

An assessment about the relationship between educational inequality and economic growth in Brazilian Northeast region

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Abstract: In this paper, we analyze the impact of education inequality on the income of formal workers in Northeast Brazil. For this study, we analyzed the data collected from censuses data and estimate a dynamic panel data model. Statistical analyses were performed by using the quasi-maximum likelihood linear dynamic panel data estimation, an approach that produces consistent estimates with large n and small T . We found a negative and statistically significant impact of education inequality on economic growth, which is convergent with the literature that advocates that an unequal distribution of education reduces growth. Our results suggest that economic policies should be targeted not only more at education but also more equal access to education.

Key words: Education inequality. Economic growth. Dynamic panel data. QML estimator. Empirical growth model.

JEL Classification: I24; O47; C23; B23; O47.

1 INTRODUCTION

There is a growing body of literature that recognizes the impact of inequality on economic growth. However, the evidence on the trade-off between inequality and growth, despite many recent studies, remains inconclusive, what has kept the debate on the role of inequality alive. In the 1950s and 1960s, there was a predominant idea that inequality generates economic growth because the rich save proportionally more than the poor, which increases the rate of investment and therefore of growth (Kuznets, 1955; Kaldor, 1957). More recently, Development economists argue that a more equal distribution of income and land plays a significant role in development, for symmetry is the high level of concentration of wealth in Latin America that impedes growth in that part of the world (Persson & Tabellini, 1994; Acemoglu & Robinson, 2000).

As Urean (2017) argues, more recent attention has focused on the role of education in the Economic growth, suggesting that education inequality plays an important role in the income inequality, and thus in the economic growth. Empirical studies such as Park (1996) and O'Neill (1995) shows that an unequal distribution of education negatively affect the income dispersion, which worsens the economic growth.

Unlike income inequality, there is a relatively small body of literature that is concerned with the effect of educational inequality on income growth. From this literature, we highlight the papers by Urean (2017), Ramesh & Jani (2009), Azuma & Grossman (2003), Yu et al. (2015), and (Digdowiseiso, 2009). Regarding Brazil, as far as we know, no study has been

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dedicated so far to this question, so this study aims to contribute to this growing area of research.

A study of Brazilian Northeast, where there is the most significant improvement in education level since 2005, is useful for exploring the relationship between the human capital dispersion and income growth. To address this issue, we use the Annual Relation of Social Information (RAIS) data, for the last 13 years, to empirically address the relationship between equity in education and income growth.

The remaining part of the paper proceeds as follows: the second Section contains a succinct analysis of the human capital theory; whose content guides the convection of work. Section 3 present the data set we used and the econometric approach. Finally, some concluding remarks and recommendations are presented, hoping that it can contribute to improving understanding about the distribution of labor income in this labor market.

2 HUMAN CAPITAL AND EDUCATIONAL INEQUALITY

Proposed by Schultz (1961) and shaped largely by Becker (2009), the theory of human capital address the homogeneity of the labor factor, insofar as it recognized that the labor market may take a long time to adjust to new equilibrium. In absence of the simplifying assumption that the labor factor is homogeneous, market clearing no longer depends on prices, but also on the set of skills, knowledge, and attributes involved and necessary to perform labor so as to produce economic value came to be called human capital. More specifically, Schultz & Schultz (1982) states that all innate or acquired human attributes which are valuable and can be augmented by appropriate investment will be human capital.

The theory of human capital was added to the neoclassical model, going on to explain the wage differences without giving up the optimization and competitiveness. Wage differences are associated with the level of human capital incorporated in the labor force, so that the market reward workers based on the amount of human capital they own. The benefits of increased education diminish as schooling continues, so investments exhibit decreasing returns and demand for human capital curves slope downward. Thus, even though the constant competition between workers, there are a set of different wages for different qualifications in the labor market and homogeneity is no longer possible.

Acquire human capital involves costs, so that the present value of future gains must be greater than the costs. Like any investment decision, investment is feasible if $\sum_{t=0}^{n-1} \frac{R_t}{(1+i)^{t+1}} \geq \sum_{t=0}^{n-1} \frac{C_t}{(1+i)^{t+1}}$ this is, given the rate i the revenue R_t overcome the costs C_t at the end of period t . Alternatively, one can states that the investment is feasible if the expected rate of return is better than any other opportunities available to the agent.

The behavior of economic agents is determined by the returns expected in the form of higher future wages, so that expected return for human capital is the key determinant, which leads to the labor market equilibrium (Bishop, 1994). If there is an excess of labor supply for any qualification level, the market will adjust through a decrease of wages, associated to reduction in investments that will migrate to more profitable qualifications. In the long run, these forces induce a change in investment schedules until equals different returns.

Workers becomes more productive and improves his economic condition as he accumulates human capital. So, investments in human capital play as a source of economic growth, while formal and informal education the main way to improve accumulation. However, acquiring knowledge requires time and dedication, which imposes a trade-off for the use of time.

Looking to improve their future earnings, workers could invest in qualification expecting higher income in the future or earn wage today giving up the qualification project. Thus, each additional year dedicated to qualification study imposes a sacrifice of present income in favor of future income plus a premium for waiting. Therefore, the worker's efforts to improve their economic condition, coupled with the demand by firms for qualified workers, have gone on to play a prominent role in economic theory.

Education and qualification are a relevant source of information for the companies, which select workers according to their accumulated knowledge and experience. However, qualification required by the firm may not be the same as that of job seekers. In this case, the positive association between qualification and productivity can become problematic.

The human capital theory has some logical inconsistencies, among others, the role of institutions and the educational system which are not addressed by the model. Access to financing differs between people, which makes resources much more dependent on circumstances defined in society than on the economic agents. Despite criticism, the human capital theory highlights investments in education and health are elements that provide higher returns.

Some studies have evidenced that the unequal distribution of school funding, qualified, experienced teachers, and technologies is the main driver of income inequalities. However, the role of educational inequality on the economic growth remains an underexplored issue. And despite the growing interest in recent years, remains a paucity of evidence about the effect of educational inequality on income growth, and hence our interest in this subject.

Within the small body of literature, we mention the study of Blanden & McNally (2015) that broadly addresses the implications of educational inequality for economic growth. They conclude that a higher economic growth depends on an increase average of education level and reduction of educational inequality. Still, according to the authors, there are two different ways to reduce educational inequality, which are: First, the pursuit of the redistributive policies and the elimination of the institutional mechanisms that discriminate individuals with low income. Second, the use of the effective educational policies to improve the attainments of underprivileged individuals.

Digdownseiso (2009) have shown that technological progress, incentives, and health links unequal distribution of education to the economic growth. Their econometric results confirmed that investments in human capital contribute to the economic growth. Gungor (2010) use the educational attainment levels to estimate the nonlinear relationship between educational inequality and economic growth. Tselios (2007) also note that educational inequality helps to explain different rates of economic growth within country's provinces. Ramesh & Jani (2009) use a Gini coefficient of primary and secondary education to show which level of education inequality helps to explain the economic growth.

Taken together, the results support the notion that a better distribution of education is key factor in economic growth. Considering the lack of studies, the purpose of this investigation is to explore the relationship between educational inequality and economic growth.

3 DATA AND ECONOMETRIC APPROACH

To address the effect of educational inequality on economic growth, we use data taken from the Getúlio Vargas Foundation (FGV), the Brazilian Institute of Geography and Statistics (IBGE), and the Institute for Applied Economic Research (Ipea). Real Gross Domestic Product (GDP) is calculated by IPEA and the General prices Index (IGP) by FGV. All other variables were calculated using information from the Brazilian Demographical Censuses from 1960 to 2010. Using the most disaggregated administrative unit in Brazil, we consider a 50-year period we make sure to carry out a long-term analysis, from rural-urban transition to a few years ago.

It is worthwhile to note that the Brazilian 1960 census was never fully processed. Even today, history remains surrounded by mysteries, but one version reports that the 1960 census was carried out before the military coup and in the 1964 confusion some of the data disappeared. Part of the government felt that the IBGE was unable to process the interviews at the planned time. A portion of the data was sent to the

United States so that it could be processed there. For this reason, access to the 1960 Census data was only possible in 1978. For this reason, we still do not have access to the complete census microdata. The States of the former Northern Region (Acre, Amazonas, Pará, Maranhão, and Piauí), Santa Catarina, Espírito Santo, the cities of Alto Garças, Rafard, and Rio de Janeiro (Formerly Federal District) would have been lost during transportation and, therefore, are missing (Barbosa et al., 2013).

GDP is used as proxy for economic growth. The series is irregular, so there are no data for the years 1960 and 1991. To overcome this limitation, we use the GDP of 1959 as the year of 1960 and interpolate the years 1985 and 1996 to estimate the GDP for the year 1991. Furthermore, the data are available at 2000 prices have been converted to 2010 prices by using the IGP. Then, we took the number of inhabitants at the censuses to calculate the Per Capita (GDP).

To obtain a measure of the educational inequality, our variable of interest, we calculate the Gini index based on the years of schooling of people aged 25 or over. In the 1960, 1970, 1980, and 1991 censuses, the information is available as levels of schooling. So, we consider the years required to attainment the level reported by the person as the years of schooling. To do so, we consider 1 year of schooling if the person declared to know how to read and write, 5 years if the person completed basic education, and so on. For the 2000 and 2010 make the information available in the form of years of schooling, then this operation was not necessary because. Once calculated the years of schooling, we obtain the Gini index (gini) for of education as a measure of the educational education.

As control variables we use the level of education and capital stock. For the first, we consider two measures, which are: the average years of schooling and the illiteracy rate. For the second, we employ an estimate of the capital stock in residential structures as proxy for

capital stock. The average years of schooling (*edu*) is calculated by dividing the accumulated years of schooling by the people aged 25 or over for each municipality and year. With respect to the illiteracy rate (*ill*), we consider people aged 15 and over who cannot read or write a simple sentence. Additionally, we also consider the educational level and illiteracy rate for men and women (*medu*, *fedu*, *mill* and *fill*) separately as in Forbes (2000).

Following Reiff & Reis (2016), we estimate of capital stock in residential structures by calculating the present value of the sum of the perpetual flow of rents discounted at the rate of 0.75% per month. The contribution of characteristics or attributes to the price of house is estimated through a hedonic price model in which the covariates are the houses' attributes plus a dummy variable indicating the state of location of the property. The estimated coefficients are used to impute the price of each property in the Demographic Census sample. The estimated capital stock is obtained by aggregating the price of each residency in the municipality and year. Finally, the capital stock (*kap*) was deflated by CPI to convert this variable in constant 2010 prices.

Prior to undertaking the regression analysis, we dealt with the difficulty faced by any research using Brazilian regional data from different years. From 1960 to 2010 the number of municipalities jumped from 2765 to 5565. So, to obtain time-consistent spatial units, we convert the municipalities into Minimum Comparable Areas (AMC) as proposed by Ehrl (2017). The compiled dataset is an unbalanced panel consisting of 695 municipalities over ten decades (from 1960 to 2010). Descriptive statistics for all variables are reported in Table 1.

We consider as baseline model a slightly modified version of the model analyzed by Forbes (2000), which takes the following form

$$\log(gdp_{it}) = \beta_0 + \beta_1 \log(gini)_{it-2} + \varphi_2 \log(gdp)_{it-1} + \beta_3 \log(edu)_{it-1} + \beta_4 \log(kap)_{it-1} + \alpha_i + \gamma_t + \varepsilon_{it} \quad (1)$$

in which $\varphi_2 = \beta_2 + 1$, $i = 1, \dots, n$ index the municipalities and $t = 1, \dots, T$ index the years, so that there are T observations on each municipality, *gdp* is the real per capita GDP, *gini* the educational inequality index, *edu* the stock of human capital, *kap* the capital, α_i capture non-observable effects due to heterogeneity, γ_t the time effect, and β the parameter vector of interest.

Rewriting equation (1) in this fashion, we use the second lag of each covariate to reduce potential endogeneity problem. Nevertheless, the predominant estimation technique, Generalized Method of Moments (GMM), might produce biased estimates on the coefficient of lagged dependent variable Judson & Owen (1999). For this reason, we take another way and the Limited-Information Quasi-Maximum Likelihood (QML) estimators for dynamic random-effects fixed-effects models proposed by Bhargava & Sargan (1983) and Hsiao et al. (2002), respectively.

For a first order auto-regressive linear dynamic panel as in (1), potentially unbalanced but without gaps, the QML is a good alternative to GMM with potential efficiency gains and better finite-sample properties. The estimator allows us to handle with the lagged dependent variable, which is correlated by construction with the unit-specific error component but requires that covariates be strictly exogenous with respect to ε_{it} (Kripfganz, 2016).

Table 1: Descriptive Statistics municipality and year.

	<i>gdp</i>	<i>pk</i>	<i>hk</i>	<i>fhk</i>	<i>mhk</i>	<i>ill</i>	<i>Mill</i>	<i>fill</i>
<i>t</i> = 1960; <i>n</i> =	862.00	737.00	737.00	737.00	737.00	737.00	737.00	737.00
<i>min</i>	0.03	0.26	1.15	0.09	0.10	0.21	0.11	0.28
μ	2.15	1.17	2.61	0.85	0.87	0.63	0.61	0.65
<i>max</i>	617.75	2.86	5.77	3.58	4.72	0.92	0.92	0.93
σ	21.05	0.40	0.70	0.44	0.52	0.10	0.11	0.10
<i>t</i> = 1970; <i>n</i> =	862.00	862.00	862.00	862.00	862.00	862.00	862.00	862.00
<i>min</i>	0.29	0.73	1.17	0.00	0.10	0.15	0.01	0.04
μ	3.39	1.38	3.74	2.26	2.57	0.57	0.40	0.45
<i>max</i>	1363.80	2.96	10.34	7.54	11.34	0.97	0.86	0.89
σ	46.48	0.32	1.83	1.80	2.35	0.22	0.23	0.21
<i>t</i> = 1980; <i>n</i> =	862.00	862.00	862.00	862.00	862.00	862.00	862.00	862.00
<i>min</i>	0.56	0.67	0.17	0.21	0.24	0.14	0.13	0.15
μ	3.61	1.69	1.14	1.29	1.09	0.56	0.57	0.54
<i>max</i>	159.44	6.47	5.32	4.34	4.74	0.79	0.83	0.79
σ	7.22	0.49	0.59	0.52	0.54	0.10	0.11	0.10
<i>t</i> = 1991; <i>n</i> =	862.00	862.00	862.00	862.00	862.00	862.00	862.00	862.00
<i>min</i>	0.52	1.18	0.69	0.88	0.68	0.06	0.10	0.08
μ	3.53	2.79	2.19	2.52	2.04	0.27	0.52	0.44
<i>max</i>	156.48	8.80	7.20	6.14	6.40	0.39	0.76	0.70
σ	6.24	0.89	0.82	0.71	0.74	0.05	0.11	0.09
<i>t</i> = 2000; <i>n</i> =	862.00	862.00	862.00	862.00	862.00	862.00	862.00	862.00
<i>min</i>	1.79	1.64	1.93	2.54	2.13	0.03	0.05	0.05
μ	4.75	3.96	3.62	4.42	3.80	0.22	0.37	0.31
<i>max</i>	285.93	11.62	8.05	8.82	7.76	0.34	0.62	0.53
σ	10.24	1.23	0.80	0.78	0.78	0.05	0.09	0.07
<i>t</i> = 2010; <i>n</i> =	862.00	862.00	862.00	862.00	862.00	862.00	862.00	862.00
<i>min</i>	2.87	2.28	1.69	2.21	1.65	0.04	0.04	0.04
μ	6.81	5.30	3.46	3.86	3.27	0.19	0.29	0.24
<i>max</i>	306.09	14.15	7.84	7.16	7.27	0.32	0.51	0.39
σ	12.07	1.48	0.89	0.76	0.80	0.04	0.07	0.06
<i>t</i> = 1960,...,2010; <i>n</i> =	5172.00	5047.00	5047.00	5047.00	5047.00	5047.00	5047.00	5047.00
<i>min</i>	0.03	0.26	0.17	0.00	0.10	0.03	0.01	0.04
μ	4.04	2.75	2.80	2.57	2.31	0.40	0.46	0.43
<i>max</i>	1363.80	14.15	10.34	8.82	11.34	0.97	0.92	0.93
σ	22.19	1.76	1.39	1.59	1.57	0.21	0.17	0.18

Source: Authors, own elaboration. Note: Statistics are the minimum of the set (*min.*), the maximum (*max.*), the average (μ), and the standard deviation (σ).

An important drawback of this method is that all the covariates must be strictly exogenous, so all leads and lags of the variables are assumed to be uncorrelated with ϵ_{it} . As Moral-Benito (2010) pointed out, this consideration rules out the possibility of feedback from lagged income to current growth determinant, which seems to be reasonable in the model.

Therefore, our specification also ensure that this assumption is satisfied, insofar as a lagged covariate cannot be affected by the future values of dependent variable.

4 MAIN RESULTS

In this section, we will illustrate some results and findings. Table 2 show the results obtained with the illiteracy rate as control variable. The inclusion of variable is due to the existence of a possible confounder, which is a municipality may have a fairly equal distribution of education levels because most formal workers have few years of schooling.

The fixed effects estimator is more accurate than the random effects estimator, but less efficient. On the other hand, the random effects model is inconsistent in the case of fixed effects. Therefore, using the incorrect specification can result in poor estimates. To assist in this choice, Tables 2 and 3 also presents the results for Hausman test. In all specifications test statistic soundly rejects the null, so the of appropriateness of RE model must not be accepted.

The achieved results are sufficiently clear and allow us to choose FE specification. In Table 2 this conclusion is reinforced by both Akaike (AIC) and Schwarz (SBC) information criteria, whose values are always lower for the FE models. In fact, as we take the first difference, the fixed effects were partially removed. There is also an additional consideration, which is the need to address time effects. The $Dt = 0$ line shows the results of a Wald test conducted under the null hypothesis that all time dummies are not jointly significant and, as one can be seen, reported statistics clearly indicates that time dummies should be included in the model.

Our variable of interest ($giniit-2$) always had a significant impact on outcome hence, it is robust in its negative influence on economic growth. The smallest estimated coefficient is -0.370 in model (2) and the highest -0.586 in model (3). Notwithstanding, AIC criteria selects model (1) while BIC criteria lead to the conclusion that the model (2) model is preferable. We choose the Schwarz criteria because the first imposes a larger penalty for additional coefficients. So, considering these results, we conclude that model (2) is the best fit.

Results in Tables 2 and 3 lead to several implications. There is strong negative effect of educational inequality on growth. The higher the educational inequality, the smaller the economic growth in the next two decades. Also, there is a positive effect of capital stock of growth only in Table 2, model (4).

Regarding to education, we consider four measure distinct measures: the illiteracy rate for male ($mill$) and female ($mill$) aged 15 and over in column (1), the total illiteracy rate (ill) for people aged 15 and over in column (2), the average years of schooling for male (mhk) and female (fhk) aged 25 and over in column (3), and the average years of schooling (hk) for all aged 25 and over in column (4). However, the indicator of education seems to have no impact on growth, at least in our estimates. One possible explanation is that the educational inequality is already capturing the effect of the educational level.

In Table 2 we re-estimate model (1) adding two new control variables: the percentage of rural people ($prur$) and percentage of people who are under 15 years ($pjov$). Both variables capture important aspects of urban-rural transition process. As people leave rural areas towards cities, Brazilian large cities have experienced rapid population and economic growth. Completely, from the 1950's to the 1970's, high birth rates combined with increasing life

expectancy, led the population to grow at unprecedented rates. So, these variables allow us to know whether the impact of educational inequality changes if we consider these issues.

Table 2: Quasi-maximum likelihood linear dynamic panel data estimates. Dependent variable is log per capita GDP.

Model	(1)	(2)	(3)	(4)
$\ln(gini)_{i,t-2}$	-0.196*** (0.00)	-0.193*** (0.00)	-0.192*** (0.00)	-0.199*** (0.00)
$\ln(gdp)_{i,t-1}$	0.388*** (0.00)	0.389*** (0.00)	0.383*** (0.00)	0.387*** (0.00)
$\ln(gdp)_{i,t-1}$				0.007 (0.84)
$\ln(ill)_{i,t-1}$		-0.053 (0.48)		
$\ln(mhk)_{i,t-1}$			-0.048 (0.43)	
$\ln(fhk)_{i,t-1}$			0.106 (0.13)	
$\ln(mill)_{i,t-1}$	0.028 (0.78)			
$\ln(fill)_{i,t-1}$	-0.052 (0.64)			
$\ln(pk)_{i,t-1}$	-0.039 (0.49)	-0.039 (0.49)	-0.032 (0.57)	-0.035 (0.54)
<i>Constant</i>	1.010*** (0.00)	0.965*** (0.00)	0.954*** (0.00)	1.030*** (0.00)
$Dt = 0 (\chi^2)$	94.54*** (0.00)	58.12*** (0.00)	54.96*** (0.00)	80.08*** (0.00)
Hausman test	53.41*** (0.00)	50.95*** (0.00)	73.61*** (0.00)	73.47*** (0.00)
<i>N</i>	862.00	862.00	862.00	862.00
<i>Nt</i>	2586.00	2586.00	2586.00	2586.00
<i>AIC</i>	1594.49	1599.66	1581.82	1587.84
<i>BIC</i>	1723.36	1705.10	1710.70	1693.28

Source: Authors, own elaboration. **Note:** Significance: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Robust standard errors in parenthesis. Hausman test was conducted with non-robust standard errors. $Dt = 0$ is the Wald test for jointly significance of time dummies. In column (1) educational level is the illiteracy rate for male (*mill*) and female (*fill*) aged 15 and over, in column (2) is the total illiteracy rate (*ill*) for people aged 15 and over, in column (3) is the average years of schooling for male (*mhk*) and female (*fhk*) aged 25 and over, and in column (4) is the average years of schooling (*bk*) for all aged 25 and over.

Table 3: Quasi-maximum likelihood linear dynamic panel data estimates. Dependent variable is log per capita GDP.

Model	(1)	(2)	(3)	(4)
$\ln(gini)_{i,t-2}$	-0.205*** (0.00)	-0.200*** (0.00)	-0.201*** (0.00)	-0.209*** (0.00)
$\ln(gdp)_{i,t-1}$	0.382*** (0.00)	0.383*** (0.00)	0.380*** (0.00)	0.382*** (0.00)
$\ln(gdp)_{i,t-1}$				-0.006 (0.85)
$\ln(ill)_{i,t-1}$		-0.096 (0.24)		
$\ln(mhk)_{i,t-1}$			-0.054 (0.37)	
$\ln(fhk)_{i,t-1}$			0.010 (0.15)	
$\ln(mill)_{i,t-1}$	-0.006 (0.95)			
$\ln(fill)_{i,t-1}$	-0.043 (0.72)			
$\ln(pk)_{i,t-1}$	-0.019 (0.76)	-0.019 (0.76)	-0.015 (0.81)	-0.014 (0.83)
$\ln(prur)_{i,t-1}$	0.043 (0.15)	0.048 (0.10)	0.036 (0.20)	0.039 (0.17)
$\ln(pjov)_{i,t-1}$	-0.197 (0.22)	-0.244 (0.13)	-0.222 (0.17)	-0.205 (0.20)
<i>Constant</i>	0.784*** (0.00)	0.651** (0.01)	0.736** (0.00)	0.829** (0.00)
$Dt = 0 (\chi^2)$	78.30 (0.00)	23.96 (0.00)	43.56 (0.00)	61.87 (0.00)
Hausman test	63.24*** (0.00)	57.97*** (0.00)	70.52*** (0.00)	77.03*** (0.00)
<i>N</i>	855.00	855.00	855.00	855.00
<i>nT</i>	2565.00	2565.00	2565.00	2565.00
<i>AIC</i>	1564.65	1569.30	1558.63	1559.22
<i>BIC</i>	1740.14	1721.39	1734.12	1711.31

Source: Authors, own elaboration. **Note:** Significance: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Robust standard errors in parenthesis. Hausman test not included. $Dt = 0$ is the Wald test for jointly significance of time dummies. In column (1) educational level is the illiteracy rate for male (*mill*) and female (*mill*) aged 15 and over, in column (2) is the total illiteracy rate (*ill*) for people aged 15 and over, in column (3) is the average years of schooling for male (*mhk*) and female (*fhk*) aged 25 and over, and in column (4) is the average years of schooling (*hk*) for all aged 25 and over.

One can note in Table 3 that there was a significant positive correlation between rural people in the initial period and the economy performance over next two decades. On the other hand, the effect of percentage of young people it is not so stable, is statistically significant only in the models (3) and (4). Anyway, model (3) reports the lowest values for AIC and BIC, which leads us to the conclusion that it produces the best fit. We also note that, according to the AIC criteria this model, although less parsimonious this model better fits the data than the model (3) in Table 2.

Taken together, these results suggest that there is an association between educational distribution and growth. This effect is significant even controlling for different confounders, which gives us some confidence in them. Even so, future research should be carried out to better explore and expand our current knowledge about this issue.

5 CONCLUDING REMARKS

Our goal in this study was to investigate the effects of educational inequality on economic growth. The statistical significance and direction of this relationship is stable across different model specifications, so the estimates hardly change from one model to another. Consequently, one of the more significant findings to emerge from this study is that education is negatively related with the economic growth over the next two decades. These basic findings are consistent with previous research, but to our knowledge this is the first report using such technique and data for Brazilian Northeast region.

Even though we get some evidence of a negative relationship between the educational distribution and growth rate of real per capita GDP, further research should be carried out to find a variable that contributes to identify a variable that constitutes an instrument that allows determining the causation. This would bring more robustness and reliability to the analysis with different model specifications.

As we have argued elsewhere educational distribution may be considered a promising aspect of economic inequality on growth, mainly because this can be one of the main principal channels of transmission of economic inequality on growth. Our findings suggest that we still have a long way to go to explore, but our data paves the way to enhanced knowledge about this issue in future investigations.

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