THE GEOGRAPHY OF INTERGENERATIONAL MOBILITY: EVIDENCE OF EDUCATIONAL PERSISTENCE AND THE “GREAT GATSBY CURVE” IN BRAZIL

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The Geography of Intergenerational Mobility: Evidence of Educational Persistence and the “Great Gatsby Curve” in Brazil

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ABSTRACT
This paper explores the variation in intergenerational educational mobility across the Brazilian states based on transition matrixes and univariate econometric techniques. The analysis of the national household survey (PNAD-2014) confirms a strong variation in mobility among the 27 states in Brazil and demonstrates a significant correlation between mobility and income inequality. In this sense, this work presents empirical evidence for the "Great Gatsby Curve" within a single country: states with greater income disparities present higher levels of persistence in education across generations. Finally, 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 robust and compelling results showing that children born into families where the parents have not completed primary education have a statistically significant reduction in their chance of completing the educational system if they live in states with a higher level of income inequality.


Keywords: Intergenerational mobility, Great Gatsby curve, socio-economic marginalization, inequality, Brazil.

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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; Smeeding et al., 2011). 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 et al., 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 (Andrews and Leigh, 2009; Chetty et al., 2014a; 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 the 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 analysed across different regions within a single country, using observations recorded and consolidated in a single database.¹

The investigation of intergenerational mobility within Brazilian states in this study is based on the educational attainment of children and their parents and applies the recently published Mobility Supplement from the nationally representative Brazilian household survey (PNAD-2014)². 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 the 27 states³. 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.⁴

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 equalisation of opportunities and a minimum level of quality.⁵

Despite the increasing scientific interest in the “Great Gatsby curve”, far too little is

¹This 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 (2014) for the United States. They analysed single data sets and found that the correlation between intergenerational mobility and inequality also holds true across provinces in these countries.

²The microdata from PNAD-2014 were only made freely available for research in November 2016.

³To be more precise, Brazil comprises 26 states plus a federal district (Distrito Federal), where the federal capital is located.

⁴See the figures in the Online Appendix for a clear picture of the variation in income inequality across the Brazilian states.

⁵The Online Appendix of this paper provides a more comprehensive and detailed overview of Brazilian educational system.
known about the causal link between inequality and intergenerational mobility, 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 (2014) 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 paper is structured as follows. The next section reviews the related literature and presents the econometric models used as the theoretical basis for the investigation. Section 3 presents the database. In the following, I describe the three different empirical approaches applied in the paper. Section 5 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 middle and the bottom of the income distribution have a greater probability of leaving school without a certificate. Section 6 concludes with a summary of the key findings.6

2 Theoretical Background and Literature Review

The term “intergenerational mobility” describes the ability of children to move beyond their social origins and achieve a socio-economic status that is not dictated by that of their parents (Fox et al., 2016; Ribeiro, 2007). In the mobility literature, the focus of the economic investigations is the measurement of the correlation between parents’ and children’s economic outcomes, in terms of income, education or 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 the 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 (Blanden et al., 2014; Black and Devereux, 2010). The studies of Solon (1992) and Zimmerman (1992) were the precursors to the modern empirical estimations of intergenerational correlation of outcomes (Björklund and Jäntti, 2009; Blanden et al., 2014; Ichino et al., 2011). In the subsequent years, motivated mainly by the theoretical contribution of Solon (2004) several researchers around the world have begun 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, 2007; Roemer, 2004; Ueda, 2009). In a second stage of the literature, researchers have focused on the variation of intergenerational mobility over time (see e.g. Aaronson and Mazumder, 2008; Björklund et al., 2009; Hertz et al., 2007; Hout and Guest, 2013; Lee and Solon, 2009; Mazumder et al., 2012) and across countries (see e.g. Aaberge et al., 2002; Ayala and Sastre, 2008; Blanden, 2013; Blanden et al., 2014; Corak, 2006; Jäntti et al., 2006).7

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6 This paper is supplemented by a comprehensive Online Appendix with relevant information concerning the educational system in Brazil, the data harmonisation, the codification process for the variables, additional figures and the formal description of the underlying theoretical models.

7 Black and Devereux (2010), Fox et al. (2016), Jantti and Jenkins (2013) and Hills et al. (2015) offer a detailed discussion of recent developments in the literature on intergenerational mobility.
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.\(^8\) Given the limited availability of lifetime income data – specially in developing countries (Azam and Bhatt, 2015; Ferreira and Veloso, 2006) – 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).

Only more recently has the economic literature dealt 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, 2014). Based on cross-country comparisons and the theoretical approach of Solon (2004), the author showed that countries with greater income disparity tend to exhibit lower levels of economic mobility between generations.

It didn’t take long for the finding of Corak (2006) to enter 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., 2014a,b; Corak, 2013a,b; Fan et al., 2015; Güell et al., 2018; Jerrim and Macmillan, 2015; Lefgren et al., 2015; Mazumder et al., 2015).

The negative relationship between inequality and intergenerational mobility illustrated by the “Great Gatsby curve” is also supported by the 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 a mathematical approach that higher-income parents have a higher capacity to invest more in human capital of their children, and they are also more inclined to make this investment if the expected earnings return on human capital increases.\(^9\)

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 over time. The “Great Gatsby curve” does not present a causality 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

\(^8\)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 do Valle Silva, 2000; Reddy, 2015; Xie and Killewald, 2013).

\(^9\)The Online Appendix provides a formal description for the Model of Solon (2004), which show how income inequality can affect the chances of intergenerational mobility.
development (Corak, 2013a; Kearney and Levine, 2014).

Recent research has offered a vast amount of evidence that childhood development has direct effects on adult economic productivity (Cunha et al., 2006; Knudsen et al., 2006; Phillips et al., 2000). Socially vulnerable families lack the socio-economic 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 (Lawrence et al., 2005; 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).

Despite this complexity, the variation in the intergenerational persistence of economic outcomes presented by the “Great Gatsby curve” calls for us to reflect on the reasons for the different levels of mobility, and how these underlying drivers can influence the ultimate outcomes. To address these questions, it is important to bear in mind the three fundamental institutions that play a strong role in children’s chances of mobility: the family, the labour market and the state (Corak, 2013a).

As described in the model of Solon (2004), the income inequality resulting from the labour 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 non-monetary resources, such as the behavioural patterns, motivations and social connections which are transmitted in the family environment and play an important role in mobility potential. Finally, the importance of public policy for intergenerational mobility relates to all key aspects that affect the interaction between families and the labour market, such as taxation and regulatory structure (Björklund and Jäntti, 2009; Corak, 2013a).

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 (Björklund and Jäntti, 2009; Chetty et al., 2014a; Fessler and Schneebaum, 2012) – this paper isn’t, in principle, looking for causal relationships, but rather aims to generate stylised facts and trends, thereby improving our understanding of the mechanisms behind the correlation between income inequality and the persistence of economic outcomes across generations represented by the “Great Gatsby curve”. Consequently, the empirical approach applied in the second part of this paper resembles that renowned paper of Kearney and Levine (2014).

Kearney and Levine (2014) 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 marginalisation.10 Based on a formal econometric model and five sources of individual-level data for the USA, the paper 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.

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10See Online Appendix for a formal description of the model of Kearney and Levine (2014), concerning the decision to drop out of school.
3 Data

The data for this study stems from the Brazilian National Household Sample Survey (PNAD), which is a representative household survey conducted annually by the Brazilian Institute of Geography and Statistics (IBGE) to collect socio-economic and demographic information about the Brazilian population, including household composition, education, labour, income, migration, and fertility.\footnote{In 2014 the PNAD’s sample consisted of 151,291 households with 362,627 individuals.}

To investigate mobility, I use the data wave 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. For the survey, respondents 16 years and older were asked to provide information about their parents’ professional occupation and level of education.\footnote{The information about the education and occupation of parents refers to the level when the respondents were 15 years old.}

The two main outcomes of interest in this paper are years of schooling and levels of education, for both children and parents.\footnote{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.} 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 education.\footnote{In practical terms, primary education in this paper means the minimum years of schooling required by law when the children and parents were of school age. Currently, the compulsory education in Brazil ends at the age of 17. See Online Appendix for an overview of the changes in compulsory education over time.}

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 attended.\footnote{Please see the Online Appendix for a detailed description of the codification process.} 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 variables related to income to estimate the indicators of inequality.

I excluded individuals under 25 years old from the sample, given that approximately 42 per cent 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. Consequently, this paper considers people born between 1940 and 1989 in the empirical analysis and works with a sample of 46,051 individuals.

I inserted a dummy variable for “economic marginalisation,” which refers to children from parents with no school certificate, in the sample. Finally, the observations were categorised into 10-year birth cohorts (1940–1949, 1950–1959, 1960–1969, 1970–1979, and 1980–1989) in order to minimise the lifecycle bias resulting from the variation in average years of schooling and in education dispersion over time (see Figures 1 and 2).\footnote{For the empirical estimations, this paper applies the weights presented in the sample, representing the inverse of the probability of an observation being selected into the sample.}

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% and the poorest 10% of the income distribution. 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.\footnote{Please see Section 4.2 for the empirical background and the Online Appendix for a full description of the harmonisation process that needed to be undertaken in order to fit the data over time.}

Table 1 reports the summary statistics on income distribution, educational attainment,
average age, and share of rural population divided by the states and macro-regions of Brazil. Figures 1 and 2 visually display the development over time of average schooling and its standard deviation, respectively. Figures 3 and 4 show the (current) strong variation in schooling and educational levels across the 27 Brazilian states.

In the light of the table 1, it is possible to observe the average educational attainment of children and parents. Note that in all states the average schooling of children is higher than that of their parents, and that the mothers are almost always more educated than their spouses.\footnote{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.} Columns (7) to (9) list the proportions of people who were enrolled in school in 2014. According to data from PNAD-2014, all states in Brazil are close to the objective of achieving universal education for children between 7 and 14 years old.\footnote{The estimated values varied between 0.965 in Acre and 0.994 in São Paulo.} However, beyond the age of primary education, the deviation in the net enrolment 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 south-eastern 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 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 3 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 north-eastern. Finally, chart 4 illustrates the main reason for these differences in average education: The share of individuals with no school-leaving certificate in the north-east states is greater than in the other macro-regions of Brazil.

4 Conceptual Framework

This paper employs a two-step empirical framework. I start by measuring intergenerational persistence in education, using linear regression models (Checchi et al., 2013) and transition matrices (Jäntti et al., 2006). I then apply an econometric method to investigate whether children from disadvantaged families have a lower chance of completing secondary education (Kearney and Levine, 2014).

4.1 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 $P$ with the number of states $S$, such that:

$$p_{ij} = P(X_{t+1} = j \mid X_t = i) \quad \text{for} \quad i, j \in S, \quad t = 0, 1, 2, ...$$  \hspace{1cm} (1)

The estimated transition matrices present two important properties:

$$\forall \quad i, j \in \mathbb{R}, \quad P(i, j) \geq 0, \quad \text{and}$$  \hspace{1cm} (2)
\[
\sum_{j=1}^{N} p_{ij} = \sum_{j=1}^{N} \mathbb{P}(X_{t+1} = j \mid X_{t} = i) = \sum_{j=1}^{N} \mathbb{P}_{\{X_{t}=i\}}(X_{t+1} = j) = 1. \tag{3}
\]

In transition matrix \(\mathbb{P}\), the value of \(p_{ij}\) 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):

\[
ImR = \frac{\text{Tr}(\mathbb{P})}{S} = \frac{\sum_{i=1}^{N} \rho_{ij}}{S} \tag{4}
\]

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 \(l\).

\[
UpM = Pr(X_{t} > l \mid X_{t+1} = l) \quad \text{and} \quad DoM = Pr(X_{t} < l \mid X_{t+1} = l) \tag{5}
\]

In order to summarise 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); Daouli et al. (2010) and calculate the Prais–Shorrocks indicator based on the trace \(\text{Tr}(\mathbb{P})\) and the number of states in the transition matrix.

\[
M_{PS}(\mathbb{P}) = \frac{S - \text{Tr}(\mathbb{P})}{S - 1} \quad \text{with} \quad M_{PS} \in [0, 1] \tag{6}
\]

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

**B. Linear Regression Model**

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

\[
educ_{i,s} = \alpha + \beta educ_{p,i,s} + \epsilon_{i} \quad \text{for} \quad i = 1, 2, \ldots, N \tag{7}
\]

where \(educ_{i,s}\) is the years of schooling of a child \(i\) resident in the state \(s\), and \(educ_{p,i,s}\) denotes the same variable for his or her parents. The error term \(\epsilon_{i}\) reflects the combined effects on a child’s education of factors orthogonal to parental education, and the slope coefficient \(\beta\) is the parameter of interest, representing the elasticity of children’s education.

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\(^{20}\)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).

\(^{21}\)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 one and all the remaining elements are zero, indicating a perfectly immobile society (Chevalier et al., 2003).
with respect to their parents’ education. The coefficient $\beta$ is commonly known in the economic literature as the “regression coefficient” and gives the value of each 1 per cent difference in parental education across families that will be transmitted as an educational difference to their children (Blanden, 2013).

Given the variation in standard deviations across states and time in Brazil, as shown in Figure 2, I follow Azam (2016); Checchi et al. (2013) and normalise the years of schooling in Equation (7) by the corresponding standard deviation. The OLS estimate of $\beta$ is given by:

$$\hat{\beta} = \rho_{cp} \sigma_{c} \sigma_{p}, \quad \text{with} \quad \sigma = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (x_{i} - \mu)^2} \quad (8)$$

where $\sigma_{c}$ and $\sigma_{p}$ correspond to the standard deviation in education for children and parents in state $s$, while the coefficient $\rho_{cp}$ captures the association between children’s and parents’ education, respectively. Based on equations (7) and (8), the resulting empirical model can be summarised as:

$$\frac{educ_{i,s}}{\sigma_{c}} = \delta + \rho \left( \frac{educ_{i,s}}{\sigma_{p}} \right) + \epsilon_i \quad \text{with} \quad \rho \in [0, 1] \quad (9)$$

In this regard, the coefficient $\rho$ 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.

Given that the estimations are based on the pooled sample, equation (9) includes a vector of dummy variables $UF$ with the state of residence of the child $i$. Moreover, I use a vector $X$ comprising controls for gender, race, and year of birth. Finally, some interaction terms between the variables are assumed. Thus, the resulting fully interacted model takes the following form:

$$\frac{educ_{i,s}}{\sigma_{c}} = \delta + \rho \frac{educ_{i,s}}{\sigma_{p}} + \eta \left( \frac{educ_{i,s}}{\sigma_{p}} \times UF_i \right) + \lambda UF_i + \gamma (X_i \times UF_i) + \epsilon_i \quad (10)$$

4.2 Linking Inequality and School Dropouts

In this section, I follow Kearney and Levine (2014) and apply a probit model aimed at investigating whether children from marginalised socio-economic 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 $i^{th}$ individual born in year $t$ has completed secondary education and this is a function of socio-economic background, income inequality in the state of residence, and individual characteristics. Thus, the empirical probit model can be written as

$$ComSec_{i,t} = \pi_0 + \pi_1 (MSB_i \times Ineq_{s,t+14}) + \pi_2 MSB_i + \pi_3 Ineq_{s,t+14} + \gamma_1 male_i + \gamma_2 rural_i + \gamma_3 bothP_i + \gamma_4 race_i + \gamma_5 birth_i + \epsilon_i \quad (11)$$

The (marginalised) socio-economic background is summarised 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 \((t + 14)\).\(^{22}\) 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 (\(bothP\)).

The parameter \(\pi_1\) 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 (11) as:

\[
\frac{\partial E(ComSec|x)}{\partial x} \bigg|_{x=\tilde{x}} = \frac{\partial F(x|\beta)}{\partial x} \bigg|_{x=\tilde{x}} = f(\tilde{x}|\beta)\beta
\]

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.

5 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. Section 5.3 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 marginalised children.

5.1 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).

\(^{22}\) 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 they 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, the equation (11) uses the 75/10 ratio from the year in which the individual turned 14 as measure of inequality.
A. Mobility Matrices

Figure 5 measures children’s probability of attaining a certain educational level as a function of parents’ education. If we analyse 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 the 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 the figure 5, the proportion of people with no school certificate and only primary education is becoming increasingly smaller.

Following on this brief description of the development of mobility over time, I now turn to the variation in the intergenerational persistence of education across the Brazilian states. Figure 6 presents the direction of mobility, displaying the results of equations (4) and (5). Figure 7 places the states in increasing order, according to the degree of mobility estimated from equation (6).

Figure 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% of children have achieved a higher level of education than their parents, while only around 15% have experienced downward mobility.

However, these values vary strongly across the states. Paraíba 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% in Pará to 52.1% in Distrito Federal.

Figure 7 ranks the Brazilian states on the basis of the Prais-Shorrocks indicator from equation (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 (bottom) persistence” displays the proportion of children from parents with tertiary education (no certificate) 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. In Brazil, 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 value also varies strongly across the states, from 32.2% in Distrito Federal to 69.7% in Piauí. Figure 7 indicates that the chances of ascending from the bottom of the education distribution are especially low for individuals living in the north-eastern states.23

With a Prais-Shorrocks index equal to 0.836, Rio Grande do Norte (RN) leads the Brazilian rankings for intergenerational mobility. The main reason for this is that RN exhibits very low persistence at the top of distribution. Only 15.1% of children from parents with a tertiary education achieved a college degree. By way of comparison, this

23The seven states with the greatest educational persistence at the bottom of the distribution, are all located in north-eastern 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%).
value is 92.4% in Distrito Federal, 82.3% in Roraima, and 78.5% in São Paulo.

Finally, Figure 7 illustrates 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%, i.e., Mato Grosso 10.9%, Amapá 11%, Roraima 16.4% and Distrito Federal 16.6%.

B. Linear Regression Model

In this section, I estimate the educational persistence between children and parents for each state based on equation (10). Figure 8 presents the results of this exercise based on a geographical breakdown. The lighter areas denote states with lower levels of educational persistence across generations (or higher mobility values).

For the sample as a whole, the correlation coefficient generated a value of 0.475, while 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) and Maranhão (0.377). Bahia (0.488), Distrito Federal (0.492), Alagoas (0.497), Acre (0.502), and Rio de Janeiro (0.510) located at the other end of the scale.

As already indicated in Figure 5, children’s chances of attaining primary education have increased significantly over time in Brazil. Accordingly, figures 1 and 2 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 (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 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 and 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 don’t 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 displays the levels of mobility (separately) across birth cohorts.

5.2 The Great Gatsby Curve

Independent of the indicator used to measure intergenerational mobility, the findings presented in Section 5.1 allow us to establish this paper’s first important result: The chances of attaining educational mobility vary significantly from one Brazilian state to another.

This section addresses the question of why intergenerational persistence in education varies so widely across Brazilian states, investigating the effect of income mobility on

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24 As can be seen from the chart 8, the educational mobility is higher in the northern region than in the other regions of the country. Among the seven states from this region, only Pará and Acre aren’t in the Top 10 of the states with the highest degree of mobility in Brazil.
educational mobility. As already discussed in Section 2, Solon (2004) has 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 Figure 8 can be explained by the significant variation in inequality across Brazilian states.

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.\footnote{A child born in 1970, for example, started school at age seven in 1977 and presumably concluded their compulsory (primary) education in 1984.}

Given the variation over time in mobility shown in Table 2, I focused the investigation on one single birth cohort containing individuals born between 1970 and 1979 in order to minimise the lifecycle bias.\footnote{The youngest cohort (1980-1989) has not been chosen for the investigation because approximately 9.2% 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 are no data available for the measure of the Gini coefficient for the years before 1976.}

Consequently, 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 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 (10),\footnote{As already observed by Chetty et al. (2014a), the cross-regional studies have exclusively used the measure of regression coefficients to investigate the variation in intergenerational mobility. In this section I therefore use the correlation coefficient as a measure of mobility in order to enable an accurate comparison of the conclusions with the results from the cross-country literature.} while income inequality is plotted on the horizontal axis. The findings confirm the statistically significant relationship between the Gini coefficient and intergenerational mobility:\footnote{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.} States with a higher level of income disparity, such as Paraíba (PB) and Ceará (CE), presented higher values of persistence in education (or low levels of mobility), while the correlation coefficients tended to be lower in states with a more equal distribution of income, such as Santa Catarina (SC) and Amazonas (AM).

5.3 Linking Inequality and School Dropouts

In this section, I move away from the analysis of intergenerational persistence in education via the correlation hypothesis to an investigation of the determinants which 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 marginalisation” presented by Kearney and Levine (2014), 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.\footnote{The Online Appendix provides a formal description of the model of Kearney and Levine (2014).}
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 marginalised population often lives in disadvantaged areas with negative neighbourhood behavioural 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).

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. Figure 11 provides the first empirical evidence for the subsequently applied econometric model. This chart presents the proportion of the population with secondary-school education, divided by the (state) inequality groups and the educational achievement of parents, which is used as a proxy for “economic marginalisation”. The findings highlight the effect of marginalisation on the decision to leave school early. Note that independent of the inequality level, less than 20% of children from illiterate parents have completed secondary education. In contrast, more than 80% of children of parents with a graduate degree have a secondary school-leaving qualification.

In addition, Figure 11 confirms that for vulnerable children, the school dropout is associated with the income inequality: The children of illiterate parents and parents with no (primary) education living in states with lower income inequality have a higher chance to complete secondary education than vulnerable children from high-inequality states.

5.3.1 Probit Latent Variable Model

In order to empirically test the assumption regarding economic marginalisation, I run equation (11) and present the results in Table 3. The first column contains the results for the whole sample, and the subsequent columns contain the values for the five-year birth cohorts.

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 “socio-economic marginalisation” 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 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% for children of parents without education.

For a better overview of the interaction between income inequality and economic

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30See Rothwell and Massey (2015) for a large and rich literature overview concerning the channels through which neighborhoods can affect future earnings.

31See Online Appendix for the identification of the states with low, middle and high levels of inequality.

32The parameters in the probit model were estimated using maximum likelihood methods.

33Because there is no nationally representative database for the period prior to 1981 that could be harmonised in a reliable way with the most recent samples of PNAD, this section limited the estimates to individuals born from the year 1965 onwards, thereby using the income inequality after the year 1981. See the Online Appendix for a detailed description of the data harmonisation.
marginalisation, I estimate the marginal effects from equation (11) and display the predicted probabilities for all the 10th values of the ratio 75/10 (from 3 to 12) in Figure 12.\footnote{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 populations is the inequality, inequality must be the cause of the differences in their likelihood of achieving a secondary education. (Williams et al., 2012)}

Note that independent of the level of inequality, children of parents with no 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.\footnote{Figure 12 shows that both curves have non-overlapping confidence intervals, demonstrating a statistically significant difference between the estimations.}

5.3.2 Robustness Checks

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

A. Alternative Econometric Approaches

As previously described, the objective of Section 5.3.1 was to identify whether children from (socio-economically) marginalised households living in states with greater income inequality are more disadvantaged in their school careers. As a proxy for socio-economic marginalisation, I used a dummy variable indicating children from parents with no primary education (NoEducP) in the equation (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 marginalisation” varies according to the parents’ economic situation, and having both parents in the household can shift the family’s budget constraints, providing higher socio-economic status for the family, similarly to a higher level of parental education. I therefore use for the variable responsible for the socio-economic marginalisation (NoEduP) the instrumental variable “both parents” (bothP) which is a binary variable equal to one if the individual lived with both parents in the household at the age of 15.

In this section, I continue to use equation (11) to study the effects of economic marginalisation 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” (both$P_i$) from the probit for $MSB_i$.\footnote{To facilitate comparison, Table 4 also contains the estimation results from the probit model in Section 5.3.1, in which the variable both$P_i$ was treated as exogenous.}

Table 4 provides the results of the robustness checks using the whole sample and confirms that the estimates from Section 5.3.1 are also robust to alternative econometric approaches. For brevity’s sake, the table reports only the coefficients $\pi_1$ from the interaction term between income inequality ($Ineq_s$) and the proxy for socio-economic marginalisation ($MSB_i$). Next, I have used margins to obtain the predicted probabilities for this interaction and have also displayed the adjusted predictions of educational chances at representative values of income inequality (APRs), i.e. for every 10$^{th}$ value for the distribution of the 75/10 ratio.\footnote{It is important to note that the estimated marginal effects refer to the component terms of socio-economic marginalisation and income inequality, and not necessarily the marginal effect of the interaction term. As explained in greater detail by Williams et al. (2012), because the value of the interaction terms cannot change independently of the values of the component terms, it is not possible to estimate a separate effect for the interaction.}

As in the main model specification, all three expanded models presented 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 marginalisation 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\% lower chance of achieving a secondary education certificate than pupils from parents with at least primary education. The same difference in the top decile is approximately 40 per cent. This empirical evidence remains practically unchanged when both$P$ 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 both$P_i$ are correlated, presents substantially lower estimated APRs than the (normal) probit model.\footnote{However, the estimates continue to indicate the same direction and statistical significance.} The adjusted predictions 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.

B. Alternative Model Specifications

In the following, I explore the dependence of parameter $\pi_1$, estimated from equation (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 socio-economic marginalisation, 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 NoEduc$P_i$.\footnote{For the specification in column 8, the empirical model assumes the following form:

$$ComSec_{i,t} = \pi_0 + \pi_1 (NoEducP_i \times Ineq_{s,t+14}) + \pi_2 (IlliteP_i \times Ineq_{s,t+14}) + \pi_3 NoEducP_i + \pi_4 IlliteP_i + \pi_5 Ineq_{s,t+14} + \gamma_1 male_i + \gamma_2 rural_i + \gamma_3 bothP_i + \gamma_4 race_i + \gamma_5 birthc_i + \epsilon_i$$}
All four expanded models generated robust results, demonstrating the significantly negative impact of income inequality on educational attainment, as already indicated in Section 5.3.1. 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 (2014), 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.

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 primary education is 21.0% at the bottom of the distribution and 42.3% at the other extreme of the inequality scale. These results are consistent with the findings presented in Figure 12 and show that – keeping all the other variables constant – the adverse effect of socio-economic marginalisation on the chance of completing secondary education tends to be stronger in states with greater income disparity.

6 Conclusion

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% in Pará, but 16.6% 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.

In addition, this study contributes to the literature that is presenting new findings on the ”Great Gatsby curve”. I have found compelling 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 level across generations tends to be stronger in states with a more unequal distribution of income.

Finally, this work has aimed directly at 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 (2014), 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.
References


Appendix: Figures

Figure 1: Development of Average Schooling, per State

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

Figure 2: Development of Inequality in Schooling, per State

Notes: Children’s education for boys and girls. Estimations of parent’s education based on educational attainment of the most educated parent. Source: PNAD-2014, own estimates.
Figure 3: Average Years of Schooling

Note: Estimations for boys and girls.
Source: PNAD-2014, own estimates.

Figure 4: Levels of Education, by Regions and States.

Note: Estimations for boys and girls.
Source: PNAD-2014, own estimates.
Figure 5: Children’s Predicted Probabilities of Educational Attainment

Notes: Children’s education for both genders. Parents’ schooling refers to the educational level of the better educated parent.
Source: PNAD-2014, own estimates.
Figure 6: Immobility Ratio and Upward–Downward Mobility

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

Figure 7: Intergenerational Mobility Indexes

Notes: The Prais-Shorrocks index provides a measure of the normalised distance between the identity matrix and the independent matrix. It takes a value of zero (one) when no (all) children move away from the educational level of their parents. The bottom-to-top 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 8: Intergenerational Persistence in Education

Note: The closer the estimated value is to one, the stronger the association between parents’ and children’s educational attainment and, consequently, the lower the intergenerational mobility.
Source: PNAD-2014, own estimates.

Figure 9: Adjusted Predictions of Birth Cohorts

Source: PNAD-2014, own estimates.
Figure 10: The Great Gatsby Curve

Notes: $r = \text{Pearson’s correlation}$. Asterisk indicates correlation coefficients with p-values of .1 or lower. Gini coefficients refer to the average values between 1984 and 1993. Source: PNADs, own estimates.
Figure 11: Educational Attainment and Inequality

![Diagram](image)

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 zero. 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.

Source: PNAD-2014, own estimates.

Figure 12: Adjusted Predictions for Secondary Education

![Diagram](image)

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 of income inequality based on the 75/10 ratio of total income of the economically active population aged 15 or over and with earnings greater than zero.

Source: PNADs, own estimates.
Table 1: Weighted Descriptive Statistics (PNAD-2014).

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<th>State</th>
<th>Pop. Abbrev.</th>
<th>Total Population</th>
<th>Average</th>
<th>Ratio in rural</th>
<th>Income distribution (R$)</th>
<th>Net enrolment ratio (age)</th>
<th>Average years of schooling</th>
<th>Obs. Fathers Mothers</th>
<th>Children Fathers Mothers</th>
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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 from column 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, respectively, the poorest 10%, the middle 50% and the richest 10%, respectively, of the income distribution.
## Table 2: Correlation Coefficients, by Birth Cohort.

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<td>217</td>
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<td>264</td>
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<td>Tocantins</td>
<td>TO</td>
<td>484</td>
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<td>73</td>
<td>0.357**</td>
<td>99</td>
<td>0.213</td>
<td>121</td>
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<td>136</td>
<td>0.414***</td>
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### North

- Rondônia: 4.454 0.425***
- Amazonas: 553 0.511***
- Amapá: 582 0.439***
- Tocantins: 582 0.439***

### North-east

- Rondônia: 3.746 0.454***
- Acre: 2.456 0.497***
- Piauí: 2.734 0.485***
- Bahia: 2.744 0.488***

### South

- Amapá: 1.083 0.434***
- Tocantins: 0.450 0.439***
- Santa Catarina: 1.210 0.469***
- Rio Grande do Sul: 1.019 0.454***

### South-east

- Rondônia: 3.840 0.438***
- Amazonas: 6.734 0.457***
- Amapá: 3.746 0.454***
- Tocantins: 3.840 0.438***

### West Central

- Rondônia: 3.840 0.438***
- Amazonas: 6.734 0.457***
- Amapá: 3.746 0.454***
- Tocantins: 3.840 0.438***

### Brazil

- Rondônia: 35.757 0.475***
- Amazonas: 5.586 0.517***
- Amapá: 5.586 0.517***
- Tocantins: 5.586 0.517***

### 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 < 0.001, ∗∗p < 0.01, ∗p < 0.05.
- Source: PNAD-2014, own estimates.
### Table 3: The Impact of Inequality on Educational Attainment.

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<td>(0.0242)</td>
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<tr>
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<td>-0.374***</td>
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<td>(0.191)</td>
<td>(0.619)</td>
<td>(0.457)</td>
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Notes: *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 4: Robustness Checks.

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<th>Alternative Model Specifications</th>
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<td>(2)</td>
<td>(3)</td>
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<tr>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
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<tr>
<td>Coefficient of MSB &amp; Inequality</td>
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<td>(0.0186)</td>
<td>(0.00436)</td>
<td>(0.00436)</td>
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<td>0.458***</td>
<td>0.370***</td>
<td>0.365***</td>
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<td>(0.00436)</td>
<td>(0.00436)</td>
<td>(0.00436)</td>
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<tr>
<td>Observations</td>
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<td>23,008</td>
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</table>

Notes: The coefficients of the interaction between the socio-economic marginalization (MSB) and the inequality level show how the effects of having (non-)educated parents on the children’s chance of schooling change by different values of inequality. The adjusted predictions at representative values (APRs) had 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 heteroskedasticity. 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.
Supporting Information

Additional supporting information may be found in the Online Appendix of this article at the author’s web site:

1. Appendix
   - Structure of Brazilian educational system
   - Codification of years of schooling
   - Data Harmonisation

2. Theoretical Models
   - A Model of the Intergenerational Transmission of Income Inequality
   - A Stylized Model of the Decision to Dropout Education System

3. Additional Figures
   - Figure A.1: Income inequality across Brazilian states
   - Figure A.2: Ratio 75/10 of income distribution