DOI: 10.1111/rode.12598

REGULAR ARTICLE

WILEY

Persistence and determinants of income inequality: The Brazilian case

Diogo Signor[1] | **Jongsung Kim**[2] | **Edinaldo Tebaldi**[2]

[1]Universidade Federal de Santa Catarina (PPGEco/UFSC), Florianópolis, Santa Catarina, Brazil

[2]Department of Economics, Bryant University, Smithfield, Rhode Island

Correspondence
Jongsung Kim, Department of Economics, Bryant University, 1150 Douglas Pike, Smithfield, RI 02917.
Email: jkim@bryant.edu

Funding Information
Diogo Signor thanks the CAPES Foundation for financial support and Prêmio CDPP.

Abstract

Latin America, which is a region known for its high and persistent income inequality levels, experienced a significant decline in income inequality since the second half of the 1990s. Brazil is a particularly interesting case in Latin America. While the country presented notable economic growth and improvements in income distribution in the early 2000s, Brazil continues to experience high levels of income inequality in comparison with other Latin American or advanced economies. This research contributes to the literature by examining the key drivers of income distribution and the degree of persistence of income inequality among Brazilian states. This research also improves upon previous works by using more recent and comprehensive data and addressing concerns regarding heterogeneity and endogeneity by using the system GMM estimation method. Our findings show that income inequality is highly persistent across Brazilian states and that government policies including income transfer programs made important contributions to reduce income inequality in Brazil. This study also shows that the decline in labor income ratios between different ethnic groups and the increase of the share of formal jobs in the labor market contributed to reduce income inequality.

JEL CLASSIFICATION
E24, N36, O15

KEYWORDS
Brazil, income inequality, Latin America

1 | INTRODUCTION

Persistent and high levels of income inequality plagued Latin American countries in the 1980s and the first half of the 1990s when those countries faced a debit crisis and introduced structural reforms (López-Calva & Lustig, 2010). This trend, however, took a different turn in the 2000s. While income inequality was increasing in many economies around the world, most countries in Latin America experienced a decline in income inequality in the 2000s (Simson, 2018). This was mostly fueled by government policies, favorable commodity export markets, steady and relatively high growth of income per capita, and increasing inflows of foreign direct investments (Andersson & Palacio, 2017).

In contrast to the policy tools that contributed to reduce income inequality in advanced economies,[1] deliberate government policies were also needed to change inequality in Latin America (López-Calva & Lustig, 2010). The literature attributes the decline of income inequality in Latin America to factors such as the decrease in inequality in hourly labor income, which is related to the returns to education, higher and more progressive government transfers (López-Calva, Lustig, & Ortiz-Juarez, 2013), inter-sectoral income convergence (Andersson & Palacio, 2017), and fiscal policy, through changes of social spending and personal income tax codes (Clifton, Díaz-Fuentes, & Revuelta, 2017).

Brazil is an interesting case to study among the Latin American countries. It is not only the biggest Latin American economy, but also the country with the third highest level of income inequality in the region (UNDP, 2018). Similar to that observed in other Latin American economies, income inequality in Brazil has been declining since the mid-1990s, with large reductions after 2002 (Brito, Foguel, & Kerstenetzky, 2017). However, there are large differences in the dynamics of income inequality across regions in Brazil over the years. The large size of the Brazilian territory and the fact that some regions have historically been economically and socially more developed than others[2] have led to significant intra-regional differences.

While there is a vast literature investigating the determinants of the decline of income inequality in Brazil since the second half of the 1990s (e.g., Araújo & Marinho, 2015; Fernandes, Cunha, & Vasconcelos, 2018; Ferreira, 2000; Ferreira, Leite, Litchfield, & Ulyssea, 2006; Ramos & Vieira, 2001; Santos, Cunha, & Gadelha, 2017; and several works discussed in Barros, Foguel, & Ulyssea 2006, 2007), this research contributes to the literature by examining two questions. First, what factors are the key drivers of the observed decline in income inequality among Brazilian states after the mid-1990s? What is the degree of persistence of income inequality among Brazilian states?

This research improves upon and extends previous works by considering new variables, utilizing a more recent and comprehensive dataset, and addressing concerns regarding heterogeneity and endogeneity by using the system GMM estimator. Our findings show that income inequality is highly persistent across Brazilian states and, different from work that uses similar methodology (e.g., Araújo & Marinho, 2015), that government policies including income transfer programs made important contributions to reduce income inequality in Brazil. This study also shows that the decline in labor income ratios between different ethnic groups and the increase of the share of formal jobs in the labor market contributed to reduce income inequality.

This paper is organized as follows. Section 2 presents a brief discussion about income inequality including differences across states in Brazil. Section 3 presents the data used in the study. Section 4 discusses the econometric model and estimation methodology. Section 5 presents and discusses empirical results and robustness tests. Section 6 summarizes the findings of this study.

2 | INCOME INEQUALITY IN BRAZIL

There is a large body of research on the determinants of income inequality in Brazil because the country is notorious for its high levels of income inequality (Barros, Foguel et al., 2007). Since the second half of the 1990s, however, income inequality has declined in Brazil, with a notable reduction in the early 2000s and relatively minor improvements more recently (Barbosa, 2016)[3].

The decline in income inequality is attributed, among other factors, to economic prosperity and financial stability that Brazil experienced at the beginning of the 21st century (Barros, Carvalho, Franco, & Mendonça, 2007), increase in the share of formal employment in the labor market (Ramos, 2015), the implementation of public policies such as income transfers to the poor (Hoffman, 2006; Soares, 2006; Soares, Soares, Medeiros, & Osório, 2006), better educational attainment (Barros, Franco, & Mendonça, 2007a; Ferreira et al., 2006), the decline of segmentation and discrimination in the labor market (Barros & Mendonça, 1995), and the minimum wage valorization policy (Brito, Foguel, & Kerstenetzky, 2017).

There are also significant regional variations in income inequality in Brazil. Figure 1 shows the trends of income inequality in five broadly defined regions in Brazil from 1996 to 2015. It shows that household per capita income inequality has been steadily declining across Brazilian regions over the years. Figure 1 also shows that the Northeast region presents the highest Gini index over the years. The Center-West region is the second most unequal region, and the North region has remained as the third one from 1996 to 2015. But in 2011, the income inequality of the North region rose to the level comparable to that of the Center-West region. The Southeast region has remained the second most equal region, and the South region has consistently maintained the lowest income inequality levels throughout the period analyzed in this research. Overall, the persistence of within-region income disparities is noticeable, which suggests that current inequality is strongly determined by past inequality.

Figures A1 to A5 in the Appendix present the Brazilian states' level of inequality using the share of income for three groups (bottom 10%, 30%, and 50%) to that of the top 10%. For all groups across all regions, we can observe that the shares of the bottom incomes are increasing, meaning that income inequality is declining. However, we can also see that there is high disparity in income distribution across Brazilian states, especially if comparing states from different regions. More precisely, while in the state of Maranhão in the Northeast region the income of the bottom 50% represents 35% of the income of the top 10% and the poorest 10% receive only 1.8% of the income that the top 10% earns, in

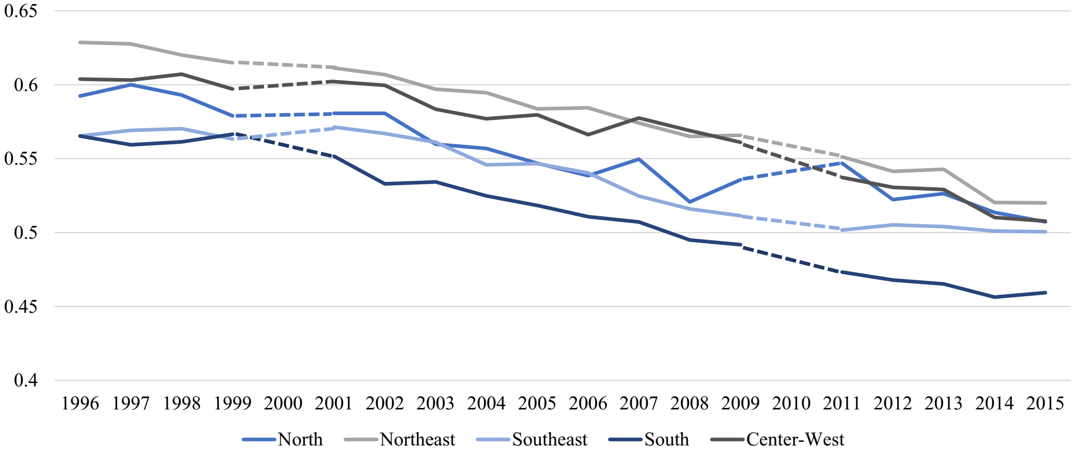

FIGURE 1 Gini index for the household per capita income in Brazilian regions, 1996–2015[a]
Note. [a]The PNAD is not available in 2000 and 2010 (Census years)
Source. Authors' estimation using data from PNAD.

the state of Santa Catarina located at the South region the income of the bottom 50% represents 75% of the income of the top 10% and the poorest 10% receive 6% of the income that the top 10% earns. In contrast, those disparities are not striking if comparing states within the same geographic region, such as comparing income distribution between Santa Catarina and Paraná or between Maranhão and Paraíba.

3 | DATA

This study examines income inequality in Brazil using microdata from the Brazilian household survey (PNAD)[4] from 1996 to 2015. The PNAD is conducted by Brazil's National Statistical Bureau (IBGE), which is responsible for collecting data on demographic and educational characteristics, labor market outcomes, and other socioeconomic aspects in Brazil. The PNAD microdata were used to create state-level variables. Because of missing data in 2000 and 2010 (census years) and the need to produce a continuous data series[5], we use the average values of each state observations from one year before and one year after those gap years[6]. State-level variables were calculated using the people's weights to produce metrics that represent the population. This study also utilizes state-level data from different governmental data sources including the Social Development and Hunger Combat Ministry (MDS), IBGE, Institute of Applied Economic Research (IPEA), and Department of the Treasury.

Table 1 lists descriptive statistics for all variables used in this study. The definition of all variables is discussed below and include: the standard deviation (SD) of the average years of education from people 25 years old and over, used to measure the disparity of educational attainment[7]; the share of workers in the formal sector, that is, workers with a job contract and paying social security contributions; and the average labor income ratio (as a percentage of total income) of the employed population. This variable is calculated by gender and ethnic groups, thus it measures earnings differences by gender and ethnic group[8]. The hourly labor income variable was created by dividing workers' total

TABLE 1 Descriptive statistics of the variables

Variables	Obs.	Mean	*SD*	Min	Max
Gini index	540	0.55	0.05	0.42	0.67
SD of years of education	540	4.68	0.26	4.01	5.43
Gender income ratio (W/M)[a]	540	0.88	0.12	0.61	1.64
Ethnic income ratio (B/W)[b]	540	0.62	0.10	0.35	1.03
Share of formal jobs	540	0.37	0.11	0.11	0.64
Yearly GDP growth	540	0.03	0.04	–0.13	0.16
GVA of agriculture	540	0.08	0.06	0.00	0.32
GVA of manufacturing	540	0.22	0.08	0.04	0.45
GVA of services	540	0.69	0.09	0.50	0.94
Share of population with BPC[c]	540	0.01	0.01	0.00	0.03
Share of families with PBF[c]	324	0.07	0.04	0.01	0.15
Share of population with RP[d]	492	0.18	0.01	0.00	0.05

Note. [a]This variable measures the average labor income ratio by gender (women's wage/men's wage). [b]This variable measures the average labor income ratio by ethnic groups (black workers' wage/white workers' wage). [c]The share of families receiving aid from government transfer programs (BPC and PBF). [d]It is not possible to estimate rural pensions for states in the North region (except TO) for the period 1996–2003 because there is no data for rural areas.

monthly labor income (from all sources) by the number of hours worked in that month. The variable for the share of population receiving aids from rural pension (RP)[9] was created from the PNAD dataset by considering the retired workers who receive a minimum wage, over 60 for men and over 55 for women, and live in rural areas[10].

The Gini Index is calculated using household per capita income, which includes all sources of income earned monthly by households[11]. We also utilize the share of families receiving income from government transfer programs—*Benefício de Prestação Continuada* (BPC)[12] and *Programa Bolsa Famíla* (PBF)[13]; the share of the gross value added (GVA) of agriculture, manufacturing and services in the total GVA, to control for job characteristics related to them[14]; and the yearly variation of GDP, as a measure of economic growth, adjusted to constant values using the GDP deflator with 2010 as base year.

4 | METHODOLOGY

This section presents an empirical analysis of the determinants of income inequality and its persistence across Brazilian states. The model includes lagged inequality and fixed effects. Thus, ordinary least squares (OLS) or fixed effects (FE) estimation would produce biased and inefficient estimates (Roodman, 2009). In addition, income inequality may affect economic growth (Barreto, Jorge Neto, & Tebaldi, 2001; Cruz, Teixeira & Monte-Mor, 2015; Koshiyama & Fochezatto, 2012), thus the economic growth variable is potentially endogenous.

To circumvent the endogeneity and heterogeneity problems in the data, we utilize an autoregressive model of first order that uses the Gini index as the dependent variable and the system GMM estimator proposed by Arellano and Bond (1991) and further developed by Arellano and Bover (1995) and Blundell and Bond (1998) to estimate the model. The system GMM estimator not only improves the precision of the estimates, but also reduces the finite sample bias (Blundell, Bond, & Windmeijer, 2000). We follow Arellano (2003) and consider the following specification:

$$y_{it} = \alpha y_{i,t-1} + \beta' x_{it} + \eta_i + \upsilon_{it}, \tag{1}$$

and

$$E(\upsilon_{it} | x_{i1}, \ldots, x_{iT}, \eta_i) = 0,\ (t = 1, \ldots, T). \tag{2}$$

In (1), there is a dynamic process because lagged y impacts y with an adjustment speed of α. The lagged value of y will be correlated by construction with η and with lagged υ, and may also be correlated with current υ if it is serially correlated. This means that the lagged y is an endogenous explanatory variable in Equation 1 with respect to both η and υ.

Arellano and Bover (1995) and Blundell and Bond (1998) find that if there is an instrumental variable that is not correlated with individual fixed effects, it is possible to improve the efficiency of the estimates by using that instrumental variable in place of the variable that is subject to endogeneity. A suitable instrumental variable can be identified by exploring the levels of the variables containing information about the parameters of interest.

To improve the properties of the standard first-differenced GMM estimator, after setting further restrictions on the initial conditions process[15], it was proposed to use a system GMM estimator with lagged differences of the variables as instruments for equations in levels, and lagged levels of the variables as instruments for equations in first differences. Blundell and Bond (1998) show that the system GMM estimator has its restrictions satisfied under stationarity and under weaker assumptions.

This would result in a precision gain for higher values of the autoregressive parameter and for a small number of time series observations. To evaluate the model results, Roodman (2009) suggests the use of the Arellano–Bond tests for first and second order correlation in first differences, the Sargan[16] and Hansen tests of overidentified restrictions, and the Difference-in-Hansen tests.

The model above is estimated for two periods: 1996 to 2015 and 2004 to 2015. For the 1996 to 2015 period, states from the North region (except the state of TO) are not included because the data for these states only include urban areas, which could potentially bias the estimates. The year 1996 is chosen as the starting point for three reasons: (i) prior to 1996, except for rural pension, there was no available comprehensive data on income transfers to the poor (BPC or PBF); (ii) prices were relatively stable because of the implementation of the Real Plan[17]; and (iii) the number of cross-sectional observations would be greater than the length of time series, which is a required condition to use system GMM, the empirical methodology utilized in this research. The period 2004 to 2015 was chosen as a subset of analysis because it includes all Brazilian states in the analysis. The 2004 to 2015 period also allows the use of the PBF data as an explanatory variable, which was available only after 2004.

Four models are estimated to consider the sensitivity of the system GMM results[18]. The first model is estimated without control dummies; the second model includes time dummies, and the third and fourth models provide alternative specifications to consider controls for economic growth cycles and election years. Economic growth cycle dummies were chosen to control for economic prosperity periods for the following periods: 1996 to 1997, 1999 to 2000, 2002 to 2008, and 2010 to 2013[19]. Election year dummies were chosen to control for state governors and presidential election years, which are usually associated with higher public expenditures for electoral motivation (Nakaguma & Bender, 2006; Persson & Tabellini, 2003; Sakurai, 2009). Federal and state elections occur every four years, where 1998 is the first election year of the period analyzed in this study. In addition, the 1996 to 2015 model considers only BPC and RP as public policies to redistribute income because PBF starts in 2004. For the 2004 to 2015 period, we cannot include all programs in the model owing to multicollinearity generated by the PBF variable. This variable shows a high correlation with many other variables in the model. One way to deal with this problem was by using GDP growth and the lagged Gini variable as instruments for PBF and not including BPC and RP in the model[20].

5 | RESULTS

Table 2 reports the effects of the explanatory variables on income inequality for 21 Brazilian states for the 1996 to 2015 period. Models 1, 3, and 4 present similar results for the estimates with respect to sign, statistical significance, and magnitude. These models satisfy the requirements of Arellano–Bond AR(1) and AR(2) tests, meaning that the autocorrelation is positive and statistically significant (at the 5% level) at the first order, but not at the second order even under 10% significance level. The Hansen test of overidentification restrictions and the Difference-in-Hansen tests of exogeneity of instrument subsets are valid for all three models at 5% significance level. Model 2, however, fails to meet some GMM requirements, thus its results should be viewed with caution. This model satisfies the Arellano–Bond AR(1) and AR(2) tests, but it presents extremely high p values for the Hansen test of overidentification restrictions and the Difference-in-Hansen tests of exogeneity of instrument subsets. The problem with Model 2 seems to be associated with multicollinearity when including time dummies and the share of population with BPC.

Models 1, 3, and 4 of Table 2 provide evidence of a strong persistence effect of income inequality across Brazilian states: between 50% and 56% of current income inequality is determined by past inequality. This result is similar to that of Araújo and Marinho (2015). However, unlike Araújo and

Marinho (2015), the BPC and the rural pension (income transfer programs) were found to have a statistically significant effect in reducing income inequality.

The empirical results also show that a decrease in the ethnic-group labor income ratio decreases inequality while a decrease in the gender labor income ratio leads to higher inequality. The former result is straightforward. Since labor income is distributed more equally among different ethnic groups, income inequality is expected to decline. The pattern of increasing inequality when women's labor income approaches the men's level is known as the "assortative mating" phenomenon in the literature, which explains the tendency for people to marry someone with similar characteristics including economic status[21]. When people with a high income tend to marry each other, this type of marriage will raise family income and, consequently increase the income gap between rich and poor families.

Another variable that had a significant effect on reducing inequality is the growth in the share of formal jobs. This result can be attributed to labor laws that formal jobs are subject to and that require better benefits and protection such as minimum wage. According to the human capital theory, income is positively correlated with educational attainment (Becker, 1994). The effect of the variation in educational attainment on income inequality is positive. The higher the discrepancy in educational attainment, the greater is the difference in income earned by people with different educational attainment and, consequently the greater is income inequality[22].

The estimates reported in Table 2 (Models 1, 3, and 4) also show a positive sign for economic growth, but none of estimates are statistically significant. This implies that for the period analyzed, economic growth did not contribute to reducing or increasing income inequality across Brazilian states. Table 3 reports the empirical results from a more recent and complete dataset. It includes the regression results for all 27 Brazilian states and uses the variables PBF, a more comprehensive government income transfer program started in 2004, instead of using BPC and RP. As in Table 2, Models 1, 3, and 4 in Table 3 report similar results in terms of the sign, statistical significance, and magnitude of estimates. These models satisfy the requirements of Arellano–Bond AR(1) and AR(2) tests. The Hansen test of overidentification restrictions is valid for all models at a level of significance of 5%.

Also Model 2 of Table 3, as in Table 2, fails to meet all of the GMM requirements. The coefficients of Models 1, 3, and 4 of Table 3 have the same signs as those presented in Table 2, but the magnitudes of the estimates and their statistical significance have slightly changed. This variation may be due to the use of all Brazilian states and one different explanatory variable for the analysis in the period 2004 to 2015. The overall findings and implications, however, remain unchanged. For instance, Table 3 shows that past inequality explains approximately 50% of the current income inequality levels observed across Brazilian states. This result reinforces the previous finding that income inequality is highly persistent across Brazilian states.

As in Table 2, reducing ethnic-group income ratio in the labor market and increasing the share of formal jobs contribute to decrease income inequality in Brazilian states. In Table 3, the effect of government transfers to the poor, focusing on the families receiving financial aid from PBF program, is also significant to reduce income inequality. This result is consistent with previous findings of Soares (2006) and Barros, Carvalho et al. (2007) about the effect of income distribution on income inequality.

The variation in educational attainment, in Table 3, has a positive and statistically significant effect on income inequality. This implies that differences in years of education explain differences in income received by families. The coefficient estimates of the gender labor income ratio show different statistical significance across different models. While the coefficient is statistically significant at the 10% level in Model 1 of Table 3, it is statistically insignificant in Models 3 and 4. This provides a weak evidence supporting the assortative matting phenomenon across Brazilian states.

Models 1 and 4 in Table 3 show that GDP growth has a statistically significant impact on income inequality, but Model 3, which controls for growth cycles, shows that the variation in GDP growth

TABLE 2 Regression analysis for the Brazilian states without North region (except TO) (Dependent variable: Gini Index; Period: 1996–2015; Number of groups: 21)

Variables	Model 1	Model 2	Model 3	Model 4
$Gini_{t-1}$	0.538***	0.399***	0.506***	0.557***
	[5.32]	[3.19]	[5.43]	[5.28]
SD of years of education	0.016*	0.018*	0.017*	0.014
	[1.80]	[1.77]	[1.83]	[1.64]
Gender income ratio	0.027*	0.040**	0.031**	0.026*
	[2.03]	[2.39]	[2.15]	[1.91]
Ethnic-group income ratio	–0.070***	–0.064***	–0.073***	–0.066***
	[–3.98]	[–3.45]	[–4.11]	[–3.69]
Share of formal jobs	–0.138***	–0.096***	–0.146***	–0.125***
	[–4.05]	[–3.51]	[–4.39]	[–3.75]
% of population with BPC	–1.005***	0.320	–1.017***	–0.810**
	[–2.96]	[0.91]	[–3.01]	[–2.61]
% of population with RP	–0.756***	–0.451*	–0.806***	–0.680***
	[–3.49]	[–1.98]	[–3.70]	[–3.37]
Yearly GDP growth	0.028	–0.001	0.027	0.042
	[0.99]	[–0.03]	[0.92]	[1.46]
GVA of agriculture	–0.092***	–0.145***	–0.098***	–0.094***
	[–3.06]	[–2.89]	[–3.09]	[–3.04]
GVA of manufacturing	–0.076*	–0.100*	–0.080*	–0.075**
	[–2.03]	[–1.93]	[–1.88]	[–2.14]
D_year 1997		0.061***		
		[3.62]		
⋮		⋮		
D_year 2015		0.004		
		[0.95]		
D_growth cycle 96–97			0.007	
			[0.84]	
⋮			⋮	
D_growth cycle 10–13			0.002	
			[1.03]	
D_election year 1998				0.002
				[0.68]
⋮				⋮
D_election year 2014				–0.015***
				[–5.02]
Constant	0.300***	0.291***	0.319***	0.290***

(Continues)

TABLE 2 (Continued)

Variables	Model 1	Model 2	Model 3	Model 4
	[5.85]	[4.24]	[6.34]	[5.11]
No. of instruments	21	35	23	24
No. of lags	5	3	4	4
AR(1) – *p* value	0.001	0.000	0.001	0.001
AR(2) – *p* value	0.355	0.431	0.320	0.345
Hansen Overid. – *p* value	0.121	1.000	0.825	0.803
Difference-in-Hansen tests of exogeneity of instrument subsets (GMM instruments):				
Hansen – *p* value	0.091	1.000	0.232	0.620
Difference – *p* value	0.435	1.000	1.000	0.929

Note. The robust one-step system GMM regression was performed. Endogenous variables instrumented: Gini_{t-1} and yearly GDP growth. ***,**,*Denote significance at 1%, 5%, and 10% levels, respectively. *t* ratio in brackets. AR(1) and AR(2) are the Arellano–Bond tests for the autoregressive process of order 1 and 2 in first differences, respectively. "Hansen Overid." are the Hansen tests of over-identification restrictions.*Source*. Authors' estimation.

is not statistically significant while the dummy variable controlling for growth cycle 2010 to 2013 is significant. This result indicates that high-income families benefited more from economic growth during this period (2004 to 2015) than the poor ones. This finding is consistent with Ravallion's (2004) finding that economic growth benefits the rich more than the poor in countries where the level of inequality is high[23].

Table 3, as in Table 2, provides evidence that states with a larger share of agricultural sector in the economy experience lower income inequality. The share of manufacturing sector is also found to have a negative effect on inequality, but none of the estimates are statistically significant. In summary, the sign of the coefficients in Tables 2 and 3 are similar, but there are noticeable differences in statistical significance for a few variables depending on model specifications. The following section tests the sensitivity of these models.

5.1 | Robustness tests

The robustness of system GMM estimates are subject to several assumptions, thus we use Model 1 to test the model's robustness. The sensitivity analysis consists of comparing previous results (Tables 2 and 3) to those obtained from (i) OLS and FE regression models, (ii) estimates using alternative number of lags as instruments, and (iii) excluding census years from the sample. To save space, all estimates are presented in Table 4, and only the results of AR(1), AR(2), and the Hansen tests of overidentification restrictions are presented for the system GMM models.

According to Bond (2002), it is useful to compare the OLS and FE estimates of the lagged variable (Gini_{t-1}) with the estimates of the system GMM. Since these two estimators, OLS and FE, have the estimates of the lagged variable biased in opposite directions, it is expected that a consistent estimator produces an estimated coefficient lying between them. The coefficients of the lagged variable for Model 1 in Tables 2 and 3 are 0.538 and 0.535 respectively, which satisfies this requirement as we can see when comparing with the coefficients of the lagged variable using OLS and FE in Table 4.

Table 4 presents system GMM results when Model 1, from Tables 2 and 3, is estimated with four or six lags as instrumental variables. The results presented in Table 4 show the coefficients have the same sign and statistical significance as those presented in Tables 2 and 3, with slight differences in

TABLE 3 Regression analysis for the Brazilian states (Dependent variable: Gini Index; Period: 2004–2015; Number of groups: 27)

Variables	Model 1	Model 2	Model 3	Model 4
$Gini_{t-1}$	0.535***	0.384***	0.500***	0.521***
	[5.15]	[3.60]	[4.41]	[5.04]
SD of years of education	0.031*	0.028	0.036**	0.031*
	[1.91]	[1.29]	[2.12]	[2.04]
Gender income ratio	0.026*	0.031**	0.025	0.023
	[1.73]	[2.46]	[1.57]	[1.57]
Ethnic-group income ratio	–0.082***	–0.080***	–0.083***	–0.078***
	[–4.44]	[–4.59]	[–4.12]	[–4.23]
Share of formal jobs	–0.154***	0.051	–0.167**	–0.130***
	[–2.89]	[0.57]	[–2.44]	[–2.96]
% of population with PBF	–0.106**	0.108	–0.116*	–0.081**
	[–2.15]	[1.26]	[–1.90]	[–2.32]
Yearly GDP growth	0.059**	0.038	0.035	0.061**
	[2.15]	[1.32]	[1.23]	[2.53]
GVA of agriculture	–0.140**	–0. 121**	–0.150**	–0.138**
	[–2.60]	[–2.53]	[–2.65]	[–2.77]
GVA of manufacturing	–0.044	–0.054	–0.050	–0.048
	[–1.44]	[–1.42]	[–1.49]	[–1.56]
D_year 2005		0.010		
		[1.65]		
⁝		⁝		
D_year 2015		–0.033***		
		[–3.54]		
D_growth cycle 04–08			0.005	
			[1. 00]	
D_growth cycle 10–13			0.005*	
			[1.90]	
D_election year 2006				0.004
				[0.75]
D_election year 2010				–0.003
				[–1.51]
D_election year 2014				–0.016***
				[–5.23]
Constant	0.232***	–	0.190***	0.228***
	[5.98]	–	[3.48]	[5.78]
No. of instruments	25	32	27	28
No. of lags	5	4	5	5

(Continues)

TABLE 3 (Continued)

Variables	Model 1	Model 2	Model 3	Model 4
AR(1) – *p* value	0.001	0.001	0.001	0.001
AR(2) – *p* value	0.113	0.169	0.111	0.106
Hansen Overid. – *p* value	0.258	0.871	0.149	0.261
Difference-in-Hansen tests of exogeneity of instrument subsets (chi^2 test for GMM instruments):				
Hansen – *p* value	0.141	0.659	0.060	0.289
Difference – *p* value	0.832	1.000	0.974	0.280

Note. The robust one-step system GMM regression was performed. Endogenous variables instrumented: $Gini_{t-1}$, yearly GDP growth, and share of population with PBF. ***,**,*Denote significance at 1%, 5%, and 10% levels, respectively. *t* ratio in brackets. AR(1) and AR(2) are the Arellano–Bond test for autoregressive process of order 1 and 2 in first differences, respectively. "Hansen Overid." are the Hansen tests of over-identification restrictions.*Source*. Authors' estimation.

the magnitude of the estimated coefficients. The only major difference is the statistical significance of the variable controlling for gender income ratio in the 2004 to 2015 period, which is not statistically significant at the 10% level when considering six lags. The lack of statistical significance was already observed in Table 3 when dummies were included in the model. In summary, the number of lags does not significantly affect the coefficient estimates reported in Tables 2 and 3.

The PNAD survey was not conducted in 2000 and 2010, which are years in which the census took place. The data for these two years were imputed using the average value from the year before and after for each variable derived from PNAD. This approach could potentially impact the estimates. Thus, Model 1 from Tables 2 and 3 is reestimated excluding those two years in two ways: considering time gaps in the time series (With gaps)[24] and assuming a continuous time series (Contin.) as if 2009 and 2011 were consecutive periods.

Table 4 shows that estimating the model "with gaps" affects the estimates. For instance, the coefficient estimate of the lagged variable is smaller, there are differences in the levels of coefficients' statistical significance, while the coefficients' signs remain the same as those reported in Tables 2 and 3. Considering continuous time, the results in Table 4 are very similar to those reported in Tables 2 and 3 with respect to sign, statistical significance and magnitude of estimates. The most relevant difference is the smaller coefficient estimate of the lagged variable[25]. Despite this effect on the magnitude of the persistence of income inequality, our sensitivity analysis shows that using mean values to fill in the data gap for 2000 and 2010 neither impacts the estimates of the model in a significant manner nor changes the conclusions of the analysis.

6 | CONCLUSION

This research analyzes the determinants of household income inequality and its persistence across states in Brazil. Our findings imply that more than half (between 50% and 56%) of the current income inequality is explained by past income inequality. This suggests that regional economic and social structures are to be blamed for supporting an economic model that perpetuates regional inequalities in Brazil.

to assign responsibility for a fault or wrong

The results also suggest that reducing the wage ratio for different ethnic groups can reduce inequality across regions in Brazil. This result can be attributed not only to the fact that different ethnic groups receive different pay for the same job, but also to the fact that some groups—African descendants for

TABLE 4 Robustness tests. Model 1 estimated with OLS and FE methods, different number of lags of instruments, and without Census' years

	1996–2015						2004–2015					
Variables	**OLS**	**FE**	**Lags = 4**	**Lags = 6**	**With gaps**	**Contin.**	**OLS**	**FE**	**Lags = 4**	**Lags = 6**	**With gaps**	**Contin.**
$Gini_{t-1}$	0.737***	0.455***	0.496***	0.535***	0.270**	0.447***	0.725***	0.322***	0.521***	0.525***	0.394***	0.453***
	[23.87]	[10.51]	[4.64]	[5.57]	[2.45]	[5.18]	[20.02]	[6.19]	[4.78]	[4.81]	[3.45]	[4.46]
SD of years of education	0.013**	0.005	0.017*	0.016*	0.030**	0.020*	0.011	0.021*	0.032*	0.033*	0.051***	0.033*
	[2.26]	[0.66]	[1.78]	[1.81]	[2.37]	[2.00]	[1.41]	[1.89]	[1.88]	[1.88]	[3.03]	[1.81]
Gender income ratio	0.017*	0.007	0.030*	0.027*	0.030	0.028*	0.021*	0.020*	0.026*	0.026	0.020	0.027*
	[1.76]	[0.78]	[2.06]	[2.04]	[1.70]	[1.96]	[1.96]	[1.86]	[1.74]	[1.69]	[1.29]	[1.90]
Ethnic income ratio	–0.053***	–0.058***	–0.075***	–0.071***	–0.103***	–0.082***	–0.062***	–0.063***	–0.084***	–0.083***	–0.112***	–0.097***
	[–5.12]	[–5.54]	[–4.08]	[–4.06]	[–4.52]	[–4.74]	[–5.09]	[–5.16]	[–4.36]	[–4.28]	[–4.30]	[–4.94]
Share of formal jobs	–0.082***	–0.184***	–0.150***	–0.139***	–0.222***	–0.167***	–0.057***	–0.342***	–0.158***	–0.164***	–0.218***	–0.167***
	[–5.91]	[–5.80]	[–4.35]	[–4.07]	[–4.73]	[–4.88]	[–2.67]	[–8.60]	[–2.87]	[–2.83]	[–4.16]	[–3.00]
% of population with BPC	–0.644***	–1.010***	–1.078***	–1.001***	–1.607***	–1.212***						
	[–3.52]	[–3.70]	[–2.94]	[–2.96]	[–3.14]	[–3.13]						
% of population with RP	–0.460***	–0.233	–0.816***	–0.759***	–1.140***	–0.892***						
	[–4.09]	[–0.98]	[–3.60]	[–3.54]	[–3.90]	[–3.95]						
% of population with PBF							–0.025	0.052	–0.109**	–0.116**	–0.154***	–0.106**
							[–1.24]	[1.43]	[–2.61]	[–2.21]	[–4.02]	[–2.09]

(Continues)

TABLE 4 (Continued)

Variables	1996–2015 OLS	FE	Lags = 4	Lags = 6	With gaps	Contin.	2004–2015 OLS	FE	Lags = 4	Lags = 6	With gaps	Contin.
Yearly GDP growth	–0.013	0.012	0.043	0.029	0.082**	0.042	0.026	0.043	0.065**	0.058**	0.093**	0.090***
	[–0.58]	[0.52]	[1.51]	[1.07]	[2.39]	[1.46]	[0.94]	[1.61]	[2.22]	[2.16]	[2.10]	[3.08]
GVA of agriculture	–0.056***	–0.021	–0.100***	–0.093***	–0.135***	–0.107***	–0.076***	0.158**	–0.143**	0.144**	–0.173***	–0.156**
	[–3.73]	[–0.58]	[–3.05]	[–3.17]	[–2.92]	[–3.25]	[–3.15]	[2.04]	[–2.61]	[2.58]	[–2.91]	[–2.64]
GVA of manufacturing	–0.040***	0.018	–0.083*	–0.076**	–0.120**	–0.093**	–0.021	0.088*	–0.046	–0.045	–0.054	–0.050
	[–2.96]	[0.65]	[–2.06]	[–2.12]	[–2.10]	[–2.37]	[–1.45]	[1.91]	[–1.45]	[–1.43]	[–1.34]	[–1.42]
Constant	0.163***	0.393***	0.330***	0.302***	0.462***	0.361***	0.149***	0.367***	0.240***	0.234***	0.277***	0.281***
	[5.01]	[8.50]	[6.42]	[6.41]	[7.22]	[9.58]	[3.67]	[6.17]	[5.87]	[5.91]	[4.88]	[7.98]
R^2	0.903	0.811					0.805	0.373				
Prob > F	0.00	0.00					0.00	0.00				
No. of instruments			19	23	21	21			22	28	25	25
AR(1) – p value			0.001	0.001	0.005	0.000			0.001	0.000	0.001	0.000
AR(2) – p value			0.371	0.359	0.244	0.448			0.114	0.113	0.271	0.188
Hansen Overid. – p value			0.319	0.700	0.331	0.191			0.140	0.326	0.112	0.128

Note. ***,**,*Denote significance at 1%, 5%, and 10% levels, respectively. *t* ratio in brackets. AR(1) and AR(2) are the Arellano–Bond test for autoregressive process of order 1 and 2 in first differences, respectively. “Hansen Overid.” are the Hansen tests of over-identification restrictions.*Source*. Authors’ estimation.

example—usually have less specialized and lower-paying jobs (Barros, Franco, & Mendonça, 2007b). This result highlights the importance of public policies to promote affirmative action and support an educational model that offers skills and opportunities to people from disadvantaged ethnic groups. This research also provides evidence that high disparities in educational attainment have contributed to increase income inequality across Brazilian states. a thing achieved, especially a skill or education.

There is also empirical evidence that an increase in the proportion of formal jobs and government aid to the poor can contribute to reduce income inequality in Brazil. Legislation that promotes job creation in the formal sector and improves work and payment conditions in general should be implemented. Rural pension, government aid to extremely poor families and to people with disabilities will also reduce inequality. Because economic growth seems to disproportionally benefit high-income families, it would be important to consider policies (e.g., tax code)[26] to promote a more fair and equal distribution of the benefits of economic growth in Brazil.

ACKNOWLEDGMENTS

Diogo Signor thanks the CAPES Foundation for financial support and Prêmio CDPP.

CONFLICT OF INTERESTS

None.

ENDNOTES

1 Such as the historical accidents of the Great Depression and wars. See Piketty (2015).

2 For more information about regional inequality in Brazil, see Monteiro Neto (2006).

3 Some recent studies (Medeiros, Souza, & Castro, 2015; Morgan, 2017) show that when different data from household surveys are used to measure inequality such as income tax, the decline in income inequality is not observed in Brazil.

4 The PNAD is conducted in the last quarter of the year by surveying a sample of household units, taken from a master sample, to ensure the data's representativeness of several geographic levels. Most research on income inequality in Brazil uses the PNAD survey. The PNAD started in 1976 and had its coverage increased over the years. Until 1981, the sample was collected only for the Northeast, Southeast, South, and urban areas of the Center-West and North regions of Brazil. After 1981, its coverage was expanded to the countryside of the Center-West, and in 1991 to the state of Tocantins (TO) in the north region. The survey achieved nationwide coverage in 2004. The PNAD survey is not conducted in census years.

5 We use a balanced panel dataset because it improves the results of the model in comparison with the unbalanced panel.

6 This method is used in Marinho and Araujo (2010), Araújo and Marinho (2015), and Santos, Cunha, and Gadelha (2017).

7 The SD is representative of the entire population that is 25 years old and over. Thus, it considers people who are in and out of the labor force. This specification implicitly assumes that education benefits people in and out of the labor force. For example, current retirement benefits of a person out of the labor force might reflect the fact that the individual has a high level of education and worked in a high-paying job when young.

8 The PNAD survey classifies people's ethnicity in more than two categories. To simplify the income categories, Asian and white individuals are taken as one group (white), and brown, Indian, and black people as another group (black).

9 Rural pension (or rural retirement) is a special social security assistance given to people from the rural sector that prove their situation as rural workers, miners or artisanal fishermen. The rural pension program was introduced by the 1988 Brazilian Constitution in response to a situation in which elderly people working in rural areas were not able to retire (Brumer, 2002).

10 This method of estimation is used in Marinho and Araujo (2010).

[11] As in other self-reported domiciliary surveys, the literature suggest that people tend to underreport total income, especially earnings from rent, interests, profits, nonmonetary, and other variable incomes (Barros, Cury, & Ulyssea, 2007; Rocha, 2003). However, the survey data is expected to provide a good approximation of labor and social security incomes (Ramos, 2015).

[12] *Benefício de Prestação Continuada* is a Federal Government income transfer program for people 65 years old and over or for people with disabilities. To apply for this program, household monthly per capita income must be less than a quarter of the current minimum wage (about U.S.$315.00 in October of 2017). Source: <http://www.previdencia.gov.br/servicos-ao-cidadao/todos-os-servicos/beneficio-assistencial-bpc-loas/>.

[13] *Programa Bolsa Família* is a Federal Government income transfer program for families living in poverty and extreme poverty situations. The program aims to ensure food and education access to households with monthly per capita income less than R$85.00 (Brazilian Real), considered to be extremely poor families. Households with monthly per capita income less than R$170.00, considered poor, can apply if they have children (the values were approximately U.S.$30.00 and U.S.$54.00 in October of 2017). Source: <http://www.caixa.gov.br/programas-sociais/bolsa-familia/Paginas/default.aspx>.

[14] Silva and Silva (2011) find that differences in labor income concentration between economic sectors and the contribution among them lead to a reduction of income inequality.

[15] $E(\mu_{it}\Delta y_{i,t\text{-}1}) = 0$, for $t = 4,5,\ldots,T$, and $E(\mu_{i3}\Delta y_{i2}) = 0$.

[16] Roodman (2009) finds that the Sargan test statistic is inconsistent with a robust one stage GMM estimation, as used in this work. Thus, in that case, a theoretically superior overidentification test is the one based on the Hansen statistic. For this reason, we will not present the Sargan test in the analysis.

[17] A set of measures taken in 1994 to stabilize the Brazilian economy.

[18] It is recommended to use time dummies in system GMM models to control for time-related shocks (Roodman, 2009). However, the use of time dummies with a relatively small panel size causes two problems. First, there is a significant collinearity between the time dummies and other variables used in the model, which affects the estimates and increase standard deviations. Second, the proliferation of instruments when using time dummies affect the validity of the instruments of the model (Roodman, 2008).

[19] Economic cycle periods defined by the *Comitê de Datação de Ciclos Econômicos*-IBRE/CODACE. Available at http://portalibre.fgv.br/main.jsp?lumChannelId=4028808126B9BC4C0126BEA1755C6C93.

[20] The Variance Inflation Factor (VIF) test for the PBF variable is 10.48 when including BPC and RP in the same equation, dropping to 4.97 when not.

[21] See: Eckland (1968) and Kalmijn (1994).

[22] Although Model 4 does not present statistical significance at 10% level for this estimate, its p value is close to it at 11.6%.

[23] Rubin and Segal (2015) present two reasons for top incomes to be more sensitive to growth. First, wealth income is responsible for a large share of the total income for top income groups, which is more sensitive to growth than labor income. Second, the top income groups tend to have occupations that pay in the form of pay-for-performance, which is also sensitive to growth.

[24] “With gaps” and “Contin.” are the column names in Table 4.

[25] This result may be due to the difference in the observations from 2009 to 2011 that reduces the impact of a “persistence effect” without a middle value.

[26] As suggested in Piketty and Saez (2006).

ORCID

Diogo Signor https://orcid.org/0000-0003-0979-2342
Edinaldo Tebaldi https://orcid.org/0000-0003-3670-3245
Jongsung Kim https://orcid.org/0000-0002-7336-2921

REFERENCES

Andersson, M., & Palacio, A. (2017). Structural change and the fall of income inequality in Latin America: Agricultural development, inter-sectoral duality, and the Kuznets curve. In L. Bértola & J. Williamson (Eds.), *Has Latin American inequality changed direction?* Cham, Switzerland: Springer Open.

Araújo, J. A., & Marinho, E. (2015). Estudo sobre a desigualdade de renda e seus determinantes no brasil [Study on income inequality and its determinants in Brazil]. *Revista de Políticas Públicas*, *19*(2), 565–574.

Arellano, M. (2003). *Panel data econometrics*. Oxford, U.K.: Oxford University Press.

Arellano, M., & Bond, S. (1991). Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. *Review of Economic Studies*, *58*(2), 277–297.

Arellano, M., & Bover, O. (1995). Another look at the instrumental variable estimation of error components models. *Journal of Econometrics*, *68*(1), 29–51.

Barbosa, R. J. (2016). Desigualdade de Rendimentos do Trabalho no Curto e no Longo Prazo: Tendências de Idade, Período e Coorte [Labor income inequality in the short and long-term: Age, period and cohort trends]. *Revista de Ciências Sociais, Rio de Janeiro*, *59*(2), 385–425.

Barreto, F. A. F. D., Jorge Neto, P. M., & Tebaldi, E. (2001). Desigualdade de renda e crescimento econômico no nordeste brasileiro [Income inequality and economic growth in the Northeast of Brazil]. *Revista Econômica do Nordeste, Fortaleza*, *32*(Special Issue), 842–859.

Barros, R. P., Carvalho, M., Franco, S., & Mendonça, R. (2007). *Determinantes imediatos da queda da desigualdade brasileira* [*Immediate determinants of the fall of Brazilian income inequality*] (Texto para discussão, No. TD 1253). Rio de Janeiro, Brazil: Instituto de Pesquisa Econômica Aplicada (IPEA).

Barros, R. P., Cury, S., & Ulyssea, G. (2007). A desigualdade de renda no Brasil encontra-se subestimada? Uma análise comparativa usando Pnad, POF e Contas Nacionais. In R. P. Barros, M. N. Foguel & G. Ulyssea (Eds.), *Desigualdade de renda no Brasil: uma análise da queda recente* [*Income Inequality in Brazil: An analysis of the recent decline*]. Brasília, Brazil: IPEA.

Barros, R. P., Foguel, M. N., & Ulyssea, G (Eds.). (2006). *Desigualdade de renda no Brasil: uma análise da queda recente* [*Income Inequality in Brazil: An analysis of the recent decline*] (Vol. *1*). Brasília, Brazil: IPEA.

Barros, R. P., Foguel, M. N., & Ulyssea, G (Eds.). (2007). *Desigualdade de renda no Brasil: uma análise da queda recente* [*Income Inequality in Brazil: An analysis of the recent decline*] (Vol. *2*). Brasília, Brazil: IPEA.

Barros, R. P., Franco, S., & Mendonça, R. (2007a). *A recente queda da desigualdade de renda e o acelerado progresso educacional brasileiro da última década* [*The recent fall of income inequality and the accelerated Brazilian educational progress of the last decade*] (Texto para discussão, No. TD 1304). Rio de Janeiro, Brazil: IPEA.

Barros, R. P., Franco, S., & Mendonça, R. (2007b). *Discriminação e segmentação no mercado de trabalho e desigualdade de renda no Brasil* [*Discrimination and segmentation in the labor market and income inequality in Brazil*] (Texto para discussão, No. TD 1288). Rio de Janeiro, Brazil: IPEA.

Barros, R. P., & Mendonça, R. S. P. (1995). *Os determinantes da desigualdade no Brasil* [*The determinants of inequality in Brazil*] (Texto para Discussão, No. TD 0377). Brasília, Brazil: IPEA.

Becker, G. S. (1994). Human capital revisited. In *Human capital: A theoretical and empirical analysis with special reference to education* (3rd ed., pp. 15–28). Chicago, IL: University of Chicago Press.

Blundell, R., & Bond, S. (1998). Initial conditions and moment restrictions in dynamic panel data models. *Journal of Econometrics*, *87*(1), 115–143.

Blundell, R., Bond, S., & Windmeijer, F. (2000). Estimation in dynamic panel data models: Improving on the performance of the standard GMM estimator. In B. Baltagi (Ed.), *Advances in econometrics, nonstationary panels, panel cointegration, and dynamic panels* (Vol. *15*, pp. 53–91). Amsterdam: JAI Elsevier Science.

Bond, S. R. (2002). Dynamic panel data models: A guide to micro data methods and practice. *Portuguese Economic Journal*, *1*(2), 141–162.

Brito, A., Foguel, M., & Kerstenetzky, C. (2017). The contribution of minimum wage valorization policy to the decline in household income inequality in Brazil: A decomposition approach. *Journal of Post Keynesian Economics*, *40*(4), 540–575.

Brumer, A. (2002). Previdência social rural e gênero [Rural security and gender]. *Sociologias*, *2002*(7), 50–81.

Clifton, J., Díaz-Fuentes, D., & Revuelta, J. (2017). Fiscal policy and inequality in Latin America, 1960–2012. In L. Bértola & J. Williamson (Eds.), *Has Latin American inequality changed direction?* Cham, Switzerland: Springer Open.

Cruz, P. B., Teixeira, A., & Monte-Mor, D. S. (2015). O efeito da desigualdade da distribuição de renda no crescimento econômico [The effect of inequality of income distribution on economic growth]. *Revista Brasileira de Economia*, *69*(2), 163–186.

Eckland, B. K. (1968). Theories of mate selection. *Biodemography and Social Biology*, *15*(2), 71–84.

Fernandes, C. B. S., M. S. Cunha, & M. R. Vasconcelos (2018). Impactos da política fiscal na desigualdade da distribuição de renda: uma análise para as unidades da federação brasileiras [Impacts of the fiscal policy on the inequality of income distribution: An analysis for income inequality]. *Annals of the XXI Encontro Regional de Economia da Região Sul*. Curitiba: ANPEC.

Ferreira, F. H. G. (2000). Os determinantes da desigualdade de renda no Brasil: luta de classes ou heterogeneidade educacional? [The determinants of income inequality in Brazil: Class struggle or educational heterogeneity?] In R. Henriques (Ed.), *Desigualdade e pobreza no Brasil* [*Inequality and Poverty in Brazil*] (pp. 131–158). Rio de Janeiro, Brazil: IPEA.

Ferreira, F. H. G., Leite, P. G., Litchfield, J. A., & Ulyssea, G. (2006). Ascensão e queda da desigualdade de renda no brasil [Rise and fall of income inequality in Brazil]. *Econômica, Rio de Janeiro*, *8*(1), 147–169.

Hoffmann, R. (2006). Transferências de renda e a redução da desigualdade no Brasil e cinco regiões entre 1997 e 2004 [Income transfer and the reduction of inequality in Brazil and five regions between 1997 and 2004]. *Econômica, Rio de Janeiro*, *8*(1), 55–81.

Kalmijn, M. (1994). Assortative mating by cultural and economic occupational status. *American Journal of Sociology*, *100*(2), 422–452.

Koshiyama, D., & Fochezatto, A. (2012). Crescimento econômico e desigualdade de renda no Brasil: uma análise de causalidade de Granger com dados em painel [Economic growth and income inequality in Brazil: An analysis of Granger causality with panel data]. *Revista Brasileira de Estudos Regionais e Urbanos*, *6*(2), 36–47.

López-Calva, L. F., & Lustig, N. (2010). Explaining the decline in inequality in Latin America: Technological change, educational upgrading and democracy. In L. F. López-Calva & N. Lustig (Eds.), *Declining Inequality in Latin America: a decade of progress* (pp. 1–24). Washington, D.C.: Brookings Institution.

López-Calva, L. F., Lustig, N., & Ortiz-Juarez, E. (2013). *Deconstructing the decline in inequality in Latin America* (Policy Research Working Paper No. 6552). Washington, D.C.: World Bank.

Marinho, E., & Araujo, J. (2010). Pobreza e o sistema de seguridade social rural no Brasil [Poverty and the rural social security system in Brazil]. *Revista Brasileira de Economia*, *64*(2), 161–174.

Medeiros, M., Souza, P. H. G. F., & Castro, F. Á. (2015). A estabilidade da desigualdade de renda no brasil, 2006 a 2012: Estimativa com dados do imposto de renda e pesquisas domiciliares [The stability of income inequality in Brazil, 2006 to 2012: Estimate with income tax data and household surveys]. *Ciência & Saúde Coletiva*, *20*(4), 971–986.

Monteiro Neto, A. (2006). *Intervenção estatal e desigualdades regionais no Brasil: contribuições ao debate contemporâneo* [*State intervention and regional inequalities in Brazil: Contributions to the contemporary debate*] (Texto para Discussão, No. TD 1229). Brasilia, Brazil: IPEA.

Morgan, M. (2017) *Extreme and persistent inequality: New evidence for Brazil combining national accounts, surveys and fiscal data, 2001–2015* (Working Paper 2017/12). Paris, France: World Wealth & Income Database.

Nakaguma, M. Y., & Bender, S. (2006). A emenda da reeleição e a lei de responsabilidade fiscal: Impactos sobre ciclos políticos e performance fiscal dos estados (1986–2002) [The amendment of the reelection and the Law of Fiscal Responsibility: Impacts on political cycles and fiscal performance of the states (1986–2002)]. *Revista de Economia Aplicada*, *10*(3), 377–397.

Persson, T., & Tabellini, G. (2003). *Do electoral cycles differ across political systems?* (IGIER Working Paper No. 232). Milan, Italy: IGIER, Bocconi University.

Piketty, T. (2015). *The economics of inequality* (3rd ed.). Cambridge, MA: Harvard University Press.

Piketty, T., & Saez, E. (2006). The evolution of top incomes: A historical and international perspective. *American Economic Review*, *96*(2), 200–205.

Ramos, C. A. (2015). A queda da pobreza e da concentração de renda no brasil. “À la recherche” da teoria perdida [The fall of poverty and income concentration in Brazil: “À la recherche” of the lost theory]. *Nova Economia*, *25*(3), 599–620.

Ramos, L., & Vieira, L. (2001). *Desigualdade de rendimentos no Brasil nas décadas de 80 e 90: Evolução e principais determinantes* [*Income inequality in Brazil in the 80s and 90s: Evolution and the main determinants*] (Texto para discussão No. TD 803). Rio de Janeiro, Brazil: IPEA.

Ravallion, M. (2004). *Pro-poor growth: A primer* (Policy Research Working Paper No. 3242). Washington, D.C.: World Bank.

Rocha, S. (2003). *Pobreza no Brasil: afinal, de que se trata?* [Poverty in Brazil: After all, what is it about?]. Rio de Janeiro: Editora FGV.

Roodman, D. (2008). *A note on the theme of too many instruments* (Working Paper No. 125). Washington, D.C.: Center for Global Development.

Roodman, D. (2009). How to do xtabond2: An introduction to difference and system GMM in Stata. *Stata Journal*, *9*(1), 86–136.

Rubin, A., & Segal, D. (2015). The effects of economic growth on income inequality in the US. *Journal of Macroeconomics*, *45*, 258–273.

Sakurai, S. N. (2009). Ciclos políticos nas funções orçamentárias dos municípios brasileiros: Uma análise para o período 1990–2005 via dados em painel [Political cycles in the budgetary functions of Brazilian municipalities: An analysis for the period 1990–2005 via panel data]. *Estudos Econômicos*, *39*(1), 39–58.

Santos, M. P., Cunha, M. S., & Gadelha, S. R. B. (2017). Distribuição de renda e desenvolvimento econômico: Análise da hipótese de kuznets para os estados brasileiros no período 1992–2010 [Income distribution and economic development: Analysis of Kuznets hypothesis for Brazilian states in the period 1992–2010]. *Revista Brasileira de Estudos Regionais e Urbanos*, *11*(2), 251–271.

Silva, F. J. F., & Silva, M. A. (2011). Desigualdade de renda no trabalho dos setores da economia brasileira, nordestina e pernambucana [Inequality in the labor income of the Brazilian, northeast and Pernambucan economic sectors]. *Economia e Desenvolvimento*, *10*(2), 36–54.

Simson, R. (2018). *Mapping recent inequality trends in developing countries* (Working Paper No. 24). London, U.K.: LSE International Inequalities Institute.

Soares, F. V., Soares, S. S., Medeiros, M., & Osório, R. G. (2006). *Cash transfers programmes in Brazil: Impacts on inequality and poverty* (Working Paper No. 21). Brasilia, Brazil: International Poverty Center, UNDP.

Soares, S. S. D. (2006). Análise de bem-estar e decomposição por fatores da queda na desigualdade entre 1995 e 2004 [Analysis of welfare and decomposition by factors of the fall in inequality between 1995 and 2004]. *Econômica*, *8*(1), 83–115.

UNDP. (2018). *Human development indices and indicators*. Washington D.C.: United Nations Development Programme.

How to cite this article: Signor D, Kim J, Tebaldi E. Persistence and determinants of income inequality: The Brazilian case. *Rev Dev Econ*. 2019;00:1–20. https://doi.org/10.1111/rode.12598

APPENDIX

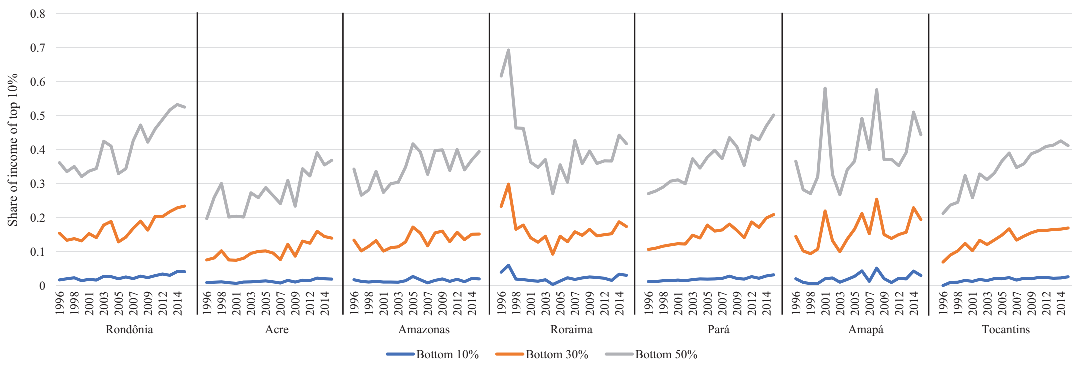

FIGURE A1 Income inequality in North Region, 1996–2015 (income share of top 10%)[a]

Note. [a]Except the state of Tocantins, the states of North region do not have data for the rural area until 2004

Source. Authors' estimation using data from PNAD.

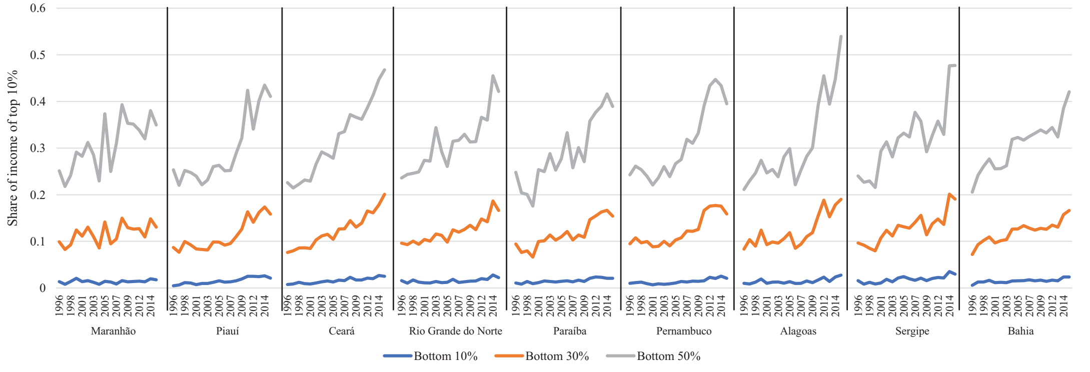

FIGURE A2 Income inequality in Northeast Region, 1996–2015 (income share of top 10%)

Source. Authors' estimation using data from PNAD.

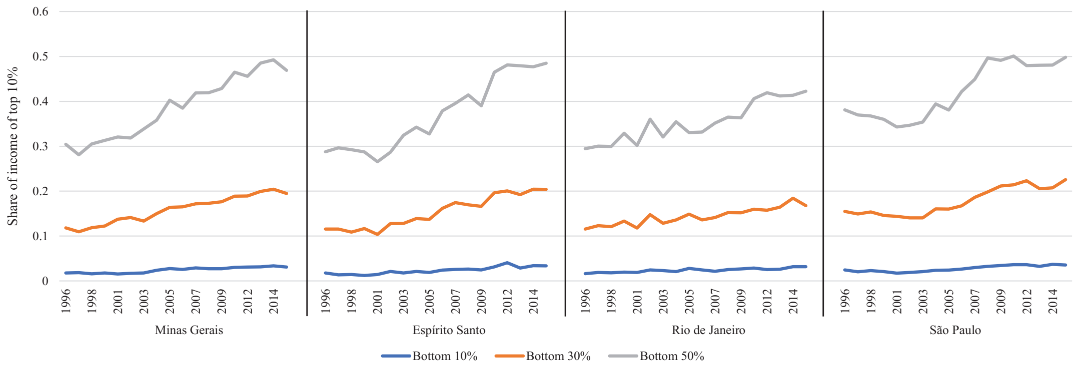

FIGURE A3 Income inequality in Southeast Region, 1996–2015 (income share of top 10%)
Source. Authors' estimation using data from PNAD.

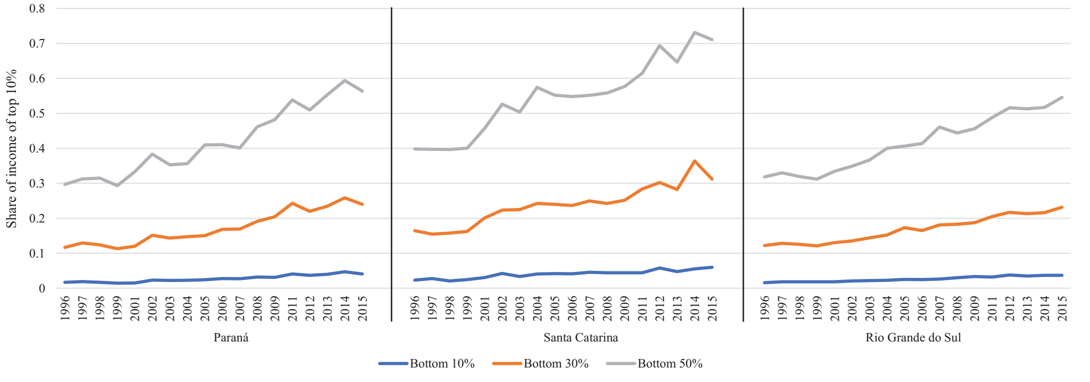

FIGURE A4 Income inequality in South Region, 1996–2015 (income share of top 10%)
Source. Authors' estimation using data from PNAD.

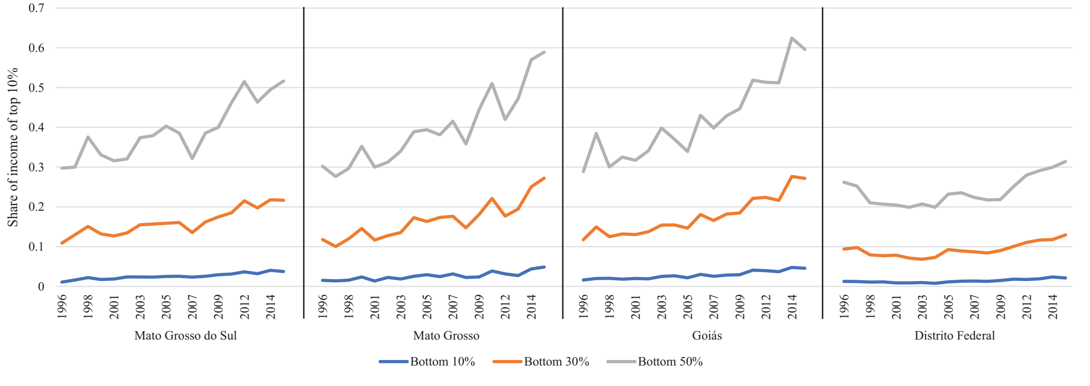

FIGURE A5 Income inequality in Center-West Region, 1996–2015 (income share of top 10%)
Source. Authors' estimation using data from PNAD.