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Poverty and economic development: Evidence for the Brazilian states

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Abstract

In the present study, our primary concern is to examine the effects of poverty on economic development across the Brazilian States from 1980 to 2015. Many studies assess the effects of economic growth and economic development on poverty incidence, but there is almost no one trying to measure the impact of poverty prevalence on economic development. The results of this paper indicate that poverty incidence is essential in the economic development of the Brazilian States. Poorer Brazilian States have lower income per worker even when controlling for investment in physical capital, human capital stock, and the effective depreciation of capital. The results point to the variables measuring extreme poverty as having more influence on the economic development of the Brazilian States in relation to the variables quantifying poverty.

JEL classification: O11; O15; R58; C23

Keywords: Poverty incidence; Economic development; Brazilian states

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1. Introduction

Poverty is a central concern to policymakers since its incidence is directly related to population welfare (Chen and Ravallion, 2013). Variables commonly pointed as relevant to reduce poverty are income growth and economic development, but there is no prevailing consensus in this debate. Deaton and Kozel (2005) highlighted critical features of this debate after the 1990s reforms in India. The source of this debate was related mainly to data collection from different sample surveys on mean consumption and the National Accounts.

Nevertheless, several studies point to the importance of economic growth in poverty reduction in the case of India. For example, based on district level per capita income data, Banerjee et al. (2015) found that growth in different regions and sectors of India has helped to reduce poverty rates. The authors' results established that income growth in agriculture was essential to reduce poverty in India from 1999–2000 to 2005–2006. Datt et al. (2016) found that the Indian economic growth after the 1990s reforms was important to reduce poverty. Their study was based on a new poverty dataset from 1957 to 2012, which was compiled by them.

Focusing on Sub-Saharan African countries, Fosu (2015) found that economic growth played a crucial role in diminishing poverty incidence. In addition, income inequality is relevant in poverty incidence since a decrease in

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income inequality reduces poverty holding constant the country's income level. Besides the vast number of studies measuring the consequences of economic growth and development on poverty, almost no attention has been given to the effects of the latter on development. One of the few studies focusing on the impact of poverty on economic growth is that of [Ravallion \(2012\)](#). His paper's results indicate that countries with a higher initial incidence of poverty tend to experience lower subsequent rate of economic growth.¹

There are at least three important channels in which poverty incidence may influence economic development. First, the population living in poverty are more susceptible to malnourishment, which affects child development. [Hanson et al. \(2013\)](#) examined changes in the human brain structure from birth to the toddler years (from 5 months to four years of age) based on two hundred and three MRI scans in the United States. Through the Random Effect method, the authors found that children from poor and near-poor socioeconomic status families have lower brain total gray matter volumes compared to those from high socioeconomic status families. They argue that brain gray matter is critical for processing information and executing actions. Therefore, children with less gray matter volume are more predisposed to having difficulty at school and, consequently, they accumulate less human capital.

Moreover, the incidence of poverty may be related to resource misallocation, which increases inefficiency. Even if malnourishment did not affect children's brain formation, poverty is likely to increase resource misallocation through inequality of opportunities. For instance, in regions where a considerable portion of the population lives in poverty, some people with high learning potential are never going to benefit from it. This can occur because they will probably not have the opportunity to attend good schools, to have parents with a good education to help them with homework, and so on. Additionally, as reported by Hart and Risley (1995, cited in [Hanson et al., 2013](#)), "... low-income parents speak less often and in less sophisticated ways to their young children, and are less likely to engage jointly with their children in literary activities such as reading aloud or visiting the library, compared to middle-income parents". (pp. 1–2).

Finally, a reduction in poverty may diminish fertility rate ([Sinding, 2009](#)). A decline in fertility rate has the potential to affect income positively in impoverished regions. For example, [Ashraf et al. \(2013\)](#) found that shifting Nigeria from the United Nations medium-fertility to the low-fertility population projection would increase income per capita by 5.6% at a horizon of 20 years, and by 11.9% at a time span of 50 years. These estimations were based on a demographic-economic simulation model in which fertility can be exogenously altered.

With this background, the present paper's goal is to analyze the impact of poverty incidence on the Brazilian States income per worker from 1980 to 2015. The latter is our measure of each state's economic development level. To the author's knowledge, there is no such kind of study with an aggregate dataset. Four measures of poverty incidence were used in the empirical analysis. Two of them are to evaluate extreme poverty (proportion of individuals living in extreme poverty — PIEP, and proportion of households living in extreme poverty — PHEP). The other two are measures of poverty (proportion of individuals living in poverty — PIP, and the percentage of households living in poverty — PHP). The use of two measures of poverty incidence – the proportion of poverty and extreme poverty – is to check if poverty incidence and severity are relevant to income per worker determination.

In the Fixed Effects (FE) estimations with robust standard errors, a 10% increase in poverty prevalence would lead to a decrease in income per worker from 1.34% to 1.64%, depending on the poverty indicator used as a regressor. The estimated coefficients are significant even after controlling for human capital stock, investment in physical capital, and effective depreciation of capital. In the Arellano-Bond estimates to deal with the reverse causality problem, the estimated coefficients of the extreme poverty incidence indexes suggest that a 10% increase in their prevalence would lead to a negative impact on income per worker from 0.89% to 2.15%. In general, the results indicate that the extreme poverty indicators have a more deleterious influence on income per worker than the poverty indicators.

Because poverty hurts economic development, public policies designed to reduce its prevalence in the Brazilian States have the potential to promote economic growth and to raise the welfare of those who need it the most. Also, some studies support the idea that poverty incidence generates negative externalities, as in [Galster et al. \(2008\)](#). Therefore, the present study gives support to the adoption of public policies designed to reduce poverty, but it does not discuss the proper public policies to be adopted with this aim.

¹ In the present study, our focus is only on the level of income per worker and not on its growth rate. Following the reasoning of the theoretical model in the next section, it makes more sense to measure the effects of poverty incidence on the level of economic development.

Besides this introduction and the conclusions, the present paper is structured into five sections. The second section introduces the theoretical model that is the base for the specification to be tested empirically. The third section describes the estimation methods with a brief explanation of their adequacy to the current study. In the following section, the dataset and its sources are shown. Finally, the fifth section presents the econometric results, starting with the Ordinary Least Square (OLS) and Fixed Effect (FE) estimates, followed by the Dynamic Panel Data (DPD) results.

2. The theoretical model

In this section, we follow [Mankiw et al. \(1992\)](#)'s theoretical model to set the relationship between the variables of interest. The production function is as following:

$$Y_{i,t} = K_{i,t}^\beta H_{i,t}^\alpha (A_{i,t} L_{i,t})^{1-\alpha-\beta} \tag{1}$$

where K_t , H_t , and L_t are the levels of physical and human capitals and labor employed in the production process at time t , while α , β , and $1 - \alpha - \beta$ are human capital, physical capital and labor participation on income, respectively. As in [Mankiw et al. \(1992 or MRW\)](#), we assume that $0 < \alpha < 1$; $0 < \beta < 1$; and $0 < \alpha + \beta < 1$. Dividing both sides of Eq. (1) by effective units of labor:

$$\hat{y}_{i,t} = \hat{k}_{i,t}^\beta \hat{h}_{i,t}^\alpha \tag{2}$$

In the above equation, $\hat{y} = Y/AL$, $\hat{k} = K/AL$, and $\hat{h} = H/AL$. Using the same assumptions as [Solow \(1956\)](#), the evolution of these two production factors can be shown as:

$$\dot{\hat{k}}_{i,t} = s_{ki,t} \hat{y}_{i,t} - (\delta + n_{i,t} + g) \hat{k}_{i,t} \tag{3a}$$

$$\dot{\hat{h}}_{i,t} = s_{hi,t} \hat{y}_{i,t} - (\delta + n_{i,t} + g) \hat{h}_{i,t} \tag{3b}$$

In Eqs. (3a) and (3b), s_k and s_h are the fraction of income invested in physical and human capital, and the dot corresponds to time differential. The growth rate of the working population is measured by n ; while g represents the rate of technological progress. Physical and human capital depreciation rates are assumed to be the same, and they are represented by δ as in [MRW \(1992\)](#). In the steady state, Eqs. (3a) and (3b) are equal to zero, with the following solutions:

$$\hat{k}_{i,t}^* = \left(\frac{s_{ki,t}^{1-\alpha} s_{hi,t}^\alpha}{\delta + n_{i,t} + g} \right)^{1/1-\alpha-\beta} \tag{4a}$$

$$\hat{h}_{i,t}^* = \left(\frac{s_{ki,t}^\beta s_{hi,t}^{1-\beta}}{\delta + n_{i,t} + g} \right)^{1/1-\alpha-\beta} \tag{4b}$$

The superscript * denotes that the variable under consideration is in the steady state. Substituting both equations into (2) and taking natural logarithms, we have:

$$\ln \hat{y}_{i,t}^* = \left(\frac{\beta}{1 - \alpha - \beta} \right) \ln (s_{ki,t}) + \left(\frac{\alpha}{1 - \alpha - \beta} \right) \ln (s_{hi,t}) - \left(\frac{\alpha + \beta}{1 - \alpha - \beta} \right) \ln (\delta + n_{i,t} + g) \tag{5}$$

Or, in terms of output per unit of labor (remember that $\ln (\hat{y}_t) = \ln y_t - \ln A_t$),

$$\ln y_{i,t}^* = \ln A_{i,t} + \left(\frac{\beta}{1 - \alpha - \beta} \right) \ln (s_{ki,t}) + \left(\frac{\alpha}{1 - \alpha - \beta} \right) \ln (s_{hi,t}) - \left(\frac{\alpha + \beta}{1 - \alpha - \beta} \right) \ln (\delta + n_{i,t} + g) \tag{6}$$

Output per unit of labor is $y = Y/L$, and y^* represents the steady-state output per unit of labor. It is assumed that g and δ are constant across the Brazilian States. A_t does not stand only for technology, but also resources endowment, climate, institutions, inefficiency, and so on. When estimated, this term is also known as Total Factor Productivity (TFP). Following MRW, but considering that poverty was in the error term, it is possible to represent productivity as:

$$\ln A_{i,t} = a_i + \lambda \ln (p_{i,t}) + \varepsilon_{i,t} \tag{7}$$

where a_i is a specific and constant state effect, p_i is the state poverty incidence and ε stands for the Brazilian States' specificities. The proportion of poverty increases inefficiency since it fosters resources misallocation among other channels, as argued previously. Therefore, λ is expected to be negative ($\lambda < 0$). Replacing Eq. (7) with (6):

$$\ln(y_{i,t}^*) = a_i + \left(\frac{\beta}{1-\alpha-\beta}\right) \ln(s_{ki,t}) + \left(\frac{\alpha}{1-\alpha-\beta}\right) \ln(s_{hi,t}) - \left(\frac{\alpha+\beta}{1-\alpha-\beta}\right) \ln(\delta + n_{i,t} + g) + \lambda \ln(p_{i,t}) + \varepsilon_{i,t} \quad (8)$$

This equation is employed by MRW (1992) in the empirical analysis. However, our measure of human capital is more closely related to stock rather than investment. In this case, we can use Eq. (4b) to find:

$$\ln(s_{hi,t}) = \left(\frac{1-\alpha-\beta}{1-\beta}\right) \ln(\hat{h}_{i,t}) - \left(\frac{\beta}{1-\beta}\right) \ln(s_{ki,t}) + \left(\frac{1}{1-\beta}\right) \ln(\delta + n_{i,t} + g) \quad (9)$$

Replacing (9) with (8) and considering that $\ln(\hat{h}_{i,t}) = \ln(h_{i,t}) - a_i - \lambda \ln(p_{i,t}) - \varepsilon_{i,t}$:

$$\ln(y_{i,t}^*) = \eta a_i + \left(\frac{\beta}{1-\beta}\right) \ln(s_{ki,t}) + \left(\frac{\alpha}{1-\beta}\right) \ln(h_{i,t}^*) - \left(\frac{\beta}{1-\beta}\right) \ln(\delta + n_{i,t} + g) + \eta \lambda \ln(p_{i,t}) + \varepsilon'_{i,t} \quad (10)$$

where $\eta = (1-\alpha-\beta)/(1-\beta)$ and $\varepsilon' = \eta\varepsilon$. Because of the restrictions on α and β – both being strictly positive and $0 < \alpha + \beta < 1$ –, it follows that $\eta > 0$. Since λ is expected to be negative; as reasoned previously, Eq. (10) gives the predicted sign of each right-hand side variable on income per worker. Investments in physical and human capitals are expected to have a positive influence on the regressand, while the effective depreciation of capital and poverty incidence should have the opposite sign. Eq. (10) is an effort to introduce one fundamental determinant of the long-run dynamism on the standard neoclassical economic growth model instead of looking only at its proximate causes. If poverty prevalence is relevant in TFP determination, it is also crucial to understand Brazilian long-run dynamism, because TFP is one of the variables with the highest impact on income per worker evolution in Brazil, as suggested by the results of Barbosa filho et al. (2010), Ferreira et al. (2008), Bacha and Bonelli (2005), and Gomes et al. (2003). For the Brazilian States, Figueiredo and Nakabashi (2016), Bonelli and Levy (2010), and Tavares et al. (2001) reach similar results.

3. Estimation methods

Following Islam (1995), the panel data method is better than Ordinary Least Squares (OLS): “panel data framework provides a better and more natural setting to control for this technology shift term ε ” (1995, pp. 1134–35). This methodology provides a better tool to deal with differences in preferences, technology, and other unobservable variables across regions which are difficult to measure, i.e., it accounts for individual heterogeneity. Because these units of analysis specification are no longer in the error term, they are less likely to be correlated with some of the explanatory variables (Islam, 1995). In the panel data framework, one should decide between Fixed and Random Effects. Following Eq. (10), a_i is a dummy variable capturing each of the Brazilian States specificities. Therefore, this method assumes that a constant term for each cross-sectional unit captures differences in the Brazilian States that are constant through time – Fixed Effect method (FE). In the Random Effects method (RE) based on (10), we would have:

$$\ln(y_{i,t}^*) = \eta a_i + \left(\frac{\beta}{1-\beta}\right) \ln(s_{ki,t}) + \left(\frac{\alpha}{1-\beta}\right) \ln(h_{i,t}^*) - \left(\frac{\beta}{1-\beta}\right) \ln(\delta + n_{i,t} + g) + \eta \lambda \ln(p_{i,t}) + u_i + \varepsilon'_{i,t} \quad (11)$$

The term u_i is the between error term, i.e., the random disturbance characterizing the i th observation. The main drawback of this approach is the assumption that the individual effects are uncorrelated with the regressors. Because our primary motivation to use panel-data estimation method is that the individual effects may be correlated with the regressors, FE seems to be the most appropriate. Furthermore, the estimated coefficients of the FE method cannot be

biased because of omitted time-invariant features. However, the FE estimator does not deal with the causality problem. Since the incidence of poverty in the Brazilian States is likely to be affected by their income per worker, as discussed in the introduction, the reverse causality problem is a major concern that must be addressed in the empirical analysis.

Holtz-eakin et al. (1988) and Arellano and Bond (1991) developed the Dynamic Panel Data (DPD) models to deal with the dynamic of the explained variable from one period to the next using the lagged dependent variable as a regressor to allow for a partial adjustment mechanism. Moreover, this method is also adequate to deal with unobserved heterogeneity (Baum, 2014). Since income per worker is persistent through time, it is essential to consider this adjustment mechanism in the estimations. Furthermore, DPD models are adequate to deal with the reverse causality problem since it uses external instruments in addition to the lagged levels of the endogenous regressors as instruments. This method is adequate for panels with large cross-sectional data and small-time series (Roodman, 2006). Therefore, it is adequate to our dataset since $n = 26$ and $T = 8$. Adding one lag of the dependent variable into Eq. (10), we have:

$$\ln(y_{i,t}^*) = \eta a_i + \rho \ln(y_{i,t-1}^*) + \left(\frac{\beta}{1-\beta}\right) \ln(s_{ki,t}) + \left(\frac{\alpha}{1-\beta}\right) \ln(h_{i,t}^*) - \left(\frac{\beta}{1-\beta}\right) \ln(\delta + n_{i,t} + g) + \eta \lambda \ln(p_{i,t}) + \varepsilon'_{i,t} \quad (12)$$

To deal with time-invariant units characteristics, the Arellano–Bond (1991) estimator uses the variables in difference since this procedure removes the constant term and the fixed unit-specific effect. The Generalized Method Moments (GMM) is used to estimate the parameters of the model, allowing for more efficient estimates of the Dynamic Panel Data model (Baum, 2014). Adding the lagged levels of the endogenous regressors as instruments turns them into pre-determined variables and, consequently, they become not correlated with the error term in Eq. (12).

Another advantage of the DPD estimation method is that it does not require, but allows for the use of external instruments that enter only in the first stage beside the lagged endogenous variables (Arellano–Bond, 1991). In the present study, we have used the Arellano — Bond Difference GMM estimator with the Stata software through Roodman (2006)'s algorithm with the finite-sample two-step estimation, since it corrects for panel-specific autocorrelation and heteroskedasticity, but the standard errors are downward biased. Therefore, to fix this problem, it is necessary to implement the two-step robust command developed by Roodman (2006) based on Windmeijer (2005). The correction makes use of a first order Taylor series expansion generating an additional term that can be used to correct for the standard errors extra variation in small samples, leading to a more accurate inference in finite samples (Windmeijer, 2005).

4. The variables and sources

The data is available for all Brazilian States from 1980 to 2015 every five years for the 26 Brazilian States,² except for the state of Tocantins in three years. The output (Y) is the state GDP at 2000 constant prices (R\$ thousand) from the Regional Accounts System of the Geography and Statistic Brazilian Bureau (IBGE). The occupied population was used for the calculation of GDP per worker (y_i) – our measure the Brazilian States economic development –, and it was elaborated by the Institute of Applied Economic Research (IPEA) based on the National Households Survey Sample (PNAD/IBGE).³ The *proxy* for the quantity of human capital is based on the average years of schooling for the population over 25 from IPEA. Following Mincer (1974) as suggested by Bils and Klenow (2000), the human capital per worker is a function of the educational return average rate (ϕ) and years of schooling (s) as in the following equation:

$$h = e^{\phi(s)} \quad (13)$$

The educational return average rate was set at 15% per additional year ($\phi = 0.15$) based on several studies for the Brazilian Labor Market. For example, Suliano and Siqueira (2012) found that the wage average return of one extra year of schooling in the Northeast and Southeast regions of Brazil were 16% in the former and 13% in the latter based on

² The Brazilian Federal District was not included in the analysis since its income is highly influenced by the government sector. Therefore, its income might have a different dynamic in relation to the Brazilian States.

³ It was considered as occupied or employed the person who worked in the last 12 months preceding the census reference date, or part of it.

the PNAD/IBGE database from 2001 to 2006. Resende and Wyllie (2006) estimated that the return of education was from 15.9 to 17.4% for men, and from 12.6 to 13.5% for women, based on the Research on Living Standards dataset (PPV-IBGE, 1996–1997). Sachsidia et al. (2004) found that the return of an additional year of schooling was between 12.9 and 16% for the 1992–1999 period. Based on the 1998 PNAD/IBGE, Loureiro and Carneiro (2001) estimated that the educational return for urban men was 18.58%, while for rural men it was 11.35%. For women, the respective values were 23.32 and 18.06%. Nakabashi and Assahide (2017) found a somewhat smaller effect of education on wages: from 7.8 to 9.9% considering the 1997–2012 period through the PNAD/IBGE dataset.

As in Caselli (2005) and Hall and Jones (1999), based on estimates from many countries from Psacharopoulos (1994, cited in HALL and JONES, 1999),⁴ we have also considered the following educational return to construct our second measure of human capital (h_2):

$$\phi(s) = \begin{cases} 0.134 & \text{if } s \leq 4 \\ 0.101 & \text{if } 4 < s \leq 8 \\ 0.068 & \text{if } s > 8 \end{cases} \quad (14)$$

Physical capital stocks indicators for Brazil or its states are not readily available. Due to this difficulty, some researchers have constructed their measure of physical capital stock for Brazil, as Morandi (2011), Morandi and Reis (2004), Pinheiro and Matesco (1989), and Doellinger and Bonelli (1987). Figueiredo and Nakabashi (2016) have constructed measures of physical capital stocks for the Brazilian States, but since they are not available for all years of the present study, the total energy consumption in each state minus its total residential consumption was employed as the physical capital *proxy*. The data is from IPEA based on the Brazilian Water and Electric Energy Department, IBGE and the Brazilian Electric Energy Company (EPE).

The effective depreciation of capital is the sum of the technology growth rate (g), the capital depreciation rate (δ) and the occupied population growth rate (n). The first term (g) is the five year-average of income per worker growth rate in Brazil from 1980 to 2015, and it is assumed to be constant across states and through time and equal to 0,90%. The capital depreciation rate (δ) is assumed to be the same rate for human and physical capitals, and constant across states and time. Based on MRW (1992), it is assumed to be equal to 3% per year or 15% in five years. The only part of the effective depreciation of capital that changes across states and through time is the occupied population growth rate (n).

To measure the incidence of poverty in the Brazilian States, the following *proxies* were used: (1) proportion of individuals living in extreme poverty (*PIEP*) according to the level of income required to buy a consumption bundle that provides the minimum calories to nourish a person based on the recommendations of the Food and Agriculture Organization (FAO) and of the World Health Organization (WHO); (2) proportion of individuals living in poverty (*PIP*) according to required calories (double the calories in relation to *PIEP*); (3) proportion of households living in extreme poverty (*PHEP*) according to the household level of income per capita required to buy a consumption bundle that provides the minimum calories to nourish the household members based on the recommendations of FAO and WHO; and (4) proportion of households living in poverty (*PHP*) and it is the double income of *PHEP*. IPEA elaborated them based on the PNAD/IBGE datasets.

Since the poverty incidence indicators were calculated based on samples (PNAD), there is a considerable change in them from one year to the next. Therefore, we have employed their four year-average to smooth the poverty indicators variation. For example, for the Brazilian States, the poverty prevalence indicators for the year of 1980 are represented by their average from 1976 to 1979; for 1985, they are the average for the 1981–1984 period, and so on. The four-year average poverty indicators are represented by *PIP4*, *PIEP4*, *PHP4*, and *PHEP4*.

The proportion of African Brazilians in the states was used as an external instrument for poverty, since in Brazil there is a high correlation between them. The black population in each Brazilian State is from the IBGE censuses. Since they are available every ten years, the proportion of black population for 1985, 1995, 2005, and 2015 was estimated based on the average composed growth rate from one census to the next. Brazilian economic historians argue that after slavery, Brazilian society was not able or willing to integrate the black population in the economy and give them access to land and the same job opportunities in relation to the white population (Gradin, 2009; Araújo, 2000). Fernandes (1968 cited in Lima, 2002) presented evidence from São Paulo municipality that in 1893 (five years after abolition),

⁴ Psacharopoulos, G. (1994). Returns to investment in education: A global update. *World Development*, 22 (9): 1325–1343.

Table 1
Summary statistics — variables in level.

Variable	Obs.	Mean	Std. Dev.	Min	Max
<i>y per worker</i>	207	13.83	5.74	3.95	34.70
<i>s</i>	205	1.04	0.61	0.31	4.36
<i>h1</i>	206	2.28	0.58	1.28	3.92
<i>h2</i>	206	1.92	0.33	1.24	2.51
$\delta + n + g$	208	1.83	0.20	1.37	2.91
<i>PIP4</i>	205	39.73	19.29	4.84	84.39
<i>PIEP4</i>	205	17.67	13.16	1.45	59.65
<i>PHP4</i>	205	33.87	17.82	3.92	79.24
<i>PHEP4</i>	205	14.36	10.89	1.45	51.22
<i>black</i>	208	0.57	0.19	0.08	0.84

y per worker is income per worker, **s** is the average growth rate of physical capital per worker, **h1** is the human capital *proxy* based on the mincerian equation with the educational return average rate of 15% per additional year ($\phi=0.15$), **h2** is the human capital *proxy* based on the mincerian equation with the educational return average based on Hall and Jones (1999) ($\phi=0.134, 0.101, 0.068$), ($\delta + n + g$) is each state effective depreciation of capital. **PHEP4** is the proportion of households living in extreme poverty, **PHP4** is the proportion of households living in poverty, **PIEP4** is the proportion of individuals living in extreme poverty, and **PIP4** is the proportion of individuals living in poverty. All poverty variables represent a four-year average. **Black** is the proportion of the black population.

good job opportunities were filled mainly by white people from the former dominant economic and social groups and by European immigrants.

The worst and less skilled jobs were relegated to the African Brazilian community and their social and economic transition to upper classes was an unusual event. With the inertia of the institutions that marginalized African Brazilians, poverty is higher among them even nowadays. Based on the 2005 Pnad/IBGE dataset, Gradin (2009) offered evidence indicating that African Brazilians accounted for almost half of the population, and about 33% of them lived in poor households (whose incomes were below 50% of the median Brazilian income), while 14% of the white population was in the same situation. The author points to discrimination in the labor market and to the lower educational quality faced by them as crucial elements to understand this situation.

Table 1 presents the summary statistics for the variables used in the empirical analysis. The dataset reveals the discrepancy in income per worker and poverty across the Brazilian States and through time. The highest income per worker state was Amazônia in 1995 (R\$ 34,000.00 in 2000 constant price), while the lowest was Maranhão in the same year. São Paulo had an income per worker ranging from 24.61 to 28 thousand Reais in the period of the study. The average proportion of households living in extreme poverty in the 2011–2014 period was only 1.45% in Santa Catarina, while it was 17.06% in Maranhão. In the period of 1976–1979, it was 51.22% in the latter state and 3.90% in São Paulo.

The natural logarithm of all the above variables were tested for the presence of unit root. We have four methods based on Fisher-type tests through the Phillips–Perron unit-root tests on each panel proposed by Choi (2001). These tests are more flexible than previous tests since they allow for a deterministic trend and one lag of the variable, for a finite or infinite number of groups (countries, regions, firms or individuals) and time series number, different types of stochastic and nonstochastic components for each group, different time series span for the groups, and the alternative where some groups have a unit root and others do not (Choi, 2001). The tests results are in Appendix A (Table A1), and they point that at least one panel is stationary for the natural logarithm of all the variables in Table 1.

5. Estimation results

5.1. OLS and panel data estimates

Table 2 reports the results considering *h1*, i.e., the human capital *proxy* based on a 15% return of an additional year of schooling on wage. As suggested by Eq. (10), all variables have been transformed into their natural logarithmic. Therefore, the estimated coefficients should be interpreted as elasticities. The results in Table 2 point to the importance of poverty incidence on income per worker, even after controlling for human and physical capitals, and the effective depreciation of capital. Table 2 indicates that poverty and extreme poverty incidences are both important in the level of

Table 2
Panel data estimations — OLS and FE robust.

		Dependent variable — ln GDP per worker							
		The poverty indicator is in the head of each column							
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
		OLS robust				FE robust			
		<i>PIP4</i>	<i>PIEP4</i>	<i>PHP4</i>	<i>PHEP4</i>	<i>PIP4</i>	<i>PIEP4</i>	<i>PHP4</i>	<i>PHEP4</i>
ln(<i>PI</i>)		−0.3645 (0.0667)***	−0.3299 (0.0429)***	−0.3690 (0.0648)***	−0.3735 (0.0447)***	−0.1341 (0.0449)***	−0.1411 (0.0345)***	−0.1447 (0.0448)***	−0.1641 (0.0422)***
ln(<i>s</i>)		0.0161 (0.0634)	−0.0100 (0.0548)	0.0165 (0.0620)	−0.0090 (0.0527)	−0.0363 (0.0421)	−0.0454 (0.0406)	−0.0386 (0.0418)	−0.0434 (0.0400)
ln(<i>hI</i>)		0.4267 (0.1415)***	0.2385 (0.1296)*	0.3577 (0.1458)**	0.1575 (0.1304)	0.0625 (0.1021)	−0.0097 (0.0917)	0.0222 (0.1027)	−0.0367 (0.0984)
ln(<i>n + g + δ</i>)		−0.0711 (0.0498)	−0.1009 (0.0461)**	−0.0733 (0.0492)	−0.1177 (0.0456)**	−0.2054 (0.0165)***	−0.2082 (0.0157)***	−0.2069 (0.0160)***	−0.2136 (0.0161)***
<i>c</i>		3.6654 (0.3714)***	3.4424 (0.2484)***	3.6745 (0.3588)***	3.5856 (0.2451)***	3.4560 (0.2192)***	3.4077 (0.1370)***	3.5027 (0.2119)***	3.4690 (0.1548)***
<i>N</i>		205	205	205	205	205	205	205	205
<i>R</i> ^{2w}						0.4418	0.4827	0.4486	0.4894
<i>R</i> ^{2b}						0.5844	0.6542	0.5741	0.6665
<i>R</i> ^{2o}		0.4940	0.5592	0.5005	0.5823	0.3333	0.4347	0.3438	0.4679
<i>F</i> (4, 200)		44.86***	58.64***	46.50***	69.19***				
<i>F</i> (4, 25)						41.05***	51.22***	43.91***	52.62***
<i>F</i> (25, 175)						33.21***	30.80***	33.19***	29.28***
sig. _u						0.3584	0.3391	0.3562	0.3317
sig. _e						0.1396	0.1344	0.1388	0.1335
<i>Rho</i>						0.8681	0.8641	0.8681	0.8604
Hausm χ^2						26.03***	39.19***	26.49***	54.01***
Wald Het.						340.36***	399.91***	327.29***	724.09***
Autocorr						31.945***	26.268***	29.725***	24.602***

Notes: standard deviations are in parentheses. *s* is the average growth rate of physical capital per worker, *hI* is the human capital proxy based on the mincerian equation with the educational return average rate of 15% per additional year, (*δ + n + g*) is each state effective depreciation of capital. *PHEP4* is the proportion of households living in extreme poverty, *PHP4* is the proportion of households living in poverty, *PIEP4* is the proportion of individuals living in extreme poverty, and *PIP4* is the proportion of individuals living in poverty. All the poverty indicators are four years average. *N* is the sample size, *R*^{2w} is the within effect of the regressors, *R*^{2b} is the between effect of the regressors, and *R*^{2o} is the overall effect of the regressors. *F*(4, 200) and *F*(4, 25) are the tests to check whether all the coefficients in the model are equal to zero, *F*(25, 175) is to test the joint hypothesis that all the dummy coefficients for the states are equal to zero, and *rho* is the intraclass correlation. Hausm χ^2 is Hausman test for Fixed vs. Random Effect. The null is that the differences in coefficients are not systematic. Wald Het. is the Modified Wald test for groupwise heteroscedasticity. The null is homoskedasticity (or constant variance). Autocorr is the Wooldridge test for autocorrelation in panel data for the FE estimates with no robust standard error. The null is no serial correlation.

* Significant at 10%.

** Significant at 5%.

*** Significant at 1%.

economic development in the Brazilian States, and that the magnitude of their effect is similar with the same statistical method. A 10% increase in poverty incidence (e.g., a state with a 20% poverty incidence and with a 10% increase in this proportion would reach a 22% poverty incidence) would reduce income per worker from 3.3 to 3.74% with the OLS estimates, and from 1.34 to 1.64% with the FE estimates.

Table 2 reports that investments in physical capital do not have a significant effect on income in any specification with both statistical methods (OLS and FE). Human capital has a positive influence on income per worker in the OLS estimates with the poverty indicators as regressors (*PIP4* and *PHP4*), and at a 10% level of significance with *PIEP4*. In the other results, the human capital coefficients are not statistically different from zero. These results are striking since several studies have shown the importance of these forms of capitals on the Brazilian development process, as in Fraga and Bacha (2013), Kroth and Dias (2012), Raiher and Dathein (2009), and Nakabashi and Salvato (2007), to

name a few. The introduction of poverty incidence turns the effects of human and physical capitals to not statistically significant, at least with the FE method, probably because the former influences both kinds of capital.

The effective depreciation of capital hurts income per worker, as predicted by the theory, and its estimated coefficients are systematically different from zero with a 1% level of significance and for all poverty indicators with the FE estimation method. With this method, a 10% increase in the effective depreciation of capital would lead to a reduction in income per worker from 2.05 to 2.14% (Table 2). The coefficient of determination (R^2) indicates that the five regressors account for more than 50% of the income per worker variation with the OLS results, and from 33 to 47% with the FE method (Table 2). It is interesting to note the increment in the coefficient of determination with the extreme poverty indicators (*PIEP4* and *PHEP4*) in relation to the poverty indicators (*PIP4* and *PHP4*), indicating that extreme poverty prevalence is more important to understand the relationship between poverty and economic development.

In Table 2, the $F(4, 200)$ tests in the OLS results, and the $F(4, 25)$ tests in the FE results point to the importance of the regressors (the null is that all estimated coefficients of the regressors are jointly zero). The $F(25, 175)$ tests indicate that at least one of the estimated coefficients of the dummy variables capturing the fixed effects is statistically different from zero, which gives support to the use of the panel data method instead of the OLS one (the null is that all the variable dummies' estimated coefficients are zero). The intraclass correlation coefficient (ρ) indicates that more than 85% of the variance is due to differences across units in the FE estimations. The modified Wald test for groupwise heteroscedasticity and the Wooldridge test for autocorrelation in panel data suggest the presence of both problems and that heteroscedasticity is more severe, as expected, since the number of observations across units is larger than the number of periods. Therefore, it is appropriate to estimate the regressions with robust standard errors as in the estimates of Table 2, since this method corrects for both problems. The Hausman tests for Fixed versus Random Effects favors the use of the former in all specifications.

In general, the results indicate that the incidence of poverty and extreme poverty are important to understand the income per worker differential across the Brazilian States. The problem of the above estimation methods is that they do not consider the reverse causality problem. Since poverty is likely to be reduced with an increase in income per worker as argued in the introduction, the previous estimates may be biased. The Dynamic Panel Data Model (DPD) is one way to circumvent this problem.

5.2. Dynamic Panel Data results

Table 3 reports the Arellano–Bond model results through the Difference GMM estimator with small-sample adjustment. Since all the regressors are potentially endogenous, we have considered them as endogenous in all specifications of Tables 3 and 4. The ln of the proportion of black population in each Brazilian State and its square were included as external instruments for poverty. The second lag of the regressors has also been used as instruments. While the first lag is potentially correlated with the current error term, the second is not. The first four columns of Table 3 make use of $h1$ and the last four of $h2$ as the human capital proxies.

Table 3 indicates the existence of an income per worker dynamic through time when $\ln(PIP4)$ and $\ln(PHP4)$ are the measures of poverty incidence since the estimated coefficients of the lagged $\ln(\text{income per worker})$ are statistically different from zero at 5% level of significance. In contrast, its estimated coefficients are not significant with the extreme poverty indicators as regressors. Regarding the poverty indicators, only the estimated coefficients of *PIEP4* and *PHEP4* are statistically different from zero. For a 10% rise in extreme poverty incidence, there is a reduction in income per worker from 0.91 to 2.15%, depending on the extreme poverty indicator and the human capital proxy.

Table 3 reports that the investment in physical capital does not have a significant influence on output per worker, except when $h2$ is the proxy for human capital, with the poverty indicators (*PIP4* and *PHP4*) as regressors, and for a 10% significance level. In both cases, a 10% growth in physical capital would lead to a near 1% increment in the regressand. The human capital proxies have a positive and significant influence on output per worker in three out of eight specifications. When their coefficients are statistically different from zero, a 10% increase in human capital would lead to an expansion in income per worker from 3.2 to 5.7%. The effective depreciation of capital has a negative and significant influence on income per worker, as previously stated. A 10% upturn in the effective depreciation of capital would lead to an income per worker contraction from 2.2 to 2.5%, a somewhat higher effect in relation to the FE estimates.

In Table 3, the $F(5, 26)$ tests point to the relevance of the regressors (the null is that the estimated coefficients of the regressors are jointly equal to zero). The Hansen tests of overidentifying restriction indicate that the instruments

Table 3
Dynamic panel — Arellano and Bond: two-step with robust standard errors.

Dependent variable — ln GDP per worker								
Instruments: second lag of the endogenous explanatory variables, the proportion of blacks and squared proportion of blacks								
Poverty indicator	(1) <i>PIP</i>	(2) <i>PIEP</i>	(3) <i>PHP</i>	(4) <i>PHEP</i>	(5) <i>PIP</i>	(6) <i>PIEP</i>	(7) <i>PHP</i>	(8) <i>PHEP</i>
Lagged ln(GDP per worker)	0.3818 (0.1381) ^{***}	0.2245 (0.1294) [*]	0.3725 (0.1384) ^{**}	0.1826 (0.1229)	0.3480 (0.1441) ^{**}	0.2201 (0.1348)	0.3441 (0.1445) ^{**}	0.1924 (0.1219)
ln(<i>PI</i>)	0.0222 (0.0461)	−0.1282 (0.0389) ^{***}	0.0024 (0.0501)	−0.2153 (0.0609) ^{***}	0.0263 (0.0457)	−0.0915 (0.0328) ^{***}	0.0107 (0.0490)	−0.1659 (0.0478) ^{***}
ln(<i>s</i>)	0.0705 (0.0535)	−0.0401 (0.0751)	0.0588 (0.0570)	−0.0943 (0.0907)	0.0973 (0.0522) [*]	0.0107 (0.0614)	0.0913 (0.0525) [*]	−0.0456 (0.0745)
ln(<i>h1</i>)	0.3271 (0.1625) [*]	−0.0373 (0.1502)	0.2862 (0.1790)	−0.2206 (0.2008)				
ln(<i>h2</i>)					0.5661 (0.2389) ^{**}	0.1467 (0.2007)	0.5416 (0.2539) ^{**}	−0.1076 (0.2360)
ln(<i>n + g + δ</i>)	−0.2498 (0.0231) ^{***}	−0.2180 (0.0250) ^{***}	−0.2479 (0.0236) ^{***}	−0.2169 (0.0244) ^{***}	−0.2462 (0.0230) ^{***}	−0.2173 (0.0237) ^{***}	−0.2450 (0.0232) ^{***}	−0.2160 (0.0207) ^{***}
N	154	154	154	154	154	154	154	154
N Inst	26	26	26	26	26	26	26	26
N Groups	26	26	26	26	26	26	26	26
F(5, 26)	60.43 ^{***}	41.13 ^{***}	55.91 ^{***}	51.81 ^{***}	65.48 ^{***}	45.09 ^{***}	65.32 ^{***}	50.81 ^{***}
Hansen	25.15	24.81	25.16	24.26	25.25	24.98	25.28	24.84
P-Value	(0.241)	(0.255)	(0.240)	(0.281)	(0.237)	(0.248)	(0.235)	(0.254)
Diff. in Hansen	24.97	24.46	24.99	23.32	24.96	24.86	24.97	24.09
P-Value	(0.162)	(0.179)	(0.161)	(0.223)	(0.162)	(0.165)	(0.162)	(0.193)
AB for AR1	−1.13	−1.38	−1.17	−1.62	−1.03	−1.17	−1.05	−1.45
P-Value	(0.260)	(0.166)	(0.241)	(0.104)	(0.305)	(0.240)	(0.293)	(0.147)
AB for AR2	−0.27	−0.06	−0.28	0.04	0.05	0.26	0.05	0.19
P-Value	(0.784)	(0.956)	(0.778)	(0.967)	(0.961)	(0.796)	(0.957)	(0.850)

Notes: standard deviations are in parentheses. *s* is the average growth rate of physical capital per worker, *h1* is the human capital *proxy* based on the mincerian equation with the educational return average rate of 15% per additional year, *h2* is the human capital *proxy* based on the mincerian equation with the educational return average based on Hall and Jones (1999), ($\delta + n + g$) is each state effective depreciation of capital. *PHEP4* is the proportion of households living in extreme poverty, *PHP4* is the proportion of households living in poverty, *PIEP4* is the proportion of individuals living in extreme poverty, and *PIP4* is the proportion of individuals living in poverty. All poverty indicators are four years average. N is the sample size, N Inst is the number of instruments in the first stage, and N Groups is the number of groups or entities. F(5, 26) is the tests to check whether all the coefficients in the model are equal to zero, Hansen is the Hansen test of overidentifying restrictions, and Diff in Hansen is a modified Hansen test for overidentifying restrictions which is adequate with many instruments. AB for AR1 and AB for AR2 are the Wooldridge tests for first and second-order autocorrelation in panel data. All explanatory variables are considered as endogenous in the above estimations.

* Significant at 10%.

** Significant at 5%.

*** Significant at 1%.

are valid (not correlated with the residuals) and the Wooldridge tests for autocorrelation do not reject the null of no first and second-order autocorrelation. Following Baum et al. (2003), the Hansen tests for overidentification evaluate the entire set of overidentifying restrictions, and if there are many excluded instruments, their power may be minimal. In these cases, the Difference-in-Hansen or Difference-in-Sargan statistic may be more appropriate since it allows for testing a subset of the original set of orthogonality conditions (Baum et al., 2003). The Difference-in-Hansen tests lead to the same conclusion.

Table 4 brings the results of the same specifications and estimation method as Table 3. The difference is that the external instrument is only the natural logarithm of the black population proportion. The results of both tables are very similar qualitatively and quantitatively. The estimated coefficients of the lagged natural logarithm of income per worker are positive, but statistically different from zero only with the poverty indicators (*PIP4* and *PHP4*) as regressors, except for *PIEP* and *h1* as regressors, and considering a 10% level of significance.

Table 4
Dynamic panel — Arellano and Bond: two-step with robust standard errors.

Dependent variable — ln GDP per worker								
Instruments: second lag of the endogenous explanatory variables, the proportion of blacks and squared proportion of blacks								
Poverty indicator	(1) <i>PIP</i>	(2) <i>PIEP</i>	(3) <i>PHP</i>	(4) <i>PHEP</i>	(5) <i>PIP</i>	(6) <i>PIEP</i>	(7) <i>PHP</i>	(8) <i>PHEP</i>
Lagged ln(GDP per worker)	0.3821 (0.1377) ^{***}	0.2267 (0.1269) [*]	0.3726 (0.1382) ^{**}	0.1856 (0.1202)	0.3483 (0.1431) ^{**}	0.2241 (0.1309)	0.3444 (0.1438) ^{**}	0.1957 (0.1198)
ln(<i>PI</i>)	0.0224 (0.0473)	−0.1275 (0.0396) ^{***}	0.0023 (0.0514)	−0.2145 (0.0623) ^{***}	0.0267 (0.0457)	−0.0897 (0.0339) ^{**}	0.0173 (0.0493)	−0.1649 (0.0496) ^{***}
ln(<i>s</i>)	0.0705 (0.0545)	−0.0405 (0.0741)	0.0586 (0.0573)	−0.0967 (0.0957)	0.0975 (0.0522) [*]	0.0108 (0.0599)	0.0915 (0.0528) [*]	−0.0467 (0.0751)
ln(<i>h1</i>)	0.3276 (0.1685) [*]	−0.0378 (0.1507)	0.2857 (0.1850)	−0.2190 (0.2021)				
ln(<i>h2</i>)					0.5669 (0.2392) ^{**}	0.1494 (0.2025)	0.5426 (0.2557) ^{**}	−0.1068 (0.2398)
ln(<i>n + g + δ</i>)	−0.2499 (0.0233) ^{***}	−0.2181 (0.0245) ^{***}	−0.2478 (0.0237) ^{***}	−0.2167 (0.0246) ^{***}	−0.2463 (0.0232) ^{***}	−0.2179 (0.0230) ^{***}	−0.2452 (0.0235) ^{***}	−0.2162 (0.0208) ^{***}
<i>N</i>	154	154	154	154	154	154	154	154
<i>N Inst</i>	25	25	25	25	25	25	25	25
<i>N Groups</i>	26	26	26	26	26	26	26	26
<i>F</i> (5, 26)	58.01 ^{***}	39.42 ^{***}	54.46 ^{***}	46.63 ^{***}	63.82 ^{***}	44.69 ^{***}	63.04 ^{***}	48.02 ^{***}
Hansen	25.15	24.75	25.16	24.15	25.23	24.86	25.27	24.79
P-Value	(0.196)	(0.211)	(0.196)	(0.236)	(0.193)	(0.207)	(0.191)	(0.210)
Diff. in Hansen	24.97	24.46	24.99	23.31	24.96	24.86	24.97	24.08
P-Value	(0.162)	(0.179)	(0.161)	(0.224)	(0.162)	(0.165)	(0.162)	(0.193)
AB for AR1	−1.13	−1.40	−1.17	−1.65	−1.03	−1.19	−1.05	−1.47
P-Value	(0.259)	(0.163)	(0.241)	(0.100)	(0.304)	(0.235)	(0.292)	(0.140)
AB for AR2	−0.28	−0.06	−0.28	0.03	0.05	0.25	0.05	0.18
P-Value	(0.782)	(0.952)	(0.777)	(0.974)	(0.963)	(0.806)	(0.959)	(0.858)

Notes: standard deviations are in parentheses. *s* is the average growth rate of physical capital per worker, *h1* is the human capital proxy based on the mincerian equation with the educational return average rate of 15% per additional year, *h2* is the human capital proxy based on the mincerian equation with the educational return average based on Hall and Jones (1999), ($\delta+n+g$) is each state effective depreciation of capital. *PHEP4* is the proportion of households living in extreme poverty, *PHP4* is the proportion of households living in poverty, *PIEP4* is the proportion of individuals living in extreme poverty, and *PIP4* is the proportion of individuals living in poverty. All poverty indicators are four years average. *N* is the sample size, *N Inst* is the number of instruments in the first stage, and *N Groups* is the number of groups or entities. *F*(5, 26) is the tests to check whether all the coefficients in the model are equal to zero, Hansen is the Hansen test of overidentifying restrictions, and Diff in Hansen is a modified Hansen test for overidentifying restrictions which is adequate with many instruments. AB for AR1 and AB for AR2 are the Wooldridge tests for first and second-order autocorrelation in panel data. All explanatory variables are considered as endogenous in the above estimations.

* Significant at 10%.

** Significant at 5%.

*** Significant at 1%.

The estimated coefficients of the poverty indicators are statistically different from zero only for the measures of extreme poverty incidence (*PIEP4* and *PHEP4*). A 10% expansion in them would lead to a decrease in income per worker from 0.90 to 2.14%, results that are very similar to those of Table 3. Physical capital estimated coefficients are significant only in two out of eight specifications, while those of human capital are statistically different from zero in three out of eight specifications in Table 4. When these coefficients are significant, they have the expected sign. The effective depreciation of capital has negative and significant estimated coefficients in all specifications, as in Table 3, and their magnitudes are similar. The tests for heteroscedasticity, autocorrelation, and overidentifying restrictions lead to the same conclusions. In a nutshell, the estimated results do not depend on the form that the proportion of the black population in the Brazilian States enters as an external instrument.

In general, the previous results point to the importance of poverty and extreme poverty incidence on income per worker. When taking into consideration the dynamics of income per worker and controlling for reverse causality through the Dynamic Panel Data models, the results are similar to those from the FE estimates with robust standard

errors, except for the fact that the coefficients of poverty incidence (*PIP* and *PHP*) are not significant. The results of OLS, FE, and DPD lead to the conclusion that poverty prevalence is relevant to understanding income per worker differentials in the Brazilian States through time, with a higher relevance of the extreme poverty indicators (*PIEP4* and *PHEP4*).

6. Conclusions

In the present study, our primary concern was to examine the effects of poverty on economic development in the Brazilian States. Many studies assess the relevance of economic growth or development on poverty reduction, but there is almost no one trying to measure the impacts of poverty incidence on economic development. The empirical results indicate that the incidence of poverty and extreme poverty are crucial to understand economic development across the Brazilian States and through time. Poorer Brazilian States have lower income per worker even when controlling for investment in physical capital, human capital stock, and effective depreciation of capital. The results point to the variables measuring extreme poverty (*PHEP4* and *PIEP4*) as more important than those quantifying poverty (*PHP4* and *PIP4*) in the income per worker determination.

In the Ordinary Least Square (OLS) estimations with robust standard errors, considering a 10% increase in poverty would lead to an adverse influence on income per worker from 3.29 to 3.73%, depending on the poverty indicator used as a regressor. The poverty estimated coefficients are significant even after controlling for human capital stock, investment in physical capital, and effective depreciation of capital. Nevertheless, the results are probably biased due to the omitted variable bias, since in the Fixed Effects (FE) estimations with robust standard errors, a 10% increment in poverty would lead to an income per worker contraction of 1.34% (*PIP4*), 1.44% (*PHP4*), 1.41% (*PIEP4*), and 1.64% (*PHEP4*), a considerable smaller effect in relation to the OLS estimates. With the Arellano–Bond models to deal with the regressor endogeneity problem, considering *h1* as a regressor, a 10% increment in poverty would lead to an income per worker contraction of 1.28% (*PIEP4*), and 2.15% (*PHEP4*). With *h2*, the negative influence on the regressand would be of 0.91% (*PIEP4*), and 1.65% (*PHEP4*). The estimated coefficients of the poverty indicators (*PIP4* and *PHP4*) are not statistically different from zero with the latter estimation method. In general, the results indicate that extreme poverty has a more deleterious influence on income per worker than poverty.

Summarizing, the results point to the importance of poverty incident, and mainly extreme poverty incidence, in understanding the economic development differentials across the Brazilian States and through time. Therefore, the formulation of public policies to reduce poverty is important to develop the Brazilian States and increase welfare. With the present study, we hope to foster some attention to studies focusing on the crucial relationship between poverty and economic development.

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Appendix A.

Table A1
Unit root tests Fisher for panel data – Philips-Perron – one lag and trend.

Variable	Inverse χ^2	Inverse normal	Inverse logit	Modified inv. χ^2
ln(y per worker)	388.98 (0.0000)***	-11.03 (0.0000)***	-19.76 (0.0000)***	33.04 (0.0000)***
ln(s)	410.58 (0.0000)***	-11.38 (0.0000)***	-21.18 (0.0000)***	35.16 (0.0000)***
ln(h1)	276.18 (0.0000)***	-7.64 (0.0000)***	-12.56 (0.0000)***	21.98 (0.0000)***
ln(h2)	200.11 (0.0000)***	-5.58 (0.0000)***	-9.12 (0.0000)***	14.52 (0.0000)***
ln($\delta + n + g$)	602.20 (0.0000)***	-19.68 (0.0000)***	-32.06 (0.0000)***	53.95 (0.0000)***
ln(PIP4)	122.487 (0.0000)***	-2.43 (0.0076)***	-4.20 (0.0000)***	6.911 (0.0000)***
ln(PIEP4)	249.68 (0.0000)***	-7.13 (0.0000)***	-11.90 (0.0000)***	19.38 (0.0000)***
ln(PHP4)	126.84 (0.0000)***	-2.75 (0.0030)***	-4.62 (0.0000)***	7.34 (0.0000)***
ln(PHEP4)	228.71 (0.0000)***	-7.14 (0.0000)***	-10.65 (0.0000)***	17.32 (0.0000)***
ln(black)	215.92 (0.0000)***	-3.58 (0.0002)***	-7.15 (0.0000)***	16.07 (0.0000)***
[ln(black)] ²	215.92 (0.0000)***	-2.01 (0.0219)**	-5.93 (0.0000)***	14.14 (0.0000)***

Ho: all panels contain unit roots; Ha: at least one panel is stationary. P-values are in parentheses.

*Significant at 10%.

** significant at 5%.

*** significant at 1%.

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