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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 univariate econometric techniques. The analysis of the national household survey (PNAD-2014) confirms a strong variation in mobility among the 27 federative units in Brazil and demonstrates a significant correlation between mobility and income inequality. In this sense, this work presents empirical evidence for the existence of the "Great Gatsby curve" within a single country: states with greater income disparities present higher levels of persistence in educational levels across generations. Finally, the paper investigates one specific mechanism behind this correlation: whether higher income inequality might lead to 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

Brazil, educational attainment, Great Gatsby Curve, human capital, inequality, intergenerational mobility

JEL CLASSIFICATION
J62; I24; I26

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 & Jäntti, 2009; Blanden, 2013; Corak, 2006). The so-called "Great Gatsby curve" (GGC) 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; Corak, 2013; Jerrim & Macmillan, 2015).

The original GGC 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 (Chetty et al., 2014; Güell et al., 2018; Jerrim and Macmillan, 2015). The demonstration of equivalence (lack of bias) is an important criterion 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 & Leigh, 2009; Boudreaux, 2014).

This paper is intended primarily to expand the available literature by providing a GGC 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. Given the lack of intergenerational income data for Brazil, the investigation of the GGC in this study is based on educational 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 the 27 states.

Despite the increasing scientific interest in the GGC, far too little is known about the causal link between inequality and intergenerational mobility, because only limited research has been undertaken on the determinants of this correlation (Jerrim & Macmillan, 2015). In this paper, I seek to fill this research gap by focusing on a possible mechanism through which inequality might affect intergenerational mobility: curtailed investment in education. Following Kearney and Levine (2016), I 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 dropout rates, thereby decreasing their chances of mobility.

The empirical findings presented in this paper indicate that the case of Brazil provides two main pieces of evidence for the existing literature. Firstly, the relationship between income inequality and intergenerational mobility illustrated in the GGC remains persistent within a single country. Secondly, 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 middle of the income distribution, children from socially vulnerable families have a higher chance of dropping out of the education system.

The remainder of this study is structured as follows. Section 2 reviews the related literature and presents the econometric models used as the theoretical basis for the investigation. Section 3 presents the database and Section 4 describes the conceptual framework. Section 5 deals with the empirical findings. Section 6 concludes.[1]

2 | THEORETICAL BACKGROUND AND LITERATURE REVIEW

Although, the empirical evidence for intergenerational educational mobility remain highly concentrated in the industrialized world, it is possible to detect in recent years an increasing academic interest in estimating mobility chances for developing countries (Torche, 2019). Recent papers on this topic have been published by Dacuycuy and Bayudan-Dacuycuy (2019) for the Philippines, Assaad and Saleh (2018) for Jordan, Li and Zhong (2017), Magnani and Zhu (2015), and Fan et al. (2015) for China, Emran and Shilpi (2015) and Azam and Bhatt (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 Neidhöfer et al. (2018) and Daude and Robano (2015) for Latin America, and Azomahou and Yitbarek (2016) for sub-Saharan Africa.

In the last decade, several studies have explored the intergenerational educational mobility in Brazil and confirmed a strong positive association between education outcomes of parents and children (see, for example, Leone, 2021; Mahlmeister et al., 2019; Ribeiro, 2017; Torche & Ribeiro, 2010). In addition, the literature points to the special relevance of gendered patterns in the intergenerational transmission of educational attainment: in Brazil, women present higher levels of mobility than men and the educational attainment of children is more strongly associated with the education of their most educated parent, regardless of sex (Leone, 2021).

In particular, from the 2000s onward, the economic literature has also started to deal with the mechanisms behind the intergenerational persistence in outcomes (Black & Devereux, 2010; Rothwell & Massey, 2015). Corak (2006) was the first to provide empirical evidence of a negative correlation between intergenerational mobility and income inequality (Kearney & Levine, 2016). 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 income mobility between generations.

It did not 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 GGC, and within a short space of time this curve gained a prominent position in the international economic community (Jerrim & 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., The Economist, 2013; The Guardian, 2012) and high-ranking policymakers (see, e.g., House, 2013; Obama, 2013). The GGC has also been addressed in a long list of recent publications in peer-reviewed journals (see, e.g., Boudreaux, 2014; Brahim & McLeod, 2016; Chetty et al., 2014; Corak, 2013; Güell et al., 2018; Jerrim & Macmillan, 2015; Lefgren et al., 2015; Neidhöfer, 2019).

The negative relationship between inequality and intergenerational mobility illustrated by the GGC is also supported by economic theory. Becker and Tomes (1986), Solon (2004), Breen and Jonsson (2005), Duncan and Murnane (2011), and Corak (2013) 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. 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.

Several studies have offered empirical evidence that childhood development has direct effects on adult economic productivity (Cunha et al., 2006; Knudsen et al., 2006). 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 (Lawrence et al., 2005; Shonkoff & 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, giving them an advantage relative to children from low-income households (Corak, 2013).

In the case of Brazil, a number of studies have been undertaken to explore the role of inequality of opportunities in generating inequality in current earnings. According to Bourguignon et al. (2007), for example, the equalization of opportunities associated with people's race, region of origin, and the education and occupation of their parents would reduce the Gini coefficient for individual earnings by 8–10 percentage points.

From this background, the variation in the intergenerational persistence of economic outcomes presented by the GGC calls for us to reflect on the reasons for the different levels of mobility, and how these underlying drivers can influence the ultimate outcomes. The GGC 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 development (Corak, 2013; Kearney & Levine, 2016).

The association between inequality and intergenerational mobility illustrated in the GGC had already been explored using education data on the measure of mobility, whereby only a handful of these studies had concentrated on developing countries. The resultant findings indicated that educational mobility is positively correlated with some 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 concluded that states with a higher per-capita expenditure on primary education achieved higher levels of mobility across generations. Similar empirical evidence were also found in comparative studies for Latin America. Using harmonized data for 18 Latin American countries, Neidhöfer (2019) confirmed a positive impact of public education spending and economic growth on the chances of intergenerational educational mobility. Using a sample for 16 countries, Behrman et al. (2001) found that public spending on primary and secondary education in particular have a positive impact on mobility, while devoting a relatively greater share of educational budgets on higher education tends to reinforce the importance of family background, thus reducing the chances of mobility. In the same study, the authors also indicated 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 (Torche, 2019).

A number of studies have also examined the impact of income inequality on the personal perceptions of success. Flechtner (2014) suggests that poverty and social disadvantage are associated with low aspiration levels. Therefore, people at the bottom of the socioeconomic ladder tend to underinvest in their human capital because they have been brought up to believe that some options for personal careers are not for "people like me" (Alsop et al., 2005). Kearney and Levine (2016) 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 top and bottom 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. Based on a formal 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.[2]

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 socioeconomic and demographic information about the Brazilian population, including household composition, education, labor, income, migration, and fertility.

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 2014 its focus was socio-occupational mobility. For the survey, respondents aged 16 years and older were asked to provide information about their parents' professional occupation and level of education.[3] The two main outcomes of interest in this paper are years of schooling and levels of education, for both children and parents.[4] The educational levels are classified into four categories: no school certificate and primary, secondary, and tertiary education, with primary education referring to the years of compulsory schooling.

Given that the PNAD does not provide the number of years of schooling for parents, I calculated this variable from information about the highest level of education attained. Next, I inserted a dummy variable for "economic marginalization," which refers to children from parents with no school certificate. In addition, I used the (total) personal income to calculate the Gini coefficient and the 75/10 ratio of income inequality (which relates the income earned by individuals in the 75th percentile to the earnings of individuals in the 10th percentile). I used information about gender, year of birth, location of residence (rural or urban areas), and whether the respondent grew up in a two-parent family as control variables. Finally, I excluded individuals under 25 years old from the sample, given that approximately 42% 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.[5] Consequently, this paper considers people born between 1940 and 1989 in the empirical analysis and works with a sample of 46, 051 individuals.[6]

4 | CONCEPTUAL FRAMEWORK

4.1 | Intergenerational educational mobility

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., 2007), this paper estimates the educational persistence between parents and children with the regression equation

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

where $educ_{is}^{c}$ is the years of schooling of a child from family i resident in state s, and $educ_{is}^{p}$ denotes the same variable for his or her parents [Correction added on 29 April 2022, after first online publication: In Eq. 1, "*ldots*" has been corrected to "...", in this version.]. 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% 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 with time in Brazil, and their resultant effects on average schooling and standard deviations (see Figures A1 and A2 in the online Supporting Information), I follow Checchi et al. (2013) and Azam (2016) and normalize the years of schooling in Equation (1) by the corresponding standard deviation. The ordinary least squares (OLS) estimate of β is given by

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

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. Based on Equations (1) and (2), the resulting empirical model can be summarized as

$$\frac{educ_{is}^{c}}{\sigma_s^c} = \delta + \rho \left(\frac{educ_{is}^{p}}{\sigma_s^p} \right) + \epsilon_i, \quad \text{with } \rho \in [0, 1]. \tag{3}$$

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.

Given that the estimations are based on the pooled sample, Equation (3) includes a vector of dummy variables *UF* with the state of residence of child i. Moreover, a vector X is included comprising controls for gender, race, and year of birth. Thus, the resulting fully interacted model takes the form

$$\frac{educ_{is}^{c}}{\sigma_s^c} = \delta + \rho \frac{educ_{is}^{p}}{\sigma_s^p} + \eta \left(\frac{educ_{is}^{p}}{\sigma_s^p} \times UF_i \right) + \lambda UF_i + \gamma \left(X_i \times UF_i \right) + \epsilon_{is}. \tag{4}$$

4.2 | Linking inequality and school dropouts

Following Kearney and Levine (2016), I 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 ($ComSec_{i,t}$) takes the value 1 if the ith individual 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

$$\begin{aligned} ComSec_{i,t} = \pi_0 + \pi_1 \left(MSB_i \times Ineq_{s,t+14}\right) + \pi_2 MSB_i + \pi_3 Ineq_{s,t+14} \\ + \gamma_1 male_i + \gamma_2 rural_i + \gamma_3 bothP_i + \gamma_4 race_i + \gamma_5 birth_i + \epsilon_i. \end{aligned} \tag{5}$$

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 ($t + 14$).[7] 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 child 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 on (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 (5).

5 | EMPIRICAL RESULTS

This section presents the study's empirical findings. Section 5.1 estimates intergenerational educational mobility and investigates whether mobility at the state level is correlated with income inequality. Section 5.2 then deals with one important mechanism behind the relationship between inequality and mobility illustrated by the GGC, namely, whether greater income inequality contributes to a higher school-dropout rate for economically marginalized children.

5.1 | The Great Gatsby curve

I estimate first the educational persistence between children and parents for each state based on Equation (4). Table 1 displays the levels of mobility across birth cohorts and the general results for all individuals born between 1940 and 1989. For the sample as a whole, the correlation coefficient generated a value of .475, while the variation in intergenerational educational persistence across Brazilian states reached a maximum of .257, which represents the difference between Rio de Janeiro (.510) and Roraima (.253).

As already discussed in Section 2, 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 1 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, as a measure of inequality this paper has used the Gini coefficients for the years in which the individuals should have concluded their compulsory schooling.

Given the variation over time in mobility shown in Table 1, I focused the investigation on one single birth cohort containing individuals born between 1970 and 1979 in order to minimize the life cycle bias.[8] 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 1 plots the GGC for the Brazilian states. On the *y*-axis we find the level of intergenerational persistence in education estimated from Equation (4), while income inequality is plotted on the *x*-axis.[9] The findings confirm the statistically significant relationship between the Gini coefficient and intergenerational mobility: 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).

5.2 | Linking inequality and school dropouts

In this subsection I move away from the analysis of intergenerational persistence in education via the correlation hypothesis to an investigation of the determinants which might better explain the association between inequality and mobility illustrated by the GGC.

For Kearney and Levine (2016) the concept of "economic marginalization" (also called "economic despair") plays a crucial role in understanding this association. Income inequality can negatively affect the perceived returns to investment in education from the perspective of an economically disadvantaged adolescent, through an effect on actual returns and/or an additional effect on the perception of those returns. Then children at the bottom of the income distribution tend to underestimate their expected-earnings premium since they do not believe that an investment in human capital can increase their chances of mobility, which leads them to leave school early.

According to the theoretical model developed by Kearney and Levine (2016), this feeling of marginalization 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 who 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 & Massey, 2015).[10]

With this problem in mind, the empirical objective of this subsection is to investigate whether children from socially disadvantaged households living in states with greater income inequality have a lower chance of completing (secondary) education.

TABLE 1 Correlation coefficients, by birth cohort. [Correction added on 29 April 2022, after first online publication: In Table 1, thousand separators in Obs. columns has been corrected from "period" to "comma", in this version.]

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	.379***	56	.115	84	.611***	121	.260**	191	.304***	217	.512***
Acre	AC	325	.502***	19	.254	39	.655***	45	.491**	92	.524***	130	.526***
Amazonas	AM	915	.419***	64	.822***	105	.463***	152	.395***	264	.361***	330	.424***
Roraima	RR	190	.253***	7	.118	32	-.0118	21	.373	55	.232	75	.401***
Pará	PA	1,673	.439***	139	.518***	230	.561***	315	.465***	430	.442***	559	.428***
Amapá	AP	198	.351***	12	.441	25	.223	35	.321	48	.511***	78	.361**
Tocantins	TO	484	.370***	56	.301*	73	.354**	98	.213	121	.476***	136	.414***
North		**4,454**	**.425*** **	**353**	**.511*** **	**588**	**.503*** **	**787**	**.401*** **	**1,201**	**.419*** **	**1,525**	**.460*** **
Maranhão	MA	620	.377***	60	.176	87	.321**	111	.384***	156	.336***	206	.462***
Piauí	PI	562	.480***	63	.696***	86	.552***	89	.458***	163	.426***	161	.529***
Ceará	CE	1,464	.440***	147	.458***	212	.456***	305	.469***	344	.493***	456	.469***
Rio Grande do Norte	RN	486	.410***	51	.631***	51	.491***	122	.437***	124	.369***	138	.468***
Paraíba	PB	598	.461***	56	.400**	74	.594***	137	.481***	153	.559***	178	.388***
Pernambuco	PE	1,965	.472***	228	.437***	291	.500***	409	.531***	483	.545***	554	.419***
Alagoas	AL	371	.497***	37	.710***	59	.649***	67	.358**	93	.500***	115	.518***
Sergipe	SE	530	.471***	58	.634***	70	.449***	94	.549***	143	.484***	165	.485***
Bahia	BA	2,744	.488***	263	.628***	378	.529***	602	.469***	644	.501***	857	.533***
North-east		**9,340**	**.466*** **	**963**	**.517*** **	**1,308**	**.519*** **	**1,936**	**.474*** **	**2,303**	**.484*** **	**2,830**	**.493*** **
Minas Gerais	MG	3,746	.454***	415	.637***	608	.433***	759	.459***	945	.450***	1,019	.491***
Espírito Santo	ES	733	.451***	56	.529***	118	.523***	152	.310***	193	.572***	214	.457***
Rio de Janeiro	RJ	2,813	.510***	359	.529***	527	.591***	536	.418***	668	.481***	723	.575***
São Paulo	SP	4,565	.449***	492	.524***	766	.495***	906	.449***	1,161	.496***	1,240	.448***

(Continues)

TABLE 1 (Continued)

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**
South-east		**11,857**	**.472*** **	**1,322**	**.556*** **	**2,019**	**.511*** **	**2,353**	**.452*** **	**2,967**	**.488*** **	**3,196**	**.499*** **
Paraná	PR	2,237	.409***	215	.456***	375	.449***	507	.363***	528	.424***	612	.480***
Santa Catarina	SC	1,083	.407***	93	.537***	182	.456***	256	.318***	275	.439***	277	.515***
Rio Grande do Sul	RS	3,120	.439***	371	.454***	586	.489***	671	.444***	693	.423***	799	.501***
South		**6,440**	**.421*** **	**679**	**.480*** **	**1,143**	**.467*** **	**1,434**	**.386*** **	**1,496**	**.427*** **	**1,688**	**.500*** **
Mato Grosso do Sul	MS	674	.476***	59	.809***	104	.464***	131	.534***	175	.546***	205	.399***
Mato Grosso	MT	695	.419***	50	.368*	100	.444***	143	.421***	187	.407***	215	.461***
Goiás	GO	1,375	.356***	129	.271**	217	.454***	267	.319***	349	.399***	413	.408***
Distrito Federal	DF	922	.492***	85	.600***	107	.590***	171	.441***	269	.475***	290	.452***
West Central		**3,666**	**.445*** **	**323**	**.482*** **	**528**	**.501*** **	**712**	**.428*** **	**980**	**.458*** **	**1,123**	**.473*** **
Brazil		**35,757**	**.475*** **	**3,640**	**.536*** **	**5,586**	**.517*** **	**7,222**	**.454*** **	**8,947**	**.492*** **	**10,362**	**.533*** **

Notes: Estimations based on OLS regressions using years of schooling of children and the better-educated of their parents. 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).

Source: PNAD-2014, own estimates

Statistical significance:

*$p < .05$,; **$p < .01$,; ***$p < .001$.

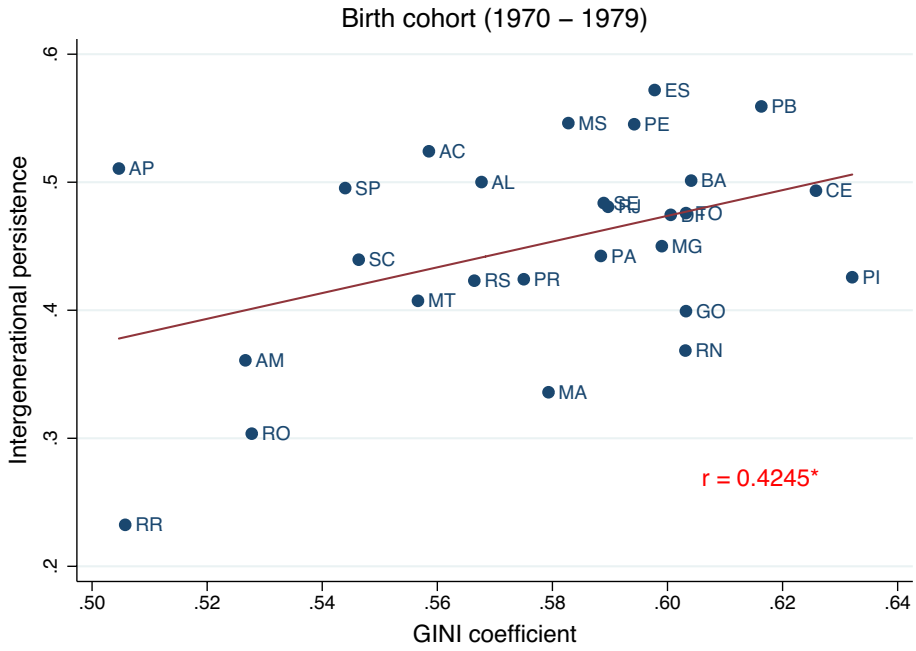

FIGURE 1 The Great Gatsby curve. r = Pearson's correlation. An asterisk indicates a correlation coefficient with a p-value of .1 or lower. Gini coefficients refer to the average values between 1984 and 1993. *Source*: PNADs, own estimates [Colour figure can be viewed at wileyonlinelibrary.com]

Figure 2 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 and the educational achievement of parents, which is used as a proxy for "economic marginalization."[11] The findings highlight the effect of marginalization on the decision to leave school early. Note that, independent of the inequality level, less than 20% of children of illiterate parents have completed secondary education. In contrast, more than 80% of children of parents with a graduate degree have a secondary school-leaving certificate. In addition, Figure 2 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.

In order to empirically test the assumption regarding economic marginalization, I run Equation (5) and present the results in Table 2. The first column contains the results for the whole sample, and the subsequent columns contain the values for the five-year birth cohorts.[12] 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 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 marginalization, I estimate the marginal effects from Equation (5) and display the predicted probabilities for all the 10th values of the ratio 75/10 (from 3 to 12) in Figure 3. Note that, independent of the

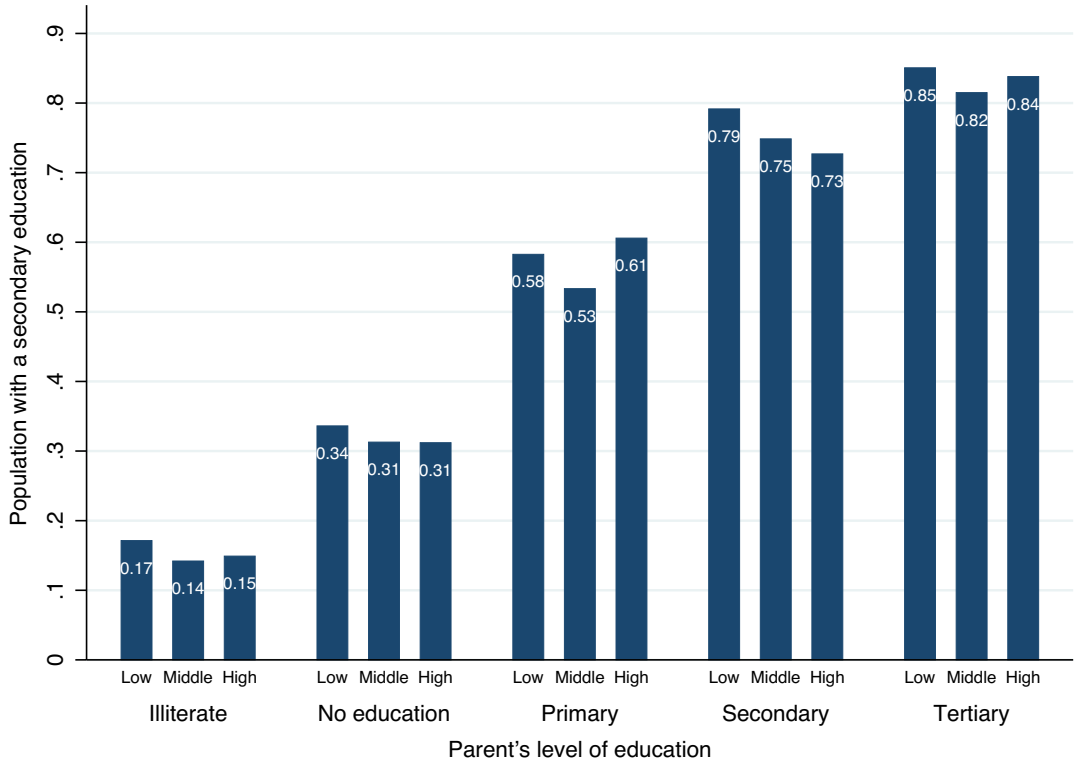

FIGURE 2 Educational attainment and inequality. Estimations of income inequality based on the 75/10 ratio of the total income of the economically active population aged 15 or over and with earnings greater than zero. The 75/10 ratio represents the relation between the income earned by individuals in the 75th percentile and the earnings of individuals in the 10th percentile. *Source*: PNAD-2014, own estimates [Colour figure can be viewed at wileyonlinelibrary.com]

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 widens.

5.3 | Robustness checks

5.3.1 | Alternative econometric approaches

In the previous subsection, as a proxy for socioeconomic marginalization, I used a dummy variable in Equation (5) indicating children of parents with no primary education ($NoEducP_i$). 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

TABLE 2 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	−.0542***	−.0486	−.0353	−.00346	−.0982**	−.0519
	(.0186)	(.0644)	(.0473)	(.0335)	(.0486)	(.0462)
Socioeconomic marginalization	−.405***	−.535	−.492*	−.705***	−.261	−.270
	(.104)	(.350)	(.287)	(.208)	(.251)	(.237)
Inequality	.0129	−.0256	.0387	−.0164	.0929***	−.0170
	(.0138)	(.0503)	(.0377)	(.0242)	(.0327)	(.0320)
Male	−.203***	−.0988*	−.114**	−.217***	−.291***	−.257***
	(.0208)	(.0531)	(.0487)	(.0455)	(.0425)	(.0445)
Rural	−.650***	−.575***	−.812***	−.784***	−.687***	−.490***
	(.0333)	(.0854)	(.0831)	(.0723)	(.0674)	(.0692)
Living with both parents	.0830***	−.0687	.0312	.0614	.0505	.256***
	(.0248)	(.0683)	(.0601)	(.0537)	(.0497)	(.0494)
Birth year	.0159***	.00722	−.00521	.0157	.0116	−.0373**
	(.00156)	(.0184)	(.0171)	(.0161)	(.0155)	(.0158)
White (reference)	–	–	–	–	–	–
Black	−.160***	−.189**	−.217**	−.0887	−.184**	−.152*
	(.0366)	(.0927)	(.0872)	(.0801)	(.0730)	(.0787)
Mixed (white/black)	−.271***	−.374***	−.305***	−.302***	−.256***	−.166***
	(.0222)	(.0568)	(.0521)	(.0489)	(.0455)	(.0476)
Asian	.296*	.635	.938***	.356	−.413	.130
	(.159)	(.387)	(.353)	(.373)	(.282)	(.355)
Indigenous	−.346*	−.653	−.555	−.209	−.147	−.381
	(.191)	(.619)	(.457)	(.396)	(.357)	(.362)

(Continues)

TABLE 2 (Continued)

Birth cohort	All	1965	1970	1975	1980	1985
Birth years	**(1965–1989)**	**(1965–1969)**	**(1970–1974)**	**(1975–1979)**	**(1980–1984)**	**(1985–1989)**
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

Notes: 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.

*$p < .05$,; **$p < .01$,; ***$p < .001$.

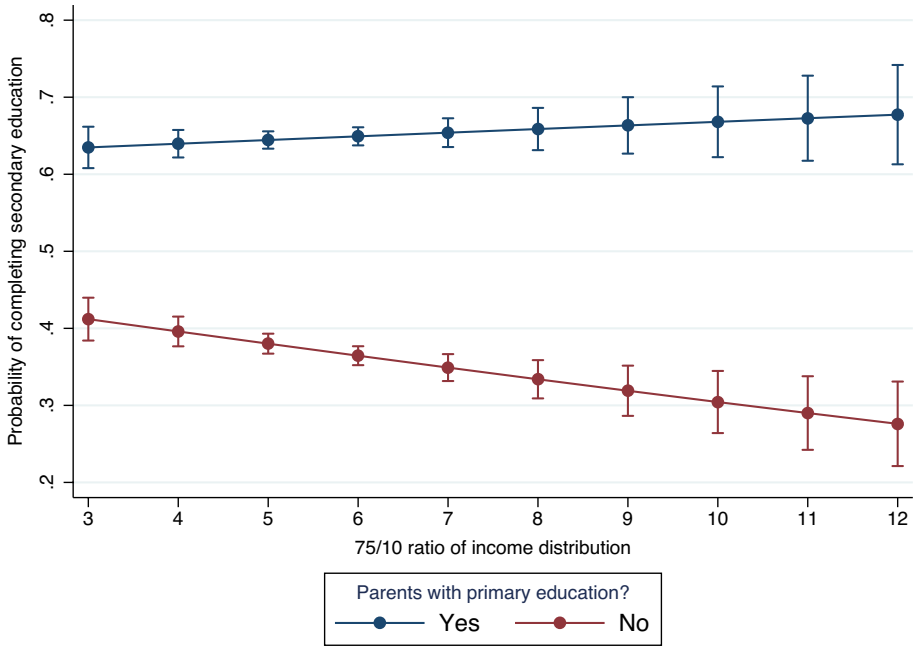

FIGURE 3 Adjusted predictions for secondary education. Estimations of income inequality based on the 75/10 ratio of total income of the economically active population aged 15 or over and with earnings greater than zero. The 75/10 ratio represents the relation between the income earned by individuals in the 75th percentile and the earnings of individuals in the 10th percentile. *Source*: PNAD, own estimates [Colour figure can be viewed at wileyonlinelibrary.com]

(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 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 subsection I continue to use Equation (5) 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: 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 ($bothP_i$) from the probit for MSB_i.[13]

Table 3 provides the results of the robustness checks using the whole sample and confirms that the estimates from Section 5.2 are also robust to alternative econometric approaches. For the sake of brevity 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 probabilities for this interaction and have also displayed the adjusted predictions of educational chances at representative values of income inequality (APRs), that is, for every 10th value for the distribution of the 75/10 ratio.

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

TABLE 3 Robustness checks

	Main Model	Alternative econometric approaches			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 Specification (1)	**–**	**No**	**No**	**No**	**No migrants**	**Ratio 90/10**	**Illiterate parents**	**Illit. & no educ.**
Coefficient of MSB # Inequality	−.0540***	−.0179***	−.0175***	−.0487***	−.0695*	−.0199**	−.0318	−.0307
	(.0186)	(.00636)	(.00636)	(.0178)	(.0418)	(.00796)	(.0227)	(.0216)
APRs for MSB and Inequality								
1bn._at	−.223***	−.220***	−.223***	−.175***	−.210***	−.209***	−.236***	−.201***
	(.0196)	(.0179)	(.0179)	(.0212)	(.0430)	(.0271)	(.0257)	(.0227)
2._at	−.244***	−.238***	−.241***	−.190***	−.237***	−.217***	−.247***	−.213***
	(.0134)	(.0125)	(.0125)	(.0210)	(.0288)	(.0242)	(.0184)	(.0154)
3._at	−.264***	−.256***	−.258***	−.205***	−.263***	−.224***	−.258***	−.225***
	(.00884)	(.00863)	(.00861)	(.0210)	(.0181)	(.0213)	(.0130)	(.0101)
4._at	−.284***	−.274***	−.276***	−.220***	−.289***	−.232***	−.268***	−.237***
	(.00876)	(.00853)	(.00851)	(.0215)	(.0183)	(.0185)	(.0115)	(.0102)
5._at	−.305***	−.291***	−.293***	−.236***	−.314***	−.240***	−.278***	−.248***
	(.0130)	(.0123)	(.0123)	(.0223)	(.0286)	(.0159)	(.0149)	(.0155)
6._at	−.324***	−.309***	−.311***	−.253***	−.338***	−.248***	−.288***	−.260***
	(.0187)	(.0177)	(.0177)	(.0235)	(.0417)	(.0133)	(.0205)	(.0225)
7._at	−.344***	−.327***	−.328***	−.270***	−.361***	−.255***	−.298***	−.272***
	(.0248)	(.0235)	(.0235)	(.0251)	(.0553)	(.0111)	(.0267)	(.0300)

TABLE 3 (Continued)

	Main Model	Alternative econometric approaches			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 Specification (1)	**–**	**No**	**No**	**No**	**No migrants**	**Ratio 90/10**	**Illiterate parents**	**Illit. & no educ.**
8._at	−.363***	−.345***	−.346***	−.287***	−.383***	−.263***	−.307***	−.283***
	(.0309)	(.0296)	(.0296)	(.0271)	(.0687)	(.00927)	(.0330)	(.0376)
9._at	−.382***	−.363***	−.363***	−.305***	−.404***	−.271***	−.315***	−.295***
	(.0369)	(.0358)	(.0358)	(.0294)	(.0819)	(.00822)	(.0392)	(.0452)
10._at	−.401***	−.381***	−.381***	−.323***	−.423***	−.278***	−.324***	−.306***
	(.0427)	(.0420)	(.0420)	(.0320)	(.0947)	(.00819)	(.0452)	(.0528)
Observations	23,008	23,008	23,008	23,008	5,340	23,008	24,842	21,668

Notes: The coefficients of the interaction between the socioeconomic marginalization (MSB) and the inequality level show how the effects of having (un)educated parents on the children's chance of schooling 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 heteroskedasticity.

Standard errors in parentheses. All predictors at their mean value.

Source: PNAD-2014, own estimates.

Statistically significant:

*$p < .05$,; **$p < .01$,; ***$p < .001$.

in the state, the lower the share of students with a secondary school-leaving certificate. 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% 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%. This empirical evidence remains practically unchanged when *bothP* is used as instrumental variable in the LPM estimation.

Last, but by no means least, 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. However, the estimates continue to indicate the same direction and statistical significance.

5.3.2 | Alternative model specifications

In the following, I explore in Table 3 the dependence of parameter π_1, estimated from Equation (5), 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 90/10 ratio 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 $NoEducP_i$.[14]

All four expanded models generated robust results, demonstrating the significantly negative impact of income inequality on educational attainment, as already indicated. 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.

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 3 and show that, keeping all the 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.

6 | CONCLUSIONS

The estimates presented in this paper are based on data from the mobility supplement to 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. Together with findings from other countries (Azam & Bhatt, 2015; Chetty et al., 2014; Güell et al., 2018), this work strengthens the assumption that mobility 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. 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 levels across generations tends to be stronger in states with a more unequal income distribution.

In addition, this work has illuminated the mechanisms underlying the link between inequality and mobility presented in the GGC, 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 empirical results reported herein should be considered in the light of two main shortcomings. First, data limitations did not allow me to calculate the Gini coefficient for the years before 1976, and consequently, the GGC was limited to the (younger) individuals born after 1970. Second, my empirical model was not able to examine the motivations for school dropout. Future studies should explore students' own stated reasons for dropping out and investigate whether these reasons are consistent with the theoretical model developed by Kearney and Levine (2016) and applied in this paper. The main challenge for this investigation is the inclusion of data on student perceptions in relation to the expected returns to education which should be isolated from dropout decisions due to academic difficulties or other external factors.

Nonetheless, the findings of this study 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.

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DATA AVAILABILITY STATEMENT

Repository name: Mendeley Data Data identification number: 10.17632/cc7g3nt5kh.1 Data available at: ftp://ftp.ibge.gov.br/Trabalho_e_Rendimento/Pesquisa_Nacional_por_Amostra_de_Domicilios_anual/microdados/2014/ Direct URL to data.

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ENDNOTES

1. This paper is supplemented by a comprehensive Online Appendix with relevant information concerning the educational system in Brazil, the data harmonization, the codification process for the variables, additional figures and the formal description of the underlying theoretical models.
2. See the online supporting Information for a formal description for the theoretical models of Kearney and Levine (2016) and Solon (2004).
3. The information about the education and occupation of parents refers to the level when the respondents were 15 years old.
4. 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.
5. According to the IBGE, the life expectancy in Brazil in 2014 was 75.2 years.
6. Table A1 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.
7. The decision to include the 75/10 ratio from the year in which the respondent was aged 14 in Equation (5) is based on the theoretical model of Solon (2004). Following this model, what is particularly relevant for the accumulation of human capital is the level of income inequality when children are self-evaluating their return to human capital, that is, they are facing a decision about whether or not to pursue more years of schooling. Then, for the Brazilian case, this "self-evaluation" could not occur before the age of 14 since schooling was compulsory for children aged between 7 and 14 years. See the online Supporting Information for a description of the model of Solon (2004) and an overview of compulsory education in Brazil.
8. 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.
9. The original GGC 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 has been considerably expanded in recent decades, the relative measure of mobility will make more sense for 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 parent–child transmission.
10. See the online Supporting Information for a detailed description of the theoretical model of Kearney and Levine (2016).

11. For this exercise, the 27 states in Brazil have been classified into three inequality groups (low, middle, and high) according to the 75/10 ratio of income distribution.
12. 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 PNAD samples, this subsection limited the estimates to individuals born from the year 1965 onwards, thereby using the income inequality after the year 1981. See the online Supporting Information for a detailed description of the data harmonization.
13. To facilitate comparison, Table 3 also contains the estimation results from the probit model in Section 5.2, in which the variable $bothP_i$ was treated as exogenous.
14. For the specification in column 8, the empirical model assumes the form

$$ComSec_{i,t} = \pi_0 + \pi_1 \left(NoEducP_i \times Ineq_{s,t+14}\right) + \pi_2 \left(IlliteP_i \times Ineq_{s,t+14}\right) + \pi_3 NoEducP_i + \pi_4 IlliteP_s + \pi_5 Ineq_{s,t+14} + \gamma_1 male_i + \gamma_2 rural_i + \gamma_3 bothP_i + \gamma_4 race_i + \gamma_5 birthc_i + \epsilon_i.$$

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SUPPORTING INFORMATION

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APPENDIX

TABLE A1 Weighted descriptive statistics

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
State		**Population**			**Income distribution (R$)**			**Net enrolment ratio (age)**			**Average years of schooling**				***SD***		
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	.2369	204	593	1,666	.9921	.7948	.2972	541	8.4842	2.9488	3.2734	4.5993	3.5316	3.9711
Acre	AC	790,101	27.27	.2591	128	400	1,500	.9653	.7616	.3191	415	7.3954	2.9512	3.7874	5.3104	4.2085	4.7970
Amazonas	AM	3,873,743	28.49	.1634	150	438	1,500	.9776	.8294	.3482	1,045	8.2446	3.8986	4.1803	4.7067	4.2232	4.2799
Roraima	RR	496,936	28.37	.1680	191	530	1,862	.9865	.7576	.3238	160	10.0415	4.1797	4.5257	4.2826	4.2936	4.3761
Pará	PA	8,073,924	29.82	.2992	133	399	1,185	.9824	.8454	.3268	2,019	7.3653	3.3370	3.6478	4.4826	3.7415	4.0299
Amapá	AP	750,912	27.46	.1039	200	499	1,860	.9917	.8541	.3197	217	9.3247	4.5997	4.2800	4.8566	4.6337	4.4242
Tocantins	TO	1,496,880	31.59	.2148	164	500	1,674	.991	.8205	.3233	545	7.6599	2.3349	2.9175	4.7665	3.3784	3.9490
North		**17,231,027**	**29.50**	**.2408**	**146**	**437**	**1,433**	**.9826**	**.829**	**.3277**	**4,942**	**7.8259**	**3.3986**	**3.7343**	**4.6621**	**3.9186**	**4.1553**
Maranhão	MA	6,850,884	30.14	.4083	89	333	1,015	.9825	.8508	.2747	864	6.2833	1.9498	2.6083	4.9003	3.3379	3.8792
Piauí	PI	3,194,718	32.26	.3247	117	400	1,114	.9879	.8552	.3149	628	6.0786	1.7586	2.2864	5.1269	3.2388	3.8753
Ceará	CE	8,842,791	33.38	.2648	120	400	1,134	.9824	.8346	.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	.2352	150	434	1,314	.9936	.8235	.2861	560	6.9774	2.3294	3.1026	4.8696	3.5646	4.0347
Paraíba	PB	3,943,885	33.08	.1839	145	436	1,400	.9752	.7962	.2943	672	6.7942	2.7729	3.0116	5.1071	4.1112	4.1259
Pernambuco	PE	9,277,727	33.50	.1894	140	437	1,308	.9831	.8162	.2627	2,541	7.4292	3.4088	3.5120	4.9493	4.3138	4.3208
Alagoas	AL	3,321,730	30.91	.2833	95	348	1,005	.9706	.7744	.2814	563	6.3830	2.9068	3.0360	5.1566	4.1516	4.2944
Sergipe	SE	2,219,574	32.09	.2812	156	431	1,200	.977	.8352	.3242	652	6.5579	1.9785	2.4805	4.8874	3.4009	3.5932
Bahia	BA	15,126,371	33.11	.2488	139	431	1,400	.985	.8461	.3171	3,359	7.1842	2.8426	3.0643	4.9479	3.9217	4.1399
North-east		**56,186,190**	**32.62**	**.2632**	**126**	**403**	**1,250**	**.9827**	**.8315**	**.2904**	**11,857**	**6.8927**	**2.6340**	**2.9858**	**4.9778**	**3.8801**	**4.1025**
Minas Gerais	MG	20,734,097	34.77	.1544	236	706	1,933	.9876	.8674	.2785	4,111	7.8235	3.4013	3.4944	4.7173	3.7202	3.8092
Espírito Santo	ES	3,885,049	34.25	.1553	225	700	2,066	.9728	.8133	.324	772	8.3036	3.3526	3.2428	4.5309	3.6945	3.6406
Rio de Janeiro	RJ	16,461,173	36.80	.0268	266	750	2,566	.9899	.8736	.3319	3,085	9.5006	6.0272	5.4156	4.3063	4.7137	4.2991
São Paulo	SP	44,035,304	35.29	.0344	326	860	2,650	.9938	.8645	.2907	4,339	9.9718	5.1388	4.7980	4.3038	4.4431	4.3142

TABLE A1 (Continued)

State		(1) Population	(2)	(3)	(4) Income distribution (R$)	(5)	(6)	(7) Net enrolment ratio (age)	(8)	(9)	(10) Average years of schooling	(11)	(12)	(13)	(14) *SD*	(15)	(16)
Name	**Abbrev.**	**Total**	**Average age**	**Ratio in rural**	**Bottom**	**Middle**	**Top**	**7–14**	**15–17**	**16–24**	**Obs.**	**Children**	**Fathers**	**Mothers**	**Children**	**Fathers**	**Mothers**
South-east		**85,115,623**	**35.41**	**.0676**	**277**	**766**	**2,405**	**.9905**	**.8645**	**.2968**	**12,307**	**9.2358**	**4.7551**	**4.4993**	**4.5212**	**4.3904**	**4.2187**
Paraná	PR	11,081,692	34.52	.1252	315	817	2,325	.9881	.8231	.2923	2,301	8.3716	3.8072	3.6635	4.6968	3.8634	3.9054
Santa Catarina	SC	6,727,148	35.59	.1589	390	1000	2,500	.9914	.8207	.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	.1501	300	850	2,500	.9869	.837	.3084	3,702	8.4965	4.0837	3.9188	4.4833	4.0926	3.9434
South		**29,016,114**	**35.69**	**.1426**	**320**	**870**	**2,444**	**.9884**	**.8278**	**.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	.1078	300	766	2,232	.9849	.7832	.2918	615	8.5436	4.1849	4.0337	4.7883	4.5221	4.5129
Mato Grosso	MT	3,224,357	32.12	.1720	285	733	2,000	.9911	.7919	.284	627	8.7704	4.2925	4.7669	4.8419	4.6268	4.7849
Goiás	GO	6,523,222	33.35	.0776	268	724	1,912	.9923	.8126	.3153	1,361	8.0773	3.0697	3.4046	4.7121	3.7236	4.0061
Distrito Federal	DF	2,852,372	32.69	.0442	301	1000	5,000	.9931	.8955	.414	408	11.7179	7.1630	7.2125	3.8968	5.2292	5.3176
West Central		**15,219,608**	**32.94**	**.0965**	**285**	**750**	**2,500**	**.9909**	**.8193**	**.3237**	**3,011**	**8.7258**	**4.0041**	**4.2698**	**4.7976**	**4.4461**	**4.6084**
Brazil		**202,768,562**	**33.55**	**.1494**	**200**	**662**	**2,000**	**.987**	**.8427**	**.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 2–9 are the author's own estimates based on all the observations from PNAD-2014. The values in columns 10–16 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%, the middle 50% and the richest 10%, respectively, of the income distribution.