	945	0.450***	1,019	0.491***
Espírito Santo	ES	733	0.451***	56	0.529***	118	0.523***	152	0.310***	193	0.572***	214	0.457***
Rio de Janeiro	RJ	2,813	0.510***	359	0.529***	527	0.591***	536	0.418***	668	0.481***	723	0.575***
São Paulo	SP	4,565	0.449***	492	0.524***	766	0.495***	906	0.449***	1,161	0.496***	1,240	0.448***
Southeast		**11,857**	**0.472*****	**1,322**	**0.556*****	**2,019**	**0.511*****	**2,353**	**0.452*****	**2,967**	**0.488*****	**3,196**	**0.499*****
Paraná	PR	2,237	0.409***	215	0.456***	375	0.449***	507	0.363***	528	0.424***	612	0.480***
Santa Catarina	SC	1,083	0.407***	93	0.537***	182	0.456***	256	0.318***	275	0.439***	277	0.515***
Rio Grande do Sul	RS	3,120	0.439***	371	0.454***	586	0.489***	671	0.444***	693	0.423***	799	0.501***
South		**6,440**	**0.421*****	**679**	**0.480*****	**1,143**	**0.467*****	**1,434**	**0.386*****	**1,496**	**0.427*****	**1,688**	**0.500*****
Mato Grosso do Sul	MS	674	0.476***	59	0.809***	104	0.464***	131	0.534***	175	0.546***	205	0.399***
Mato Grosso	MT	695	0.419***	50	0.368*	100	0.444***	143	0.421***	187	0.407***	215	0.461***
Goiás	GO	1,375	0.356***	129	0.271**	217	0.454***	267	0.319***	349	0.399***	413	0.408***
Distrito Federal	DF	922	0.492***	85	0.600***	107	0.590***	171	0.441***	269	0.475***	290	0.452***
West Central		**3,666**	**0.445*****	**323**	**0.482*****	**528**	**0.501*****	**712**	**0.428*****	**980**	**0.458*****	**1,123**	**0.473*****
Brazil		**35,757**	**0.475*****	**3,640**	**0.536*****	**5,586**	**0.517*****	**7,222**	**0.454*****	**8,947**	**0.492*****	**10,362**	**0.533*****

Notes: Estimations based on OLS regressions using years of schooling of children and their (better-educated) parent. Results are controlled by the variation over time in standard deviation in education. The lower the correlation coefficients, the lower the persistence in education across generations (or the higher the level of mobility). Statistically significant: $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.
Source: PNAD-2014, own estimates.

Table 2.3. The Impact of Inequality on Educational Attainment

Birth Cohort	**All**	**1965**	**1970**	**1975**	**1980**	**1985**
Birth years	(1965–1989)	(1965–1969)	(1970–1974)	(1975–1979)	(1980–1984)	(1985–1989)
Socioeconomic Marginalization # Inequality	-0.0542***	-0.0486	-0.0353	-0.00346	-0.0982**	-0.0519
	(0.0186)	(0.0644)	(0.0473)	(0.0335)	(0.0486)	(0.0462)
Socioeconomic Marginalization	-0.405***	-0.535	-0.492*	-0.705***	-0.261	-0.270
	(0.104)	(0.350)	(0.287)	(0.208)	(0.251)	(0.237)
Inequality	0.0129	-0.0256	0.0387	-0.0164	0.0929***	-0.0170
	(0.0138)	(0.0503)	(0.0377)	(0.0242)	(0.0327)	(0.0320)
Male	-0.203***	-0.0988*	-0.114**	-0.217***	-0.291***	-0.257***
	(0.0208)	(0.0531)	(0.0487)	(0.0455)	(0.0425)	(0.0445)
Rural	-0.650***	-0.575***	-0.812***	-0.784***	-0.687***	-0.490***
	(0.0333)	(0.0854)	(0.0831)	(0.0723)	(0.0674)	(0.0692)
Living with both parent	0.0830***	-0.0687	0.0312	0.0614	0.0505	0.256***
	(0.0248)	(0.0683)	(0.0601)	(0.0537)	(0.0497)	(0.0494)
Birth year	0.0159***	0.00722	-0.00521	0.0157	0.0116	-0.0373**
	(0.00156)	(0.0184)	(0.0171)	(0.0161)	(0.0155)	(0.0158)
White (reference)	-	-	-	-	-	-
Black	-0.160***	-0.189**	-0.217**	-0.0887	-0.184**	-0.152*
	(0.0366)	(0.0927)	(0.0872)	(0.0801)	(0.0730)	(0.0787)
Mixed (white/black)	-0.271***	-0.374***	-0.305***	-0.302***	-0.256***	-0.166***
	(0.0222)	(0.0568)	(0.0521)	(0.0489)	(0.0455)	(0.0476)
Asian	0.296*	0.635	0.938***	0.356	-0.413	0.130
	(0.159)	(0.387)	(0.353)	(0.373)	(0.282)	(0.355)
Indigenous	-0.346*	-0.653	-0.555	-0.209	-0.147	-0.381
	(0.191)	(0.619)	(0.457)	(0.396)	(0.357)	(0.362)
Constant	-30.86***	-13.43	10.54	-30.38	-22.57	74.74**
	(3.109)	(36.29)	(33.80)	(31.78)	(30.73)	(31.47)
Observations	23,008	3,699	4,223	4,724	5,387	4,975
Pseudo R2	0.113	0.122	0.113	0.122	0.121	0.074

Notes: The variable *Inequality* refers to income inequality, measured by the 75/10 ratio, in the individual's state of residence 14 years after their birth ($t + 14$). The coefficients of the interaction between socioeconomic marginalization and the inequality level show how the effects of having (un)educated parents on the children's chance of achieving a secondary education change by different values of inequality. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$. Standard errors in parentheses. dy/dx for factor levels is the discrete change from the base level. All predictors at their mean value.
Source: PNAD-2014, own estimates.

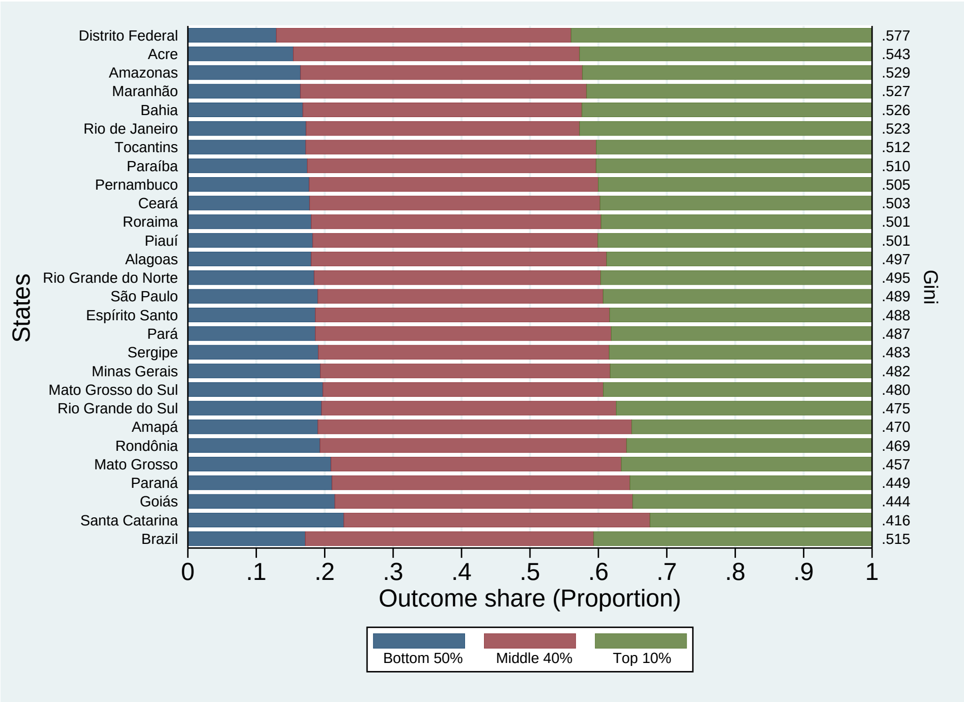
Table 2.4. Robustness Checks

	Main Model	A. Alternative Econometric Approaches			B. Alternative Model Specifications			
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Model	**Probit**	**LPM**	**LPM**	**Bivariate Probit**	**Probit**	**Probit**	**Probit**	**Probit**
Estimation method	**MLE**	**OLS**	**2SLS**	**MLE**	**MLE**	**MLE**	**MLE**	**MLE**
Changes to Specidication (1)	**-**	**No**	**No**	**No**	**No Migrants**	**Ratio 90/10**	**Illiterate Parents**	**Illite. & No Educ.**
Coefficient of MSB # Inequality	-0.0540***	-0.0179***	-0.0175***	-0.0487***	-0.0695*	-0.0199**	-0.0318	-0.0307
	(0.0186)	(0.00636)	(0.00636)	(0.0178)	(0.0418)	(0.00796)	(0.0227)	(0.0216)
APRs for MSB and Inequality								
1bn._at	-0.223***	-0.220***	-0.223***	-0.175***	-0.210***	-0.209***	-0.236***	-0.201***
	(0.0196)	(0.0179)	(0.0179)	(0.0212)	(0.0430)	(0.0271)	(0.0257)	(0.0227)
2._at	-0.244***	-0.238***	-0.241***	-0.190***	-0.237***	-0.217***	-0.247***	-0.213***
	(0.0134)	(0.0125)	(0.0125)	(0.0210)	(0.0288)	(0.0242)	(0.0184)	(0.0154)
3._at	-0.264***	-0.256***	-0.258***	-0.205***	-0.263***	-0.224***	-0.258***	-0.225***
	(0.00884)	(0.00863)	(0.00861)	(0.0210)	(0.0181)	(0.0213)	(0.0130)	(0.0101)
4._at	-0.284***	-0.274***	-0.276***	-0.220***	-0.289***	-0.232***	-0.268***	-0.237***
	(0.00876)	(0.00853)	(0.00851)	(0.0215)	(0.0183)	(0.0185)	(0.0115)	(0.0102)
5._at	-0.305***	-0.291***	-0.293***	-0.236***	-0.314***	-0.240***	-0.278***	-0.248***
	(0.0130)	(0.0123)	(0.0123)	(0.0223)	(0.0286)	(0.0159)	(0.0149)	(0.0155)
6._at	-0.324***	-0.309***	-0.311***	-0.253***	-0.338***	-0.248***	-0.288***	-0.260***
	(0.0187)	(0.0177)	(0.0177)	(0.0235)	(0.0417)	(0.0133)	(0.0205)	(0.0225)
7._at	-0.344***	-0.327***	-0.328***	-0.270***	-0.361***	-0.255***	-0.298***	-0.272***
	(0.0248)	(0.0235)	(0.0235)	(0.0251)	(0.0553)	(0.0111)	(0.0267)	(0.0300)
8._at	-0.363***	-0.345***	-0.346***	-0.287***	-0.383***	-0.263***	-0.307***	-0.283***
	(0.0309)	(0.0296)	(0.0296)	(0.0271)	(0.0687)	(0.00927)	(0.0330)	(0.0376)
9._at	-0.382***	-0.363***	-0.363***	-0.305***	-0.404***	-0.271***	-0.315***	-0.295***
	(0.0369)	(0.0358)	(0.0358)	(0.0294)	(0.0819)	(0.00822)	(0.0392)	(0.0452)
10._at	-0.401***	-0.381***	-0.381***	-0.323***	-0.423***	-0.278***	-0.324***	-0.306***
	(0.0427)	(0.0420)	(0.0420)	(0.0320)	(0.0947)	(0.00819)	(0.0452)	(0.0528)
Observations	23,008	23,008	23,008	23,008	5,340	23,008	24,842	21,668

Notes: The variable *Inequality* refers to income inequality, measured by the 75/10 ratio, in the individual's state of residence 14 years after their birth ($t + 14$). The coefficients of the interaction between socioeconomic marginalization (MSB) and the inequality level show how the effects of having (un)educated parents on the children's chance of achieving a secondary education change by different values of inequality. The adjusted predictions at representative values (APRs) fixed the covariate "ratio 75/10" to each of the 10 deciles of the inequality distribution, showing respectively the gap in the chances to achieve a secondary school certificate for the two investigated populations—children from parents with and without (primary) education. For the LPMs, the standard errors are robust to arbitrary heteroskedasticy. Statistically significant: $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$. Standard errors in parentheses. All predictors at their mean value.
Source: PNAD-2014, own estimates.

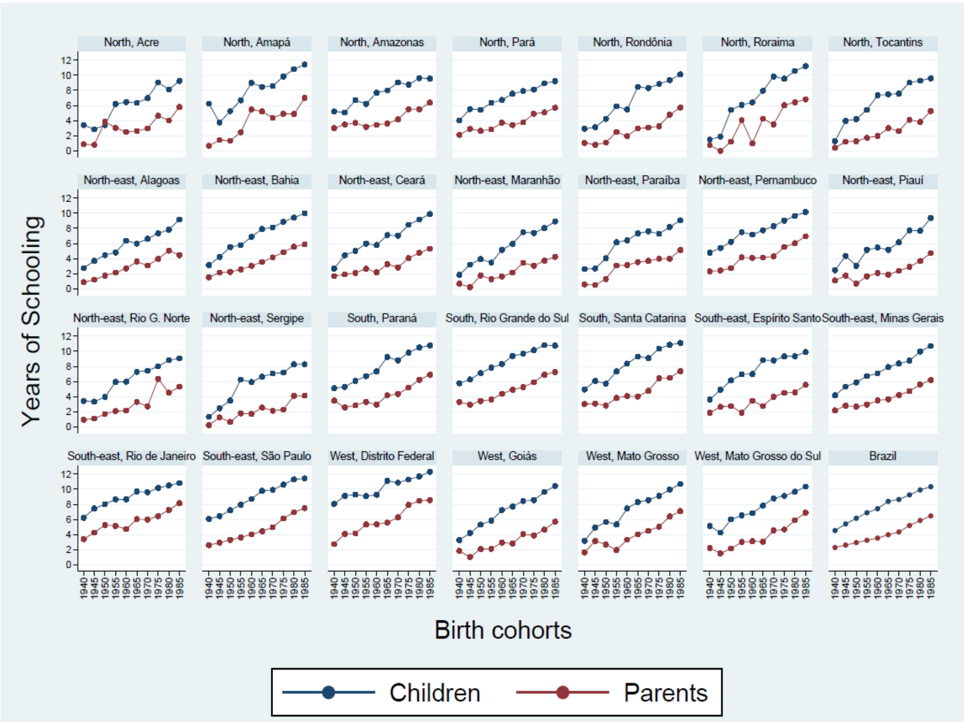
2.B Figures

FIGURE 2.1: Income Inequality across States



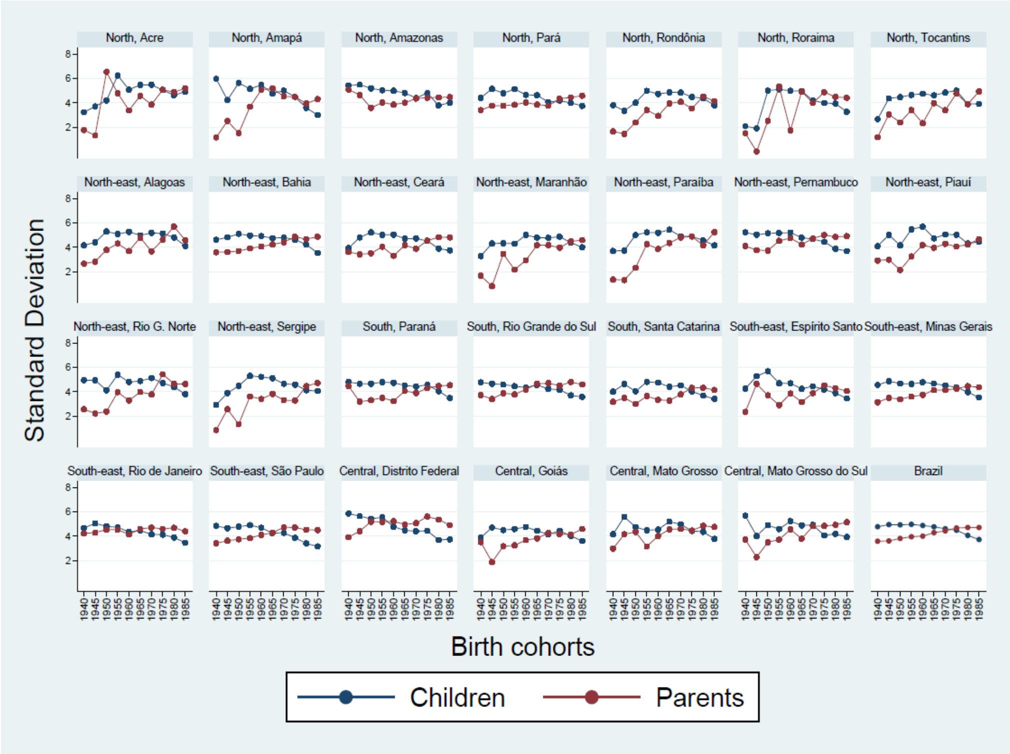
Note: Estimations based on self-declared per capita domiciliary income.
Source: PNAD-2014, own estimates.

FIGURE 2.2: Development of Average Schooling



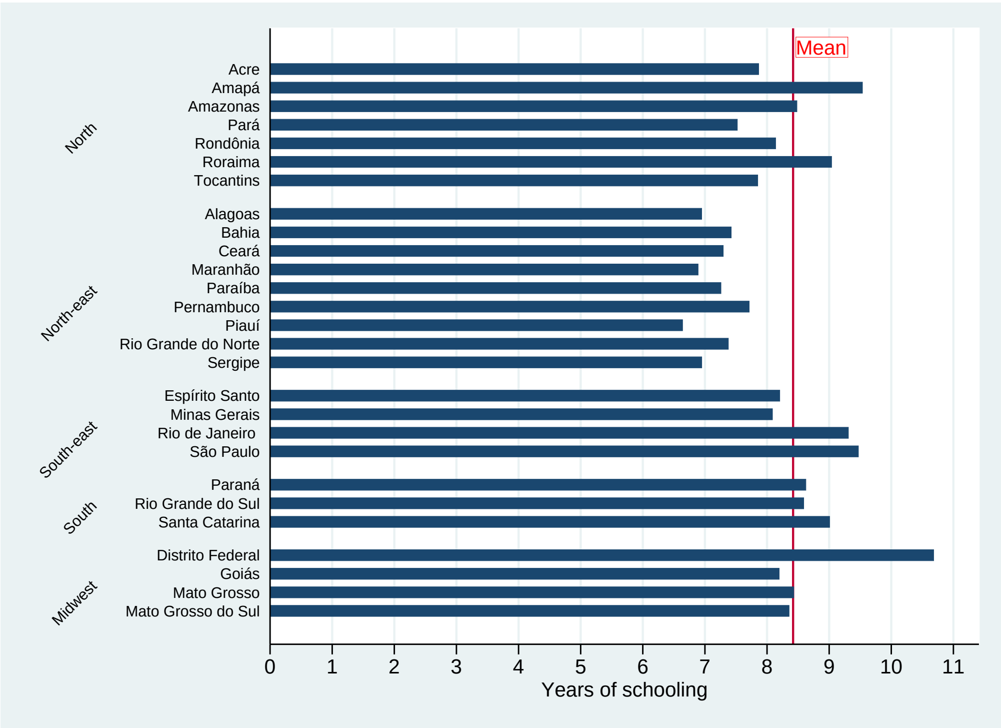
Notes: Children's education for boys and girls. Estimations of parent's education based on educational attainment of the most-educated parent. Birth cohort refers to the birth year of the offspring.
Source: PNAD-2014, own estimates.

FIGURE 2.3: Development of Inequality in Schooling



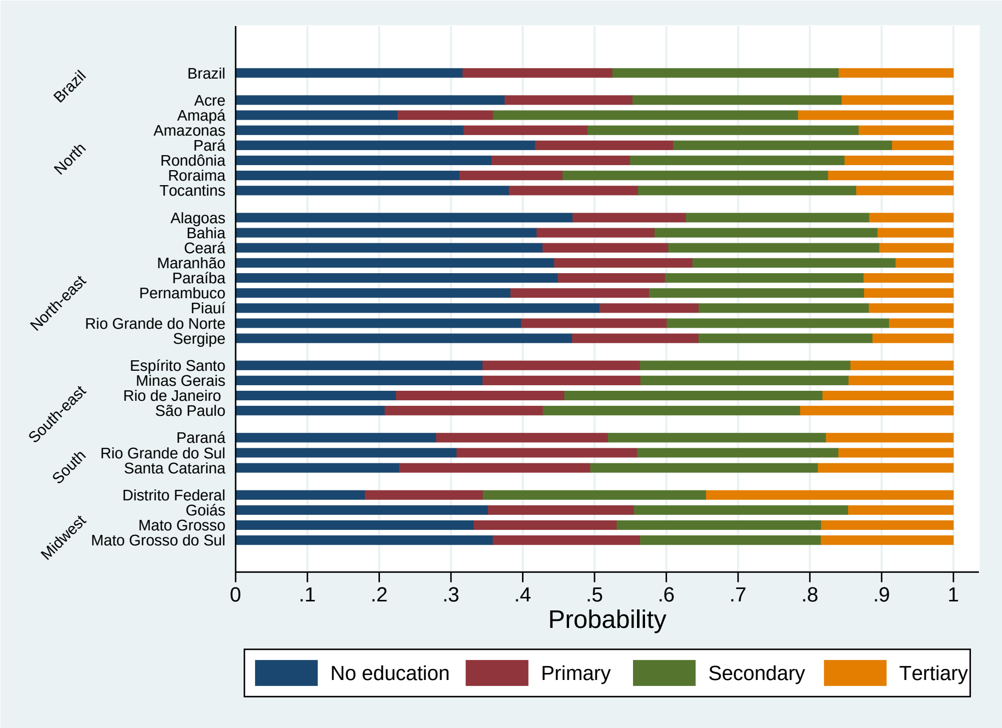
Notes: Standard deviation calculated using years of schooling. Children's education for boys and girls. Estimations of parent's education based on educational attainment of the most-educated parent. Birth cohort refers to the birth year of the offspring.
Source: PNAD-2014, own estimates.

FIGURE 2.4: Average Schooling, by States



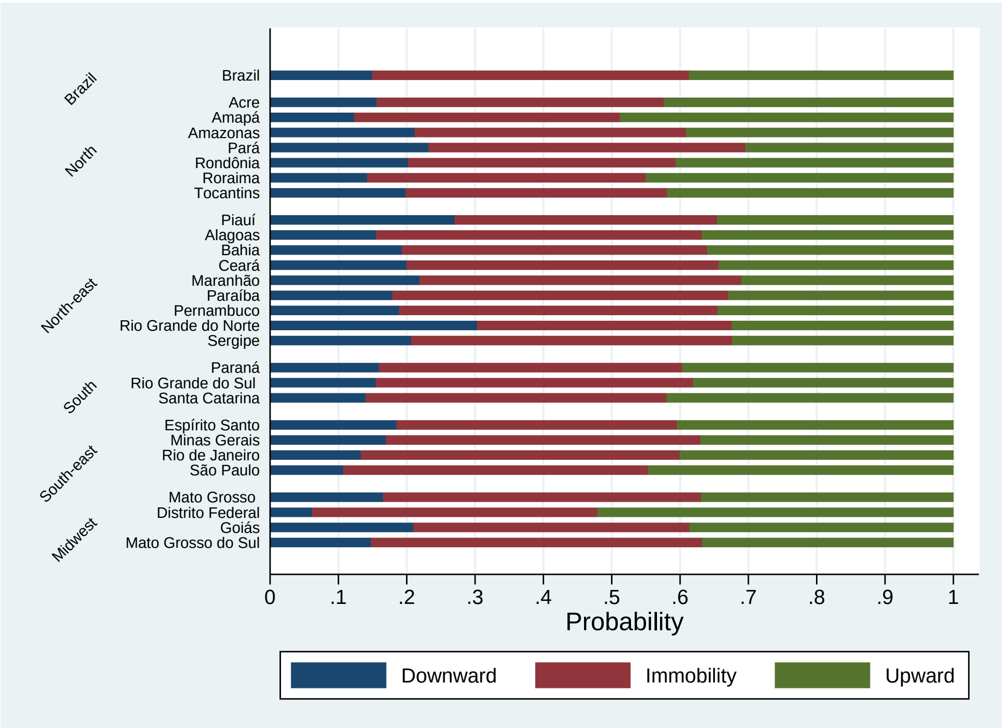
Note: Calculation using years of schooling of the respondents (descendant's generation). Values for boys and girls.
Source: PNAD-2014, own estimates.

Figure 2.5: Average Educational Levels, by States



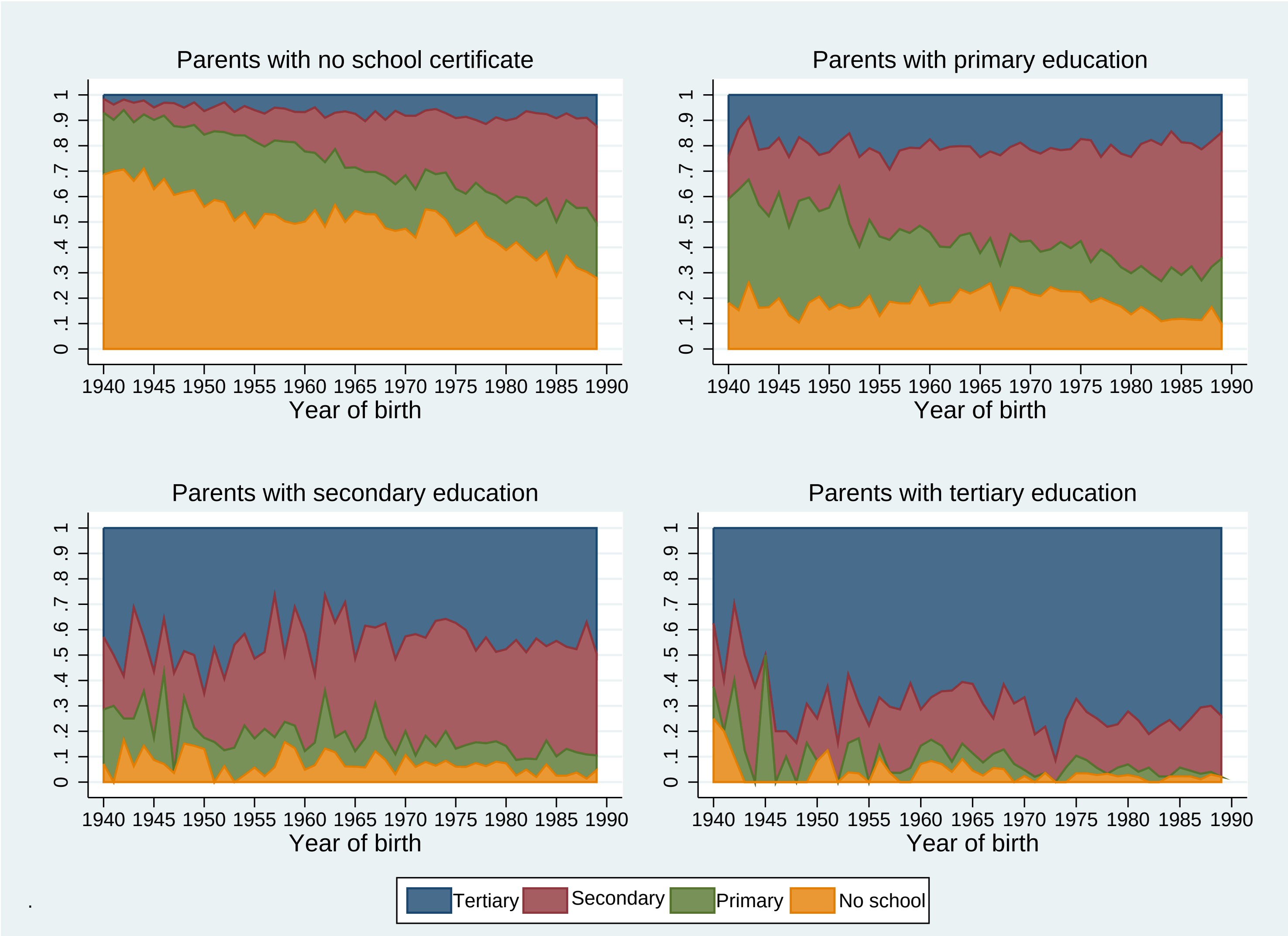
Note: Calculation using educational levels of the respondents (descendant's generation). Values for boys and girls.
Source: PNAD-2014, own estimates.

Figure 2.6: Immobility and Up–Downward Mobility



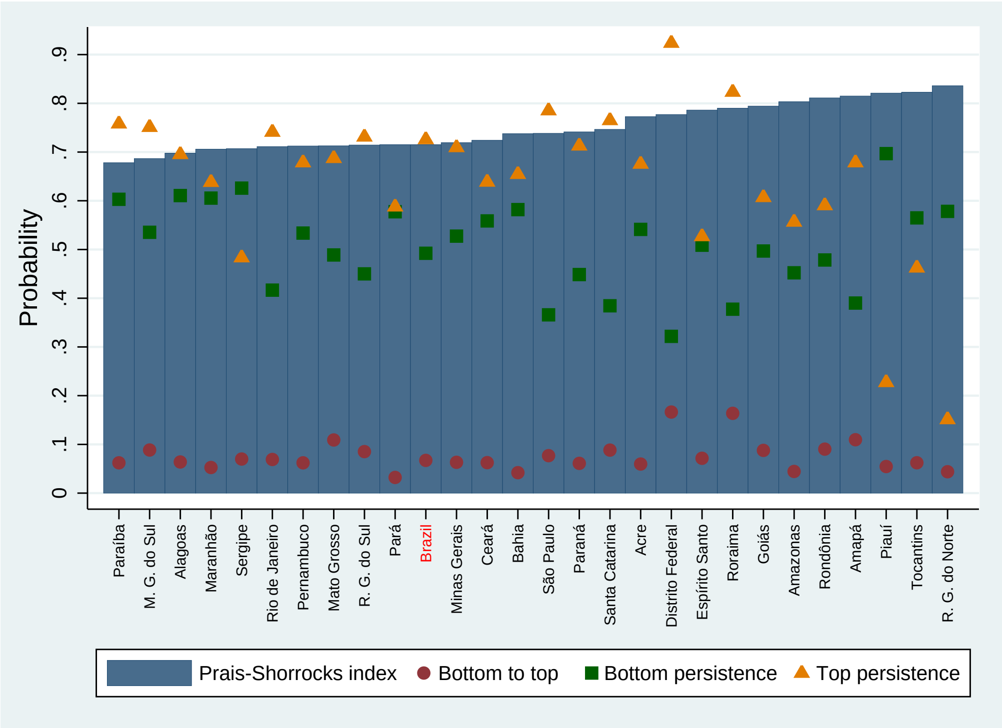
Note: Downward (upward) mobility depicts the share of children who have achieved a lower (higher) level of education than their most-educated parent.
Source: PNAD-2014, own estimates.

Figure 2.8: Children's Predicted Probabilities of Educational Attainment



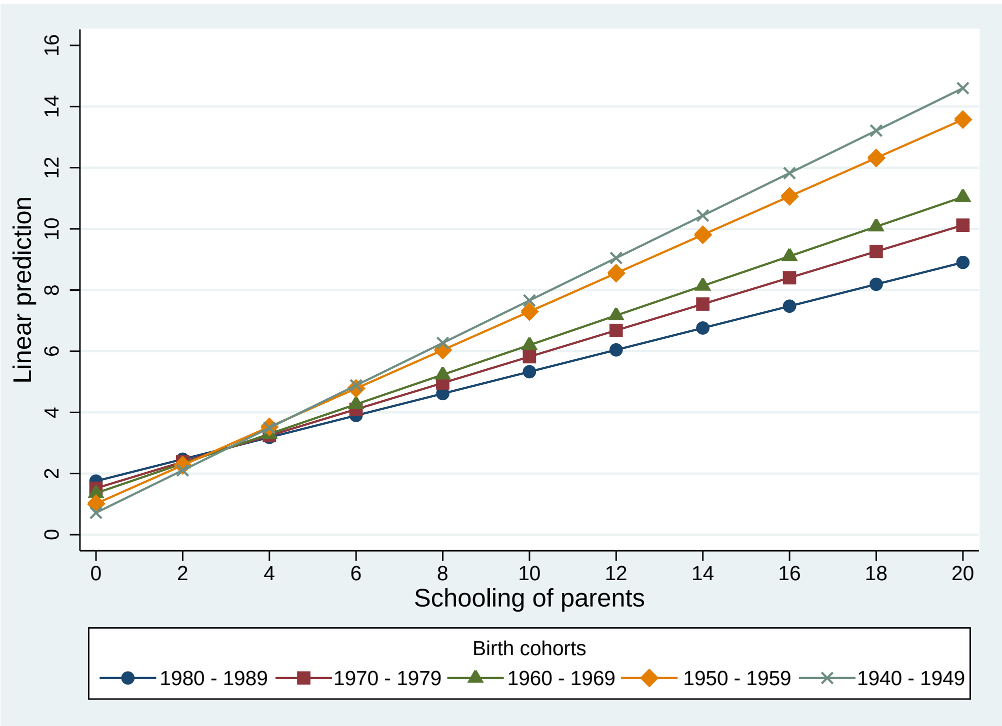
Notes: Children's education for boys and girls. Parents's schooling refers to the educational attainment of the better-educated parent. Year of birth refers to the birth year of the offspring.
Source: PNAD-2014, own estimates.

FIGURE 2.7: Intergenerational Mobility Indexes



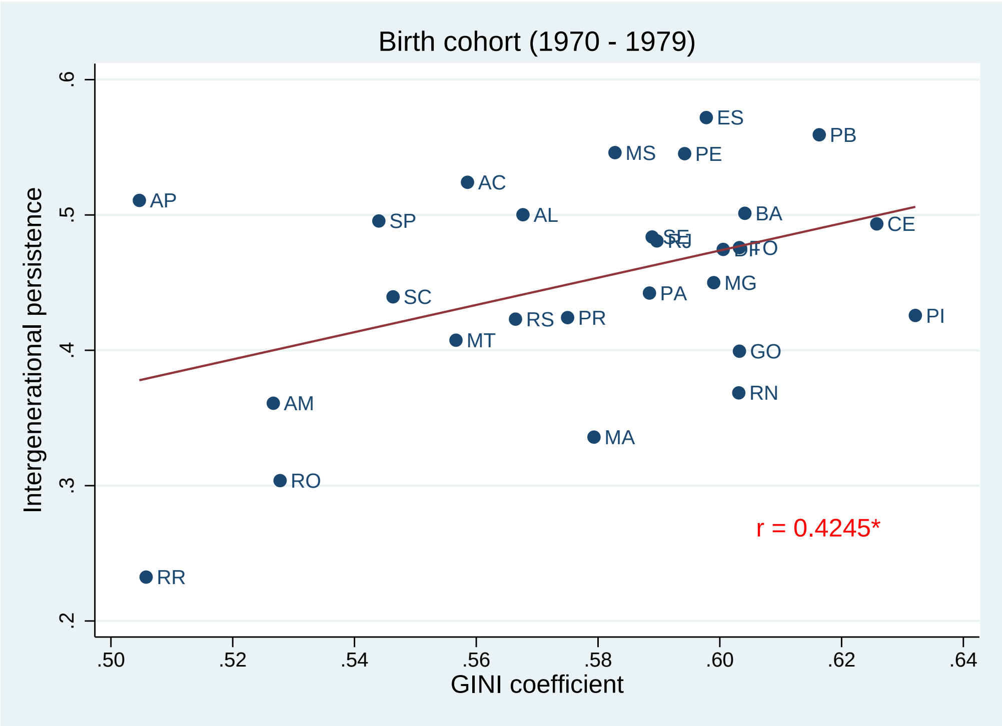
Notes: The Prais-Shorrocks index provides a measure of the normalized distance between the identity matrix and the independent matrix. It takes a value of 0 (1) when no (all) children move away from the educational level of their parents. The bottom-to-top index reports the proportion of individuals born into families with no education that have achieved a university degree. The top (bottom) persistence shows the share of children born to parents with tertiary (no) education who have attained the same educational level as their parents.
Source: PNAD-2014, own estimates.

FIGURE 2.9: Adjusted Predictions of Birth Cohorts



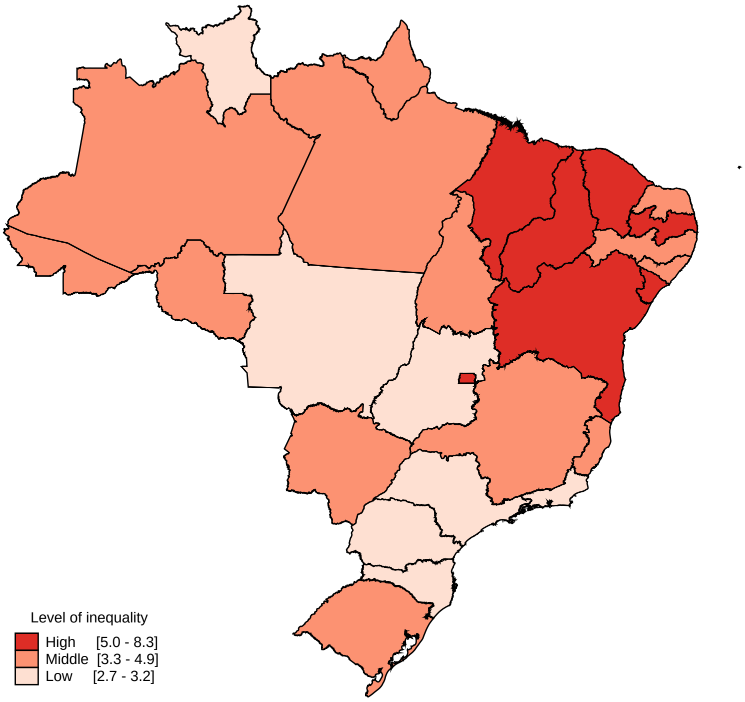
Notes: Figure presents the predictive margins from equation (2.10) with a two-way interaction (education by birth cohort) to investigate how children's chances of mobility change according to their year of birth. Parents's schooling refers to the educational attainment of the better-educated parent.
Source: PNAD-2014, own estimates.

FIGURE 2.10: The Great Gatsby Curve



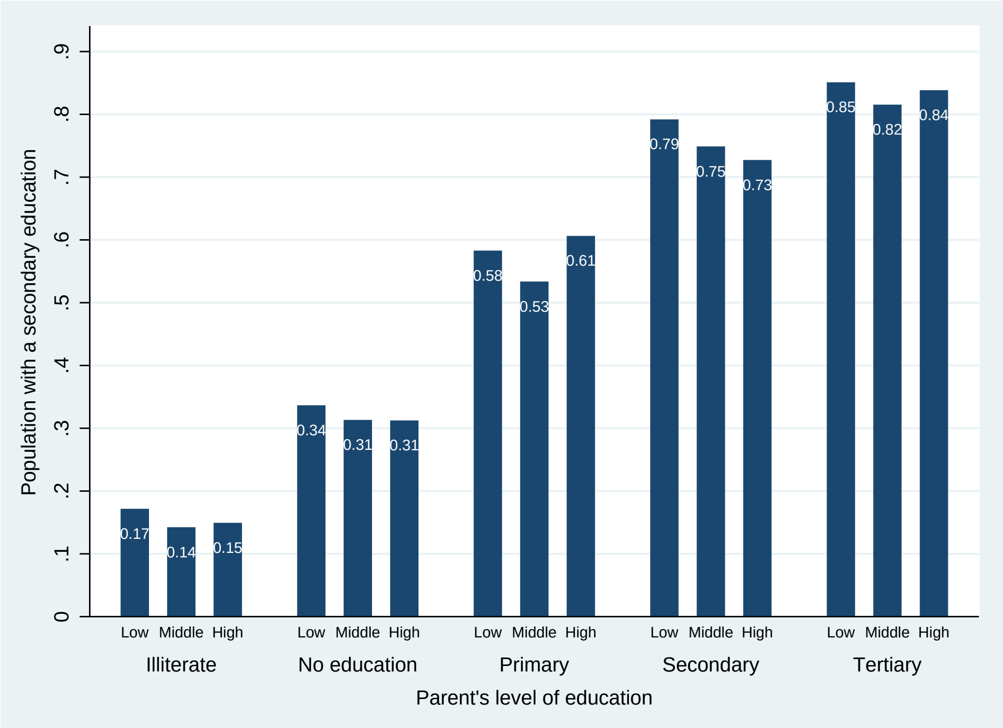
Notes: r denotes Pearson's correlation. Asterisk indicates correlation coefficients with p-values of .1 or lower. Intergenerational persistence was estimated using equation (2.10) and years of schooling of children and their parents. Gini coefficients refer to the average values between 1984 and 1993. See Table 2.2 for the exact values of the coefficients and the name of states.
Source: PNADs, own estimates.

FIGURE 2.11: 75/10 Ratio of Income Distribution



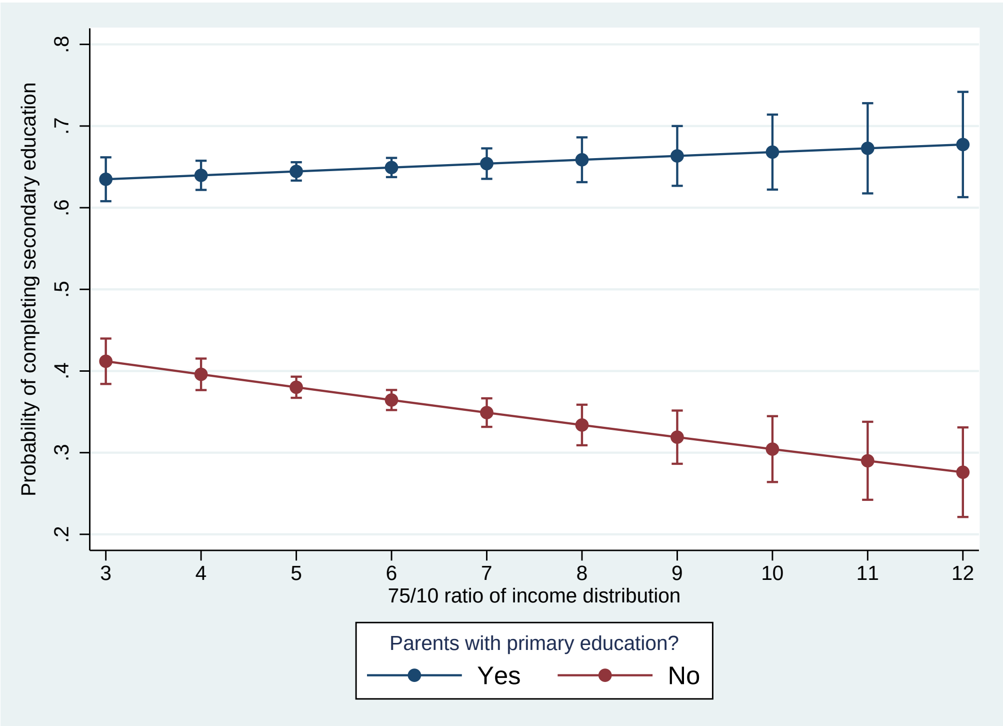
Notes: The 75/10 ratio represents the relation between the income earned by individuals in the 75th percentile and the earnings of individuals in the 10th percentile. Estimations based on total income of the economically active population aged 15 or over with earnings greater than 0.
Source: PNAD-2014, own estimates.

FIGURE 2.12: Educational Attainment and Inequality



Note: Estimations of income inequality based on 75/10 ratio of total income of the economically active population aged 15 or over and with earnings greater than 0.
Source: PNAD-2014, own estimates.

FIGURE 2.13: Adjusted Predictions, Secondary Education



Notes: The 75/10 ratio represents the relation between the income earned by individuals in the 75th percentile and the earnings of individuals in the 10th percentile. Income inequality based on total income of the economically active population aged 15 or over and with earnings greater than 0. 75/10 ratio using income levels in the individual's state of residence 14 years after their birth ($t + 14$).
Source: PNADs, own estimates.

2.C A Model of the Intergenerational Transmission of Inequality

The model of Solon (2004), which is based on the theoretical approach of Becker and Tomes (1979, 1986), has been used in the economic literature as the starting point to understanding the correlation between income inequality and intergenerational mobility.[42]

In this model, the family i is composed of a parent from generation $t-1$ and a child from generation t and it is assumed as an intergenerational decision-maker that should allocate the lifetime earnings gained from parent $y_{i,t-1}$ into only two goods: the parent's own consumption $C_{i,t-1}$ and investment in the child's human capital $I_{i,t-1}$, subject to budget constraints:[43]

$$y_{i,t-1} = C_{i,t-1} + I_{i,t-1} \tag{2.C.1}$$

The investment $I_{i,t-1}$ presents diminishing marginal returns on education and will form the child's stock of human capital h_{it} used in the future to produce economic value in the labor market:

$$h_{it} = \theta \ \log \ I_{i,t-1} + e_{it} \tag{2.C.2}$$

The diminishing marginal returns to education in equation (2.C.2) refer to the fact that (more) investments produce even a positive marginal product for human capital stock $\theta > 0$, but of a lesser and less additional value, due to the semi-log form of the function. The error term e_{it} accounts for the variation in the child's human capital endowment that cannot be explained by the investment of parents, referring mainly to genetic endowment and personality traits which are also transmitted in the family environment and play an important role in human capital accumulation.

The independent human capital endowment e_{it} follows a first-order autoregressive process as:

$$e_{it} = \delta + \lambda \, e_{i,t-1} + \upsilon_{i,t} \tag{2.C.3}$$

in which $\upsilon_{i,t}$ represents a white-noise error term and the parameter λ is a heritability coefficient with $\lambda \in [0, 1]$.

Solon (2004) assumed in his model that the lifetime income of child y_{it} can be regarded as a semi-log earnings function, where p represents the earnings return to human capital:

$$log \ y_{it} = \mu + p \ h_{it} \tag{2.C.4}$$

Substituting equation (2.C.2) into equation (2.C.4) we have:

$$\log \ y_{it} = \mu + p \ \theta \ log \ I_{i,t-1} + p \ e_{it} \tag{2.C.5}$$

From equation (2.C.5) the value $p \ \theta$ can be interpreted as the elasticity of the child's income in relation to the human capital investment $I_{i,t-1}$, representing in this

[42]The description of the theoretical model of Solon (2004) in this appendix refers to the simplified version of the model presented by Solon (2014).

[43]For purposes of simplification, the model of Solon (2004) presented in this section does not take into account variables such as taxation, government investment in children, borrowing, and bequeathing financial assets. See Becker and Tomes (1986) for a more complete version of the model.

way the earnings return on human capital investment, in the following briefly termed γ:

$$\log\ y_{it} = \mu + \gamma\ log\ I_{i,t-1} + pe_{it} \tag{2.C.6}$$

To make the optimal decisions concerning the investment in the child's human capital, the family considers a two-good world, in which the parents' lifetime income $y_{i,t-1}$ needs to be allocated between their own consumption $C_{i,t-1}$ and investment $I_{i,t-1}$ in the child's human capital. The family wishes to maximize the utility, denoted $U_i(C_{i,t-1}, I_{i,t-1})$, subject to the budget constraint in (2.C.7):

$$U_i = (1-\alpha)\log\ C_{i,t-1} + \alpha \log\ y_{it} \tag{2.C.7}$$

with $\alpha \in [0,1]$ indicating the degree of altruism of parents for child's income y_{it} in relation to their own consumption $C_{i,t-1}$. Plugging (2.C.1) and (2.C.6) into equation (2.C.7):

$$U_i = (1-\alpha)\log\ \underbrace{(y_{i,t-1} - I_{i,t-1})}_{C_{i,t-1}} + \alpha\,\underbrace{(\mu + \gamma \log\ I_{i,t-1} + pe_{it})}_{y_{it}} \tag{2.C.8}$$

And rewriting it:

$$U_i = (1-\alpha)\log\ (y_{i,t-1} - I_{i,t-1}) + \alpha\mu + \alpha\gamma \log\ I_{i,t-1} + \alpha pe_{it} \tag{2.C.9}$$

In order to solve the problem, the main condition for the maximization of the utility function is that:

$$\frac{\partial U_i}{\partial I_{i,t-1}} = \frac{-(1-\alpha)}{y_{i,t-1} - I_{i,t-1}} + \frac{\alpha\gamma}{I_{i,t-1}} = 0 \tag{2.C.10}$$

Solving for the optimal choice of $I_{i,t-1}$, we can rewrite the first-order condition as:

$$I_{i,t-1} = \left\{ \frac{\alpha\gamma}{1-\alpha(1-\gamma)} \right\} y_{i,t-1} \tag{2.C.11}$$

Note that the investment in the child's human capital $I_{i,t-1}$ increases by increasing parents income $y_{i,t-1}$, altruism α, and earnings return on human capital investment γ. From these results, we can deduce the two most important conclusions from the model of Solon (2004): First, parents with higher income have a higher financial capacity to invest in the human capital of their children and, second, they also have a greater incentive to make this investment if the return on investment in human capital increases over time.

2.D A Model of the Decision to Drop Out of the Education System

Kearney and Levine (2016) presented the theoretical model used in this paper to explain the causal relationship between higher income inequality and the higher probability that children from socially disadvantaged families will drop out of school.

Let us assume that the child (student) tends to maximize an intragenerational utility function between utility in the current (t) and future period ($t+1$). If the student drops out of the education system in t, he or she will achieve the current-period utility u^d and the present discounted sum of future period V^d. Otherwise, the student has u^e and V^e from the decision to remain enrolled in the school. The generalization of the individual decision to drop out can be written as:

$$u^d + E(V^d) > u^e + E(V^e) \tag{2.D.1}$$

Given the positive returns to education, we assume that dropping out of school has a negative effect on the utility in period $t+1$, due to the reduction in the level of future consumption, such that $E(V^e) > E(V^d)$.

The decision to drop out of education will be never optimal so long as $u^d \leq u^e$. However, if $u^d > u^e$ in the case that the student's participation in the school system is associated with substantial utility costs, such as psychological costs, then dropping out of school can be considered an alternative.

Suppose that the child's utility in the future can achieve U^{high} or U^{low}, meaning a high or low value respectively, and U^{low} represents the utility level in the case that the child drops out of school. If the student remains enrolled in the education system, he or she will have the probability $p \in [0,1]$ of attaining the high-utility position. Assuming V^{low} as the deterministic present discounted value of the utility, we can rewrite equation (2.D.1) as:

$$u^d + V^{low} > u^e + pV^{high} + (1-p)V^{low} \tag{2.D.2}$$

By rearranging the terms in equation (2.D.2), the condition for remaining in school yields:

$$\left[pV^{high} + (1-p)V^{low}\right] - V^{low} > u^d - u^e \tag{2.D.3}$$

Thus, the student will continue studying as long as the likelihood of attaining a high utility in the future is greater than the current loss of utility caused by school attendance and the consequent sacrifice of leisure. Given the uncertainty associated with the future, the child cannot determine p with the best possible accuracy in the period t, working in this way with its individual subjective perception of success q.

Let us assume q as a function of p and x, such that $q = q(p, x)$ in which x represents external factors affecting the individual's perception of returns to schooling. Kearney and Levine (2016) have pointed out that these external factors can be influenced strongly by the lived experience during childhood and adolescence. Children who grow up in poverty have restricted contact to highly qualified individuals and may assume that a college degree is an objective very far from their reality, leading to an underestimation of the propability p. As a result, at the same level of p, students from different socioeconomic backgrounds (SES) will present different individual perceptions of q.

This means that, income inequality will affect the perceived returns on education q in two ways: First, it affects x given that the higher the inequality, the higher the perception of social exclusion for poor children. Second, higher income inequality will increase the current return on investment in schooling, leading to a rise in the individual perception of return p. Then the condition for the student to continue studying follows:

$$\left[qV^{high} + (1-q)V^{low}\right] > V^{low} + (u^d - u^e) \tag{2.D.4}$$

From equation (2.D.4) it becomes evident that the chance of remaining enrolled rises with increasing q. As a consequence thereof, the student will invest more time in schooling if he or she notes that this investment will increase the chance of achieving V^{high}. However, if children are right in assuming that independently of their educational attainment they will never leave the situation of social exclusion, meaning if q is very low, this increases the incentive to drop out of school.

Solving equation (2.D.4) for q, we can define the reservation subjective probability q^r required for students' continuation of schooling:

$$q \geq q^r = \left\{\frac{u^d - u^e}{V^{high} - V^{low}}\right\} \tag{2.D.5}$$

The derivative from equation (2.D.5) to the socioeconomic backgrounds (SES) represented an increasing function at point q, indicating that the higher the SES, the greater is the perception of sucess as a consequence of educational attainment, such that:

$$\frac{\partial q}{\partial (SES)} > 0 \tag{2.D.6}$$

Kearney and Levine (2016) propose that the perception of sucess q can also be described as a function of SES and income inequality in the society. For children from socially weaker families, the increase in the gap between the bottom and middle of the income distribution might lead to a reduction of the subjective perception p.

$$\frac{\partial q}{\partial (SocIneq)} < 0 \tag{2.D.7}$$

In practice, it means that the farther away poor children's experiences are from the experiences of the middle class, the greater their perception of "social exclusion," strengthening in this way the individual view that "it is not for people like me."

2.E Structure of the Brazilian Educational System

The current Brazilian educational system is anchored in the 1988 Constitution, which recognizes education as a right for the population and an obligation of the government.

The same legislation distributes the responsibility for education between all three administrative levels of the federation: the federal, state, and municipal governments. Thus, the municipalities are responsible for providing and regulating preschool and primary education, while the states are involved with the same tasks for the secondary education. The federal government plays only a secondary role in this context, providing financial and technical assistance to the states and municipalities in order to promote equality of opportunity and minimum quality standards.

The main responsibility of the federal government lies in providing education in its institutions—the vast majority of them related to tertiary education—and in regulating the private sector, which is free to operate within all three educational levels.[44] After 1996, which saw the publication of the Law of Directives and Bases of National Education (Lei de Diretrizes e Bases da Educação) or LDB, the central government also became responsible for defining a common national basis for curricula in primary and secondary education, which needs to be used by states and municipalities as the basis for the development of their own curriculum.

Since the 1934 Constitution there has been compulsory education in Brazil. However, in the beginning only children aged between 7 and 10 years old were obliged to undertake full-time education. Over the years the obligatory period of schooling has grown steadily, so that in 1971 compulsory education ended at the age of 14 and in 2010 at 17.[45] The next table provides an overview of the Brazilian educational system and the changes made to it over the last six decades.

TABLE 2.5: Structure of Brazilian Educational System

Year	Level	Duration (in years)	Age group	Compulsory
Until 1971	Pré-escola (Preschool)	3	4 to 6	No
	Escola primária (Primary school)	4	7 to 10	Yes
	Ginásio (Lower high school)	4	11 to 14	No
	Colégio (High school)	3	15 to 17	No
	Ensino superior (College)	variable	≥ 18	No
1971 to 1995	Pré-escola (Preschool)	3	4 to 6	No
	1º grau (1st Degree)	8	7 to 14	Yes
	2º grau (2nd Degree)	3	15 to 17	No
	Ensino superior (College)	variable	≥ 17	No
1996 to 2009	Educação infantil (Early childhood education)	7	0 to 6	No
	Ensino fundamental (Primary education)	8	7 to 14	Yes
	Ensino médio (Secondary education)	3	15 to 17	No
	Ensino superior (College)	variable	≥ 17	No
Since 2010	Educação infantil (Early childhood education)	4	0 to 3	No
	Ensino pré-fundamental (Pre-primary education)	2	4 to 5	Yes
	Ensino fundamental (Primary education)	9	6 to 14	Yes
	Ensino médio (Secondary education)	3	15 to 17	Yes
	Ensino superior (College)	variable	≥ 17	No

Source: Law 5,540 of 28/11/1968, Law 5,692 of 11/08/1971, Law 9,394 of 20/12/1996, and Constitutional Amendment 59 of 11/11/2009.

Currently, the Brazilian educational system is composed of five distinct levels: early childhood, pre-primary, primary, secondary, and tertiary education. Individuals aged between 4 and 17 years old are obliged to attend school. Children under 4

[44] Own calculations on the basis of the National Household Sample Survey (PNAD) from 2014 indicated that the share of students enrolled in private institutions in Brazil reached respectively 14 percent in primary, 13 percent in secondary, and 75 percent in tertiary education.

[45] See Wjuniski (2013) for a detailed description of the changes over time in the legal framework for the educational system in Brazil.

may attend the optional early childhood education. Attendance at the pre-primary educational level, usually at the age of 4, is the first phase of compulsory education. This is followed by the primary educational level, which comprises nine years of schooling. The third level of the educational system in Brazil is known as secondary education and lasts for a period of three years. Students who complete this level have the right to attend vocational training, or to start pursuing higher education qualifications: a bachelor's degree, for example, usually takes four years. Individuals who hold a university degree are eligible to undertake graduate studies, which consist of a master's degree followed, potentially, by a doctoral degree.

The current requirement that children complete 14 years of compulsory education in Brazil was stipulated by constitutional amendment 59 of November 11, 2009, which created an obligatory 2+9+3 pattern in the education system. This was an increase from the previous system (valid until 2009), where students were required to remain in school only for nine years.[46]

[46] Although the increasing of the compulsory education level via the constitutional amendment had already been established in September 2009, the states and municipalities had until 2016 to achieve its full implementation.

2.F Codification of Years of Schooling

Based on the PNAD sample, this paper used two main variables related to education for the investigation of intergenerational mobility: the number of completed years of education (years of schooling) and the (highest) educational level achieved. The PNAD already provides both variables for the children's generation, but for the parents the information on years of schooling is missing.

Given this limitation, I calculated the parents' years of schooling according to their educational levels. Table 2.6 presents the matching procedure used for the codification.[47]

TABLE 2.6: Codification of Parents' Years of Schooling

Years of Education =

00	*if*	Only pre-primary education
00	*if*	Went to school, but never completed $1st$ grade
02	*if*	Completed $1st$ grade but didn't complete all grades up to $4th$ grade (before 1971)
02	*if*	Uncompleted literacy classes (young people and adults)
03	*if*	Attended literacy classes (young people and adults), but do not know if they were completed
03	*if*	Attended primary school, but do not know if all grades up to $4th$ grade were completed (before 1971)
04	*if*	Completed up to $4th$ grade
05	*if*	Completed literacy classes (young people and adults)
05	*if*	Completed $1st$ grade but didn't complete all grades up to $8th$ grade (after 1971)
06	*if*	Completed $5th$ grade but didn't complete all grades up to $8th$ grade (before 1971)
07	*if*	Attended $1st$ degree, but do not know if all grades up to $8th$ grade were completed (after 1971)
07	*if*	Attended lower high school, but do not know if all grades up to $8th$ grade were completed (before 1971)
08	*if*	Completed up to $8th$ grade
09	*if*	Completed $9th$ grade but didn't complete all grades up to $11th$ grade
10	*if*	Attended $2nd$ degree, but do not know if all grades up to $11th$ grade were completed (after 1971)
11	*if*	Completed up to $11th$ grade
13	*if*	Completed $1st$ year in college/university, but didn't graduate
14	*if*	Attended college/university, but do not know if graduated
15	*if*	Graduated college/university
16	*if*	Incomplete master or doctorate
17	*if*	Attended master's or doctoral studies, but do not know if they were completed
19	*if*	Completed master's or doctorate

It is important to note that the information concerning the parents' educational level is based on the self-declaration of their children –namely the individuals who were interviewed by PNAD–and refers to educational attainment of parents when the children were 15 years old.[48] Thereby, three variables from PNAD have been used for the codification of parents' years of schooling: (a) the highest level of education attended; (b) whether the first year (grade) of this attended level was completed; and (c) whether the attended level was also completed.

For the first variable, 10 different educational levels were permitted: kindergarten, literacy classes for six-year-olds, literacy classes for young people and adults, primary school, lower high school, high school, 1st degree/primary education, 2nd degree/secondary education, college, and master's or doctorate. For the second and third variables only three answers were possible: yes, no, or unknown.

[47]See Table 2.5 for a overview of the different educational levels used in the codification.

[48]Because the investigation of intergenerational mobility in this paper is based on children born between 1940 and 1989, the reform of the education system through constitutional amendment 59 of November 11, 2009 had no consequences for the codification of parents' education.

2.G Data Harmonization

The empirical investigations in this paper are based on the Brazilian National Household Sample Survey (PNAD). This nationally representative survey has been conducted annually since 1976 by the Brazilian Institute of Geography and Statistics (IBGE) and gathers information about household composition, educational attainment, labor-market status, income, and a set of demographic variables (age, gender, location, race, etc.).[49]

In principle, it is possible to observe a relative consistency between the different sets of PNAD microdata over time. However, through the years the PNAD has undergone some restructuring in methodological terms, and for this reason some variables are not available for all the years and/or may not have been collected in the same way.

For this paper, the particularly relevant change was the reformulation of the definition of labor activities that occurred in 1992. The new formulation aimed to integrate some subsamples of the population involved in economic activities that were previously not included in the occupied population. Particularly noteworthy was the establishment of three additional categories of workers: those involved in production for self-consumption, construction for their own personal use, and paid domestic work. For this reason, it was necessary to harmonize all the PNAD's microdata to make the information about income inequality used in the investigations of the Great Gatsby curve and the decision to drop out of school compatible. For the standardization process, I took the survey from 1981 as the initial base and made the subsequent PNADs compatible with it. This required that only those variables that already existed in the 1981s' sample be maintained for the investigation.[50]

For the measures of the Gini coefficient and 75/10 ratio, I followed the theoretical approach of Hoffmann (2006) and calculated the income inequality based on (positive) monthly personal income for the economically active population aged 15 or over. In the integrated data there are 12 variables related to income that are common to all the samples. For the investigation, I used the variable (personal) monthly income from all sources, which is derived from the sum of all job income, retirement, pension, rent, allowances, and other sources. Subsequently, the variable related to income was deflated to the year 2012 with help of an income deflation based on the National Consumer Price Index (INPC). Not least, I omitted the observations with income equaling zero to exclude those individuals performing unpaid work (care work, voluntary work, etc.) from the analysis.

In this paper, the economically active population consists of those individuals who were either employed or actively seeking employment in the PNAD reference week. Finally, because the state of Tocantins was created only in year 1989, I aggregated its data with Goiás for those years in which the separation had already occurred.[51]

The investigation of mobility conducted in this study is based on an intertemporal choice about (more) educational attainment that occurred 14 years after the birth of the children. Therefore, the first PNAD sample (1981) was used to investigate the

[49] Until 2003 the rural areas of Rondônia, Acre, Amazonas, Roraima, Pará, and Amapá were not part of the PNAD. These six states compose Brazil's northern region and their population living in rural areas constitutes around 3 percent of the total Brazilian population.

[50] This standardization process was made using the "*datazoom – pnad*" package developed by the Department of Economics at Pontifical Catholic University of Rio de Janeiro (PUC-Rio), which aimed at compiling all the variables over the last four decades that could be obtained and organized in a conceptually consistent way.

[51] In the 1988 Brazilian Constitution, the state of Tocantins was officially created from the northern two-fifths of Goiás and admitted as a new state.

educational choices of the individuals born in 1967, and the PNAD from 2003 for the investigation of children born in 1989. Because there is no nationally representative databases for the period prior to 1981 that could be harmonized in a reliable way with the PNADs generated after 1981, this paper limited the estimations of income inequality to the individuals born from the year 1965 onward.[52]

[52] For the individuals born in 1965 and 1966, I used the inequality level from 1981 as a proxy. In the years 1991, 1994 and 2000 the PNAD was not carried out. For that purpose, I used the inequality levels for the respective following years (1992, 1995 and 2001) by the investigation of individuals born respectively in 1977, 1980 and 1986.

CHAPTER 3

Does a Productivity Bonus Pay Off?

3.1 Introduction

Currently, there is a broad consensus among the scientific community that teacher quality plays a critical role in promoting student academic achievement (see e.g. Canales and Maldonado, 2018; Dee and Wyckoff, 2015; Harris and Sass, 2011). For this reason, reforms meant to change the ways teacher are compensated have flourished around the world (Yuan et al., 2013). In this context, the pay-for-performance (PFP) programs has often been suggested as a possible mechanism to improve professional engagement in schools and, consequently, the performance of students (Barrera-Osorio and Raju, 2017; Loyalka et al., 2019; Muralidharan and Sundararaman, 2011).

However, the rapid expansion of these incentive-pay programs for teachers remains extremely controversial in part because of mixed evidence on their impact on academic achievement, which can be found in both developing and industrialized countries (Britton and Propper, 2016).[53] This paper contributes to this increasing academic debate, providing empirical evidence from Brazil on the effectiveness of teacher bonuses. Its goal is to examine whether the PFP program implemented in the Brazilian state of São Paulo in 2008 has led to improved student performance. This bonus is a group-based incentive, rewarding school staff for the achievement of predefined targets related to the improvement of education quality, measured by student performance and passing rate by school level.

Until 15 years ago, teachers in Brazil were compensated exclusively based on tightly structured rules based only their own educational level and professional experience, instead of job productivity. However, since the turn of the 21st century there has been a growing interest in flexible payment systems linking remuneration and performance. Almost half of the 27 Brazilian states have already implemented PFP systems for educational employees (Scorzafave et al., 2015).[54]

In spite of this fast growth, rigorous empirical evaluations of the impact of the Brazilian bonus programs on students' performance remain extremely limited.[55] This reduced number of empirical evaluations of the teacher bonus in Brazil has a great deal to do with the data limitations, since no assessment process was implemented together with the bonus programs (Bresolin, 2014). To address this data restriction, the current paper will conduct an ex-post impact evaluation based on a quasi-experimental design. To that end, the analysis focuses on schools within a single city in Brazil in order to create, as far as possible, similar treatment and comparison groups in terms of baseline (pre-intervention) characteristics.

In this paper I apply panel data from the Longitudinal Study of Quality and Equity in Brazilian Elementary Education (GERES), which tracked academic outcomes of 21,529 students enrolled in more than 300 schools during their first four years of primary education, recording the performance of these pupils in five different waves in the subjects Portuguese language (reading) and Math. GERES was a project conducted independently of the government by a group of Brazilian universities, and

[53] Making a review of the US and international evidence on the effectiveness of teacher pay on student academic achieviements, Hanushek (2003) for example reports that only 20 percent of 119 estimates found a positive effect of teacher wages on school performance.

[54] The Brazilian states with bonus programs for educational employees are: Acre, Amazonas, Ceará, Espírito Santo, Goiás, Minas Gerais, Paraíba, Pernambuco, Rio de Janeiro, Roraima, São Paulo, Sergipe, and Tocantins (Scorzafave et al., 2015).

[55] To the best of my knowledge, only Lepine (2016) and Oshiro et al. (2015) presented empirical evidence of PFP program's effects on student achievements for Brazil (see section 3.2).

its proficiency tests were not used to calculate the teacher bonus.[56] Since GERES collected data both in schools where a teacher bonus program had been implemented (state education network) and in schools outside the program (municipal and private network), the current paper utilizes a quasi-experimental setting in which the introduction of the incentive pay was treated for a subgroup of (state) schools.

This paper will evaluate the impact of teacher bonuses on students from the city of Campinas in the state of São Paulo. In October 2007, São Paulo launched the cornerstone for a merit-pay program in which all employees in the (state) educational system are eligible for an (annual) bonus of up to 2.9 times their (monthly) salary. The determining factor for the calculation of the additional pay is the performance improvement of students in the given school. Given that Brazilian law allows state, municipal, and private schools to operate in the same city, the implementation of teacher bonuses exclusively within the state education network created a perfect scenario for investigation. In this paper, the impact evaluation of the teacher bonus will be carried out using the students enrolled in state schools as treatment group, whereby the pupils from municipal schools are used as a reference point.[57]

The main empirical findings of this study indicated that the implementation of the performance-based bonuses to teachers in the state schools of São Paulo had no statistically significant impact on the performance of students in Math and Portuguese. In the first year of the bonus program, the test scores in treatment (state) schools were slightly lower than those in comparison (municipal) schools (-0.016 standard deviation for Portuguese and -0.041 SD for Math). But none of this variation was statistically significant. The results from alternative specifications, placebo tests, and robustness checks also support these main findings.

The remainder of the paper is structured as follows. Section 3.2 discusses key theoretical underpinnings for this study. The next section provides background information on the teacher bonus program of the state of São Paulo. Section 3.4 outlines the data and research design used for the estimates, and the subsequent section describes the estimation strategy. Section 3.6 presents the main empirical results, section 3.7 the alternative specifications, section 3.8 the placebo tests, and section 3.9 the robustness checks. Finally, the last part of this paper concludes.[58]

3.2 Literature Review

The impact of teacher merit-pay programs on student performance remains a central concern for the public sector worldwide, since the existing literature on this topic presents mixed empirical evidence. While some studies suggest that the implementation of teacher bonuses had a positive impact on the performance of students (see e.g. Britton and Propper, 2016; Dee and Wyckoff, 2015; Duflo et al., 2012; Imberman and Lovenheim, 2015; Lavy, 2009; Loyalka et al., 2019; Muralidharan and Sundararaman, 2011), other papers could not confirm this association (see e.g. Barrera-Osorio and

[56] The calculation of the teacher bonus in the state of São Paulo is based on the student test scores in the government standardized exam known as SARESP (Evaluation System of Learning Achievement in the State of São Paulo). See appendix for more information on SARESP.

[57] As Table 3.5 shows, the (treatment and comparison) groups present very similar indicators concerning student performance, school infrastructure, and staff characteristics. See section 3.4 for a more in-depth explanation of these descriptive statistics, and the appendix for a comprehensive overview of the major competencies of states and municipalities regarding the education system.

[58] This paper is supplemented by an appendix with further valuable data related to the education system of São Paulo state, GERES database, formal description of the estimators, and additional tables and figures.

Raju, 2017; Behrman et al., 2015; Glewwe et al., 2010; Springer et al., 2012; Yuan et al., 2013).

Despite increasing interest in the last few years, available rigorous evidence on the impact of teacher merit programs in developing countries continues to be underrepresented in the literature. Exceptions to this limitation are the works of Loyalka et al. (2019) for China, Barrera-Osorio and Raju (2017) for Pakistan, Behrman et al. (2015) for Mexico, Duflo et al. (2012) and Muralidharan and Sundararaman (2011) for India, and Glewwe et al. (2010) for Kenya. The evidence for Brazil is also rarely reported. To the best of my knowledge, all the empirical investigations relating to this topic are limited to the studies of Lepine (2016) and Oshiro et al. (2015), which examined the teachers bonus program of the state of São Paulo using data from the standardized performance test called "Brazil Exam" (*Prova Brasil*). Applying a difference-in-difference (DiD) approach in which the students from municipal schools were the comparison group, Lepine (2016) finds that the bonus program had positive effects on student achievement. A similar study by Oshiro et al. (2015), however, shows mixed results in assessing the impact of teacher bonuses through propensity score matching and DiD. According to the authors, the bonus had positive and significant effects on Math tests (0.42 standard deviation) and Lecture tests (0.14 standard deviation) for the fourth grade between 2007 and 2009, but no effects were found for the eighth grade of elementary school.[59]

A feasible explanation for the mixed findings in the literature is the diversity of empirical strategies applied to estimate the effectiveness of merit-pay programs on education achievements. Empirical studies using cross-sectional data, like the Brazil Exam, are not above criticism because the data structure does not enable control for fixed and random effects (Loeb and Page, 2000). For this reason, the vast majority of articles in top-tier peer-reviewed journals uses panel data for the impact evaluation, in which the academic performance of students is collected before and after the implementation of the PFP program (see e.g. Barrera-Osorio and Raju, 2017; Behrman et al., 2015; Britton and Propper, 2016; Dee and Wyckoff, 2015; Imberman and Lovenheim, 2015; Lavy, 2009; Loyalka et al., 2019; Yuan et al., 2013).

In this context, randomized controlled trial (RCT) experiments have earned a well-respected reputation to determine the causal effect of teacher bonus programs. When students are randomly assigned to treatment and control groups, researchers make sure that the possible changes in student performance by the treatment group will have nothing to do with any individual characteristics, but only reflect the impact of the bonus (Gertler et al., 2016). Among the randomized experiments investigating the impact of performance pay for teachers, we can highlight the empirical studies of Loyalka et al. (2019) for China, Barrera-Osorio and Raju (2017) for Pakistan, Muralidharan and Sundararaman (2011) for India, Glewwe et al. (2010) for Kenya and Fryer (2013), Goodman and Turner (2013), and Springer et al. (2012) for the US.

Despite the increasing use of RCTs for the evaluation impact of teacher bonuses, it is important to underline that the application of those studies presupposes that the random assignment occurs before the public intervention (Petrou and Gray, 2011), which in many situations—as in the case of the Brazilian bonus programs—is not possible, since the intervention has already happened. Then, in such cases, the use of a quasi-experimental design with a DiD approach is a way of getting around the non-random assignment, since the "common trends" assumption assumes that in absence

[59]Another study worth mentioning is Scorzafave et al. (2015), which investigated the impact of bonus programs on the proficiency inequality of students from elementary schools. Using data from the Brazil Exam, the paper confirmed an increase in proficiency inequality in schools that adopted the teacher bonus policies.

of treatment (the implementation of the bonus) the difference in student test scores between control and treatment groups would be constant over time (Deschenes and Meng, 2018).

Therefore, the methodology employed in this paper is closely related to the studies of Britton and Propper (2016) for England and Imberman and Lovenheim (2015) for the US and Lavy (2009) for Israel, which apply a nonrandom sorting of students to examine the effects of teacher merit-pay programs on school performance. As I will do in this paper, these authors also use value-added models in order to exclude the effects of the (initial) student ability from the evaluation of the bonus. Including the lagged student achievement as control variable in the investigation, the studies made sure that the empirical model will estimate the impact of bonuses as a function of student test-score growth and not individual ability in general (Hanushek and Rivkin, 2012).

3.3 The Teacher Bonus Program

Over the last few decades, the so-called pay-for-performance programs have gained increased importance as a tool for quality improvement in the Brazilian education system. In 2007 Amazonas became the first state to implement a bonus system in order to motivate teachers to increase their efforts in teaching activities. In subsequent years, this example was followed by many other states (Scorzafave et al., 2015). Consequently, to date 13 of the 27 Brazilian states have a performance-pay system for school employees. However, due to the administrative autonomy guaranteed by the Constitution of 1988, each Brazilian state has full independence to implement and consolidate its educational-legal framework, which has had the effect of creating divergent legal bases for the calculation of teacher premiums.[60]

The PFP program for teachers in the state of São Paulo, which will be the object of this study, started in the 2008 academic year.[61] In April 2009, the state paid the bonus for the first time, distributing 590.6 million Brazilian reais (BRL)—which was equivalent to approximately USD 260 million at that time—among 195,504 educational professionals, around 82 percent of them teachers. This merit-pay program is a yearly financial bonus paid to all employees of the São Paulo State Secretariat of Education (SEE-SP) according to the achievement of targets relating to the Education Development Index of the State of São Paulo (IDESP), which establishes individual targets for each school annually (Bresolin et al., 2018).[62] The IDESP is a synthetic indicator of education quality calculated per school on the basis of two components: student performance and academic passing rate. While the latter refers to the share of students who have completed all grades "on time," performance is assessed using scores in SARESP, which is an annual (compulsory) standardized test of Mathematics and Portuguese for all students in Grades 3, 5, 7, 9 of primary school, as well as those in the final year of secondary education (Oshiro et al., 2015).[63]

[60]See appendix of this paper for a more detailed description of the Brazilian education system.

[61]The teacher-incentive system in São Paulo was introduced by Law No. 1,017 of October 15, 2007, and supplemented by Decree No. 52,719 of February 14, 2008 and Law No. 1,078 of December 17, 2008. See Figure 3.1 in the appendix for a chronological presentation of the most important issues relating to the implementation of the teacher bonus in the state of São Paulo.

[62]The SEE-SP is the government agency responsible for operating all state-run schools in the state of São Paulo, and it manages the largest education system in Brazil, with around 5,400 schools and 3.7 million students, corresponding to 36 percent of the total student population in the country (INEP, 2019b).

[63]The appendix of this paper provides a more comprehensive description of IDESP, presenting its formal composition and calculation methodology.

According to the definition of education quality used by the SSE-SP, a good school is one in which two objectives are connected: first, that the students learn the skills and competencies required for their respective classes and, second, that this learning process takes place in the expected time. For this reason, IDESP combines the student performance and academic passing rate in a balanced manner, creating an important trade-off for the schools: Schools have a strong incentive to hold back the students with low proficiency levels in order to avoid a reduction in the schools' average SARESP scores. But at the same time, the retention of pupils in the same grade will negatively affect the academic passing rate, thereby undermining the overall IDESP index (SSE-SP, 2018).

The distribution of bonuses is linked to the IDESP improvement that takes place during the period considered (school year), and the targets for the following year are established based on IDESP reached in the current year. Since the management of IDESP is done individually per school, the teacher bonus is a group-based incentive at the school level, meaning that there is no reward calculated individually per worker, but all employees based in the school are remunerated at the same rate. Therefore, the total value of bonus payments received by school staff members will be proportionate to the achievement of the school's goals. Schools that achieve 100 percent of the target will receive 100 percent of the bonus, equivalent to an additional payment of 20 percent of the annual salary of the employees. The schools with 50 percent goal achievement will earn 50 percent of the bonus (10 percent of the annual salary), and so on. Schools that exceed their target can receive a bonus up to 120 percent, and no penalty will be applied for schools in which IDESP performance declines from the prior year or remains constant.[64]

3.4 Data, Sample, and Research Design

3.4.1 Data and Sample

The empirical analyses of this paper are based on the database from GERES. Starting in 2005, this project followed a group of 21,529 students enrolled in 309 (municipal, state, and private) schools throughout their first four years of primary education, creating panel data of student performance. GERES was a public-private-funded project developed and implemented by a consortium of six Brazilian universities with the goal of monitoring the proficiency of students in Mathematics and Portuguese (reading) over time in five Brazilian municipalities: Belo Horizonte, Campinas, Campo Grande, Rio de Janeiro, and Salvador.[65]

After deciding which cities should be involved in the project, sampling techniques were employed to guarantee the representativeness of the school's selection. First, a probabilistic sample of schools was determined for each municipality using the 2003 school census as a base. Then, within the selected schools, all the students enrolled in the first year of primary education were selected to participate in the project and monitored throughout their first four years of schooling (2005–2008).

In total, the GERES sample covered 10 percent of all schools located in the selected cities, but—in order to ensure transparency—some important caveats of the

[64] Besides student performance and passing rate, the SEE-SP considers two additional components for the management of the target system: teacher attendance and the socioeconomic status of the school. See appendix of this paper for a formal presentation of the mathematical method behind the Indicator for Realization of Targets, the index used to calculate the teacher bonus.

[65] The GERES database is not publicly accessible. Permission requests should be submitted to the members of the project via GERES homepage.

sample selection need to be acknowledged. From the complete list of schools in the cities, GERES excluded from the sample all schools located in rural areas, schools with only multiple-grades classes in the first grade, schools with first-grade pupils attending exclusively evening classes, as well as public schools with fewer than 20 students enrolled in the first year of compulsory education, and private schools with fewer than 10 students in the first grade or with more than three classes devoted to the students from the first grade.[66]

Figure 3.1 presents the timing of data collection for the GERES waves, the academic years, and the implementation schedule for the bonus program in the state of São Paulo. Note that the so-called GERES students were evaluated five times in terms of Math and Portuguese standardized academic tests.[67] Because the school calendar in Brazil starts in late February and ends in November, the first GERES wave was conducted in March 2005 in order to measure the skills and abilities of children at the beginning of schooling; thereafter, the tests were carried out at the end of the academic years—respectively in November 2005, 2006, 2007, and 2008—in order to calculate the level of learning achieved in the respective period.

Aside from taking the standardized academic tests, the students were asked to provide comprehensive information on themselves (gender, race, learning motivation, family structure) and their families. A second version of the questionnaire on family background was filled in by the parents of the children focused on the socioeconomic status of the family, presenting data on income, educational level, and professional activity of parents, as well as on the existence of durable goods in the household, such as car, refrigerator, TV, computer, and so on.

In addition, GERES collected extensive data from the school principals and teachers. The last dataset covered all teachers involved in the project and included items on their professional qualifications, teaching methods, personal behavior, and expectations of student performance. In the same way, the school principals were invited to answer questions regarding their education and work experience, but also items that may moderate the performance of students, such as infrastructure of the schools, the selection process for staff, and the professional culture at the school.[68]

Because Campinas is the only city from the GERES sample located in the state of São Paulo, where the teacher bonus program was introduced, I restrict the following empirical analyses in this paper to the schools situated in Campinas. For Campinas GERES has tracked the performance of 4,881 students from 189 different classes in 60 schools (see Table 3.5). Figures 3.2, 3.3, and 3.4 present the distribution of test scores by GERES in Math and Portuguese, allowing for a detailed analysis of the common trends' assumption. Note that in both subjects, pupils enrolled in state and municipal schools achieved similar test scores over time, but their performance was lower than those from private schools.[69] This difference had already appeared at the beginning of schooling and persisted over time, however with different trends:

[66]Multiple-grades classes are classes in which the students from different grades (and ages) study together in a same classroom under the same teacher. Evening classes are classes held in the evenings (starting from 4 p.m.), normally for adults. Please see appendix for more detailed information on the sample construction.

[67]External students who migrated to GERES classes were included in the sample and participated in the subsequent academic tests of the project, while GERES students who left the participating schools became missing values for the subsequent tests. Students who repeated one or more school years continued to participate in the tests regardless of their achievement.

[68]See appendix of this paper for more information about the GERES database, or Brooke and Bomamino (2011) for the complete description of the methodology applied in GERES, or Franco et al. (2008) for a summary overview.

[69]By constructing the scales of proficiency, GERES used the Item Response Theory (IRT) to equalize the scales for the different years of schooling. See appendix for further information on IRT.

for Portuguese the gap in performance between public and private schools remained constant over time, while for Math it increased considerably.[70]

Table 3.5 reports the descriptive statistics and independent *t*-tests for all the variables used for the estimates in section 3.6. For case of ease viewing, I display the data individually by state, municipal, and private schools, and estimate *t*-tests to compare the means between the groups. Note that the state and municipal schools have similar statistics regarding the characteristics of their students, teachers, and infrastructure. The data from private schools differ widely from those of state and municipal ones, since the private schools present on average better infrastructure and students with a higher socioeconomic status.

3.4.2 Quasi-Experimental Design

The ex-post impact evaluation carried out in this paper is based on a quasi-experimental design using schools from the city of Campinas, which is located in the state of São Paulo and situated approximately 62 miles from the state capital.[71] According to the latest data from the Brazilian Institute of Geography and Statistics (IBGE), Campinas has a population of 1,204,073, making it the third-most populous municipality in São Paulo state and the fourteenth-most in Brazil.

In agreement with the last school census (see INEP, 2019b), the Campinas school district with its approximately 238,000 students is the third-largest district in the state of São Paulo.[72] In 2018 the system was composed of 658 schools, whereby around half of them were primary schools (Grades 1–9) with 6,720 assigned teachers (61 percent of the total) and 123,678 students (52 percent of the total). Empirical evidence from large-scale evaluations of educational achievement showed that the quality of public schooling in Campinas—measured by academic achievement and pass rate—is very similar to the average value in the state of São Paulo, but higher than the mean for Brazil.[73] The same indicators confirm the trend already shown by the GERES dataset: the performance of students enrolled in public schools is lower than those from private schools (see INEP, 2019a).

Due to the strong differences in the characteristics of public and private schools described above, this paper excludes students from private schools from the following empirical investigations in order to create, as far as possible, very similar treatment and comparison groups. Therefore, I apply a DiD approach in which the 2,158 students from state schools are the treatment and the 1,919 pupils from municipal schools the comparison group. Since the GERES project collected the academic performance of the participants between the years of 2005 and 2008, I integrate into the DiD the test scores of four waves before and one wave after the implementation of the teacher bonus program.

[70] For Math, the score gap between state and private schools rose from 26 points in wave 1 to 69 points in wave 5, while for Portuguese it stayed constant over time at around 25 points.

[71] I use the expression "quasi-experimental design" for this approach because it is structured like an experimental design, but it lacks the key feature of the latter—namely random assignment. Quasi-experimental design is also called Non-Equivalent Groups Design (NEGD) and is always applied for ex-post impact evaluations, given that after the intervention it is no longer possible to randomly assign individuals to treatment and control groups (White and Sabarwal, 2014).

[72] Of the 238,314 pupils enrolled in the Campinas school system in 2018, 46 percent were enrolled in state, 24 percent in municipal, 1 percent in federal, and 29 percent in private schools (INEP, 2019b).

[73] The "Índice de Desenvolvimento da Educação Básica" (IDEB) is the most important assessment system for educational quality in Brazil, sorting schools according to a scale ranging from 0 (bad) to 10 (excellent). In 2017 the IDEB value of public schools in Campinas was 6.57, compared with 6.60 for the state of São Paulo and 5.94 for the whole country (see INEP, 2019a).

3.5 Estimation Strategy

The evaluation of the impact of teacher bonuses in this paper is based on the educational production function, which is widely used in the literature as the empirical framework to investigate student achievement (Hanushek and Rivkin, 2012):[74]

$$\mathbf{P}_{ijst} = f\,(\,\mathbf{B}_i, \mathbf{S}_i, \mathbf{C}_i, \mathbf{A}_i\,) \tag{3.5.1}$$

where $\mathbf{P}_{ijst}$ denotes the academic performance of student i in school j on subject s at time t and is defined as a function of $\mathbf{B}_i$ representing student background characteristics, $\mathbf{S}_i$ school inputs, $\mathbf{C}_i$ teacher and class inputs, and $\mathbf{A}_i$ the initial ability of student i. For brevity's sake, I aggregate all variables presenting in $\mathbf{B}_i$, $\mathbf{S}_i$, and $\mathbf{C}_i$ into a single vector $\mathbf{X}'_{ijst}$.[75] Then, the reduced form for the linear model with the panel structure is:

$$\mathbf{Y}_{ijst} = \alpha + \beta\mathbf{X}'_{ijst} + \varphi A_i + \epsilon_{ijst} \tag{3.5.2}$$

with $\mathbf{Y}_{ijst}$ denoting the score achieved in the GERES proficiency tests, and ϵ_{ijst} being the stochastic term adding to the model all the unobservable inputs affecting student performance.

The estimation of equation (3.5.2) will generate biased results if the error term ϵ_{ijst} is correlated with the explanatory variables in $\mathbf{X}'_{ijst}$. Endogeneity problems will occur, for example, if the locality of a student's residence affects school choice, or if schools are able to select students based on their academic achievement or socioeconomic status. Given that empirical evidence has already indicated the existence of these links in Brazil (see e.g. Alves et al., 2015; Bartholo, 2013), this paper follows Imberman and Lovenheim (2015), Schwerdt and Wuppermann (2011), and Woessmann and West (2006) and uses school-fixed effects to account in the empirical model for the nonrandom sorting of students into classrooms. In addition, I include time-fixed effects to control the estimations for variables that changed over time but not across schools, such as public policies or regulations (Deschenes and Meng, 2018). Therefore, I set out a three-way error component for the stochastic term:

$$\epsilon_{ijst} = \mu^j + \mu^t + \nu_{ijst} \tag{3.5.3}$$

with $\nu_{ijst} \sim IID(0, \sigma^2_\epsilon)$, and μ^j and μ^t representing a set of school and time-fixed effects respectively.

One important peculiarity of the educational production function is its cumulative character over time (see e.g. Andrabi et al., 2011; Britton and Propper, 2016; Hanushek, 2002). The student achievement at time t depends not only on the educational inputs applied during t, but also the sum of all inputs that have already been integrated into the student-learning process plus the initial ability A_i (Rothstein, 2010; Todd and Wolpin, 2003). Then, from a policy point of view, it is important to isolate the gain in student performance over the time periods and relate them to their respective inputs (Andrabi et al., 2011; Hanushek and Rivkin, 2012). Assuming that the educational achievements accumulate over time T, and the importance of the prior inputs for current student performance depreciates over time at a constant rate θ, equation (3.5.2) can be rewritten as:

[74] The crucial theoretical foundations for the educational production function were developed by Boardman and Murnane (1979), Hanushek (1971, 1979), Margo (1986), and Summers and Wolfe (1977). See Hanushek (2002, 2008), Pritchett and Filmer (1999), and Todd and Wolpin (2003) for a more detailed analysis of the educational production function.

[75] Table 3.5 lists the explanatory variables used in the model and their descriptive statistics.

$$\mathbf{Y}_{ijst} = \sum_{t=0}^{T} \alpha(1-\theta)^{T-t} + \sum_{t=0}^{T} \beta \mathbf{X}'_{ijst}(1-\theta)^{T-t} + \sum_{t=0}^{T} \varphi A_i(1-\theta)^{T-t} + \sum_{t=0}^{T} \epsilon_{ijst}(1-\theta)^{T-t} \tag{3.5.4}$$

Following Hanushek and Rivkin (2012), equation (3.5.4) can be broken down into current ($t = T$) and previous factors ($t = T - 1$), such as:

$$\begin{aligned}\mathbf{Y}_{ijst} = {} & \underbrace{\alpha + \beta \mathbf{X}'_{ijst} + \varphi A_i + \epsilon_{ijst}}_{\text{current}} \\ & \underbrace{+\sum_{t=0}^{T-1} \alpha(1-\theta)^{T-t} + \sum_{t=0}^{T-1} \beta \mathbf{X}'_{ijst}(1-\theta)^{T-t} + \sum_{t=0}^{T-1} \varphi A_i(1-\theta)^{T-t} + \sum_{t=0}^{T-1} \epsilon_{ijst}(1-\theta)^{T-t}}_{\text{previous}}\end{aligned} \tag{3.5.5}$$

The empirical estimation of equation (3.5.5) is faced with two main challenges: the integration of longitudinal data tracking the independent variables for all time periods before t, and the need to quantify the initial ability of children before school enrollment. Due to the difficulty of dealing with these conditions, empirical works make use of the value-added strategy. Given that the relationship in (3.5.5) holds true over time, the previous determinants of performance can be reduced to $(1-\theta)\mathbf{Y}_{ijs,t-1}$, indicating that the student's achievement in time $t-1$ is a reliable proxy for the prior inputs and initial ability involved in the learning process of pupils (Andrabi et al., 2011; Hanushek and Rivkin, 2012; Rothstein, 2010).

By assuming that the current academic performance of students can be determined as a function of the (depreciated) lagged test scores and the current factors affecting their performance in period t, the lagged value-added model is:

$$\mathbf{Y}_{ijst} = \alpha + \pi(1-\theta)\mathbf{Y}_{ijs,t-1} + \sum_{t=0}^{T} \beta \mathbf{X}'_{ijst} + \epsilon_{ijst} \tag{3.5.6}$$

Therefore, the DiD approach to estimate the intent-to-treat effects of teacher bonuses is:

$$\mathbf{Y}_{ijst} = \alpha + \phi Treated + \gamma Post + \delta(Treated \times Post) + \pi(1-\theta)\mathbf{Y}_{ijs,t-1} + \sum_{t=0}^{T} \beta \mathbf{X}'_{ijst} + \epsilon_{ijst} \tag{3.5.7}$$

where $Treated$ is a dummy variable indicating the treatment group (1 if state schools) and $Post$ a time dummy equal to 1 if the incentive pay is implemented (2008). Consequently, the parameter of interest, δ, is the interaction term between the dummies for treatment group and post-exposure period, indicating the variation in student achievement that has resulted from the implementation of the teacher bonus. In this case, the value-added model ensures that the impact of the bonus in equation (3.5.7) is estimated as a function of student test score growth—occurring between the periods pre- and post-bonus implementation—and not student achievement levels.

3.6 Baseline Results

In this section, the results are estimated separately for Mathematics and Portuguese. Students are indexed $i = 1, \ldots, N$ and observed once per period $t = 1, \ldots, T$ in school $j = 1, \ldots, J$. The data are strongly balanced with $N^* = \sum_{i=1}^{N} T_i$ observations (student periods) in total, and for each observation the set of explanatory variables presented in Table 3.5 is available. Since the teacher bonus program was implemented only within the state education network, I use the 2,158 students enrolled in state schools as the treatment, and the 1,919 pupils from municipal schools as the comparison group. Post-treatment are the test scores achieved in November 2008, pre-treatment are the scores from 2005 to 2007.

Because the performance of students on GERES presents an increasing scale of scores over time (see Figure 3.2), I standardize the test scores within year and subject to have a unit variance with mean 0 and standard deviation 1, therefore the estimated coefficients need to be interpreted as a unit of a standard deviation. To check the sensitivity of the results, the estimates are based on two different models: ordinary least squares (OLS) and fixed effects (FE). While the OLS ignores the panel structure of the data, the FE models identify the longitudinal nature of GERES and control for school- and time-fixed effects.[76] Finally, standard errors are robust and clustered at the class level, given the correlation in student performance within classes.

Table 3.1 presents the coefficient for the DiD estimator, which refers to the parameter of interest, δ, in equation (3.5.7) and tell us whether the teacher bonus program has generated any effect on the performance of students. I first consider omitting the dynamic structure of the educational production function and estimate in columns (1) and (2) the empirical model with no lagged dependent variable. Then, column (3) reports the results of the full-lagged value-added model, thereby controlling the model for the individual academic ability of students.[77]

In its first year of implementation, the PFP program in the state of São Paulo generated no statistically significant impact on the performance of students for both Math and Portuguese. This result is relatively robust for the model specifications with and without the covariates reported in Table 3.5. The OLS estimates even present statistically significant values for the DiD; however, they are caused by a lack of control for the unobserved heterogeneity and the poor fit of the model (see R-square). The analysis of results reveals an increase in the goodness of fit between the OLS and FE, confirming that the panel structure and the consequent controlling for fixed effects is crucial for the identification strategy. The control for prior student achievement in column (3) helps even more with regard to the explanation of the variance in student performance, increasing considerably the model's fit. With a S-square close to 0.6, the value-added models indicate no statistically significant coefficients for the DiD, confirming that after the bonus scheme's implementation, students from state schools in Campinas achieved no different performance in (Math and Portuguese) proficiency tests than their peers from municipal schools.

[76]This paper follows the standard approach used in the literature (see e.g. Barrera-Osorio and Raju, 2017; Britton and Propper, 2016; Imberman and Lovenheim, 2015; Loyalka et al., 2019) and does not include individual fixed effects in the investigation. The introduction of individual fixed effects in a value-added model causes a series of econometric concerns in relation to endogeneity, given that the lagged test score is correlated with the error term. This occurs because the demeaning process for the estimation of the individual fixed effect creates a correlation between regressor and error term, biasing the coefficients downward (Nickell, 1981).

[77]The difference in the number of observations between columns (2) and (3) refers to the missing values regarding the lagged dependent variable included in the dynamic specification.

Table 3.1. Impact of Teacher Bonuses on Student Performance

Panel A: Portuguese

	No Control Variables			With Control Variables		
	OLS	FE	FE	OLS	FE	FE
	(1)	(2)	(3)	(1)	(2)	(3)
DiD	-0.286***	-0.009	-0.007	-0.070	-0.010	-0.016
	(0.101)	(0.065)	(0.033)	(0.079)	(0.062)	(0.038)
$\mathbf{Y}_{t-1}$	-	-	0.756***	-	-	0.703***
			(0.010)			(0.014)
No. Observations	19,611	19,611	12,244	6,489	6,489	4,511
No. Clusters	746	746	691	363	363	359
R-square	0.039	0.288	0.630	0.230	0.288	0.601
Control variables	No	No	No	Yes	Yes	Yes
Fixed effects	No	Yes	Yes	No	Yes	Yes
Lagged values	No	No	Yes	No	No	Yes

Panel B: Mathematics

	No Control Variables			With Control Variables		
	OLS	FE	FE	OLS	FE	FE
	(1)	(2)	(3)	(1)	(2)	(3)
DiD	-0.255***	-0.006	-0.016	-0.046	0.017	-0.041
	(0.098)	(0.063)	(0.042)	(0.082)	(0.064)	(0.048)
$\mathbf{Y}_{t-1}$	-	-	0.714***	-	-	0.665***
			(0.010)			(0.014)
No. Observations	19,520	19,520	12,103	6,461	6,461	4,446
No. Clusters	746	746	687	363	363	357
R-square	0.034	0.253	0.598	0.199	0.256	0.585
Control variables	No	No	No	Yes	Yes	Yes
Fixed effects	No	Yes	Yes	No	Yes	Yes
Lagged values	No	No	Yes	No	No	Yes

Notes: Dependent variable is student performance (test scores), which are normalized to mean 0 and standard deviation 1. Control variables include the full set of explanatory variables presented in Table 3.5. Fixed effects control for the average differences across schools and years. Data are not nested within schools. Standard errors are robust to heteroskedasticity and clustered at class level. t statistics in parentheses. $*p < 0.1, **p < 0.05, ***p < 0.01$.
Source: GERES database (2005–2008), own estimates.

3.7 Alternative Specifications

The primary identification strategy presented in the previous section was concentrated on the investigation of state versus municipal schools in Campinas in order to reduce the effects of unobserved heterogeneity on the results. This section will relax this restriction and expand the analysis to two larger comparison groups. The first one applies the same research design—focused on the students from Campinas—as in the section before, but uses as comparison group the 804 students enrolled in private schools there. While the later expands the DiD analysis to all cities involved in the GERES project, it limits the estimations to students enrolled in state schools. Therefore the treatment group continues to be formed by pupils from state schools in Campinas, but we have as a control group students enrolled in state schools in all other GERES cities.[78]

Table 3.2 presents the results from this exercise. For reasons of brevity, it reports only the estimates for the full-lagged value-added model from equation (3.5.7). While columns (1) and (3) refer to the model with no control variables, columns (2) and (4) integrate the full set of explanatory variables presented in Table 3.5.

Table 3.2. Alternative Specifications of the Research Design

	(A) State vs. private Schools				(B) Campinas vs. other Cities			
	Portuguese		Mathematics		Portuguese		Mathematics	
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
DiD	-0.020	0.035	0.032	0.051	-0.018	0.099	0.079	0.158
	(0.035)	(0.045)	(0.043)	(0.059)	(0.047)	(0.072)	(0.056)	(0.092)
$\mathbf{Y}_{t-1}$	0.719***	0.686***	0.695***	0.673***	0.740***	0.701***	0.678***	0.671***
	(0.011)	(0.016)	(0.012)	(0.015)	(0.011)	(0.018)	(0.012)	(0.017)
No. Observations	8,939	4,062	8,875	4,019	9,647	3,075	9,598	3,024
No. Clusters	492	299	488	298	626	270	625	269
R-square	0.687	0.683	0.669	0.681	0.628	0.612	0.591	0.601
Control variables	No	Yes	No	Yes	No	Yes	No	Yes
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lagged value	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Specification A concentrates the investigation on Campinas estimating the DiD between state schools (treatment group) and private schools (control). Specification B expands the DiD analysis to all GERES students enrolled in state schools, in which 1 are students from Campinas and 0 otherwise. Dependent variable is student performance (test scores), which are normalized to mean 0 and standard deviation 1. Control variables include the full set of explanatory variables presented in Table 3.5. Fixed effects control for the average differences across schools and years. Data are not nested within schools. Standard errors are robust to heteroskedasticity and clustered at class level. t statistics in parentheses. $*p < 0.1, **p < 0.05, ***p < 0.01$. Source: GERES database (2005–2008), own estimates.

The empirical findings presented in Table 3.2 are very similar to those of the previous section. Both specifications reveal no statistically significant impact of teacher bonuses on the performance of students. In specification A, the use of the private schools in the comparison group changes the sign of the DiD coefficients for Math and Portuguese—indicating that the teacher bonus program had a positive impact on test scores. The same trend can be found with specification B too—comparing the students enrolled in state schools in Campinas with their peers from other GERES cities. Note that after the implementation of the bonus scheme, students from (state schools in) Campinas achieved a 0.099 SD higher performance in Portuguese than their peers from the other GERES municipalities. However, as in section 3.6, none of these changes were statistically significant.

3.8 Placebo Tests

To check the reliability of the findings presented above, this section will apply falsification tests, replicating the exact same identification strategy employed in section 3.6, but using outcomes that are known to be unaffected by the implementation of the teacher bonus program. The placebo tests are based on two different specifications. For the first ("fake" implementation date), I run the placebo test by redoing the same analysis—on state and municipal schools in Campinas—using a year in which the teacher bonus scheme had not yet been implemented (2007). In the second specification, the DiD is based on a "fake" treatment group that was not exposed to the bonus program. In this case, the same implementation timetable as in section 3.6 was

[78] Students from Belo Horizonte were excluded from the specification B, because in 2008 the state of Minas Gerais, where the city is located, also implemented a teacher bonus program.

assumed, but I exclude students from Campinas from the investigation and apply the research design "state vs. municipal schools" for all other GERES students.[79]

Table 3.3. Placebo Tests

	Fake Implementation Date				Fake Treatment Group			
	Portuguese		Mathematics		Portuguese		Mathematics	
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
DiD	-0.037	-0.062	0.053	-0.028	-0.012	-0.073	0.031	-0.055
	(0.038)	(0.059)	(0.044)	(0.060)	(0.045)	(0.076)	(0.052)	(0.090)
$\mathbf{Y}_{t-1}$	0.721***	0.664***	0.675***	0.620***	0.719***	0.686***	0.670***	0.662***
	(0.012)	(0.019)	(0.012)	(0.019)	(0.008)	(0.014)	(0.008)	(0.016)
No. Observations	9,133	3,019	9,004	2,952	22,437	4,268	22,284	4,236
No. Clusters	498	265	494	263	1,745	530	1,747	530
R-square	0.608	0.565	0.583	0.553	0.539	0.573	0.483	0.510
Control variables	No	Yes	No	Yes	No	Yes	No	Yes
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lagged value	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The first placebo test performs the DiD analysis with a fake date for the implementation of bonus (2007 instead of 2008). The second one uses a fake treatment group expanding the investigation to all GERES students with the exception of those from Campinas and Belo Horizonte, being pupils enrolled in state (municipal) schools the treated (control) group. Dependent variable is student performance (test scores), which are normalized to mean 0 and standard deviation 1. Control variables include the full set of explanatory variables presented in Table 3.5. Fixed effects control for the average differences across schools and years. Data are not nested within schools. Standard errors are robust to heteroskedasticity and clustered at class level. t statistics in parentheses. $*p < 0.1, **p < 0.05, ***p < 0.01$.
Source: GERES database (2005–2008), own estimates.

As in the section before, Table 3.3 also focuses on the coefficients of the full-lagged value-added model from equation (3.5.7). Once again, both specifications reveal no significant difference between the treatment and the comparison groups. Therefore, the placebo tests show that an impact from the teacher bonus program on student achievement does not exist when it "should not" exist. Note that the DiD coefficients are relatively low, and not statistically insignificant.

3.9 Robustness Checks

The empirical findings presented so far have confirmed that the implementation of the teacher bonus program had no impact on the performance of students in Math and Portuguese. To confirm the robustness of this evidence, I now change the estimation procedure used for the empirical investigation of the bonus scheme's impact in order to check whether the results remain the same. Therefore, this section estimates the equation (3.5.7) using generalized method of moments (GMM) estimations. In contrast to the standard models used previously (OLS and FE) that do not control for individual fixed effects, the GMM models apply first-difference transformation and instrumental variables to automatically eliminate time-invariant characteristics (gender, race, parental education, etc.), and student fixed effects in the error terms (see e.g. Kripfganz and Schwarz, 2019; Wooldridge, 2016).

Table 3.4 reports the empirical results from equation (3.5.7) using the classic Arellano and Bond (1991) difference GMM estimator, where the instruments are used as moment conditions. However given that the educational achievements by GERES schools strongly persist over time, the table presents also the findings from the Blundell and Bond (1998) system GMM estimator in order to increase the precision of

[79] Specification 1 ("fake" date) excludes the test scores from the year 2008 from the investigation, while specification 2 excludes students from Belo Horizonte, because the state of Minas Gerais also implemented a PFP program for officials employed in state schools from 2008 onward.

Table 3.4. Robustness Checks

	Difference GMM				System GMM			
	Portuguese		Mathematics		Portuguese		Mathematics	
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
DiD	0.025	0.027	0.012	-0.008	0.018	-0.005	-0.030	-0.073
	(0.028)	(0.039)	(0.039)	(0.056)	(0.035)	(0.042)	(0.056)	(0.070)
$\mathbf{Y}_{t-1}$	0.240***	0.295***	0.135***	0.203***	0.671***	0.713***	0.586***	0.603***
	(0.046)	(0.056)	(0.038)	(0.060)	(0.041)	(0.050)	(0.045)	(0.068)
AB for AR(1)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
AB for AR(2)	0.151	0.204	0.058	0.177	0.002	0.084	0.002	0.096
Sargan	0.152	0.050	0.423	0.571	0.590	0.442	0.597	0.789
No. Observations	7,180	3,504	7,040	3,438	12,244	8,264	12,103	8,181
No. Clusters	539	280	534	280	691	400	687	398
Control variables	No	Yes	No	Yes	No	Yes	No	Yes
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lagged value	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Dependent variable is student performance (test scores), which are normalized to mean 0 and standard deviation 1. Control variables include the full set of explanatory variables presented in Table 3.5. Data are not nested within schools. Standard errors are robust to heteroskedasticity and clustered at class level. t statistics in parentheses. Estimations based on two-step GMM with Windmeijer (2005) corrected standard errors. The zero hypothesis of the Sargan test is H0: overidentifying restrictions are valid. For the Arellano-Bond test, AR(1) and AR(2) are respectively tests for first-order and second-order correlation in the first-differenced residuals under the null hypothesis of H0: no autocorrelation. For the Arellano-Bond and Sargan tests the p-values are reported. $*p < 0.1, **p < 0.05, ***p < 0.01$.
Source: GERES database (2005–2008), own estimates.

the estimates.[80] Both estimators have been generated on the basis of two-step GMMs in order to improve the robustness of the coefficients in relation to heteroscedasticity and autocorrelation. Finally, because the GERES panel data contain large N but small T, I use the finite-sample correction described in Windmeijer (2005) to address the bias in the two-step standard errors.[81]

Since the GMM estimates are based on instrumental variables, the results from the Sargan and Arellano-Bond tests assume a crucial role for the validity of the models (Baum et al., 2007). The Sargan test for joint validity of the instruments with p-values higher than 0.01 indicates that the instruments are all orthogonal to the model error term and, consequently, the model presents no overidentification problem. The Arellano-Bond test for serial correlation of the residuals rejected the null hypothesis (no autocorrelation) of first order, and confirms the absence of second-order serial correlation in the disturbances of the first-difference equations, confirming that the Arellano and Bond (1991) assumptions are satisfied (see e.g. Baltagi, 2008).

The results presented in Table 3.4 are in line with the findings from the earlier sections: the implementation of the teacher bonus program had no statistically significant impact on the performance of students in Math and Portuguese. Both the Difference and System GMM estimators provide consistence estimates for the dynamic panel model in equation (3.5.7). However, as noted by Roodman (2009), the System GMM improves the accuracy of the estimators because it addresses the

[80] Blundell and Bond (1998) and Arellano and Bover (1995) show that regarding panel data with high persistence the classic Difference GMM estimator can provide poor finite-sample properties (bias), because the past lagged values convey little information about the future changes. The System GMM is then an expanded version of the Difference GMM in which instead of transforming the regression to eliminate the individual fixed effects, it transforms the instrument variables to make them exogenous to the fixed effects. Therefore, with the inclusion of additional moment restriction, the use of lagged first differences as instruments in the level of the equation addresses the bias arising from the standard GMM estimator (Baltagi, 2008; Jessen et al., 2018; Roodman, 2009). See the appendix for a more comprehensive formal description of the GMM estimators.

[81] Both GMM estimators were implemented in this paper with the Stata command *xtabond2*. In the model specification, all the explanatory variables were treated as strictly exogenous, and the lagged student score was listed as an endogenous variable, being included as an internal instrument.

problem of missing values from unbalanced panels. Given these unbalanced panels, as is the case with the GERES dataset, if some values of $Y_{i,t-1}$ are missing then the first-differenced transformation by the Difference GMM will present missing values for $\Delta Y_{i,t-1}$. Meanwhile, the Blundell and Bond (1998) System GMM estimator will circumvent the existence of these missing in the data due to the orthogonal-deviations transformation.

3.10 Conclusion

Pay-for-performance programs are the subject of many often very heated debates—both among politicians and the public at large. Currently, it is not possible to identify an international scientific consensus in this regard, given the mixed empirical evidence presented to date. In this way, this paper has contributed to the small but growing literature on the effectiveness of incentive-pay programs for teachers.

The present study dealt with the researching of the impact on student academic achievement of the implementation of a teacher bonus program in the state of São Paulo (Brazil) in 2008. The main findings, based on value-added models, suggested that providing further financial incentives for school staff members has not resulted in a statistically significant impact on student performance in Math or Portuguese: one year after the bonus scheme's implementation, students in incentive (state) schools scored 0.016 and 0.041 standard deviations lower than students in control (municipal) schools in Math and Portuguese tests respectively. But no coefficient was statistically significant. The application of alternative empirical specifications, placebos tests, and robustness checks also supports these findings.

There are three important caveats to bear in mind when drawing conclusions regarding this paper. First, the empirical evaluation was based on a quasi-experiment situated in the city of Campinas; as in all experiments, the empirical evidence is limited to that place, only one of 645 municipalities in the state of São Paulo. Hence, extrapolations to other populations should be treated with caution.

The other important limitation of this study is that the DiD approach used only one year as the post-treatment period (2008).[82] It would be of great importance to extend this timeline one or two more years. The review of the literature using a longer time period (see e.g. Barrera-Osorio and Raju, 2017; Glewwe et al., 2010; Imberman and Lovenheim, 2015) indicated that in principle two opposite effects are conceivable: the impact of the teacher bonus program may be larger in subsequent years, since the credibility and results of the program have already been established by the educational staff, or the gains of student performance might decrease over time should the novelty of the program wear off and teacher engagement in school decrease due to the existence of free-riding in the context of group-based bonus programs. Unfortunately, the current data limitations for Brazil did not allow me to examine empirically to what extent these two effects have prevailed.

Another area of uncertainty is the transferability of the results to students enrolled in higher grades. The author does not exclude the possibility of different bonus impacts occurring according to the grade and age of students. The literature related to the importance of parental educational involvement for student academic performance suggests that children have better achievement outcomes when parents are involved in their education (see e.g. Harris and Robinson, 2016), but the strength of this

[82] The limitation to a single post-treatment period is not an exclusivity of this paper. Lavy (2009), Loyalka et al. (2019), and Muralidharan and Sundararaman (2011) are just some examples among a long list of prestigious research projects based on the same approach.

association varies according to socioeconomic status (Benner et al., 2016), ethnicity (Wang and Sheikh-Khalil, 2014), and school grades (Assefa and Sintayehu, 2019; McBride et al., 2009). It is therefore not surprising when the impact of teacher bonuses varies according to the grade and age of the child. This paper focused its investigation on pupils enrolled in the first four years of schooling, and the author supposes that for these grades parents have a higher chance of supporting effectively the school activities of their offspring. However the older the children, the lower the probability that their parents—especially those with low educational-attainment levels—can continue to help them with increasingly more complicated schoolwork, which in turn increases the importance of teachers for student performance.

Despite these caveats, this paper clearly demonstrated the inefficiency of the program—at least in its first year of implementation. In addition, the current study points to the importance of using valued-added models in the investigation of teacher bonus programs. Since student performance has a cumulative character over time, individuals' prior academic achievements should be taken into account in future analyses of the bonuses programs existing in Brazilian schools. The paper showed that fixed-effect models alone are inappropriate for this empirical investigation, since they are not able to capture the dynamic relationship between prior and future student test scores. Empirical models with no control for students' previous accomplishments generate overestimated results for the impact of the bonus scheme on student performance, by attributing predictive power to the program—when, in truth, it should be attributed to the learning capacity of students instead.

Appendix

3.A Tables

Table 3.5. Descriptive Statistics and Results of Independent *T*-Tests

	Mean			T-Test			
	(1)	(2)	(3)	State vs. Municipal		State vs. Private	
	State	Municipal	Private	Diff.	t-test	Diff.	t-test
Student Features							
Male	0.5145	0.5464	0.5436	-0.032***	-5.08	-0.029***	-3.32
Race							
White	0.3958	0.3387	0.5823	0.057***	9.46	-0.187***	-21.71
Mixed	0.4000	0.4190	0.2865	-0.019***	-3.09	0.113***	13.47
Black	0.1245	0.1535	0.0276	-0.029***	-6.68	0.097***	18.59
Asian	0.0289	0.0342	0.0587	-0.005**	-2.39	-0.030***	-9.10
Indigenous	0.0432	0.0454	0.0437	-0.002	-0.87	-0.001	-0.16
Socioeconomic Status	-0.0877	-0.1684	0.7892	0.081***	14.82	-0.877***	-113.13
Household Income							
Very Low	0.0866	0.0934	0.0020	-0.007**	-1.97	0.085***	21.39
Low	0.3311	0.3394	0.0275	-0.008	-1.47	0.304***	45.10
Medium	0.3428	0.3552	0.1343	-0.012**	-2.15	0.209***	28.79
High	0.2060	0.1904	0.4098	0.016***	3.25	-0.204***	-29.02
Very High	0.0335	0.0216	0.4265	0.012***	6.06	-0.393***	-80.58
Education Mother							
Less then 4 years	0.1353	0.1867	0.0033	-0.051***	-10.77	0.132***	25.81
4 years	0.2956	0.3335	0.0321	-0.038***	-6.30	0.263***	37.79
8 years	0.2515	0.2373	0.0819	0.014**	2.55	0.170***	24.54
Secondary	0.2691	0.2222	0.4137	0.047***	8.42	-0.145***	-18.18
Tertiary	0.0485	0.0204	0.4690	0.028***	12.02	-0.421***	-76.12
Education Father							
Less then 4 years	0.1439	0.1734	0.0011	-0.030***	-5.91	0.143***	27.01
4 years	0.2900	0.3386	0.0497	-0.049***	-7.67	0.240***	33.72
8 years	0.2567	0.2473	0.0972	0.009	1.57	0.159***	22.32
Secondary	0.2643	0.2193	0.4011	0.045***	7.71	-0.137***	-16.89
Tertiary	0.0451	0.0213	0.4508	0.024***	9.82	-0.406***	-71.64
Teacher Features							
Male	0.0183	0.0276	0.0064	-0.009***	-4.56	0.012***	5.26
Education Level							
Less than Secondary	0.0001	0.0067	0.0000	-0.007***	-8.10	0.000	0.61
Secondary	0.0039	0.0002	0.0000	0.004***	5.93	0.004***	3.89
Vocational	0.1819	0.1238	0.0451	0.058***	11.68	0.137***	21.01
Tertiary	0.8077	0.8632	0.9132	-0.056***	-10.83	-0.106***	-15.30
Master	0.0064	0.0061	0.0379	0.000	0.30	-0.031***	-13.94
Doctorate	0.0000	0.0000	0.0039	0.000	.	-0.004***	-6.41
Age							
Up to 24	0.0309	0.0515	0.1134	0.021***	-7.55	-0.082***	-20.08
25–29	0.0319	0.0410	0.0984	-0.009***	-3.51	-0.066***	-16.61
30–39	0.3127	0.2456	0.4096	0.067***	10.94	-0.097***	-11.05
40–49	0.4253	0.3230	0.2985	0.102***	15.51	0.127***	14.06
50–54	0.1223	0.1463	0.0768	-0.024***	-5.12	0.045***	7.82
More than 55	0.0768	0.1927	0.0033	-0.116***	-25.00	0.074***	17.19

Continued on next page.

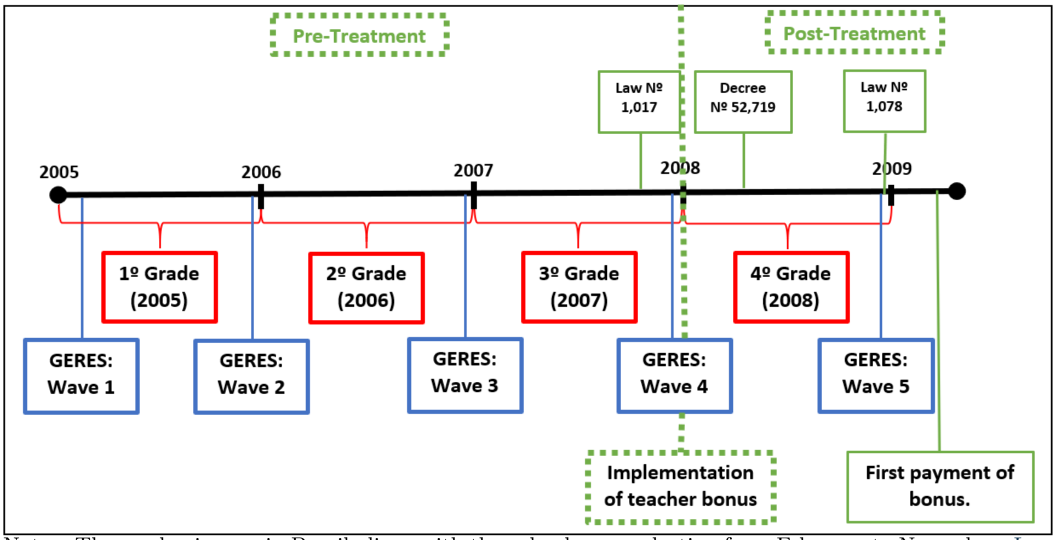
Table 3.5 – *Continued from previous page.*

	Mean			T-Test			
	(1)	(2)	(3)	State vs. Municipal		State vs. Private	
	State	Municipal	Private	Diff.	t-test	Diff.	t-test
Years of Experience							
Less than 1	0.0060	0.0000	0.0084	0.006***	8.09	-0.002	-1.62
1–2	0.0031	0.0063	0.0205	-0.003***	-3.39	-0.017***	-10.65
3–4	0.0254	0.0214	0.0845	0.004*	1.94	-0.059***	-16.08
5–10	0.0869	0.1770	0.0668	-0.090***	-19.51	0.020***	3.94
11–15	0.2996	0.1787	0.2631	0.121***	20.92	0.037***	4.31
More than 15	0.5789	0.6166	0.5567	-0.038***	-5.61	0.022**	2.40
Weekly teaching hours							
Up to 20	0.1468	0.0189	0.2940	0.128***	34.60	-0.147***	-20.46
21–25	0.3235	0.0825	0.4835	0.241***	45.52	-0.160***	-17.91
26–30	0.3641	0.3604	0.0590	0.004	0.55	0.305***	37.96
31–40	0.1366	0.4363	0.0708	-0.300***	-50.80	0.066***	10.91
More than 41	0.0290	0.1018	0.0928	-0.073***	-21.52	-0.064***	-16.36
Schools that work							
Only One	0.7072	0.7260	0.7638	-0.019***	-3.03	-0.057***	-6.79
Two	0.2768	0.2525	0.2284	0.024***	4.00	0.048***	5.91
Three or more	0.0160	0.0215	0.0079	-0.006***	-2.95	0.008***	3.74
Other Job							
No	0.5120	0.4962	0.4875	0.016**	2.29	0.024***	2.61
Yes, with education	0.4366	0.4390	0.4326	-0.002	-0.35	0.004	0.43
Yes, outside education	0.0514	0.0648	0.0798	-0.013***	-4.15	-0.028***	-6.45
School Features							
Library	0.8913	0.7322	0.9640	0.159***	30.80	-0.073***	-14.27
Computer lab	0.2262	0.8540	0.8894	-0.628***	-124.35	-0.663***	-93.85
Science lab	0.0337	0.0024	0.7755	0.031***	18.32	-0.742***	-157.07
Sports court	0.8915	0.7658	0.9135	0.126***	25.81	-0.022***	-4.05
Art room	0.1398	0.0455	0.4520	0.094***	25.36	-0.312***	-44.25
Intimidation of students	0.2864	0.3081	0.1420	-0.022***	-3.39	0.144***	17.91
Intimidation of staff	0.2825	0.3374	0.2477	-0.055***	-8.50	0.035***	4.14
Violence against students	0.3447	0.3750	0.0955	-0.030***	-4.53	0.249***	30.50
Violence against staff	0.2370	0.2693	0.0450	-0.032***	-5.34	0.192***	26.63
Depredation	0.4158	0.5218	0.1271	-0.106***	-15.35	0.289***	33.55
Drug use	0.3930	0.5701	0.0791	-0.177***	-25.58	0.314***	37.71
Interference of drug cartel	0.3648	0.5107	0.0753	-0.146***	-21.04	0.289***	35.50
Students	2,158	1,919	804				
Classes	74	73	42				
Schools	20	20	20				
Waves	5	5	5				

Notes: This table provides descriptive statistics for panel data structure in which each student i was tracked during the five sample waves. t-tests compare the variables across school types. $*p < 0.1, **p < 0.05, ***p < 0.01$.
Source: GERES database (2005–2008); author's own estimates.

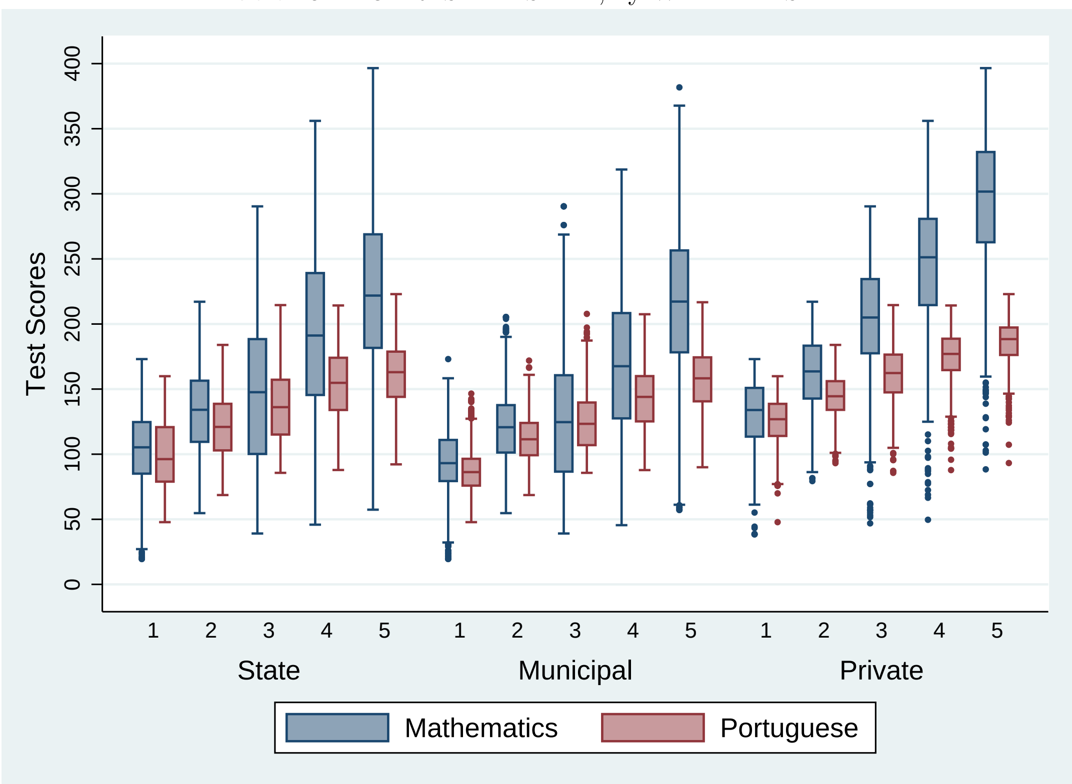
3.B Figures

Figure 3.1: Data Collection and Bonus Implementation



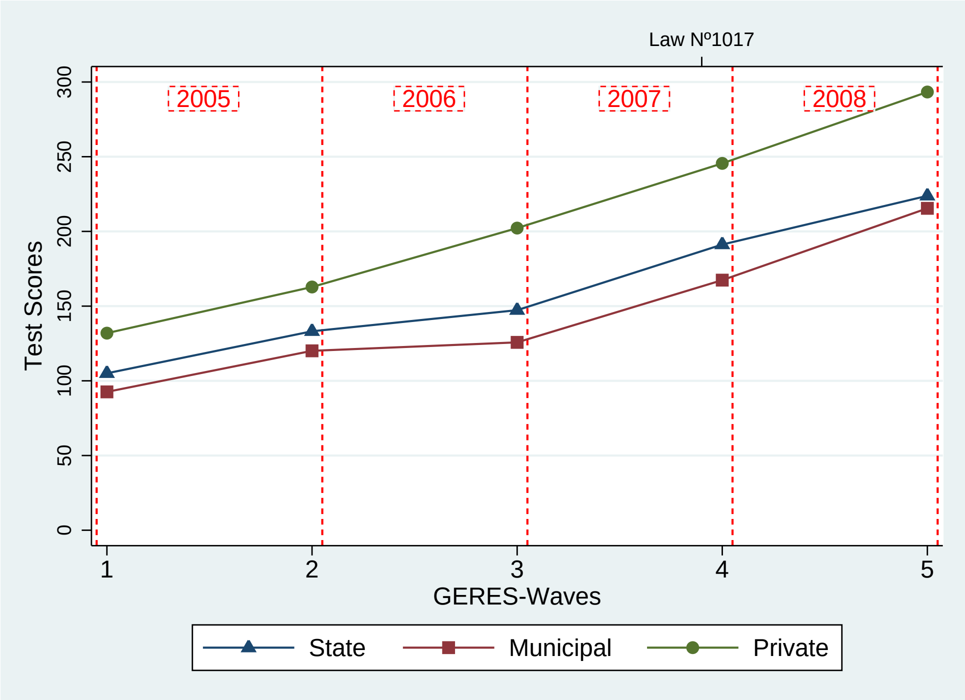
Notes: The academic year in Brazil aligns with the calendar year, lasting from February to November. Law No. 1,017 of October 15, 2007 introduced the teacher-incentive bonus in the state of São Paulo, and Decree No. 52,719 of February 14, 2008 and Law No. 1,078 of December 17, 2008 supplemented it. In April 2009, the state paid the productivity bonus for the first time, which was based on the previous year's targets.
Source: Author's own elaboration, based on data of GERES and Official Gazette of the State of São Paulo.

Figure 3.2: GERES Test Scores, by Waves and Schools



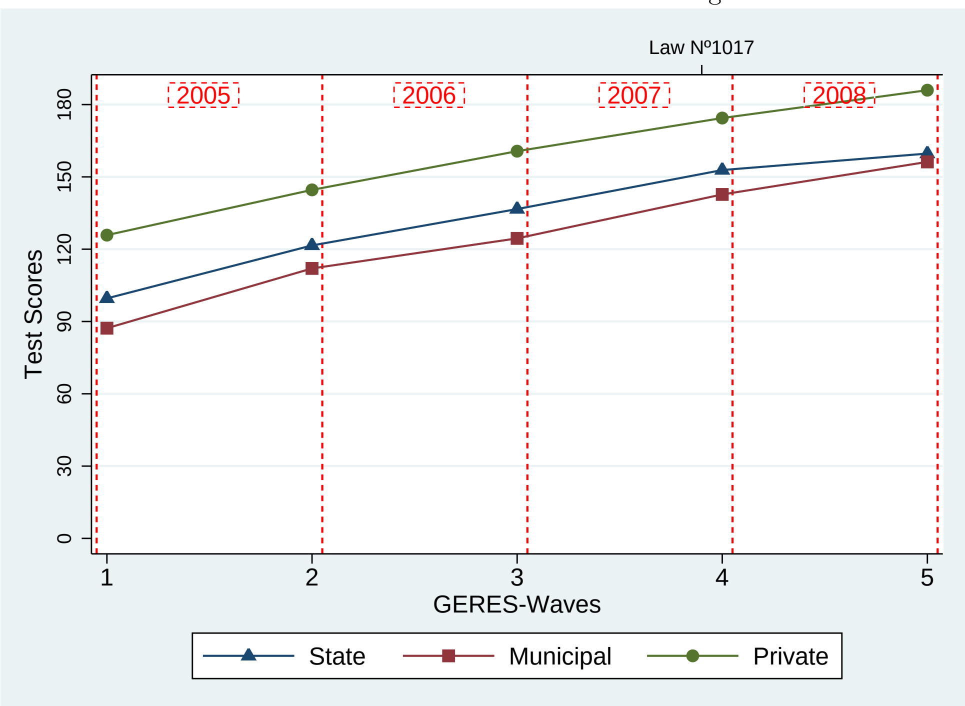
Notes: The proficiency (test scores) on GERES was estimated using the Item Response Theory. Each (of the five) GERES waves was composed of standardized tests for Mathematics and Portuguese. The waves were conducted in March 2005 and November 2005, 2006, 2007, and 2008.
Source: GERES database (2005–2008); author's own estimates.

Figure 3.3: Student Performance in Mathematics



Notes: The proficiency (test scores) on GERES was estimated using the Item Response Theory. The reported values refer to the average test scores calculated by type of school. Law No. 1,017 of October 15, 2007 introduced the teacher-incentive system to the state of São Paulo, and its first year of implementation was 2008. The academic year in Brazil aligns with the calendar year, lasting from February to November. The dashed red lines illustrate academic years.
Source: GERES database (2005–2008); author's own estimates.

Figure 3.4: Student Performance in Portuguese



Notes: The proficiency (test scores) on GERES was estimated using the Item Response Theory. The reported values refer to the average test scores calculated by type of schools. Law No. 1,017 of October 15, 2007 introduced the teacher-incentive system to the state of São Paulo, and its first year of implementation was 2008. The academic year in Brazil aligns with the calendar year, lasting from February to November. The dashed red lines illustrate the academic years.
Source: GERES database (2005–2008); author's own estimates.

3.C Brazilian Educational System

The legal framework for the current education system in Brazil was established by the National Educational Bases and Guidelines Law from 1996 and Constitutional Amendment No. 59/2009. Currently, the education system is divided into five levels: early childhood education, pre-primary, primary, secondary, and higher education. The first level is not obligatory and is intended for children between the ages of 0 and 3. The legislation for compulsory education stipulates mandatory schooling for children in the age group of 4 to 17 years old, comprising in this way pre-primary (two years), primary (nine years), and secondary schooling (three years).[83] Individuals who have completed their secondary education become eligible for higher education, but the effective admission to these institutions is dependent primarily on the institutions' application procedures.

At all five educational levels, students may choose to attend (free, tax-funded) public schools, or (privately funded) private schools.[84] The Constitution of 1988 obliged the public sector to provide free and universal access to (compulsory) education for all and divided this responsibility among the different levels of competence: the federal government has a relatively limited responsibility concerning the education system, almost restricted to managing federal universities, legislating on the guidelines and bases for national education, and providing technical and financial aid to the states and municipalities in order to ensure a minimum quality standard for all administrative units making up the Federation.[85] By contrast, the states and municipalities are primarily responsible for the functioning of public schools, playing a crucial role in defining and structuring the curriculum frameworks, teaching methods, and didactic material in their school districts.[86]

Articles 10 and 11 of the National Educational Bases and Guidelines Law (LDB) establish more comprehensively the competencies of states and municipalities regarding the education system. Municipalities are obliged to provide early childhood education, pre-primary and primary schooling, while the main responsibility of states lies in secondary education. However, the LDB foresees in its Article 10(6) that states need to ensure universality of primary education in cases where the municipalities are not able to guarantee all citizens this fundamental right. Consequently, in 2018 a total of 30,377 state schools provided primary schooling for 15,946,416 students, comprising approximately 33 percent of the total number of primary students; in the same year 23,103,124 students (47 percent) were enrolled in 110,220 municipal schools, 8,995,249 (19 percent) in 40,641 private schools, and 411,078 (1 percent) in 701 federal schools (INEP, 2019b).

[83] Prior to the enactment of Constitutional Amendment no. 59, dated November 11, 2009, schooling in Brazil was compulsory for children between the ages of 7 and 14, and the education system had a 8+3 structure corresponding to eight years of (compulsory) primary education and three years of secondary schooling.

[84] According to school census data from the year 2018, approximately 18.6 percent of the 48.5 million students in Brazil are enrolled in private schools (INEP, 2019b).

[85] Concrete examples of the intervention of the federal government in the educational system are the promulgation of the National Educational Bases and Guidelines Law (LDB) in 1996, creating the principal legal framework regulating means and powers for educational actions, and the adoption of the National Education Plan enacted in 2014, which established a set of 20 development goals to be achieved by 2024.

[86] In Brazil a total of 181,939 schools operate in the education system, among these 22.3 percent are private, 60.6 percent are municipal, 16.7 percent are state, and 0.4 percent are federal (INEP, 2019b).

3.D Education Development Index

The teacher bonus program investigated in this paper is part of the School Quality Program (Programa de Qualidade da Escola) launched in 2007 by the São Paulo State Government. This program has set long-term goals for the improvement of the quality of schools within the state education network, which must be reached by 2030.[87]

To ensure that these goals are being met, the state has also created short-term targets for the schools in order to annually monitor the development of the education system. These short-term targets are referred to as the Education Development Index of the state of São Paulo (IDESP) and used to calculate teacher bonuses.

IDESP evaluates the quality of the education system divided by levels of schooling: lower primary education (Grades 1–5), upper primary education (Grades 6–9), and secondary education (Grades 10–12). The program's goal is that by 2030 all state schools in São Paulo achieve student performances similar to those in OECD countries. In practical terms, this means an IDESP of 7.0 in the first level, 6.0 in the second, and 5.0 in the third level of schooling.

The methodology employed by IDESP enables the schools to annually monitor their progress toward the long-term goals. To that end, at the beginning of each academic year the São Paulo Secretariat of Education (SEE-SP) publishes the annual targets for the schools, considering their current performance in relation to the 2030 goals. IDESP is calculated individually for each school s and educational level l based on two different indexes: the indicator of performance (IP_{sl}) and the average passing rate (PR_{ls}):

$$IDESP_{sl} = IP_{sl} \cdot PR_{sl} \tag{3.D.1}$$

These two indexes complement each other and are combined to create a synthetic indicator for quality, which promotes both learning achievement and grade progression. From the perspective of the government, it is not desirable for a student to repeat the same grade several times to learn the corresponding academic content; at the same time, students with learning deficits should not move on to the next grade.

The indicator of performance, IP_{sl}, is measured as the average score of students by the goverment-run compulsory standardized test SARESP, and for this calculation only the results in Math and Portuguese (reading) for the 5th, 9th, and 12th grades of schooling are taken into consideration. In accordance with the scores obtained by the SARESP test, the students are grouped into four categories of learning achievement: below the basic (BB), basic (Ba), appropriate (Ap), and advanced (Ad). Table 3.7 describes the reference values for the definition of these performance levels.

Table 3.7. Reference values for SARESP

Level	5th Grade		9th Grade		12th Grade	
	Mathematics	Portuguese	Mathematics	Portuguese	Mathematics	Portuguese
Below Basic	$x < 175$	$x < 150$	$x < 225$	$x < 200$	$x < 275$	$x < 250$
Basic	$175 \leq x < 225$	$150 \leq x < 200$	$225 \leq x < 300$	$200 \leq x < 275$	$275 \leq x < 350$	$250 \leq x < 300$
Appropriate	$225 \leq x < 275$	$200 \leq x < 250$	$300 \leq x < 350$	$275 \leq x < 325$	$350 \leq x < 400$	$300 \leq x < 375$
Advanced	$x \geq 275$	$x \geq 250$	$x \geq 350$	$x \geq 325$	$x \geq 400$	$x \geq 375$

Note: x denotes the student score by SARESP.
Source: Author's own compilation, based on SSE-SP (2018).

[87] Unless otherwise indicated, the following statements are based on the technical note regarding the School Quality Program published by the São Paulo Secretariat of Education. See SSE-SP (2018).

Then, the indicator of performance, IP_{sl}, refers to the relative number of students at each of these four performance levels and is calculated on the basis of the school quality gap:

$$Sgap_{sgj} = (3 \cdot BB_{sgj}) + (2 \cdot Ba_{sgj}) + (1 \cdot Ap_{sgj}) + (0 \cdot Ad_{sgj}) \tag{3.D.2}$$

where BB_{sgj}, Ba_{sgj}, Ap_{sgj}, and Ad_{sgj} are the percentage of students in the respective performance level listed in Table 3.7, calculated individually for each of the three grades g (5th, 9th, and 12th) and two disciplines j (Math and Portuguese). Therefore, the school gap ranges from 0, when all students have achieved the level "advanced," to 3, when all of them are found in the category "below the basic."

Using the school quality gap, the indicator of performance, can be calculated as follows:

$$IP_{sgj} = \left(1 - \frac{Sgap_{sgj}}{3}\right) \cdot 10 \tag{3.D.3}$$

Finally, the indicator of performance ranges on a scale from 0 (maximal gap in quality) to 10 (no gap), and is reported individually for each school s and grade g based on the average values for Mathematics and Portuguese.

The other indicator of education quality used in the IDESP measure is the passing rate (PR_{sl}), which is calculated using the data from the Brazilian School Census as:

$$PR_{sl} = \frac{A_{sl}}{T_{sl}} = \frac{\text{Number of approved students in level of schooling } l}{\text{Total number of students in level of schooling } l} \tag{3.D.4}$$

The passing rate is also calculated individually for each school and it refers to the proportion of students approved by each of the three levels of schooling l: lower primary education (Grades 1–5), upper primary education (Grades 6–9), and secondary education (Grades 10–12).

3.E Indicator for Realization of Targets

As described above, each school receives individual short-term targets, the so-called IDESP, to be reached in the academic year. After the end of the evaluated period (in March of the following year to be more precise), the SEE-SP publishes the degree of achievement of IDESP, and consequently the value of the teacher bonus to be paid to educational staff.[88] For this purpose, peculiarities in regard to student bodies of the schools are also taken into consideration with the help of the Indicator for Realisation of Targets (ICM, or Índice de Cumprimento de Metas), which is measured individually for each school s and level of schooling l as follows:

$$ICM = [\max(IC; IQ)] \cdot [1 + (NSE \cdot MOD)] \tag{3.E.1}$$

with

$$IC = \text{Compliance Index} = \left(\frac{IDESP_{EF} - IDESP_{BASE}}{IDESP_{META} - IDESP_{BASE}}\right) \tag{3.E.2}$$

and

$$IQ = \text{Additional for Quality} = \left(\frac{IDESP_{EF} - IDESP_{AG}}{IDESP_{MF} - IDESP_{AG}}\right) \tag{3.E.3}$$

where $IDESP_{EF}$ is the IDESP achieved in the evaluated period, $IDESP_{BASE}$ the value considered as the basis (previous year), $IDESP_{META}$ the target for the evaluation period, $IDESP_{MF}$ the final goal for 2030, $IDESP_{AG}$ the aggregate result for all schools in the evaluation period, $INSE$ the indicator for socio-economic status of the school, and MOD the modulator with the weight to be applied to the $INSE$.[89]

The compliance index (IC) refers to the proportion of the target that the school has achieved in each of the phases of schooling; in other words, it indicates how much the school has progressed in the evaluated period in comparison to the expected value. As from 2009, the additional aspect quality (IQ) also came to be used to measure the ICM and, consequently, to calculate the teacher bonus. This indicator illustrates the success of the considered school in achieving the long-term goal for 2030, indicating to what extent the school is on its way to achieving the final goal compared to the other schools.

Because IC and IQ are exclusionary in equation (3.E.1), education system employees will get the bonus in two different situations: first, if the school education quality, measured by IDESP, improved in the evaluated year (IC > 0) and, second, if the school's results were higher than the average value of IDESP achieved in the evaluated year (IQ > 0).[90]

Finally, the Indicator for Realization of Targets (ICM) will be applied in the calculation of the teacher bonus as follows:

$$\text{Bonus} = 0.2 \cdot \text{ICM} \cdot \sum Y_{i,t} \cdot \frac{\sum WD_{i,t}}{\sum WD_t} \iff \frac{\sum WD_{i,t}}{\sum WD_t} \geq \frac{2}{3} \tag{3.E.4}$$

[88]Teachers, principals, and other administrative officials who work in more than one school or educational level receive their bonus with a value proportionate to the workload allocated to each function.

[89]See section 3.F for a description of the indicator for socioeconomic status and its modulator.

[90]The payment of the bonus in case of IQ > 0 and IC ≤ 0 is based on the premise that the improvement of the education quality becomes even more difficult when the school has already achieved a high level of performance. For this reason, the SEE-SP recognizes the need to remunerate these "good" schools for the already-existing high performance.

with ICM $\in [0, 1.2]$ and $\sum Y_{i,t}$ denoting the sum of the remuneration received by the official i in the evaluated period t, $\sum WD_t$ the amount of working days in t, and $\sum WD_{i,t}$ the sum of days worked by the official i in period t.

Note that the bonus is proportional to the effective days worked in t, but no bonus will be paid for employees with a proportion of working days lower than two-thirds. Moreover, the ICM used for the measurement of the bonus in equation (3.E.4) is limited to values between 0 and 1.2. For the cases in which ICM $= 0$ (IC ≤ 0 and IQ ≤ 0), the teachers will be paid no bonus. Similarly, the ICM included in equation (3.E.4) will not exceed the value of 1.2 even when the results from (3.E.1) are higher than 1.2.[91]

[91] Only for illustration purposes: assuming, for example, $\sum WD_{i,t} = \sum WD_t$, and ICM=1, the educational staff will receive an additional payment of 20 percent of their last gross annual salary.

3.F Indicator for Socioeconomic Status

For the calculation of the annual teacher bonus, the SEE-SP also takes into consideration the Indicator for Socioeconomic Status (INSE or Indice de Nível Socioeconômico) of the schools where the educational staff are employed. This inclusion aims to valorize the efforts of teachers working in less privileged communities, incorporating into the evaluation of education quality the (negative) out-of-school factors that are largely beyond the teachers' control but have strong impacts on the educational achievement of students.

The idea behind the INSE goes back to Bourdieu (1986). In his theory of cultural reproduction, the author argued that cultural capital (e.g. economic and social capital) has a significant impact on student achievements. Because families with high socioeconomic status can provide their children with more cultural capital, these children enjoy an advantage in the educational system when compared with their peers from socially disadvantaged households (Jaeger and Møllegaard, 2017).

The data for the construction of the INSE were collected by means of questionnaires that were distributed to the parents of students in the years 2008, 2009, and 2010, containing specific questions on the family income, education level, and occupation of parents, and the existence of consumer durables in the household, such as car, TV, DVD player, washing machine, fridge, and so on. Using these data and Item Response Theory (IRT), the SEE-SP has constructed a single index for the socioeconomic status of the students. Finally, the INSE for the school was determined as the arithmetic average INSE of all students formerly enrolled in this school, and takes values from 0 to 10, with a value of 0 (10) corresponding to the schools with the highest (lowest) socioeconomic status.

The modulator (MOD) is also integrated into equation (3.E.1) to calculate the teacher bonus. It is a relative weight applied to the INSE in order to calibrate the progress of the school toward its targets ($IDESP_{META}$). This weight indicates the degree of influence of socioeconomic status on the performance of students for each school.

3.G GERES Data

The GERES microdata is the result of the project entitled *"Estudo Longitudinal da Geração Escolar"* (Longitudinal Study of Quality and Equity in Brazilian Elementary Education), the first longitudinal data study in education concluded with success in Brazil.[92] This project tracked 21,569 children from 309 Brazilian schools during their first four years of schooling in order to gather information about their academic performance and the educational inputs involved in the learning process.[93]

Table 3.8 describes the timeline for the GERES project. The GERES project began in 2004 with the creation of the institutional structure for the project, and ran for seven years until the publication of the dataset and its supporting materials in 2011.

Table 3.8. Timeline for Test Application

Year	Timeline	Activities
2004	March to December	Preparation phase and pre-testing
2005	March/April	Tests of Mathematics and Portuguese (Wave 1) Questionnaire for schools Questionnaire for school principals
	September to December	Questionnaire for students' parents
	October/November	Tests of Mathematics and Portuguese (Wave 2) Questionnaire for teachers
2006	November	Tests of Mathematics and Portuguese (Wave 3) Questionnaire for teachers
2007	November	Tests of Mathematics and Portuguese (Wave 4) Questionnaire for teachers Questionnaire for students (pre-testing version) Questionnaire for schools
2008	November	Tests of Mathematics and Portuguese (Wave 5) Questionnaire for teachers Questionnaire for students (extended version)

Source: Author's own compilation, based on Brooke and Bomamino (2011).

The idea for GERES came from a desire to create a new, and for Brazil at that time unique, longitudinal dataset tracking students' academic achievement over time. This dataset complements the already extensive list of cross-sectional educational data existing in the country.[94] The project was governed by six Brazilian universities, and co-funded by the Ford Foundation and the Brazilian government by means of

[92]The first longitudinal study in the Brazilian education system was called "*Avaliação do desempenho: fatores associados*" and was conducted between 1999 and 2003, tracking the performance of students between Grades 4 and 8 of primary education. However, due to technical problems, the database has never been published (Brooke and Bomamino, 2011).

[93]Unless otherwise indicated, all following explanations related to the database are based on Brooke and Bomamino (2011), the book provided as supplementary material to the GERES microdata.

[94]With the implementation of the Brazilian National Evaluation System of Basic Education (SAEB) in the mid-1990s and the consequent expansion of educational assessment tests at the state and municipal levels in the following years, Brazil has established a comprehensive and broad framework for the evaluation of student achievement. However, although pupils undertake the performance tests in several years of their school life, for data privacy reasons the competent governmental authorities have never provided to the research community the individual student ID numbers, which would allow us to track the performance of students over time.

public resources from the Research Support Foundation of the State of Rio de Janeiro (FAPERJ), the Research Support Foundation of the State of Minas Gerais (FAPEMING), and the National Institute of Educational Studies and Research (INEP).[95]

The 309 public and private schools involved in GERES are situated in five densely populated cities in Brazil: Belo Horizonte, Campinas, Campo Grande, Rio de Janeiro, and Salvador, each city being located in a different state. The selection of these municipalities was made with one specific goal in mind: the reduction of logistics issues related to the test application, given that the cities are home to the main campuses of the participating universities. The cities chosen, a probabilistic procedure was then carried out for the representative selection of the 21,569 "GERES students."

After the selection of the students, the application of proficiency tests and survey questionnaires took place between 2005 and 2008. In each of these years, GERES collected data on the academic achievement of students in Mathematics and Portuguese, as well as the individual characteristics of their teachers.[96] Moreover, the project was complemented by two questionnaires on school features: one of school principal characteristics, and three household questionnaires aimed at gaining a better understanding of the familial contexts of the students involved in the project.

Table 3.9. GERES Sample Size

		Total	GERES			
City	**Type**	**Schools**	**Schools**	**% Sample**	**Classes**	**Students**
Belo Horizonte	State	155	20	12.9	64	1,682
	Municipal	135	20	14.8	88	2,036
	Private	144	20	13.9	32	669
Campinas	State	95	20	21.1	74	2,158
	Municipal	39	20	51.3	73	1,919
	Private	47	20	42.6	42	804
Campo Grande	State	70	20	28.6	38	845
	Municipal	76	19	25.0	97	2,418
	Private	80	20	25.0	27	342
Rio de Janeiro	State	-	-	-	-	-
	Municipal	765	30	3.9	90	2,527
	Private	805	30	3.7	55	1,032
Salvador	State	67	21	31.3	25	692
	Municipal	332	20	6.0	113	3,032
	Private	278	20	7.2	30	544
Special schools		9	9	100.0	35	869
Total		**3,097**	**309**	**10.0**	**883**	**21,569**

Notes: Special schools refer to federal schools or classes in participating universities. Because of the municipalization of primary education in Rio de Janeiro, no state schools were included in the GERES sample.
Source: GERES database (2005–2008); author's own compilation based on Brooke and Bomamino (2011).

Table 3.9 illustrates the sample construction. First, using the 2003 school census

[95]The universities involved in the planning and execution of the GERES project were: University of Minas Gerais (UFMG), University of Juiz de Fora (UFJF), University of Campinas (UNICAMP), University of Mato Grosso do Sul (UEMS), Pontifical Catholic University of Rio de Janeiro (PUC-Rio), and University of Bahia (UFBA).

[96]Note that in the year 2005 students were tested twice (Waves 1 and 2). The first test in March sought to quantify the cognitive skills of children at the beginning of the education system, and the second one in November to measure the academic achievement at the end of the first year of education.

a probabilistic sample of schools within the cities was chosen.[97] Next, the following schools were excluded from the analysis: schools in rural areas, schools with only multi-grade classrooms in the first-grade, schools with first-grade pupils attending exclusively evening classes,[98] as well as private schools with fewer than 10 students and public schools with fewer than 20 students enrolled in the first year of compulsory education. In addition, given the process of municipalization of schools that occurred in the state of Rio de Janeiro, no (remaining) state school from this city has been added to the GERES sample.[99]

After all these exclusions, a new weighting adjustment—regarding the size of the schools and the average socioeconomic status of their students—was undertaken to ensure the reliability and representativeness of the data. Table 3.9 above summarizes the main statistics involved in the sample construction. Note that GERES covers a total of 10 percent of the schools in the five selected municipalities, but the sample size varies strongly across the cities. For Campinas, the city investigated in the paper, the GERES sample covers 21.1 percent of the state, 51.3 percent of the municipal, and 42.6 percent of the private schools.

Once the sample was defined, all the pupils enrolled in the first year of compulsory education in these schools were selected for the project and had their academic achievements tracked during their first four years of schooling (Grades 1–4).[100] Table 3.10 summarizes the sample variation over time.

Table 3.10. GERES Sample per Wave

		Number of Schools / Wave					Number of Students / Wave				
City	**Type**	**1st**	**2nd**	**3rd**	**4th**	**5th**	**1st**	**2nd**	**3rd**	**4th**	**5th**
Belo Horizonte	Special	1	1	1	1	1	88	85	87	89	92
	State	20	20	20	20	20	1,521	1,554	1,649	1,670	1,654
	Municipal	20	20	20	20	20	1,840	1,888	2,096	2,044	2,000
	Private	19	19	19	19	19	641	646	655	653	653
Campinas	State	20	20	20	20	16	1,939	2,017	2,095	2,201	1,860
	Municipal	21	21	21	21	21	1,691	1,761	1,886	2,084	2,203
	Private	20	20	20	19	18	768	781	748	766	738
Campo Grande	State	19	19	19	18	18	734	825	864	875	833
	Municipal	20	20	20	20	20	2,171	2,247	2,197	2,311	2,115
	Private	20	20	20	18	14	315	330	260	211	188
Rio de Janeiro	Special	8	8	8	8	8	730	720	740	764	799
	Municipal	30	30	30	36	35	2,271	2,230	2,224	3,575	3,802
	Private	30	30	30	30	28	971	949	934	935	778
Salvador	State	11	11	11	10	-	571	575	757	845	-
	Municipal	26	26	26	26	-	2,278	2,332	2,629	2,657	-
	Private	18	18	18	17	-	495	488	512	477	-
Total		**303**	**303**	**303**	**303**	**238**	**19,024**	**19,428**	**20,333**	**22,157**	**17,715**

Notes: Special schools refer to federal schools or classes in participating universities. Because of the municipalization of primary education in Rio de Janeiro, no state schools have been included in the GERES sample. Due to administrative issues the students from the city of Salvador were removed from the GERES project in year 2008, and therefore they have no test scores for Wave 5.
Source: GERES database (2005–2008), own compilation based on Brooke and Bomamino (2011).

Note that already by the first wave, approximately 10 percent of GERES students did not take the tests, and in the following years other losses of data occurred as well.[101] First, the schools from Salvador were withdrawn from the sample in the fifth wave due to internal issues of the local government and, second, the pupils

[97] The school census is a compulsory annual data collection covering all levels of education in Brazil. This statistical survey contains detailed information about students, classes, teachers, and public and private schools in the country. See Diniz (2007) for more details.

[98] In Brazil, classes starting from 4 p.m. are considered evening classes.

[99] See Gomes (2008) and Nogueira and Rangel (2011) for more information about the municipalization of schools in Brazil.

[100] Students who repeated a grade continued regularly taking part in the GERES waves.

[101] Students who missed the test could not retake it on another date, but they remained in the sample and were able to participate in the other waves of GERES.

that migrated to schools not part of GERES were no longer tracked. By contrast, the "external" students who had transferred to GERES classes were added to the sample. In total, $7,003$ students completed all five waves of the project.

The test scores identifying the proficiency of students were calculated independently for Math and Portuguese using the Item Response Theory (see section 3.H). In each wave, the researchers involved in the project prepared two versions of the test (the "easy" and the "difficult" exam for both Math and Portuguese) in order to minimize the possibility of measuring error by students with (very) different cognitive skills.[102] Then, students were allocated to the particular version of the test by taking into consideration their academic achievement in the previous wave; for the first wave, allocation was based on the basis of the student performance informed by the schools. Finally, the order of the questions in the test was arranged by ever-increasing difficulty level, the goal of which was to reduce the stress impact of the test, thereby improving the comparability of the results across children with distinct levels of stress management.

Finally, Table 3.11 presents the average test scores of the GERES project and their respective standard deviations. Note that, on average, the performance of students improves over time, but so does the difference in performance between the schools. Pupils enrolled in private schools perform increasingly better than those from state and municipal schools, and the gap between them gradually widens as the children get older.

Table 3.11. Test Scores per Wave (Mean and Standard Deviation)

		Wave 1		Wave 2		Wave 3		Wave 4		Wave 5	
City	**Type**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**
Mathematics	Special	142.29	20.84	170.11	24.46	217.67	40.10	259.67	43.43	301.47	48.13
	State	102.33	28.65	131.48	31.62	146.21	52.46	188.29	59.20	229.87	63.05
	Municipal	101.27	24.98	128.74	28.59	135.31	49.18	174.48	56.32	217.79	57.67
	Private	128.92	25.74	159.19	28.37	198.55	47.41	240.35	53.84	293.61	52.62
	Total	**107.95**	**28.78**	**136.22**	**32.00**	**151.25**	**55.81**	**190.39**	**62.01**	**235.19**	**64.96**
Portuguese	Special	139.64	14.49	151.84	15.17	169.81	19.70	179.53	18.42	188.50	16.74
	State	101.24	15.01	120.84	21.93	136.00	25.41	151.50	25.46	162.79	24.76
	Municipal	101.15	22.60	118.54	19.88	131.03	23.81	145.39	24.94	158.68	23.92
	Private	129.64	18.27	145.02	17.23	160.67	22.44	172.27	22.92	185.32	18.13
	Total	**107.61**	**25.60**	**124.88**	**22.73**	**138.47**	**26.80**	**151.95**	**26.75**	**164.75**	**25.33**

Notes: Special schools refer to federal schools or classes in participating universities.
Source: GERES database (2005–2008); author's own estimates.

[102] The development of two versions of the tests was necessary because the pre-testing phase showed very different educational outcomes: some students achieved a success rate of 100 percent, while others had only wrong answers.

3.H Item-Response Theory

The proficiency test scores by GERES were estimated using Item Response Theory (IRT), an approach widely applied in studies of cognitive traits and educational outcomes.[103] In comparison with the Classical Test Theory (CTT), IRT can capture in a more effective way the relationship between the measurement process and the latent trait: in this case, academic ability in Mathematics and Portuguese (Hambleton and Swaminathan, 2013). In Brazil, IRT has also been adopted by government-run large-scale evaluations of educational achievements, such as SAEB and Prova Brasil.

IRT makes use of an explicit mathematical model to predict the likelihood that a certain student will give a certain response to a certain item. Therefore, the hit probability for each response is derived as a function of student ability and predetermined item parameters (Linden and Hambleton, 2013). Let us assume Y as a dichotomous response to item J with $Y_1, \cdots, Y_j$, where $Y_j = 1$ indicates a correct response and $Y_j = 0$ otherwise, then the probability of a correct answer can be estimated with a Three-parameter Logistic (3PL) model as follows:

$$P(Y_{jg} = 1|a_j, b_j, c_j, \theta_i) = c_j + \frac{(1 - c_j)}{1 + e^{-Da_j(\theta - b_j)}} \tag{3.H.1}$$

where $P(Y_{jg} = 1|)$ denotes the probability of the answer Y_{ig} that is attributed to student i in group g is correct given the item's discrimination a_j, the item's difficulty b_j, the pseudo-guessing parameter c_j presenting the likelihood for a casual hit of the item, and the ability of student θ_i. In addition, the 3PL makes use of a scaling constant D, which is set to $D = 1$ or $D = 1.7$ depending on whether a logistic or normal-ogive metric is desired (De Ayala, 2013; LeBeau and McVay, 2017).

The GERES proficiency tests were designed in two versions (an easy and a difficult one). Consequently, a total of 10 different tests for each subject has been developed. To link the scores across all these tests, the researchers involved in the project used a methodology called "concurrent calibration," which consist of estimating the proficiency levels and the item parameters in a single calibration run, placing all parameter estimates onto a common scale (Kang and Petersen, 2012). Through this equating procedure, the students treated as a reference group on the base scale had an ability estimated at a mean of 0 and a standard deviation (SD) of 1. For the following waves, the mean and SD of the ability distribution were newly estimated by the item and ability parameter calibration process within each dataset.[104] The calibration of the parameters was carried out by Maximum Marginal A Posteriori (MMAP), which was adapted for a model with multiple groups, and the proficiency levels were estimated by the Expected A Posteriori (EAP) method using normal prioris for all the groups.[105]

[103] Unless otherwise indicated, the explanations of IRT are based on Brooke and Bomamino (2011).

[104] For all estimates, the researchers employed the statistic software BILOG-MG, which uses marginal maximum likelihood to estimate the item parameters for the 3PL model in equation (3.H.1).

[105] For the theoretical foundations of Maximum Marginal A Posteriori (MMAP) and Expected A Posteriori (EAP), see Doucet et al. (2002) and Kolen and Tong (2010) respectively.

3.I GMM Estimator

Because the lagged dependent variable in a dynamic linear panel data model with individual fixed effects is endogenous—meaning, correlated with the idiosyncratic error term—the standard estimators (FE, RE, FD) will be inconsistent (Bond, 2002). For this reason, the use of Generalized Method of Moments (GMM) has gained fundamental importance for empirical investigations with panel data (see e.g. Baltagi, 2008; Pesaran, 2015). The most significant contributions to the development of GMM estimators date back to Arellano (1989), Arellano and Bond (1991), Blundell and Bond (1998), and Hsiao (1986), and consist of a two-phase approach: first, the unobserved individual-specific effects are eliminated by means of first difference, and then, second, the first difference or the lagged dependent variable is used as an instrument.[106]

In the interests of simplification, but without loss of generality, let us consider a reduced autoregressive model with no regressors:

$$y_{it} = \gamma y_{i,t-1} + u_{it} \tag{3.I.1}$$

for $i = 1, \ldots, N$, and $t = 1, \ldots, T$. The variable $y_{i,t-1}$ is the lagged value of y_{it}, and the stochastic term is formed by a two-way error component, such as $u_{it} = \mu_i + \nu_{it}$ with $\mu_i \sim \text{IDD}(0, \sigma_\mu^2)$ and $\nu_{it} \sim \text{IDD}(0, \sigma_\nu^2)$.

By applying first difference in (3.I.1) to offset out the individual effects, we have:

$$(y_{it} - y_{i,t-1}) = \gamma(y_{i,t-1} - y_{i,t-2}) + (\nu_{it} - \nu_{i,t-1}) \tag{3.I.2}$$

By $t = 3$, (3.I.2) can be rewritten as:

$$(y_{i3} - y_{i,2}) = \gamma(y_{i,2} - y_{i,1}) + (\nu_{i3} - \nu_{i,2}) \tag{3.I.3}$$

Note that in (3.I.3), $y_{i,1}$ can be used as valid instrument, because it is correlated with $(y_{i,2} - y_{i,1})$, but not with $(\nu_{i3} - \nu_{i,2})$ as long as the ν_{it} are not serially correlated. For $t > 3$ this pattern is repeated with the addition of an extra valid instrument for each time period, so that by the end, the matrix of instruments W_i for period T is:

$$W_i = \begin{pmatrix} [y_{i1}] & 0 & \cdots & 0 \\ 0 & [y_{i1}, y_{i2}] & 0 & \vdots \\ \vdots & 0 & \ddots & 0 \\ 0 & \cdots & 0 & [y_{i1}, \ldots, y_{i,T-2}] \end{pmatrix} \tag{3.I.4}$$

Then, the matrix of instruments is $W = [W_1', \ldots, W_N']'$, and it is based on the moment conditions $E(W_i'\Delta_{\nu_i}) = 0$. By pre-multiplying differenced equation (3.I.2) in vector form by W', we have:

$$W'\Delta y = W'(\Delta y_{-1})\gamma + W'\Delta\nu \tag{3.I.5}$$

Note that the instrumental procedure still does not account for the differenced error term in equation (3.I.2).

According to Habimana (2017), the differenced MA(1) error term $\Delta\nu_i$ has mean zero and variance $E(\Delta\nu_i\Delta\nu_i') = \sigma_\nu^2 G$, where $\Delta\nu_i' = (\nu_{i3} - \nu_{i2}, \ldots, \nu_{iT} - \nu_{i,T-1})$ and:

[106] Unless otherwise stated, the following formal description is based on Baltagi (2008).

$$G = \begin{pmatrix} 2 & -1 & 0 & \cdots & 0 & 0 & 0 \\ -1 & 2 & -1 & \cdots & 0 & 0 & 0 \\ 0 & -1 & 2 & \cdots & 0 & 0 & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots & \vdots & \vdots \\ 0 & 0 & 0 & \cdots & 2 & -1 & 0 \\ 0 & 0 & 0 & \cdots & -1 & 2 & -1 \\ 0 & 0 & 0 & \cdots & 0 & -1 & 2 \end{pmatrix} \tag{3.I.6}$$

Therefore, the Arellano and Bond (1991) preliminary one-step estimator can be found performing GLS on equation (3.I.5) with the application of the G matrix:

$$\begin{aligned} \hat{\gamma}_1 = [(\Delta y_{-1})' W (W'(I_N \otimes G) W)^{-1} W'(\Delta y_{-1})]^{-1} \\ \times [(\Delta y_{-1})' W (W'(I_N \otimes G) W)^{-1} W'(\Delta y)] \end{aligned} \tag{3.I.7}$$

Following Hansen (1982), the optimal GMM estimator of γ with $N \to \infty$ and T fixed is equivalent to (3.I.7), except

$$W'(I_N \otimes G)W = \sum_{t=1}^{N} W_i' G W_i \tag{3.I.8}$$

is replaced by

$$V_N = \sum_{t=1}^{N} W_i' (\Delta \nu_i)(\Delta \nu_i)' W_i \tag{3.I.9}$$

where $\Delta\nu$ is obtained from the preliminary one-step estimator $\hat{\gamma}_1$. Then, to provide more powerful coefficients with a smaller asymptotic variance, I follow the standard practice found in the literature and employ a two-step procedure to improve the efficiency of the GMM estimator (Hwang and Sun, 2018). The resulting two-step Arellano and Bond (1991) estimator is given by:

$$\hat{\gamma}_2 = [(\Delta y_{-1})' W \hat{V}_N^{-1} W'(\Delta y_{-1})]^{-1} \times [(\Delta y_{-1})' W \hat{V}_N^{-1} W'(\Delta y_{-1})] \tag{3.I.10}$$

Blundell and Bond (1998) showed that the lagged-level instruments of Arellano and Bond (1991) are weakened when y exhibits a substantial persistence and/or when the variance of the unit-specific error component (σ_μ) increases relatively to the variance of the idiosyncratic error term (σ_u).

To illustrate this point further, let us consider again the model with a lagged dependent variable from (3.I.1). By $T = 3$ the first-stage IV regression can be estimated by running Δy_{i2} on y_{i1}. For $t = 2$, for example, (3.I.1) can be rewritten simply by subtracting y_{i1} from both sides of the equation:

$$\Delta y_{i2} = (\gamma - 1) y_{i,1} + \mu_i + \nu_{i2} \tag{3.I.11}$$

Because $E = (y_{i1}\mu_i) > 0$, the expression $(\gamma - 1)$ is expected to be biased upwards. Then the probability limit of $\hat{\gamma}$ is:

$$plim(\hat{\gamma}) = (\gamma - 1) \frac{k}{\sigma_\mu^2 / \sigma_u^2 + 1} \tag{3.I.12}$$

where $k = \frac{(1-\gamma)^2}{1-\gamma^2}$. Hence, $plim(\hat{\gamma}) \to 0$ if $\gamma \to 1$ and/or $\sigma_\mu^2/\sigma_u^2 \to \infty$.

CHAPTER 4

Addressing Changes in Professional Behavior by Teacher Bonuses

4.1 Introduction

As already mentioned in Chapter 3, the use of pay-for-performance (PFP) programs in schools is seen by some public actors as a key tool to improve professional engagement in classrooms and, consequently, the performance of students (Barrera-Osorio and Raju, 2017; Loyalka et al., 2019). For this reason, these programs have been implemented in several countries in order to correct eventual market-efficiency problems deriving from traditional fixed-salary schedules (Balch and Springer, 2015; Liu et al., 2016). This is because many studies have indicated that years of experience and educational degrees of teachers alone are not strongly correlated with students' academic achievements (see e.g. Kane et al., 2011; Rivkin et al., 2005; Rockoff, 2004)

Although it is possible to find considerable support for teacher performance-related-pay programs across economists, it is difficult to draw any conclusions based on teachers' own perceptions (Leigh, 2013). Especially in the US, the studies concerning teacher attitudes toward PFP programs form a long tradition and report mixed findings (see e.g. Ballou and Podgursky, 1993; Goldhaber et al., 2011; Russ, 2015; Stephens, 2015). In general, the teacher support for bonus programs is higher when the educators work in hard-to-staff schools, but it decreases when the program links the bonus to student test scores alone (Liu et al., 2016).

Muralidharan and Sundararaman (2011) were the first authors to examine teacher attitudes toward a PFP program in a developing country. Applying qualitative interviews to collect the opinions of teachers concerning an experimental performance-based bonus scheme for teachers in the Indian state of Andhra Pradesh, the authors found strong support for it. Over 80 percent of the teachers had a favorable opinion about the idea of linking a component of pay to measures of performance; this support increased even further when teachers were randomly assigned to a merit-pay program. Using questionnaires with closed- and open-ended items conducted in a northeastern city of China, Liu et al. (2016) found meanwhile that 48.5 percent of the surveyed teachers supported the PFP programs at their schools.

Despite this research on teacher support for merit pay, there is very limited evidence in the literature showing how PFP programs can directly affect student outcomes (Hanushek and Woessmann, 2011; Nyberg et al., 2018). In theory, the change in teaching practices is a necessary condition for a causal relationship between these two outcomes (Jones, 2013), but a more insightful understanding of the mechanisms behind this association is required to support public decisions concerning the optimum design of PFP programs in the education system (Stephens, 2015). Therefore, researchers have appealed to the academic community to expand the empirical analysis to teachers' perceptions related to merit pay (see Marsh, 2014; Viscardi, 2014).

The current paper will follow this guidance and present the studied teachers' perspectives in relation to one merit-pay program in the Brazilian education system. Internationally comparative studies have already shown that the performance of students and the salaries of teachers in Brazil are low compared with other countries. In the PISA 2018, for example, 15-year-olds in Brazil score 413 points in reading literacy compared to an average of 487 points in OECD countries, and similar gaps were found also for Mathematics and Science (see Schleicher, 2019). According to the 2018 Global Teacher Status Index (see Dolton et al., 2018), the average annual salary of a Brazilian starting secondary school teacher was USD 13,000 (adjusted for purchasing power parity, PPP). Therefore, Brazil sits in eighth position in the ranking of countries with the lowest-paid teachers.

Against this background, many school districts in the country started to link additional remuneration for teachers with the improvement of academic achievements among students. However despite the increasing number of teacher bonus programs in Brazil, scholars have encountered substantial difficulties in gathering reliable data to assess the impact of these PFP programs, since most of them have been implemented in ways that hinder the creation of statistically valid comparison groups (Bresolin, 2014). To the best of my knowledge, in Brazil no empirical evaluation began in advance of the implementation of the teacher bonus programs—thus rendering impossible the use of randomized control trials to investigate their impact.

As a consequence, the scientific monitoring and evaluation of teacher bonus programs in Brazil is rarely reported. To the best of my knowledge, only three studies have been able to overcome the existing data limitations and thus examined empirically the impacts of the teacher bonus scheme in Brazilian schools. While Lepine (2016) and Oshiro et al. (2015) evaluate the effects of PFP programs for teachers vis-à-vis the academic achievements of students, Bresolin (2014) researches questions similar to those investigated in this paper. The author investigates the impact of teacher bonus programs on: (i) teachers' pedagogic practices; (ii) absenteeism and teachers' rotation; and, (iii) interlocution with family members in order to ensure students' presence at school. For the study, Bresolin (2014) applies the data from the Prova Brasil (Brazil Test) questionnaire—which was answered by principals, teachers, and students—and a propensity score matching methodology to calculate the differences in outputs between the states that implemented the PFP programs for teachers and those who did not. According to the author, the bonus program had a positive impact on the teachers' absenteeism and on the frequency with which they correct students' homework.

In order to counterbalance the current data limitations, this paper has carried out an own data collection in Brazil and applied a mixed-methods design to investigate the effects of a teacher bonus program there on the professional practices and behaviors of educators. In order to address the research questions in a rigorous and systematic manner, I create a research approach integrating quantitative surveys and qualitative interviews. Using an explanatory sequential design—which is considered the most straightforward approach in undertaking mixed-methods research (Creswell and Clark, 2017)—I first collect quantitative data for the descriptive survey research. Then, second, I include qualitative information to generate more in-depth explanations of the initial findings. As highlighted in the literature (see Morse, 1991), this design is strongly recommended for research projects in which there is a need to develop a comprehensive background against which to understand the empirical findings provided by the quantitative investigation.

The use of mixed-methods research for the investigation of PFP programs in the education system is becoming increasingly common in the literature.[107] Therefore, conceptual similarities can be found between this research project here and existing studies. Brasington (2016) utilizes a mixed-methods design—including online surveys, qualitative interviews, and analysis of district documents—to investigate changes in educators' motivation and job performance with the implementation of a merit-pay program in a suburban school district of Michigan. While the online survey was designed to address school educators' perceptions related to the merit-pay program, the group and individual interviews were conducted to enhance and elaborate on data collected from the surveys. Also for the US, Marsh (2014) uses a mixed-method approach for the investigation of teacher perceptions concerning the performance-based pay of the Pandora School District in Missouri. He first drew on a questionnaire

[107] See Nyberg et al. (2018) for a recent cross-disciplinary review and meta-analysis regarding collective PFP programs.

to flesh out the opinions and perceptions of teachers on the topic, and then from those respondents he selected a subsample for in-depth and intensive interviewing. Similarly, Liu et al. (2016) applies quantitative and qualitative data collection to investigate the attitudes of Chinese teachers toward performance-related pay, and the underlying factors influencing their expressed attitudes.

For comparison purposes, this chapter maintains the focus of the investigation on the schools of Campinas, as in Chapter 3. Therefore, the data for the current paper stem from teachers who worked in the state elementary schools in Campinas during the 2020 school year. As already described in detail in Chapter 3, Campinas is a Brazilian municipality with around 1.2 million inhabitants located in the state of São Paulo. In 2008, the state implemented a PFP program for all staff employed in the São Paulo State Education Network (SEE-SP). This is a collective bonus program that rewards staff according to the achievement of pre-set targets related to academic performance and the pass rate of students, the so called Education Development Index of the State of São Paulo (IDESP). All employees from the SEE-SP are eligible for the bonuses, which is paid once a year and ranges in amount from 0 to 20 percent of the individual's annual salary depending on the success of the school in achieving the IDESP in the previous year (Castro and Lopes, 2016).

The 12-year interval between the implementation and evaluation of the bonus program is an empirical strategy aimed at identifying its long-term incentive effects. While the most renowned evidence on teacher bonuses found in the literature stems from experimental studies using a maximum of two years' distance as the post-treatment period (see e.g. Glewwe et al., 2010; Lavy, 2009; Muralidharan and Sundararaman, 2011), this paper argues that a broader time investigation is necessary to capture the long-term effects of PFP programs (Lazear, 2003). Educators need some years to adapt themselves to the bonus scheme's legal guidelines and to identify the genuine capacity of their schools to achieve the established targets. Moreover, the lack of bonuses in some schools or the variation in educational inputs across schools can lead to a migration of staff to the best working environments, thus changing the general equilibrium within the labor market (Brooke, 2013; Woessmann, 2011).

This paper examines three important pathways through which a teacher bonus program could generate impacts on the academic achievements of students. First, did the program create an additional incentive for educators to enter/remain in the state education network? Second, did the bonuses lead to a reduction of teacher absenteeism? Third, did the PFP scheme generate an improvement of teacher behaviors and practices in the classroom? In addition, dishonest behavior and the level of support for the bonus scheme will be investigated among teachers in order to identify the negative impacts of the PFP program too.

To test these hypotheses, the remainder of the paper is structured as follows. In the next section, I describe the theoretical motivation and hypotheses for the research. Section 4.3 presents background information on the Brazilian education system. The subsequent section then describes the methodological design and procedures, while section 4.5 reports the empirical results. Finally, section 4.6 concludes with a discussion of the main findings and their policymaking implications.

4.2 Theoretical Motivation and Hypotheses

As in other countries around the world, the implementation of teacher bonuses in Brazil was also justified by the expectation of an increase in student performance

(Oshiro et al., 2015). According to Yuan et al. (2013), two main theoretical frameworks can help explain the link between performance incentives and teachers' motivation: expectancy theory (Vroom, 1964) and goal-setting theory (Locke, 1968). Vroom's expectancy theory suggests that the motivation of teachers in relation to the bonus program is dependent on three main factors: expectancy, instrumentality, and valence. Expectancy because the amount of effort that teachers expend to meet the program targets is dependent on the belief that their higher personal effort will yield student benefits in terms of academic achievement. Instrumentality refers, meanwhile, to the genuine likelihood of receiving the bonus in case of meeting performance expectations; valence is the private desirability of attaining the bonus. Locke's goal-setting theory complements this expectancy theory, stating that teachers' motivation will be also affected by their individual perception of the fairness of the bonus program, and by their understanding of the program's content-related design and goals.

These different theories have already been extensively explored and reported in the literature. Heneman (1998), for example, investigates in the US the Charlotte-Mecklenburg school-based performance-related-pay program for teachers based on expectancy and goal-setting theory, concluding that the full motivational potential of the bonus scheme was not realized due to perceived deficiencies in the design of the program. By contrast, Kelley and Protsik (1997) indicate that the Kentucky school-based PFP program provided a positive motivating force for the improvement of teaching approaches in schools where the conditions of expectancy, goal-setting, and contingency theories were met.

Since the success of implementing PFP programs in the education system depends heavily on their support by teachers in the classroom (see e.g. Ballou and Podgursky, 1993; Liu et al., 2016), this paper integrates the expectancy and goal-setting theories into the evaluation of bonuses offered in the Brazilian education system. It strives to identify the individual knowledge base, acceptance, and preferences of teachers in relation to the PFP program in which they are involved. Therefore, the first hypothesis of this paper can be derived as follows:

Hypothesis 1: *Teachers do support the PFP program of the SEE-SP as a mechanism to improve teaching quality.*

The PFP program implemented in state schools of São Paulo ties the bonuses to measures of student achievement, as a public-policy tool to improve education quality. Therefore, to understand the dynamic behind bonus programs in the education system, it is necessary to highlight the main effects that are expected to take place when teachers receive the opportunity to connect salary improvements with the improvement of student outcomes.

First, performance-related-pay programs have the capacity to reform the single salary schedule, providing financial incentives for more productive workers to enter and stay in the teaching profession (Goodman and Turner, 2013). Wage differentiations between high- and low-performing staff is an elementary condition for the intrinsic motivation of teachers (Muralidharan and Sundararaman, 2011), since hard-working ones tend to become dissatisfied if they see no difference in earned income between them and those who shirked their duties (Kremer et al., 2005). Several studies of teacher turnover have found that high-ability teachers are more likely to leave the profession than their less-able peers (see e.g. Murnane and Olsen, 1990; Podgursky et al., 2004). As such, the second hypothesis is:

Hypothesis 2: *The bonus program has created an additional incentive for educators to enter/continue working in the state education network.*

Work attendance is another possible mechanism linking the bonus program to student performance. Given the inherent difficulty of quantifying teachers' effort in the classroom, researchers have used work attendance as a proxy for the evaluation of the effectiveness of PFP programs in the education system (Goodman and Turner, 2013). Duflo et al. (2012) show, for example, that monitoring and financial incentives can reduce teacher absence and increase learning in India. With the bonus program, work absenteeism in treatment schools decreased 21 percent and this increase in instruction time has resulted in higher student test scores. The same study also confirms that despite this increase in instruction time, the teachers did not compensate for their higher attendance by teaching less. In the moment of monitoring, teachers from treatment and comparison schools had similar chances to be present in the classroom, to use the blackboard, and to be involved in teaching activities.

In the case of the bonus program in São Paulo, the absenteeism rate of teachers enters directly into the calculation of the bonuses paid. This is done by penalizing every single absence with a reduction in additional payments (Oshiro and Scorzafave, 2011). For this reason, the third hypothesis concerns the link between teacher bonuses and work absenteeism:

Hypothesis 3: *The bonus program has led to a reduction of teacher absenteeism.*

The most common argument cited in the literature in favor of teacher bonuses is that financial incentives provide these individuals with an additional motivation to put more effort into the instruction process (Gneezy et al., 2011; Lavy, 2009). In the literature, there is ample evidence supporting the argument that PFP programs change teacher behavior. However, supporters and opponents of PFP programs in the education system generally disagree about the reason for this change occurring. While the former argue that teachers will undertake changes to promote a broad capital acquisition by their students, skeptics point out that teachers are able to manipulate student performance by short-term strategies focusing efforts on skills and actions that inflate student scores in the standardized tests used for the calculation of bonuses (Glewwe et al., 2010).

The first argument is supported by the work of Muralidharan and Sundararaman (2011), which investigates the impact of a teacher incentive program in rural India using student test scores in Math and Language tests. The authors indicate that in those schools with the incentive program not only is academic achievement in these two subjects higher, but also so is the performance of students in Science and Social Studies too (for which there were no incentives)—suggesting that teacher bonuses generate positive spillover effects on learning outcomes in nonincentivized subjects. According to the study, teachers in incentive-receiving schools were more likely to make additional effort in their teaching activities—such as extra classes after school, giving additional homework, and providing students with more practice tests. Similar empirical findings were found in Israel (see Lavy, 2009), where the implementation of teacher bonuses has led to a gain in student performance due to positive changes in teachings methods, more after-school teaching, and increased feelings of responsibility for meeting students' educational needs. As such, the fourth hypothesis relates to evidence for changes in teaching practices due to bonuses:

Hypothesis 4: *Due to the bonus program, teachers have improved their teaching practices and behaviors.*

Opponents of merit-pay programs in schools frequently cite the principal-agent theory to claim that performance-based compensation can result in less collaborative school environments. Information about teachers' work effort is asymmetric, since their activities in the classroom largely go unobserved by the principal. Therefore, linking teachers' financial incentives exclusively to one single output—for example, the student performance measured by academic scores—might lead to the negligence of other desirable student outputs, such as cultural appreciation, physical fitness, personal development, interpersonal skills, and mutual tolerance (Levačić, 2009).

One of the most frequently expressed criticisms in this regard is "teaching to the test," a teacher practice aimed at narrowing the curriculum in order to artificially increase the performance of students per the government-run tests used for bonus calculations (Podgursky and Springer, 2007). Glewwe et al. (2010), for example, apply a randomized controlled trial in Kenyan primary schools to investigate the effects of teacher bonuses on the performance of students, and confirm that the program has led to an increase in test scores on the official exams associated with teacher incentives—but no performance gain was found by independent proficiency tests using different evaluation formats. A key finding of the study is that teacher attendance and homework assignment remained unaffected in bonus-program schools, but the preparation sessions for the government-run proficiency tests increased.

Furthermore, other examples of manipulative behavior by teachers have already been reported in the literature. Behrman et al. (2015) demonstrate that the reason for the higher test scores in schools with teacher bonus programs can be explained, in part, by the higher rate of student cheating in the administrative exams used for the calculation of bonus payments. Jacob (2005) shows that teachers tend to exclude weak students from testing, Figlio and Winicki (2005) find evidence that schools increase the caloric content of meals on testing days in order to boost short-term student performance, while Jacob and Levitt (2003) point to (illicit) dishonest teacher practices in order to inflate test scores, such as providing correct answers to students or changing the latter's responses on submitted answer sheets. Against this background, the fifth and final hypothesis of this paper concerns increased attempts at cheating by teachers in order to inflate student test scores with regard to the standardize academic tests used for bonus calculations:

Hypothesis 5: *Teacher bonuses generated an increase in cheating among staff.*

4.3 The Brazilian Context

The Brazilian constitution shares responsibility for the country's educational system between all three levels of the Federation. While the federal government's role is limited to the setting of curriculum guidelines and the provision of financial and technical assistance to the subnational levels, states and municipalities are primarily responsible for maintaining public education. Consequently, these two subnational authorities operate the overwhelming majority of public schools in the country and are the key players behind the wage policies for teachers (Becker, 2014).

Up until the start of this century, the remuneration of teachers in Brazil was based on a uniform pay system that ensured the same salary for those with the same years of experience and education level. But after the turn of the millennium the idea of merit pay for educators would grow in popularity with the proliferation of the (large-scale) standardized tests for the evaluation of student achievement (Brooke, 2016). Then, public authorities began to introduce performance-monitoring frameworks for schools in order to improve the quality of education, and to use teacher bonuses as an accountability tool to influence educational outputs (Bresolin et al., 2018).[108]

Starting with Rio de Janeiro in 2001, several school districts in Brazil would implement accountability programs in which the payment of financial bonuses to teaching staff is dependent on the achievement of targets related to students' academic performance (Brooke, 2016).[109] Apart from the teacher bonus scheme of the city of Sobral—which pays out specifically based on individual performance—all other PFP programs in Brazil are group incentive-based ones that use performance measures at the aggregate level (normally, school) to reward the efforts of educators in a collective manner (Brooke, 2013).

This is the case also for the teacher bonus program of São Paulo, Brazil's richest and most populous state. With approximately 4.3 million students, 5,300 schools, and 220,000 teachers, the SEE-SP is the largest education system in Brazil (SEE-SP, 2020b). At the time of the bonus implementation (2008), the base salary for teachers working full time (40 hours per week) in elementary state schools was BRL 1,309.17 (ca. PPP USD 663.69) per month—equivalent to 2.8 times higher than the national minimal wage at the time (Barbosa and Fernandes, 2016).[110] Compared to the salaries paid in the other 26 Brazilian states, the wage paid in São Paulo held 11th position in the ranking of highest teacher salaries nationwide (APEOC, 2010).

In October 2007 the state of São Paulo launched the "School Quality Program" (SQP), with the purpose of (i) establishing clear and objective criteria for the performance evaluation of schools and (ii) setting the targets need to promote quality standards in the education system (Castro and Lopes, 2016). The SQP was made responsible for the implementation of the IDESP, which is a composite indicator of school quality based on two main components: the pass rate, indicating the share of students who have completed the respective educational levels on time; and, the performance rate, which is measured as the average scores of students per the government-run compulsory standardized test called the "Evaluation System of Learning Achievement in the state of São Paulo" (SARESP).[111]

The IDESP establishes annual and individual quality targets for each school and educational level: lower primary education (Grades 1–5), upper primary education (Grades 6–9), and secondary education (Grades 10–12). At the beginning of the school year, the SEE-SP publishes the IDESP for the current year (used as a target) and the IDESP achieved in the previous one, thereby enabling the different stakeholders to track the progress of the school in achieving these goals (Castro and Lopes, 2016).

The teacher bonuses are calculated according to the degree of IDESP improvement reached by the school in which the staff are employed and proportional to their work attendance in the year in question; no bonuses are paid to teachers with a work-absenteeism rate higher than one-third of classes missed.[112] In 2009, for example, the maximum bonus paid to teachers corresponded to 2.9 times their (monthly) salary and was reached when the absenteeism (in 2008) was zero and the target achievement

[108] See Bonamino and Sousa (2012) and Andrade (2008) for a historical overview of the different phases in the evaluation of the educational system in Brazil.

[109] Currently, 13 of the total 27 Brazilian states are using teacher performance-related-pay programs (Scorzafave et al., 2015); similar initiatives can also be found at the municipal level (see e.g. Mec/Inep, 2005). However, the total number of municipalities with teacher bonus programs still remains unknown (Brooke, 2016)

[110] In 2020 the base salary for teachers working full-time in the SEE-SP was BRL 2,888.24 (SEE-SP, 2020a), which equated to USD 561.39 (PPP conversion rate on July 23, 2020).

[111] The SARESP was applied for the first time in 1996 using a probability sampling of schools; after 2003 it became compulsory for all state schools in São Paulo (Andrade, 2008).

[112] See Oshiro et al. (2015) for a mathematical and detailed description of the IDESP's calculation.

was equal to 120 percent (or more). In case of no work absenteeism and a IDESP improvement of 100 percent, the additional payment was equivalent to 2.4 times their monthly salary, and so on (e.g. 50 percent improvement = 1.2 times salary gain) (Oshiro et al., 2015).

In April 2009 the SEE-SP paid out teacher bonuses for the first time, disbursing around BRL 590.6 million related to the achievement of the IDESP in the year 2008 (Lepine, 2016). Oshiro et al. (2015) show that between 2008 and 2012, around 200,000 staff in the SEE-SP benefited each year from the teacher bonus; the average bonus paid ranged from BRL 1,789.47 to 3,020.91, which corresponded to approximately 1.9 and 2.5 times the monthly salaries, respectively. Finally, reports from the SEE-SP—obtained for this paper through the Law on Access to Public Information—indicate that on average 55 percent of São Paulo state's lower primary schools achieved the IDESP in the period 2008–2018, while the equivalent figures were 44 percent for upper primary schools and 48 percent for secondary schools (see Figure 4.1).

4.4 Methodology

This paper follows Liu et al. (2016) and Burns et al. (2009) in developing a mixed-methods research approach that includes questionnaire surveys and interviews to investigate the impact of the teacher bonus program. This empirical approach is based on the complementary nature of quantitative and qualitative methods, and brings three main gains for the research. First, the majority of questions are prepared ahead of time, reducing the amount required for the qualitative interviews; second, it provides reliable comparable data across respondents; and, third, perhaps the most important point: it encourages two-way communication, functioning as an extensive tool of data collection (Adams, 2015). Therefore, these different research approaches enable me to develop a comprehensive understanding of teacher attitudes toward the PFP program (Burns et al., 2009) and to triangulate the results to illuminate in more detail the theoretical concerns involved in the research. This serves to confront the contradictions in, and to highlight, the fragmented and multifaceted nature of beliefs related to the bonus program (Brannen, 2005).

4.4.1 Instrumentation

For data collection, the paper applied two independent but complementary research instruments. For the quantitative research, I created a structured questionnaire—which was based on the empirical investigation of Burns et al. (2009), Liu et al. (2016), and Soto-Pérez et al. (2020)—containing 40 questions that examine individual attitudes toward the teaching profession, levels of acceptance of PFP programs, and experience with the IDESP.[113] Following Liu et al. (2016), these questions asked individuals about their level of agreement with a series of statements related to the topics of investigation, and were measured on a five-point Likert scale ranging from strongly disagree (1) to completely agree (5). In order to reduce the time spent on filling out the questionnaire and consequently to increase the likelihood of reliable responses,

[113] For teachers with work experience in the period prior to the bonus program's inception, the questionnaire contains 15 additional questions related to changes in teaching practices in the classroom.

the author created an online survey and sent it to the participating schools via email in the 30th calendar week of 2020.[114]

Since structured surveys are not efficient in providing an in-depth understanding of the statements and perspectives of respondents (Weiss, 1998), the paper applied qualitative (remote) interviews to complement and supplement the data gathered in the survey. For this, I used a semi-structured interview guide that contains open-ended questions—thus allowing participants to express own narratives embedded in their personal experiences related to the bonus program. Besides the introduction and concluding thoughts, the interview guide—which was based on the work of Burns et al. (2009) and can be found in Appendix E—highlights two main topics related to PFP programs: expectancy theory and teaching practices in the classroom. For the latter, two different effects of the teacher bonus program were investigated: the "good" practices in the learning process that may have changed with the bonus scheme's introduction and the dishonest behavior of teachers regarding inflating students' academic scores per the government-run tests used for the calculation of bonuses.

Between August and September 2020, the author conducted the semi-structured, open-ended interviews with the teachers. All the data collection was strictly confidential, anonymous, and taken remotely using video-conferencing software (Microsoft Teams and Skype). Then, the resulting interviews, each between 20 to 43 minutes long, were tape-recorded, fully transcribed, and analyzed to illuminate the main aspects vis-à-vis the research questions.

All the interviews followed a predetermined path, and were managed using the interview guide. At the beginning of the interview, the author introduced himself to the respondents and explained the aims of the research. The participants were informed about the semi-structured nature of the research, and encouraged to share their personal experiences with the bonus program. In the same manner, the interviewer explained the necessity of introducing extra questions about unexpected but relevant pieces of information that emerged during the conversations. Next, the author confirmed the confidentiality of the data, and asked permission to tape-record the interviews.

During the interviews, I started with the introductory questions and moved on gradually to the more complex ones, taking care not to ask anything too probing. Furthermore, on some occasions, I made reference (anonymously, of course) to statements provided by other respondents in order to validate information already gathered. Once I was aware that all topics had been discussed, I asked the respondent if he/she had anything further to add. Then I thanked them for their participation, explained the next steps in the data analysis, and promised to send them a copy of the final version of the study once it had been completed. Immediately afterward, I summarized the main impressions of the interview in a protocol to make easier the latter's transcription and the analysis of its contents.

4.4.2 Sample Selection

The empirical research was conducted in the Brazilian city of Campinas with teachers from state primary schools. With a population of over 1.2 million people, Campinas is the third-most populated municipality in the state of São Paulo. According to the 2018 school census, the school district of Campinas enrolls approximately 124,000 students in 658 schools, from which 175 (28.8 percent) are state-run institutions

[114]The author used the software EFS Survey for the creation of the online survey, which can be found online via this link (in Portuguese) or in Appendix D. The online survey was open for participation during the 35 days between July 13 and August 16, 2020.

where 4,729 teachers are employed. Of these 175 state schools, 112 provide primary education—in which 71,509 students are enrolled and 1,932 teachers employed (INEP, 2019b).

Using the online search tool for schools from the SEE-SP,[115] I collected the contact details of the state primary schools in Campinas and phoned the principals of all 112 to explain about the research project and to identify a willingness to cooperate. Next, I sent an email to the principals with a formal invitation to participate in the survey. This email also included the link to the online questionnaire, to be forwarded to the teachers employed in the school. Finally, two weeks after the email, the author contacted the school principals via phone once again to ask about the forwarding of said email to the teachers.[116]

For the qualitative interviews, the paper applied a common practice used in mixed-method analysis and derived the subsample for the qualitative research from the overall quantitative sample (Thompson, 2004). For this purpose, I used the online questionnaire as a starting point for the selection of those to participate in the interviews. In the introduction to the survey, the author informed the participants about the two forms of data collection for the research project and mentioned the existence of the subsequent interviewing. Then, those with an interest in participating in the semi-structured interviews were asked to declare this willingness in question 37 of the questionnaire.

4.5 Empirical Findings

This section summarizes and discusses the main results, divided into three parts. The first applies a descriptive-survey research design to report the quantitative findings related to the questionnaire. The second part complements this with individual insights generated by the interviews with open-ended questions. The third and final part triangulates the data from both methods in order to provide support or additional evidence for the preference patterns of respondents.[117]

4.5.1 Quantitative Results

Table 4.1 below summarizes the responses from the 53 teachers employed in 25 different schools who completed the structured questionnaire. The sample was composed of 35 female and 18 male teachers, on average 46 years old and with 13 years of experience. Only 2 percent of the teachers have no tertiary education, while 73 percent have a bachelor's degree as their highest educational level, 19 percent a master's, and 6 percent a doctorate. Some 74 percent of the respondents exclusively dedicate themselves to teaching in the SEE-SP, while 26 percent work also in the private or

[115]The online search tool can be accessed directly at: `http://www.educacao.sp.gov.br/central-de-atendimento/index_escolas.asp`.

[116]In addition to the direct communication with the schools, the author also made a formal request to the Campinas Regional Board of Education for the distribution of the online survey to the teachers. However, this request was never answered.

[117]In the interest of transparency, it is important to highlight the role of the COVID-19 pandemic in the data collection for this study. The author had planned a research stay in Campinas for May 2020 to collect the necessary information from the teachers of the SEE-SP. However, with the COVID-19 outbreak in Brazil and the consequently travel restrictions and school closures, the author was forced to realize all data collection remotely. It is to be expected that without the pandemic, the number of participants in the questionnaire survey would be higher since the author would have visited personally the schools to collect the data and the teachers would not have been overloaded with the extra work of switching their activities to online learning.

municipal education system. For clarity, Table 4.1 groups the questions by their respectively hypotheses and reports the percentage of responses for each of the five-point Likert-scale alternatives.[118]

Table 4.1. Quantitative Results from Structured Questionnaire

Item	Statement	Likert Scale (in %)					Descriptive	
		1	2	3	4	5	Mean	N
	HYPOTHESIS 1							
Q15	I support remuneration policies based on productivity	45	25	6	15	9	2.19	53
Q16	The bonus is a positive tool to improve teaching	53	15	10	11	11	2.13	53
Q17	The bonus program is fair to teachers	62	13	15	4	6	1.77	53
Q18	I am satisfied with the bonuses that I received in recent years	68	19	13	0	0	1.45	53
Q19	The bonus does not evaluate important aspects of my teaching	7	4	6	21	62	4.25	52
Q20	The bonus program improves teamwork	41	25	15	17	2	2.13	53
Q26	The IDESP is clearly defined and comprehensible	32	26	26	14	2	2.26	53
Q27	The IDESP improves the quality of the education system	28	36	23	7	6	2.26	53
Q28	I believe in the IDESP's calculation	30	25	26	17	2	2.36	53
	HYPOTHESIS 2							
Q07	Teacher is an undervalued profession	10	4	5	8	73	4.31	52
Q08	The SEE-SP is looking to improve working conditions	28	30	25	13	4	2.34	53
Q09	I enjoy teaching	0	0	2	23	75	4.74	53
Q10	I am satisfied with the wage I receive	64	19	9	4	4	1.64	53
Q14	I would prefer to work in a private school	30	13	17	21	19	2.84	53
Q21	The bonus program helps to attract effective teachers	60	19	8	9	4	1.77	53
Q22	The bonus program helps to retain effective teachers	64	13	13	6	4	1.72	53
Q23	The bonus provides me an extra incentive for my improvement	48	23	15	8	6	2.00	52
Q24	The bonus is an incentive to stay working in the SEE-SP	55	19	13	4	9	1.94	53
Q25	The bonus paid is large enough	70	17	5	4	4	1.55	53
	HYPOTHESIS 3							
Q41	My work absenteeism is lower	43	11	25	3	18	2.43	28
Q52	With the bonus, the work absenteeism at my school decreased	37	33	15	11	4	2.04	28
Q53	With the bonus, the stress involved in teaching become greater	8	11	23	23	35	3.39	28
Q54	With the bonus, the resentment among teachers increased	11	7	22	30	30	3.46	28
	HYPOTHESIS 4							
Q11	If I work hard, my students will improve their performance	13	19	32	21	15	3.06	53
Q12	Teachers are limited in what they can achieve	6	4	13	41	36	3.98	53
Q13	I exceed the average performance of my colleagues	13	15	30	30	12	3.11	53
Q29	A poor result per the IDESP leads me to change my teaching	25	21	28	17	9	2.66	53
Q42	I give more homework to students	36	32	21	7	4	2.11	28
Q43	I bring more work home	25	8	21	21	25	3.14	28
Q44	I more frequently use the textbooks in the classroom	21	18	32	18	11	2.79	28
Q45	I more frequently use multimedia in the classroom	21	18	21	29	11	2.89	28
Q46	I participate more in the definition of content	32	11	25	25	7	2.64	28
Q47	I participate more in parent-teacher meetings	21	7	36	11	25	3.11	28
Q48	I make more suggestions to improve my school	18	15	32	14	21	3.07	28
Q49	There is more brainstorming between teachers	7	7	18	47	21	3.68	28
Q50	I help my colleagues more frequently with their work	18	0	25	36	21	3.43	28
Q51	With the bonus, I receive more support from my colleagues	33	26	30	11	0	2.11	28
Q55	The bonus program has not affected my performance	0	7	11	18	64	4.39	28
	HYPOTHESIS 5							
Q30	I assign Portuguese and Math skills a higher importance	15	20	23	23	19	3.09	53
Q31	I use the prior SARESP exercises as preparation for the SARESP	19	13	34	23	11	2.94	53
Q32	We apply mock tests for the SARESP in my school	11	23	25	26	15	3.11	53
Q33	We offer reinforcement classes for the SARESP in my school	21	25	19	25	10	2.77	52
Q34	Before the SARESP, the students receive extra preparation	13	19	27	25	16	3.10	52
Q35	I had knowledge of cheating regarding the SARESP	62	38	-	-	-	1.38	52
Q36	In my opinion, cheating occurs often regarding the SARESP	3	12	38	25	22	3.50	32

Notes: Data collection was carried out through structured questionnaires with 53 teachers from the SEE-SP in the municipality of Campinas (see structured questionnaire in Appendix D). Data are not representative of the whole population. The questions ask teachers about their level of agreement with the respectively statements, and were measured on a five-point Likert scale ranging from strongly disagree (1) to completely agree (5). Questions 41 to 55 are answered only if the answer to Q5 (worked in the SEE-SP in the pre–bonus program period) was "Yes." For Q35, response 1 is "Yes" and 2 "No."
Source: Author's own data collection, 2020.

[118] The online questionnaire had a completion rate of 25 percent. From the 217 individuals who accessed the link to the online survey, 128 (59 percent) read the introduction only, 34 (16 percent) broke off the questionnaire before its conclusion, and 2 (9 percent) overlooked all questions.

Table 4.1 indicates reduced support for PFP programs among teachers: some 45 percent of participants strongly disagreed with the statement "I support the variable remuneration policies for teachers according to their productivity" (Q15). Talking more specifically about the teacher bonus program of the SEE-SP, attitudes are more critical besides. Per answers to Q16, only 22 percent of respondents consider the bonus program a positive tool to improve teaching activities (answers 4 + 5), three-quarters find the bonus program unfair to teachers (answers 4 + 5 per Q17), and no one indicates being satisfied with the bonuses received in recent years (answers 4 + 5 per Q18). In addition, there seems to be a consensus that the teacher bonus program in state schools of São Paulo does not take into consideration important aspects of teaching activities, since 83 percent of respondents answered the alternatives four or five to Q19.

H2—asserting that the teacher bonus program might have created an additional incentive for work in the SEE-SP—can be rejected categorically per the majority of the teachers' responses. Only 10 percent of participants believe that the teacher bonus program can help to retain more effective teachers (Q22) while 13 percent indicate that it can help to attract (new) qualified professionals to state schools (Q21). The overwhelming majority of respondents do not see the bonus program as an incentive to stay working in the SEE-SP (74 percent per Q24), while 87 percent of them stated that the bonus is not large enough to motivate them to put more effort into their job (Q25).

In relation to the impact of the bonus program on work absenteeism (H3), Table 4.1 suggests a small but positive impact. Some 21 percent of respondents confirm that their absence from work is now lower than in the period pre-bonus (Q41), while 15 percent believe that work absenteeism in the school as a whole has decreased (Q52).

The empirical evidence for H4—which investigates the changes in teaching practices and behaviors due to the bonus program—is mixed. For the questions related to teaching activities (Q42–Q48), the answers are relatively evenly distributed over all five alternatives. But the data indicated a higher level of brainstorming between teachers since the implementation of the bonus program (68 percent per Q49) and a higher willingness to help their work colleagues (57 percent per Q50).

Finally, there is H5—which investigates the dishonest behavior of teachers in relation to the assessment basis for the bonus program. In this case, the quantitative survey reports a robust finding: cheating is an element present with the bonus program. Some 62 percent of participants confirm having knowledge of such practices (see list in Appendix D) vis-à-vis the standardized state-run test SARESP (Q35), which is used as the measure of student performance and consequently for the calculation of teachers' bonuses. For 15 percent of respondents, these dishonest actions are common practice in the state schools of São Paulo (Q36). There is also evidence for the "teaching to the test" notion. A considerable number of teachers report that they use prior SARESP exercises as preparation for the test (Q31), apply mock tests for the SARESP (Q32), offer extra tuition classes (Q33), and give extra preparation to the students in the weeks before the test (Q34). A further indication of "teaching to the test" is the higher importance assigned to Portuguese and Math skills by teachers (Q30), since the SARESP evaluates only these two skills among students.

4.5.2 Qualitative Results

The research project conducted remote interviews with 11 teachers from nine different schools of the SEE-SP with the aim of collecting qualitative data related to the bonus program.[119] Table 4.2 lists the main data of interviewed teachers.[120]

Table 4.2. Interview Participants

Teacher	School	Gender	Age	Experience	Duration
ID 1	A	Male	29	8	28:11
ID 2	B	Female	34	6	31:34
ID 3	C	Male	54	23	41:24
ID 4	A	Female	34	7	22:14
ID 5	D	Female	61	32	34:36
ID 6	E	Male	43	15	43:08
ID 7	C	Female	43	19	32:16
ID 8	F	Female	39	8	20:22
ID 9	G	Male	32	6	38:24
ID 10	H	Female	33	6	23:08
ID 11	I	Female	52	25	33:01

Notes: Interviews conducted in August and September 2020. Teachers were randomly assigned to numbers between 1 and 11, and schools to letters between A and I. Experience is expressed in years of teaching, duration of the interview in minutes.
Source: Author's own data collection, 2020.

The resulting 5.8 hours of recorded material were fully transcribed and then evaluated qualitatively. In order to consolidate the major statements and issues arising from the open-ended questions, I followed Heneman (1998) and applied an analytic framework to transform the personal narratives of the participants into declarative statements. For this purpose, I utilized the software f4analyse to structure the data, compare statements, and to summarize the main findings from the interviews.

For the coding system, I first used the five hypotheses from section 4.2 derived from the literature, and, in sequence, seven additional codes were identified using the information presented in the interviews. Then, I organized the coding system hierarchically and clustered all the relevant text passages according to their respectively codes.[121] Next, I checked the degree of agreement of participants with these statements, providing in this way two main benefits for the analysis: the identification of individual teacher perceptions and viewpoints, and the representation of possible consensus among participants in respect to those views.

Table 4.3 reports the main statements that arose from the interviews, and their respective degrees of support among the teachers.

[119] From the 53 teachers that completed the online questionnaire presented in the previous section, 15 demonstrated interest in participating in the qualitative interviews; four did not react to subsequent emails seeking to arrange an appointment however.

[120] To safeguard the confidentiality of the data, this paper does not provide the name of the teachers and schools involved in the research. Instead of that, the teachers were randomly assigned to numbers between 1 and 11, and the schools to letters between A and I.

[121] See supplementary files "Transcription" for the written record of the completed oral interviews, and "Coding" for a complete overview of the coding system and associated wordings.

Table 4.3. Content Analysis of Interviews

Item	Statement	Agreement
	HYPOTHESIS 1	
I01	The bonus program should not exist	Consensus
I02	The resources dedicated to the bonus should be incorporated into the teachers' salaries instead	Consensus
I03	Teachers have difficulty in understanding the calculation of the bonus payments	Consensus
I04	The bonus payment is unfair since it is not correlated with teaching quality	Consensus
I05	The bonus ptogram generates frustration among staff of the same school	High
I06	Teachers do support the use of standardized tests to evaluate the performance of students	High
I07	The level of knowledge required by the SARESP is similar to the program content of the state	High
I08	The SARESP does not provide students an incentive for participation in the test, biasing its results, and consequently, the calculation of bonus payments	High
I09	It is a problem that the SARESP evaluates only the Portuguese and Math abilities of students	High
I10	The bonus program has weakened union struggles for salary increases	Low
I11	The bonus results discourage teachers in their activities	Low
	HYPOTHESIS 2	
I12	The salary for teachers in the SEE-SP is very low	Consensus
I13	Teachers from the SEE-SP complement their income with other professional activities	Mixed
I14	The additional payment related to the bonus is welcome, but it does not solve the salary problem	Consensus
I15	In many years, teachers received no bonus	High
I16	The value of the bonus payment has constantly decreased over the years	High
I17	The bonus payment is notably low for teachers at the beginning of their careers	High
I18	The bonus presents no additional incentive for young teachers to start working in state schools	High
I19	The bonus presents no additional incentive for teachers to continue working in the SEE-SP	High
	HYPOTHESIS 3	
I20	The bonus program helps to decrease work absenteeism	Mixed
I21	Other employee benefits, such as seniority leave and remuneration per year of service, have a higher impact on work absenteeism than the bonus program	High
I22	Teachers do not know that work absenteeism affects the bonus program	Low
I23	Due to the bonus program, some teachers continue to work despite health restrictions	Low
	HYPOTHESIS 4	
I24	The bonus program has changed my teaching activities	Low
I25	The bonus provides me no additional incentive for the improvement of my teaching practices	Consensus
I26	My changes in teaching are motivated by the needs of my students and not by the bonus	Consensus
I27	The SARESP results lead to the creation of a school action plan to improve student achievement	High
I28	The action plan is a helpful tool for the improvement of learning activities	High
I29	Teachers work together and help each other to meet the IDESP	High
I30	Teachers of all subjects need to include the Portuguese and Math contents in their teaching activities	High
I31	Poor IDESP results make me feel extremely sad and downcast about my work	Low
I32	The bonus program has created extra pressure for teachers of Portuguese and Math	High
	HYPOTHESIS 5	
I33	Teachers believe that cheating during the SARESP creates bias in the results	High
I34	Gifts or awards are distributed for student participation in the SARESP	High
I35	There are measures to exclude low-performing students from the SARESP	Mixed
I36	In the weeks before the SARESP, students receive extra preparation for the test	High
I37	Schools apply mock tests for the SARESP	Mixed
I38	Teachers revealed the answers of the SARESP questions during the test	Low
I39	Portuguese and Math skills receive higher importance in teaching	Consensus
I40	The SARESP structure helps to combat cheating during the test	High

Notes: Data collection was carried out through remote interviews with 11 teachers from the SEE-SP in the municipality of Campinas (see semi-structured interview guide in Appendix E). Data analysis using the software f4analyse.
Source: Author's own data collection, 2020.

The qualitative interviews provided complementary insights into teacher perceptions of the bonus program. All the interviewees are quite opposed to the bonus program as it is currently structured. According to respondents, the scheme should be abolished (I01) and its resources incorporated into teachers' normal salary (I02). This low support for the bonus program can be explained by the lack of expectancy and instrumentality, which are—according to expectancy theory (Vroom, 1964)—necessary conditions for being personally motivated to get behind such a scheme. Because the teacher bonus is awarded on the basis of a collective PFP program at school level, the individual effort of a teacher in the classroom will not lead necessarily to successful goal attainment: in this case, student learning.

This feeling of powerlessness is particularly true for those who do not teach Mathematics and Portuguese, since the SARESP evaluates only these two skills (I09). Even when there is learning success, the bonus program lacks instrumentality since the SARESP does not provide the students with an incentive to participate and does not pay out for individual effort vis-à-vis the test, which results in biased proxies for learning outcomes (I08). In addition, the bonus program of the SEE-SP violates the assumptions of Locke's goal-setting theory (Locke, 1968), since the teachers do not consider the program fair (I04) and they have tremendous difficulty in understanding the formula used in the bonus scheme—and so to prove its calculation was indeed carried out correctly (I03).

Table 4.3 also provides in-depth data validating H2. There seems to be a broad consensus that teachers' salary in the SEE-SP is very low (I12), and the money from the bonus program is greatly appreciated—but it is too low to play a fundamental role in career plans (I14). Respondents highlighted that the bonus scheme does not provide necessarily an incentive to remain in the SEE-SP (I19), because it is not a right guaranteed by law (I15) and the value of the bonus—when received—has decreased over time (I16). Since the bonus amount is proportional to the gross wage of the teachers, which again depends on their years of experience, those at the beginning of their careers generally receive a very modest bonus (I17). Consequently, they do not see it as an incentive to enter into the SEE-SP either (I18).

In relation to work absenteeism (H3), the interviews revealed divided and diverse views. Some teachers believe that the bonus can help to decrease work absenteeism, while for others it has no impact (I20). The majority of respondents see, however, other labor rights such as seniority leave and remuneration per year of service as more efficient mechanisms to combat absences at work than the bonus (I21).

Referring to H4, respondents indicated that the bonus program had not really changed their teaching practices and behaviors in the classroom (I24). All confirmed teaching improvements during their careers, but as a result of professional development over time and motivated mainly by the needs of students, and not by the implementation of the bonus scheme (I26). The teachers do not see the bonus program as an incentive for the improvement of their teaching (I25), but see the SARESP as a good instrument for the evaluation of student performance (I06). Based on its results, the teachers can create collectively an action plan to improve student achievement in their schools (I27). This teamwork—which aims at optimizing teaching activities (I28) and, consequently, seeks to improve the learning outcomes—was mentioned by several teachers as a helpful tool for the improvement of teaching practices (I28).

Finally, the qualitative research presented complementary insights into the dishonest behaviors of teachers regarding the SARESP (H5). A frequently cited consequence of the implementation of the school targets (IDESP) was the shift of the teaching focus overwhelmingly to Math and Portuguese skills (I39). Since only these two subjects are tested by the SARESP, teachers from all other subjects (such as Geography, Biology, Philosophy, and the like) needed to change their programmatic content in order to develop students' Math and Portuguese skills in an integrated and interdisciplinary manner (I30). This focus on Math and Portuguese created for the teachers of these two subjects extra work pressure, since they become particularly responsible for low performance levels per the SARESP—and, consequently, for the low level of bonus payments (I32).

Although most of the teachers believe that the cheating vis-à-vis the SARESP creates a bias in the performance results (I33), not all the illicit actions listed in the interview guide (see Appendix E) occur with the same intensity. According to many respondents, the SARESP structure itself already helps to combat cheating during the test (I40), because no teacher applies the test in the same school as the one that he/she works in. Nevertheless, respondents confirmed three instances of cheating with regard to the SARESP that they had personally witnessed.

A relatively common practice in schools is the distribution of gifts or awards for participation in the SARESP (I34). Since the schools have strong budgetary restrictions, these "incentives" for participation are normally things with no (or reduced) costs, such as an additional point in the final grade, or the visit to a (free) cinema during the class, or the distribution of water or chocolate during the test. The second cheating practice reported in the interviews is the use of measures to exclude low-performing students from the SARESP (I35). In this case, these pupils are advised to stay at home on the day of the test or they are temporarily withdrawn from the class some minutes before the SARESP application. Two respondents mentioned during the interviews that they witnessed cases in which the teacher provided the answers for students during the test (I38), but in sequence they complemented that by saying that, in their view, this cheating may have been an isolated incident since they would experience it only once during their entire professional life. The interviews also found evidence for mock tests (I37) and extra preparation for the SARESP (I36), confirming once again the "teaching to the test" idea. Teachers highlighted, however, that these mock tests and extra preparation are not exclusively focused on the SARESP, but they help students with regard to all performance tests that they will engage in during their school life, such as the ENEM, college admission exam, public tender, and so on.

4.5.3 Data Triangulation

This section applies data triangulation to link together the empirical evidence from the questionnaires and interviews, so as to present a better understanding of the impact of the teacher bonus program. For the sake of illustration, I follow a common method used by policy-related qualitative studies (see Corden and Sainsbury, 2006) and thus include in the text some verbatim quotations from research participants. This helps explore their practices and beliefs related to the bonus program, and to make these issues more credible and easier to understand.

Since teacher opposition is the main reason for the failure of merit-pay programs (Ballou and Podgursky, 1993), I start by investigating the support among respondents for the PFP program of the SEE-SP. As already described, the quantitative and qualitative research shows a very low level of agreement with the bonus scheme. The words of a 29-year-old teacher help to understand the reasons for the strong rejection of H1 by the teachers spoken with.

> *"I see no harm in having a bonus scheme linking an additional payment to the improvement of student outcomes, but I see the teacher bonus program of the SEE-SP very critically because it is used to mask the lack of wage policies."* (ID 1, § 45)

This general dissatisfaction with the salary paid to teachers in public schools was already identified in the online survey (see Q10 in Table 4.1), and the topic was always present in the qualitative interviews. Respondents seem to have lost trust in the SEE-SP providing a fair wage for its teachers. Therefore, the attempts at reforming the payment structure—as the case of the bonus program represents—are perceived as palliative measures that do not resolve the real wage problem.

Another reason for the frustration of teachers in relation to the bonus program is the methodology used for its calculation. The teachers know that the IDESP results are not free of bias, and see this pressure for results as a negative for the learning process itself.

> *"The association of the bonus with the achievement of the IDESP is mistaken, because the statistics used for the calculation of the targets can be manipulated by the schools. Teachers create, for example, very simple re-tests for poorly performing students so as to increase their chances of success, and, consequently, to improve the pass rate vis-à-vis the IDESP."* (ID 3, § 37)

The lack of transparency in the calculation of bonus payments is another important factor that massively harms the ability of the program to motivate teachers. This difficult in estimating the value of the bonus or in proving the calculations of the SEE-SP are indeed correct was confirmed by Q26 (Table 4.1) and I03 (Table 4.3) already, and furthermore mentioned by a veteran Math teacher with 19 years of teaching experience.

> *"For me, is not clear why one teacher receives more and another one less. It is explained to us that the bonus is related to work absenteeism, to the performance of students, etc., but I cannot make the calculation by myself. At least, I was never able to calculate how much bonus I would receive."* (ID 7, § 60)

In addition to this transparency problem, the teachers evaluate the bonus program as extremely unfair. This point was already illustrated by Q17 (Table 4.1) and I04 (Table 4.3); the interviews provided the explanation for this gap in perceived fairness. The bonus is calculated at school level according to the achievement of the IDESP. Therefore, the percentage of goal attainment is the same for everyone in the school. However, the bonus paid is also proportional to the gross annual salary, which, in turn, means that it is dependent on the period of work in the SEE-SP and the number of classes per week; no proxy for teaching quality is added to this calculation. The teachers know about the work performance of their colleagues, and become frustrated when low-performing staff receive a higher bonus than they do. A female teacher made this problem clear.

> *"The value of the bonus is proportional to the period of service in the SEE-SP and the number of classes per week. So in my school, for example, in the year in which we had a good performance regarding the SARESP and I received BRL 500 as a bonus, the teacher receiving the highest bonus was the Physical Education teacher—who was removed later from the school due to sexual harassment claims."* (ID 2, § 62-63)

Another teacher shared:

> *"The value of bonus is different for the teachers of the same school. This generates frustration because we are a team."* (ID 4, § 65)

H2 was aimed at identifying whether the bonus program has created an additional incentive for staff to enter/continue working in the SEE-SP. As already mentioned, the results from Tables 4.1 and 4.3 reject categorically this hypothesis; the response of a 43-year-old teacher helps us to understand why the bonus program plays practically no role in long-term career planning.

> *"The bonus is not official. If the government chooses to stop paying the bonus, it can stop at any time. The bonus is not a labor right like the salary that we know that we will receive every month and the money that we can count on. We never know whether we will receive the bonus or not, and how much it will be."* (ID 7, § 64)

The person in question complemented this perception with a concrete example.

> *"There were years in which I worked hard and my students still had a good performance with regard to the SARESP, but I received no bonus due to the high dropout rate in the school."* (ID 7, § 58)

Besides this legal uncertainty regarding the payment scheme, many teachers stated that the values of the bonuses paid have strongly declined in the past few years, thus reducing even further the marginal returns offered by the additional payment. All these factors have contributed to the teacher bonus program not having the motivational potential that it might do. A male teacher who has worked since 2012 in the SEE-SP summarizes the importance of the teacher bonus program as follows:

> *"I am not sure if the bonus has nowadays a relevance to creating a negative or positive impact. I think that it became so outdated in relation to what it idealizes and what it really practices that the teachers became indifferent to this program."* (ID 1, § 63)

It is difficult to imagine that the bonus program created an additional incentive for young teachers to start working in the SEE-SP since, as described in the previous section, the value of the bonus payments to this group is especially low. When asked if the bonus played a role in the decision to become a teacher in state schools, a 33-year-old female respondent—who had started her career after the implementation of the program in 2008—said:

> *"No. I did not want to work more in the private market, because I was frequently exploited in the (private) school."* (ID 10, § 19-20)

Another young teacher highlighted the role of the bonus scheme for junior employees:

> *"The bonus is much less important for me and for all young teachers. I do not count on the bonus, no one does. The bonus is relevant only for teachers with extensive experience in the SEE-SP. To me it does not mean shit."* (ID 2, § 89)

To conclude, an English teacher with eight years of SEE-SP experience reported her familiarity with the bonus program as follows:

> *"I got [the bonus] only once, and I received around BRL 20."* (ID 8, § 73)

H3 was interested in identifying whether the implementation of the bonus program has had a positive impact on work absenteeism; responses related to it in sections 4.5.1 and 4.5.2 provide a mixed picture here. First of all, it is necessary to mention that many teachers are not aware that work absenteeism negatively affects the bonus being paid. This fact became clear in an interview with a male respondent teaching in the SEE-SP since 2011, who currently occupies the position of school principal.

> *"I have never heard about this link. I think that people do not know that."* (ID 6, § 80)

Despite this lack of information, there seems to be a consensus that the bonus program did not affect the absence of respondents themselves, given that they declared having no problem with work absenteeism.

> *"The impact of the bonus on my work absenteeism is very low, because I usually am not absent from work."* (ID 9, § 72)

However respondents believed that the bonus program may have had a positive impact on the absence of their work colleagues, especially those with high absenteeism before the scheme's introduction. This view was confirmed by a 61-year-old teacher with seven years of experience as an educational coordinator.

> *"Those people that were absent without any reason and were not compromised with the school, they started to avoid, to think better about, their work absenteeism with the introduction of the bonus program."* (ID 5, § 54)

The interviews helped also to clarify the mixed empirical evidence related to H4—namely if teachers have improved their teaching practices due to the bonus program's introduction—and as found in sections 4.5.1 and 4.5.2. Although some teachers confirmed in the structured questionnaires certain modifications to their teaching since the implementation of the bonus scheme (see Table 4.1), the interviews made clear that these changes have not resulted from the program itself but rather from the accounting system created with the IDESP. When asked whether the bonus could have provided teachers an additional motivation to put more effort into their teaching practices, a 32-year-old Philosophy teacher remarked:

> *"I don't feel encouraged to improve my teaching activities due to the bonus alone, and I think that this is also the case with many of my colleagues."* (ID 9, § 70)

Despite this lack of motivating power on the part of the bonus, H4 cannot be entirely rejected—since the teachers confirmed that SARESP results are used to identify learning deficits within the school, and, consequently, to create a better learning plan for the students (see statements I06, I27, and I28 in Table 4.3). As this work plan is normally created jointly by all educators of the school, teachers can benefit from a spillover effect triggered by the joint discussion of the continuous improvement of learning practices. In describing this association, a teacher with eight years of experience said:

> *"The only changes—I made—were due to the collective learning plan. When we receive the SARESP results, the Regional Board of Education demands of us an action plan that should be created and implemented by the school unit as a whole."* (ID 1, § 54)

And he added:

> *"I have seen positive effects of the bonus program on the teachers of PEB1 [lower primary education], who received a greater form of support from their peers to improve the teaching methods."* (ID 1, § 63)

This higher bonus-program impact for teachers of PEB1 was also reported by other respondents, who emphasized the greater teamwork capacity of those teachers. Because they are responsible for all subjects taught in the classroom, they can provide better mutual assistance in the development of learning activities.

> *"There is a demand for results that stems from the Regional Board of Education, but also from our peers. I work in all levels of education, but especially in PEB1 we like to work together to address the learning deficits of students."* (ID 4, § 58)

Another key issue related to teaching activities that arose through the interview process was the focus on Math and Portuguese skills—as already reported in the previous sections with relation to dishonest behavior (H5). Some teachers view this evolution with a highly critical eye, and hold the SARESP mainly responsible for that. As one teacher contended:

> *"For me, is very clear that this focus contributes very little to the general improvement of the academic achievement of students and much more to inflating the school's performance with regard to the SARESP. Then we [the teachers] receive the bonus, and the government utilizes this improvement as data."* (ID 9, § 29)

This need for generating "good" statistical data was also mentioned in answer to the questions related to other cheating practices vis-à-vis the SARESP. According to many teachers, the IDESP has genuinely created a process of continuous improvement in schools, but this pressure for results is also responsible for the cheating. Addressing this association, a (current) school principal with 15 years of teaching experience remarked:

> *"I see a lot of people mobilized to ensure good results regarding the SARESP at the end of year. This mobilization is characterized by the elaboration of an improvement plan to overcome the learning deficits that will really produce interesting results for the schools. But the schools apply also short-term actions to inflate students' performance vis-à-vis the test. I see—I always saw—schools hiding students from the test. Students who would have no chance to achieve good marks in the SARESP. Then, the schools hide these pupils, they leave them at home on the day of the test. The schools start to make threats to high-performing students with regard to participation in the test: for example, if you do not take the SARESP, your class will run out of something at the end of year."* (ID ,6 § 44)

This practice of excluding low-performing students from the SARESP seems to be very widespread among pupils with disabilities, the students with so-called special educational needs. A teacher with experience in the application of the SARESP explained this exclusion as follows:

> *"The students with special needs are, for example, in the ninth grade, but they can neither read nor write. You look at these pupils and you note immediately that they have a disability. Then, the teacher says to them: we will have the government test on day X, please do not come to class on this date."* (ID 4, § 36)

As already mentioned in sections 4.5.1 and 4.5.2, this research found clear evidence for the notion of educators "teaching to the test." Most of the teachers highlighted, however, that in theory at least extra preparation for the SARESP would not be necessary, since the specific knowledge requirements for the SARESP are in line with the programmatic content of the SEE-SP. The latter is communicated to the schools at the begin of the school year. For instance, one veteran teacher with experience as school coordinator said:

> *"The programmatic content that we need to work in the state schools of São Paulo involves all the academic skills necessary per the SARESP."* (ID 5, § 29)

However the teachers reported to have difficulties in applying all the programmatic content during the school year, since they have students with very different learning capacities in the same class. This requires extra time for teaching. Consequently some content runs behind schedule, as was explained by a graduate in Pedagogy who teaches all subject matters for PEB1 students:

> *"Last year in November for example, one month before the SARESP, the students stayed one hour longer in the classroom for extra tutoring and I will not deny that I was aiming here at the SARESP. The test was coming, and I noted some learning deficits among the students that we needed to address up until the day of the SARESP."* (ID 10, § 32)

However, according to the interviewees, this additional hour for SARESP preparation is not a common practice by schools. Instead, normally, the preparation is integrated into the school timetable, as one teacher reported:

> *"The intensive preparation for the SARESP starts in September; then, from that date, we work in the classroom only on the contents requested by the SARESP. But in a differentiated manner for high- and low-performing students."* (ID 11, § 39)

She concluded by describing the activities undertaken as part of this intensive preparation as a clear SARESP training exercise, where no new content is taught. Instead, the children are made familiar with the structure of the test.

> *"With the intensive course, teachers use the prior SARESP to explain the [structure of the] test and to practice the exercises with students. This is a clear training for the test."* (ID 11, § 41)

4.6 Conclusion

This paper applied own data collection and mixed-methods research—combining information from 53 questionnaire respondents and 11 qualitative interviews—to investigate the effects of the implementation of a teacher bonus program on the professional practices and behaviors of teachers in Brazil. Since a sustainable solution to the problem of students' poor academic performance passes necessarily through the improving of teaching practices (Woessmann, 2011), this paper has examined the key mechanisms through which the bonus can generate improved academic achievement.

By and large, the quantitative and qualitative findings highlight the ineffectiveness of the teacher bonus program of the state of São Paulo. This paper has shown that the bonus scheme did not create an additional incentive for teachers to start/continue working in the SEE-SP, and it was not directly responsible for the improvement of teaching activities. The results do point to certain positive effects of the program: namely the reduction of work absenteeism and the monitoring of student achievement. However, both effects are achievable also without the bonus program. As mentioned by the respondents themselves, other programs—such as seniority leave and remuneration per year of service—seem to be more efficient in combating work absenteeism than teacher bonuses. In the same vein, the use of performance tests and their associated targets (respectively the SARESP and IDESP), do not necessarily have to be connected to the bonus program.

The in-depth interviews set out to explore the reasons for the inefficiency of the program, and delivered compelling results: Although teacher support is an essential condition for the success of any merit-pay program implemented in schools (Ballou and Podgursky, 1993), the educators employed in the state schools of São Paulo are strongly against the bonus program of the SEE-SP as it is currently structured. Further, they do not see the bonus scheme as an effective mechanism to improve their teaching practices. Despite some respondents having indicated that they had a favorable attitude toward PFP programs in general, they were unanimous in recognizing that the bonus of the SEE-SP fails to reward individual efforts made in the classroom.

To the best of my knowledge, this extremely low support of teachers for the bonus program is a very singular case in the international literature. As illustrated in section 4.1, the empirical evidence from other countries, such as India (see Muralidharan and Sundararaman, 2011), China (see Liu et al., 2016), and the US (see Firtell, 2019), reveals a different picture. This has a great deal to do with the general wage policy in the state schools of São Paulo. The longstanding tradition of the SEE-SP paying low wages to its teachers hinders the acceptance of the bonus program among staff, since they do not see this additional pay as a solution to the bigger wage problem.

The research project also confirmed for Brazil the existence of negative side effects to the bonus scheme. Respondents indicated that practices related to "teaching to the test," such as extra preparation and mock tests for the SARESP, have become very common in schools. In addition, they confirmed the existence of cheating vis-à-vis the SARESP, such as the exclusion of low-performing students from the test and the distribution of solutions during the course of it. Although these two practices do not seem to be in widespread use in schools, many teachers were aware of them at least.

In closing, it is important to stress that this research is only a limited study; as with most works, it has certain limitations to it. First, the full potential of the approach has not been proven since only 53 of the around 2,000 teachers employed in the state (primary) schools in Campinas answered the questionnaire. Therefore, a higher participation rate would have been desirable. Likewise, only 11 of the 53 contacted teachers agreed to be interviewed. Additional interviews would have been of great value to identify more personal experiences related to the bonus program. Second, the word limitation imposed by academic papers led to only a selection of verbatim quotations to be used in this study. I was very careful here to avoid selection bias, since many other interesting statements in relation to the bonus program were made during the 5.8 hours of interviews. Despite all these precautions in processing the responses and the use of theoretical foundations for the choice of the quotations, problems of selection bias cannot be excluded. And, last but not least, I was challenged all the time to isolate my own biases and perspectives from the interpretation of the findings; of course, all my decisions taken may be questionable.

Despite these limitations, the author allows himself to make some suggestions to be considered in future policymaking and public debates on the teacher bonus program of the SEE-SP. After the interpretation of all the empirical evidence collected by this research project, the author found no effective mechanism linking the current PFP program of the SEE-SP with the potential improvement of student achievement. This paper has shown that the program was not effectively targeted in many important regards. First, teachers cannot understand the calculation of the bonus payments, thus hampering the transparency of the program. Second, many components used in the measurement of bonus payments are beyond the control of individual teachers, such as the dropout rate and the performance of all students in the school—thus limiting the possibility of effectively influencing the final result. Third, the calculation of the bonus via the results of the SARESP—which evaluates only Math and Portuguese skills—generates a counterproductive pressure on the teachers of these two subjects, and feelings of powerlessness for all the other teachers. And, finally, the SARESP provides no incentive for student participation in / preparation for the test, thus functioning as a poor proxy for student performance.

For all these reasons, the state of São Paulo should seriously consider reforming the bonus program of the SEE-SP in order to create a regulatory framework in which its around 220,000 teachers feel more rewarded for their efforts in the classroom. Empirical evidence from other countries shows that such reform is indeed possible. In the US, for example, the support for PFP programs among teachers has increased over time (Koppich, 2010), given the participation of the two largest teachers' unions (American Federation of Teachers and National Education Association) in the elaboration of the performance-compensation system (Forand, 2012; Liu et al., 2016). Maybe similar integration could be profitable also for the Brazilian case.

Appendix

4.A Supplementary Data

Supplementary data to this article can be found on the author's homepage. The files provide the following additional supporting information:

1. Transcription (link: https://rb.gy/drwmzk).
   ⟹ File contains the written record of the complete oral interviews.

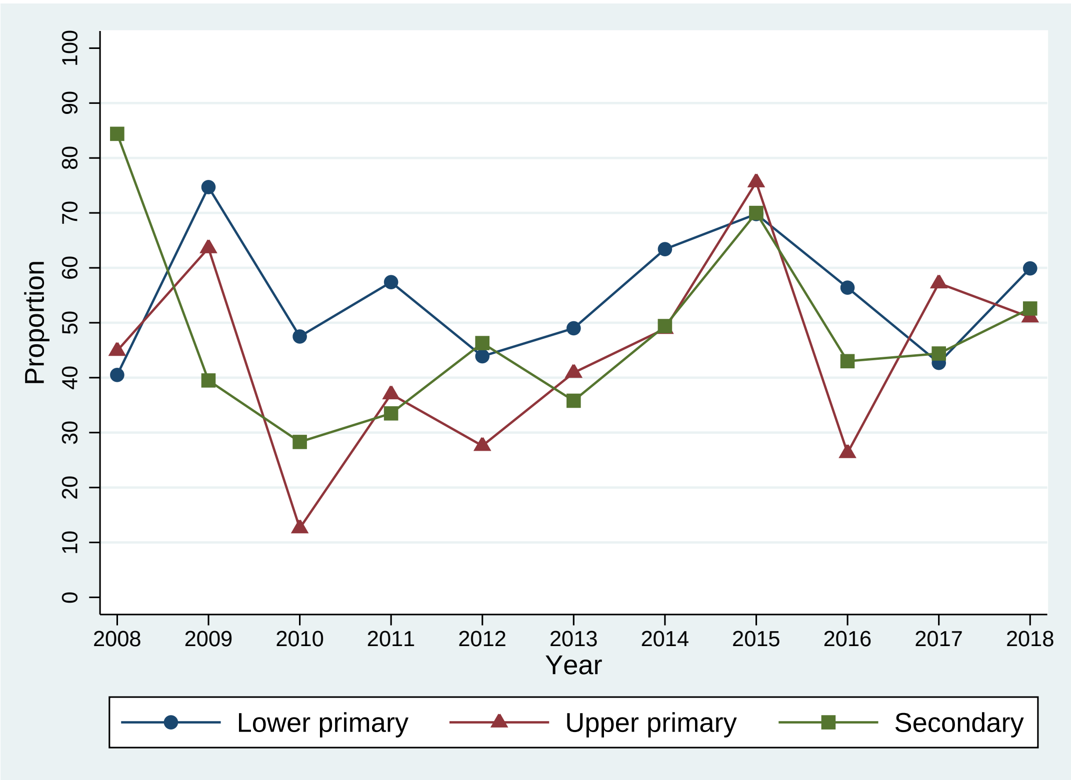
2. Coding (link: https://rb.gy/dq8tx8).
   ⟹ File contains the complete view of the codes and the associated wordings.

4.B Data Accessibility

The author has made the data from the survey accessible to the public.
Repository name: Mendeley Data.
Data identification number: DOI: 10.17632/sf3frsthcj.1

4.C Figures

FIGURE 4.1: Achievement of the IDESP, by School Level



Notes: Figure shows the proportion of state schools that have achieved (at least 100 percent of) the IDESP in the year of reference. Lower primary schools are from Grades 1 to 5, upper primary are Grades 6 to 9, and secondary education are Grades 10 to 12. Data were obtained by means of the Law on Access to Public Information with the Protocol 237542011816.
Source: SEE-SP (2020); author's own elaboration.

4.D Structured Questionnaire

Dear Teacher,

My name is Tharcisio Leone, I am a researcher at the German Institute for Global and Area Studies and Free University of Berlin and I am investigating the effects of the implementation of teacher bonus programs in the state schools of São Paulo.

You have been chosen for this investigation because you are working in a state primary school in Campinas. Today you receive a structured questionnaire with 40 questions about your perceptions of and experience with the teacher bonus program. The survey should take approximately 15 minutes to complete, and should be submitted electronically using the form available at:

`https://ww3.unipark.de/uc/team_tleone/598f/`

Please mark only ONE response to each question, and indicate the extent to which you agree or disagree with each of the following statements using the following five-point Likert scale:

1 = Strongly disagree
2 = Disagree
3 = Undecided
4 = Agree
5 = Agree completely

Your participation in this survey is voluntary, and you may refuse to answer specific questions if you do not wish to answer them. All your answers will be kept strictly confidential, and never associated with your name. No individual responses will be published or shared. Instead, your responses will be combined with others and reported only on an aggregate level.

Please note that this questionnaire is limited to multiple-choice questions and does not allow an explanation of your responses. But in a second phase of this research project I will conduct qualitative interviews, in which you will have the chance to explain your personal narrative regarding your experience with the bonus program.

I thank you greatly in advance for completing and returning this questionnaire, and I assure you that you will receive a copy of the final version of this study once it has been completed.

If you have any questions about the survey, please contact:

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A. Individual Characteristics

Q01: How old are you? I am ________ years old

Q02: What is your gender? ☐ Male ☐ Female ☐ Prefer not to answer

Q03: What is the highest degree you hold?
☐ Secondary ☐ Vocational ☐ Bachelor ☐ Master ☐ Doctorate

Q04: How many years of experience do you have as teacher? ________ years

Q05: Were you already working in the SEE-SP in the year 2007? ☐ Yes ☐ No

Q06: Do you work in the private or municipal education system? ☐ Yes ☐ No

B. Attitudes toward Teaching

	← strongly disagree				agree completely →
Q07: In my opinion, teacher is an undervalued profession . . .	☐	☐	☐	☐	☐
Q08: In my opinion, the SEE-SP is constantly looking to improve working conditions . . .	☐	☐	☐	☐	☐
Q09: I enjoy teaching . . .	☐	☐	☐	☐	☐
Q10: I am satisfied with the wage I receive . . .	☐	☐	☐	☐	☐
Q11: I believe that if I work hard, my students will improve their academic performance . . .	☐	☐	☐	☐	☐
Q12: Teachers are limited in what they can achieve because the home environment of students has a large impact on their achievement . . .	☐	☐	☐	☐	☐
Q13: I exceed the average performance of my colleagues . . .	☐	☐	☐	☐	☐
Q14: I would prefer to work in a private school . . .	☐	☐	☐	☐	☐

C. Bonus Acceptance

	← strongly disagree				agree completely →
Q15: I support the variable remuneration policies for teachers according to their productivity . . .	☐	☐	☐	☐	☐
Q16: The teacher bonus program is a positive tool to improve teaching . . .	☐	☐	☐	☐	☐
Q17: The teacher bonus program is fair to teachers . . .	☐	☐	☐	☐	☐
Q18: I am satisfied with the bonuses that I received in recent years . . .	☐	☐	☐	☐	☐
Q19: The teacher bonus program does not evaluate important aspects of my teaching performance . . .	☐	☐	☐	☐	☐
Q20: The teacher bonus improves teamwork . . .	☐	☐	☐	☐	☐
Q21: The teacher bonus helps to attract effective teachers . .	☐	☐	☐	☐	☐

Q22: The teacher bonus helps to retain effective teachers . . . ☐ ☐ ☐ ☐ ☐

Q23: The teacher bonus provides me with an extra incentive to improve my teaching practices . . . ☐ ☐ ☐ ☐ ☐

Q24: For me, the teacher bonus is an incentive to stay working in the SEE-SP . . . ☐ ☐ ☐ ☐ ☐

Q25: The teacher bonuses are large enough to motivate me to put extra effort into teaching . . . ☐ ☐ ☐ ☐ ☐

D. Experience with the IDESP

agree completely →
← strongly disagree

Q26: The IDESP is clearly defined and comprehensible . . . ☐ ☐ ☐ ☐ ☐

Q27: The IDESP contributes to improve the quality of the education system . . . ☐ ☐ ☐ ☐ ☐

Q28: I believe in the competence and impartiality of the SEE-SP in calculating the achievement of the IDESP . . . ☐ ☐ ☐ ☐ ☐

Q29: A poor result per the IDESP leads me to change my teaching . . . ☐ ☐ ☐ ☐ ☐

Q30: I assign Portuguese and Math skills a higher importance in teaching . . . ☐ ☐ ☐ ☐ ☐

Q31: I often use the prior SARESP exercises as preparation in the classroom for the SARESP . . . ☐ ☐ ☐ ☐ ☐

Q32: In my school, we often apply mock tests for the SARESP ☐ ☐ ☐ ☐ ☐

Q33: In my school, we often offer reinforcement classes for the SARESP . . . ☐ ☐ ☐ ☐ ☐

Q34: In the weeks before the SARESP, the students often receive extra preparation for the test . . . ☐ ☐ ☐ ☐ ☐

E. Cheating

Q35: Are you aware of previous cheating per SARESP? ☐ Yes ☐ No

⟹ Cheating is for example:
(i) when students with low performance levels are excluded from the testing or "advised" not to participate in SARESP;
(ii) when students know the questions before the test;
(iii) when teachers give the answers to students, or help them to answer the questions during the test.

agree completely →
← strongly disagree

Q36: In my opinion, cheating occurs often with regard to the SARESP. . . . ☐ ☐ ☐ ☐ ☐

F. Qualitative Interview

Q37: Would you like to participate in a face-to-face interview? ☐ No ☐ Yes

Q38: Your name: ____________________

Q39: Your email: ____________________

Q40: School name: ____________________

⟹ Questions Q41 to Q55 only answered if Q04 is a "Yes."

G. Teaching activities

⟹ When I compare my teaching activities before and after the teacher bonus program's implementation, I can say that with the bonuses paid:

	← strongly disagree				agree completely →
Q41: My work absenteeism is lower	☐	☐	☐	☐	☐
Q42: I give more homework to students	☐	☐	☐	☐	☐
Q43: I bring more work home	☐	☐	☐	☐	☐
Q44: I more frequently use the textbooks in the classroom	☐	☐	☐	☐	☐
Q45: I more frequently use multimedia formats (DVDs, PC, projectors) in the classroom	☐	☐	☐	☐	☐
Q46: I participate more frequently in the definition of the programmatic content by other teachers	☐	☐	☐	☐	☐
Q47: I participate more frequently in parent-teacher meetings	☐	☐	☐	☐	☐
Q48: I make more frequent suggestions on how to improve my school	☐	☐	☐	☐	☐
Q49: There is more brainstorming between teachers for the improvement of teaching	☐	☐	☐	☐	☐
Q50: I help my colleagues more frequently with their work	☐	☐	☐	☐	☐

G. Teaching Practices

Q51: Since the teacher bonus program was implemented, I receive more support from my colleagues	☐	☐	☐	☐	☐
Q52: Since the teacher bonus program was implemented, work absenteeism at my school has decreased	☐	☐	☐	☐	☐
Q53: Since the teacher bonus program was implemented, the stress involved in teaching at my school has become much greater than before	☐	☐	☐	☐	☐
Q54: Since the teacher bonus program was implemented, the level of resentment among teachers at my school has increased	☐	☐	☐	☐	☐
Q55: I was already working as effectively as I could before the implementation of the bonus program, so that it did not affect my performance	☐	☐	☐	☐	☐

4.E Interview Guide

Dear Teacher,

My name is Tharcisio Leone, I am a researcher at the German Institute for Global and Area Studies and Free University of Berlin and I am investigating the effects of the implementation of teacher bonus programs in the state schools of São Paulo.

As part of this research, I am conducting interviews with teachers who have directly experienced the bonus program. Your personal accounts will help me better understand the impacts of the teacher bonus program, and provide valuable information for the study.

This interview contains open-ended questions allowing you to express your own narratives as embedded in one's personal experiences related to the bonus program. If necessary, I will add more detailed questions in order to understand better your explanations.

The interview should take approximately 30 minutes, and your participation is voluntary. You can also refuse to answer any question you do not wish to, and you are free to stop the interview at any time.

All your answers will be kept **strictly confidential**, and I will not identify any individuals by name in the study report. Moreover, no individual response will be shared with third parties or otherwise broadcast.

If you agree, I will start to record this interview now. Once recorded, interviews will be transcribed and the recordings subsequently destroyed. All identifying information will be removed from transcripts, so that your identity will remain anonymous.

(After the interview)

I thank you greatly for your participation in this research project, and I assure you that you will receive a copy of the final version of this study once it is completed.

For any further information about the study, please do not hesitate to contact me.

A. Introduction

⟹ Initially, I am interested in knowing more about your teaching experience.

1. How long have you been a teacher at this school and in the São Paulo state network?
2. Have you already taught in any other school system, such as in private or municipality schools or in another federal state?
   - If yes, for how many years and why did you change?
   - If not, why not and do you have any interest in transference to another school?

⟹ Now I would like to know more about the work environment in your school.

3. In your opinion, what are the school's primary strengths and weaknesses?
4. Are you satisfied with the performance of students in this school?

B. The SARESP

⟹ Now I would like to ask you some questions about the SARESP test.

1. In your opinion, what is the attitude of students toward the SARESP?
   - Do they strive for a good performance in it? Do they like to participate in the test?
2. Do the SARESP results have a subsequent impact on your teaching activities?
   - How do you use the results? How do you link these with the programmatic content?
3. In your opinion what is the impact of the SARESP on the education system?
4. Is the practice of "teaching to the test" common in some schools?
   - Does this practice occur in your school too? If so, how?
   - Is this practice an individual-teacher action or coordinated by the school? Does it affect your regular programmatic content with the students?
5. Is dishonest behavior common practice?

   ⟹ I will now list some practices that have been registered in the academic literature, and I want to know if you have already experienced these in the SEE-SP schools.
   - Mock tests for the SARESP; tutoring for the test; awards for high-performing students taking the SARESP; "advice" to poor-performing students not to take the test; helping students during the test; distribution of answer-sheet templates before/during the test.

C. Expectancy Theory

⟹ Now I would like to ask you some questions about the teacher bonus program.

1. In your opinion, why has the SEE-SP implemented the teacher bonus program?
2. Do you believe that is correct to link teachers' additional pay to improvement in student performance?
3. On the whole, do you support the bonus program of the SEE-SP?
4. In your view, are the bonus rules well defined, transparent, and fair?
5. How often do you receive the bonus payments? Are you satisfied with these payments?

D. Teaching Practices

⟹ The next questions address your teaching activities and how the teacher bonus affected them.

1. Have you already changed the way you teach as a consequence of the IDESP results?
   - If yes, please describe the kind of changes and tell me if they were voluntary or not.
   - If not, have you already been advised to change?
2. Did the teacher bonus program provide you an additional incentive for making these changes?
3. What impact has the bonus program had on your work absenteeism?
   - Do you avoid going on sick leave because of the teacher bonus program?

E. Concluding Thoughts

⟹ Finally , I would like to ask you for some concluding thoughts about the bonus program.

1. In your opinion, what have the main impacts of the teacher bonus program been?
2. If you could make changes to the teacher bonus program, what would they be?
3. Is there anything else that you would like to add in this interview?

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English Summary (Abstracts)

Striving for Educational Improvement:
Essays on Intergenerational Mobility and Teacher Bonus Programs in Contemporary Brazil

by Tharcisio Leone

Chapter 2: The Geography of Intergenerational Mobility

This paper explores the variation in intergenerational educational mobility across Brazilian federal states based on Markov transition matrixes and univariate econometric techniques. The results confirm a strong variation in mobility among the 27 Brazilian states and present empirical evidence for the "Great Gatsby curve" within a single country: states with greater income disparities present higher levels of persistence in educational outcomes across generations. In addition, I investigate one specific mechanism behind this correlation —namely whether higher income inequality might lead to a lower investment in human capital among children from socially vulnerable households. The paper delivers compelling results showing that children of parents with no education have a statistically significant lower chance of completing the educational system if they live in states with a higher level of income inequality.

Chapter 3: Does a productivity bonus pay off?

This article uses a quasi-experimental design and longitudinal data on academic achievement to evaluate ex post the impact on student performance of an incentive-pay program for teachers in Brazil. I apply a difference-in-difference approach comparing students in state schools that are subject to the teacher bonus program with students from municipal schools without it. The main findings indicate that the implementation of performance-based bonuses being paid to teachers in the state schools of São Paulo had no statistically significant impact on the performance of students in Math and Portuguese. In the first year of the bonus program, the test scores in treatment schools were slightly lower than those in comparison schools. But none of this variation was statistically significant. The results from alternative specifications, placebo tests, and robustness checks also support these core findings.

Chapter 4: Addressing changes in professional behavior by bonuses

How can a bonus program affect the performance of teachers in classrooms? This paper collects data from teachers employed in Brazilian state-run schools to examine the key mechanisms through which a bonus scheme can have a causal effect on the academic achievements of students. Using mixed-methods research and data triangulation from questionnaires and semi-structured interviews with teachers, the study finds limited empirical evidence supporting the positive impact of the teacher bonus program of the state of São Paulo. According to the teachers, the bonus has led to a reduction of work absenteeism in schools; however it has created no additional incentives for educators to start/continue working in the state education network, and it was not directly responsible for the improvement of teaching activities in the classroom either. The empirical findings also show that the bonus program has extremely low support among teachers, and it has led to an increase in cheating among staff.

Zusammenfassung

Striving for Educational Improvement:
Essays on Intergenerational Mobility and Teacher Bonus Programs in Contemporary Brazil

von Tharcisio Leone

Diese kumulative Dissertation besteht aus drei eigenständigen empirischen Arbeiten zum Thema Bildungsökonomie in Brasilien, wobei jeder dieser drei Forschungsartikel ein eigenes Kapitel abbildet. Der erste Artikel (Kapitel 2) beschäftigt sich mit der Variation von intergenerationaler Bildungsmobilität zwischen den brasilianischen Bundesstaaten. Die beiden weiteren Artikel (Kapitel 3 und 4) befassen sich mit einer wissenschaftlichen Evaluierung des Bonusprogramms für Lehrkräfte des Bundesstaates São Paulo, das im Jahr 2008 eingeführt wurde. Beide Studien haben die Gemeinsamkeit, dass sie die Effektivität des Bonusprogramms untersuchen, wobei jedes Vorhaben unterschiedliche Forschungsfragen behandelt und verschiedene empirische Methoden verwendet.

Das erste Kapitel *"The geography of intergenerational mobility"* verwendet die zuletzt veröffentlichten Mobilitätsdaten für Brasilien (PNAD-2014), um eine umfassende und aktuelle Analyse der Bildungsmobilitätschancen in der brasilianischen Gesellschaft darzustellen. Diese Studie zielt auf die Erweiterung der Literatur zur *"Great Gatsby curve"* ab, indem sie den Zusammenhang zwischen Einkommensungleichheit und intergenerationaler Mobilität auf nationaler Ebene untersucht. Zudem wird ein spezifischer Mechanismus der *"Great Gatsby curve"* berücksichtigt, indem untersucht wird, ob Einkommensungleichheit die Bildungsergebnisse von Kindern aus sozial schwachen Familien beeinflusst. Unter Verwendung von Querschnittsdaten aus einer bundesweit repräsentativen Haushaltsbefragung trägt diese Studie mit den folgenden empirischen Ergebnissen zur Literatur bei: Zum einen lässt sich die *"Great Gatsby Curve"* für die Bundestaaten Brasiliens abbilden. Die Bundesstaaten Brasiliens mit der höchsten Einkommensungleichheit sind diejenigen mit der geringsten intergenerationalen Bildungsmobilität und vice versa. Zum anderen zeigen die Ergebnisse, dass die negative Auswirkung von Einkommensungleichheit auf Bildungsergebnisse eine mögliche Erklärung für diesen Zusammenhang darstellt. Jeder zusätzliche Punkt in dem 75/10 Verhältnis der Einkommensungleichheit senkt die Wahrscheinlichkeit, dass Kinder von Eltern mit geringer Bildung einen Sekundarschulabschluss erreichen, um 5,4 Prozent.

Die zweite Studie *"Does a productivity bonus pay off?"* verwendet Paneldaten (GERES) zu den akademischen Leistungen von SchülerInnen aus den Jahrgangsstufen eins bis vier und untersucht mithilfe von *"value-added models"* die Auswirkung eines Bonusprogramms für Lehrkräfte auf die schulischen Leistungen von Kindern. Diese Studie begrenzt die Untersuchung auf die Stadt Campinas und verwendet einen Differenz-von-Differenzen-Ansatz, in welchem die SchülerInnen aus staatlichen Institutionen die Treatment-Gruppe und gleichaltrige SchülerInnen aus kommunalen Schulen die Kontrollgruppe bilden.

Damit kommt die zweite Studie zu dem Ergebnis, dass die Einführung des Bonusprogrammes für Lehrkräfte im Bundestaat von São Paulo keinen statistisch signifikanten Einfluss auf die Leistungen der SchülerInnen in Mathematik und Portugiesisch hatte. Nach dem ersten Jahr des Bonusprogrammes lagen die Prüfungsergebnisse von SchülerInnen aus staatlichen Schulen geringfügig unter denen aus den kommunalen Schulen, wobei dieser Unterschied nicht statistisch signifikant ist. Die Ergebnisse von alternativen Spezifikationen, Placebotests und Robustheitsprüfungen bestätigen diese Erkenntnis.

Das letzte Kapitel *"Addressing changes in professional behavior by teacher bonus"* konzentriert sich ebenfalls auf die Evaluierung des Bonusprogramms für Lehrkräfte des Bundesstaats São Paulo. Der Fokus liegt hier jedoch auf der Untersuchung von möglichen Änderungen bei der Lehrtätigkeit, die aufgrund der Einführung des Bonus entstanden und mitverantwortlich für die Verbesserung der Leistungen der SchülerInnen sein könnten. Das Forschungsvorhaben interessiert sich für die individuellen Wahrnehmungen und Ansichten der Lehrkräfte in Bezug auf die Effekte des Bonusprogramms auf ihre beruflichen Aktivitäten und ihr Verhalten im Schulwesen. Für diese Studie führte der Autor eine eigene Datenerhebungen mittels eines standardisierten Fragebogens und Interviews mit LehrerInnen aus den staatlichen Schulen von Campinas durch und verwendet quantitative und qualitative Forschungsmethoden (*"mixed-methods research"*) für die Auswertung der Ergebnisse. Nach Auffassung der Lehrkräfte hat das Bonusprogramm keinen zusätzlichen Anreiz für die Arbeit in den staatlichen Schulen von São Paulo oder für die Verbesserung der Lehrtätigkeit geschaffen. Stattdessen kam es vielmehr zu einer Zunahme eines unehrlichen Verhaltens in den Schulen. Den befragten LehrerInnen zufolge war die einzige positive Auswirkung des Bonusprogramms die Verringerung von Fehlzeiten.

Declaration of Authorship

Erklärung gem. § 4 Abs. 2

Hiermit erkläre ich, dass ich mich noch keinem Promotionsverfahren unterzogen oder um Zulassung zu einem solchen beworben habe, und die Dissertation in der gleichen oder einer anderen Fassung bzw. Überarbeitung einer anderen Fakultät, einem Prüfungsausschuss oder einem Fachvertreter an einer anderen Hochschule nicht bereits zur Überprüfung vorgelegen hat.

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Hiermit erkläre ich, dass ich die vorliegende Dissertation selbstständig und ohne fremde Hilfe verfasst, andere als die angegebenen Quellen und Hilfsmittel nicht benutzt und alle den benutzten Quellen wörtlich oder sinngemäß entnommenen Stellen als solche kenntlich gemacht habe. Auf dieser Grundlage habe ich die Arbeit selbstständig verfasst.

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