Poverty and Economic Development: evidence for the Brazilian States

Luciano Nakabashi

Professor of Economics at São Paulo University and Visiting Scholar at University of Illinois.
Faculty of Economics, Business Administration and Accounting of Ribeirão Preto (FEA-RP/USP). Av. Bandeirantes, 3900 - Monte Alegre, CEP: 14040-900 - Ribeirão Preto/SP, Brazil. E-mail: luciano.nakabashi@gmail.com.

Abstract:

In the present study, our main concern is to examine the effects of poverty on economic development across the Brazilian States from 1980 to 2010. There are many studies assessing the relevance of economic growth and development in poverty reduction, but there are almost no one trying to measure the influence of poverty on economic development. The empirical results indicate that the incidence of poverty is important in the Brazilian States economic development. Poorer Brazilian States have lower income per worker even when controlling for investment in physical and human capitals and for the effective depreciation of capital. The results point to the influence of the variables measuring extreme poverty on development level across the Brazilian States in relation to the variables quantifying poverty. Some of the effects seem to be driven via productivity. The Brazilian States with higher proportion of poverty population are the same with lower Total Factor Productivity (TFP) and this effect holds even when taking into consideration the reverse causality problem. The present study hypothesis is that poverty induces to resources misallocations, with adverse effects on TFP.

Key Words: Poverty; Economic Development; Brazilian States.

JEL: O11; O15; R58; C23.

Funding: This work was supported by the São Paulo Research Foundation – FAPESP [grant number 2015/16539-1].

1. Introduction

Poverty is a main concern to policy makers since its incidence is direct related to the level of the population welfare. In this sense, one important element is the absolute and relative poverty reduction since the 1990s in the developing countries, as registered by Chen and Ravallion (2013). Variables commonly highlighted as relevant to reduce poverty are income growth and economic development, but there is no major consensus in this debate.

An exemplar case is the dispute that took place about the influence of growth on poverty in India. Deaton and Kozel (2005) highlighted key features of this debate after the 1990's reforms. The source of this debate was related mainly to data collection from different sample surveys on mean consumption and the Indian National Accounts. The authors stated that "Although there are almost certainly errors in both sets of estimates, the view of what is happening to poverty depends a good deal on how much of the discrepancy is attributed to each set". (p. 180).

Nevertheless, there are several studies pointing to the importance of economic growth on poverty reduction in the case of India. For example, based on district level per capita income data, Banerjee, Banik and Mukhopadhyay (2015) found evidence 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 important to reduce poverty in India between 1999-2000 and 2005-2006.

Datt, Ravallion and Murgai (2016) found that the Indian economic growth after the 1990's reforms was important to reduce poverty. Their study was based on a new dataset on poverty from 1957 to 2012, which was compiled by them. Their results point to the following conclusion:

> "Even though a trend decline in poverty emerged around the early 1970s, the year 1991-92 – the benchmark year for economic reforms in India – stands out as the year of the great divide… There was a significant spurt in economic growth, driven by growth in the tertiary sector and to a lesser extent, secondary sector. The pace of poverty reduction also accelerated, with a 3-4 fold increase in the proportionate rate of decline in the post-91 period… Despite the increase in inequality, we find greater post-91 responsiveness of poverty to growth in the aggregate, regardless of whether growth is measured based on national accounts or survey-based consumption". (p. 26).

Focusing on Sub-Saharan African countries, Fosu (2015) found results supporting the view that economic growth has played a crucial role to diminish poverty incidence. In addition, income inequality has also been important in poverty incidence since lower income inequality reduces poverty holding constant the country's income level.

Besides the great amount of studies measuring the consequences of economic growth on poverty, almost no attention has been given to the effects of poverty on development, measured as the level of income per worker in the present study. One of the few studies focusing on the effects of poverty on economic growth is that of Ravallion (2012). His paper`s results indicate that countries with higher initial incidence of poverty tend to experiment lower subsequent rate of economic growth [1].

There are at least three important channels in which the incidence of poverty can influence the level of economic development. First, the population living in poverty are more susceptible to malnourishment, and the latter affects child development. Hanson et al. (2013) examined changes in 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. Most of children were followed longitudinally every half year. By means of Random Effect Method, the authors found that children from poor and near poor socioeconomic status families[2] have lower brain total gray matter volumes in relation to those from high socioeconomic status families. In addition, the former group also experimented reduced total gray matter growth trajectory. They argue that brain grain matter is critical for processing information and to execute action. Therefore, children with less volume of it are more inclined to have difficult at school and, consequently, to 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 rise resource misallocations through inequality of opportunities. For instance, in regions where a great proportion of the population lives in poverty, some people with a high potential of learning and executing productive activities are never going to benefit from it since they will not have the opportunity to frequent good schools, to have parents with good education to help them with homework, and so on. In addition, 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) sustains:

> "Economists and demographers for the most part agree that important ingredients of improved living standards, such as urbanization, industrialization and rising opportunities for non-agrarian employment, improved educational levels, and better health all lead to changed parental perceptions of the costs and benefits of children, leading in turn to lower fertility. In other words, there is no longer much debate about whether or not improved economic conditions, whether at the family level or at the societal level, lead to lower fertility". (p. 3023).

A decline in fertility rate have a potential to affect income positively in poor regions. For

[1] In the present study, our focus is only on the level of income per worker and not on the rate of income growth since in the Arellano-Bond estimations we lose two time periods to instrument the lagged income per worker variable. Since only four time periods are available in the dataset for the 26 Brazilian States, we would have only 26 observations to estimate the poverty effects on income per worker growth. In addition, in the reasoning given in the present paper, it makes more sense to measure the effects of poverty incidence on economic development.

[2] Family income below 200% Federal Poverty Level.

example, Ashraf, Weil and Wilde (2013) found that shifting Nigeria from the United Nation medium-fertility to the low-fertility population projection would increase income per capita by 5.6 percent at a horizon of 20 years, and by 11.9 percent at a horizon of 50 years. These estimations were based on a demographic-economic simulation model in which fertility can be exogenously altered. That relationship between fertility and income is explained in their model mainly by four channels:

> "The simple dependency effect (fewer dependent children relative to working adults) is the dominant channel for the first several decades. At longer horizons, the effects of congestion of fixed resources (à la Malthus) and capital shallowing (à la Solow) become more significant than dependency, although the latter remains important. The fourth most important channel in the long run is the increase in human capital that follows from reduced fertility". (p. 3).

With this background, the present paper objective is to analyse the impact of people living below poverty line on the Brazilian States income per worker between 1980 and 2010. The latter variable is the measure of each state level of economic development. To the author's knowledge, there is no such kind of study with aggregate dataset.

Four measures of poverty 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) and the other two are measures of poverty in the Brazilian States (proportion of individuals living in poverty – PIP, and proportion of households living in poverty – PHP). The use of two measures of poverty - proportion of poverty and proportion of extreme poverty - is to check if the degree of poverty is important on income per worker determination.

The Fixed Effect (FE) estimates with robust standard errors indicate that an increase in the proportion of poverty in 10% has a negative impact on the level of income per worker from 1.7% to 2.5% in the Brazilian States depending on the poverty indicator used as a regressor, even after considering for human capital stock, investment in physical capital and effective depreciation of capital. All measures of poverty have a negative effect on the economic development of the Brazilian States and their coefficients are statistically different from zero.

In the Arellano-Bond estimates, the extreme poverty indicators seem to be more important since their coefficients are significant at the 5% level while those of the poverty indicators are not significant. The extreme poverty estimated coefficients suggest that a 10% increase in its incidence would lead to a negative impact on per capita income from 6.2% to 6.7%. Considering the effects of extreme poverty on Total Factor Productivity (TFP), a 10% intensification in the former is related to a 5% decrease in the latter. Therefore, the primary way in which poverty reduces income per worker appears to be through TFP.

Because poverty hurts economic development, public policies designed to reduce the incidence of poverty in the Brazilians States have the potential to promote development, in addition of their positive effect on the welfare of those who need the most. In addition, some studies support the idea that poverty incidence generates negative externalities, as in Galster, Cutsinger and Malega (2008).

Besides this introduction and the conclusions, the present paper is structured in five sections. In the second, it is exposed the theoretical model that is the base for the specification to be tested empirically. In the third, the estimation methods are presented with a brief explanation of their adequacy to the current study. In the following section the dataset and its sources are presented. In the next one, some preliminary results are presented based on graphical analysis. Finally, the empirical results are presented and analysed.

2. The theoretical model

In this section, we are heavily based on Mankiw, Romer and Weil (1992)'s theoretical model to set the relationship among the variables of interest. Nakabashi and Salvato (2007) have used a similar framework to estimate the effects of human capital quality on the Brazilian States income per worker. The production function is the following one:

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

where K_t, H_t e L_t are the level of physical capital, human capital, 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. Dividing both sides of equation (1) by effective units of labor:

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

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:

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

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

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

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

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

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

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

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

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

Output per unit of labor is $y = Y/L$, and the steady state output per unit of labor is represented by y^*. It is assumed that g and δ are constant across the Brazilian States. A_t does not stand only for technology, it also represents resources endowment, climate, institutions, inefficiency, and so on. Following MRW (1992), but considering that poverty was in the error term, it is possible to represent productivity as:

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

where a_i is a specific and constant State effect, p_i is the state incidence of poverty, and ε stands for countries 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 ($\lambda < 0$). Using equation (7) into (6):

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

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 equations (4b) to find:

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

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

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

where η = (1 – α – β)/(1 – β) and ε’ = ηε.

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 and technology across regions, which are difficult to measure, and because the specification of these units of analysis is no longer in the error term, it is less likely to be correlated with some of the independent variables (ISLAM, 1995).

In panel data framework, one should decide between Fixed and Random Effects. Based on equation (10), a_i is a dummy variable detaining the specificity of each Brazilian State. Therefore, this model assumes that differences across units can be captured in a constant that differs across units and this dissimilarity can be estimated by Fixed Effect (FE). If we use Random Effects (RE) method based on (10), we would have

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

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 individual effects are uncorrelated with the other regressors. Because our main motivation to use panel-data estimation method is that these individual effects can be correlated with the other regressors, FE seems the most appropriate method. However, the FE estimator does not deal with the causality problem. Since the incidence of poverty in the Brazilian States are likely to be affect by their income per worker level, as discussed in the introduction, the reverse causality problem is a major issue that must be considered in the empirical analysis.

The Dynamic Panel Data (DPD) models were developed to deal with the dynamic of the variables in different periods of time with the inclusion of the lagged dependent variable as a regressor and it is also adequate to deal with unobserved heterogeneity. In addition, this method is adequate to deal with the reverse causality problem since it uses the lag of the right-hand variables as instruments. Because the lagged dependent variable tends to be endogenous, deeper lags of the dependent variable can be used as instruments for differenced lags of the dependent variable. In addition, it is possible to include strict exogenous instruments within this method. Adding one lagged dependent variable into equation (11):

(12)

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

The Arellano-Bond (1991) estimator uses the variables in difference and the Generalized Method Moments (GMM) to estimate the parameters of the model. They show that an efficient estimator can be obtained with all lagged values of the regressand and the regressors as instruments.

4. The variables and sources

The period of study is composed by the years 1980, 1991, 2000, 2010 for the 26 Brazilian States[3]. Since the data is available for all years and Brazilian States, we have a balanced panel. The output (Y) is the state GDP at 2000 constant prices (R$ thousand) from the Geography and Statistic Brazilian Bureau (IBGE). Employed workers were used for the calculation of GDP per worker (y_i), which was elaborated by the Institute of Applied Economic Research (IPEA) based on the IBGE demographic censuses [4]. This variable is our measure the Brazilian States development level.

The *proxy* for quantity of human capital $(h1)$ is based on average years of schooling of the population over 25 from IPEA. Following Mincer (1974), the human capital per worker is a function of the educational return average rate (ϕ) and years of schooling (μ) as in the following equation:

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

The educational return average rate was set to 15% per additional year $(\phi = 0.15)$ based on several studies for the Brazilian labor market. For example, Resende and Wyllie (2006) found that the return of education is between 15.9% and 17.4% for men, and 12.6% and 13.5% for women, based on the Research on Living Standards dataset (PPV-IBGE, 1996-1997). Sachsida, Loureiro and Mendonça (2004) found evidence that the return of an additional year of schooling was between 12.9% and 16% through different methods employed to mitigate the estimation bias, for the 1992-1999 period. Based on the 1998 National Sample Households Survey (PNAD/IBGE), Loureiro and Carneiro (2001) estimated that the educational return for urban man was 18.58% while for rural one it was 11.35%. For women, the respective values were 23.32% and 18.06%.

As in Figueiredo and Nakabashi (2016), we have used a second measure of human capital to capture its qualitative aspects $(h2)$. This second *proxy* is a multiplicative term between h in equation (12) and the Basic Education Development Index (IDEB) mean score in 2005 (simple average of the fifth, ninth years and twelfth years of school)[5]. In other words, the Brazilian States educational system quality was measured as the state's IDEB mean score.

IDEB was created in 2005 by Anísio Teixeira National Institute of Educational Studies and Research (INEP) to evaluate students test performance in Brazil. As a first approximation, it seems reasonable to assume some form of interaction between human capital qualitative and quantitative

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

[4] In the census, 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.

[5] For example, if z is a Brazilian state average IDEB score, then its human capital is $z * h$, where $h = e^{(0.15*u)}$, and u is the average school years of its population with 25 years or more.

aspects in a way that we have one variable capturing both aspects. This assumption is taken from Lucas (1988) growth model.

Another assumption for the construction of the *proxy* is that the quality gap across states does not change over time, which is necessary since the tests evaluating students' performance are recent. We consider it to be a reasonable assumption since it takes a long time to change the school system of a whole Brazilian State in relation to other States, and even more time for the children under the new school system enter in the labor force in a way to have a relevant influence on its quality. In addition, Figueiredo and Nakabashi (2016) show the high correlation between quantitative and qualitative aspects of human capital, and the stability in the relative quantitative aspect of human capital among the Brazilian states, which gives empirical support to that assumption.

In the empirical analysis, it is importance to distinguish the human capital qualitative aspects since one potential channel in which poverty affects income per worker is via human capital qualitative aspect as indicated in the introduction. If this is true, poverty should decrease the quality of human capital and when it is considered in the estimates, the poverty effect should become less important.

In relation to the parameter of capital participation in income, it is assumed $\alpha = 0.4$, in line with previous studies for the Brazilian economy, such as Pereira (2012), Barbosa Filho et al. (2010), Coelho and Figueiredo (2007) and Gomes, Pessôa and Veloso (2003).

Capital is measured according to each Brazilian State total physical capital (private capital - machinery, equipment and non-residential capital, plus residential capital - KT_i) from Reis *et al.* (2005) for years 1970 and 1980 and updated by Figueiredo and Nakabashi (2016) by means of Coelho (2006)'s methodology. The residential energy consumption (REC_i) was considered as a *proxy* for residential capital. This variable and total physical capital (KT_i) of each Brazilian State are available from IPEA and they were used to calculate $K_{i,t}$. The ratio among these capital stocks (KT_i/REC_i) is assumed to be constant and equal to that of 1985. For 1990, 2000, and 2010, only residential energy consumption is available for the Brazilian States. If the ratio remains constant, it is possible to recover each state physical capital stock $\left(K_{i,t}\right)$ for 1990, 2000 and 2010 via the following equation:

$$(14) \qquad K_{i,t} = \left[REC_{i,t} * \left(KT_{i,1985}/REC_{i,1985}\right)\right]$$

The assumption that underlies this *proxy* is that, in the long run, residential capital is a constant share of total capital, which is a reasonable one because of the arbitrage process, i.e. through the exit and/or entry of firms in and across markets.

Four variables were used to measure each Brazilian State the incidence of poverty: 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 of calories in relation to PIEP); 3) proportion of households living in extremely 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 the Food and Agriculture Organization (FAO) and of the World Health Organization (WHO); and 4) proportion of households living in poverty (PHP) and it is the double of the PHEP income. All the indicators were elaborated by IPEA.

The proportion of African Brazilian in the States were used as instruments of poverty since in Brazil there is a high correlation between poverty and proportion of African American. Proportion of black people in each Brazilian State is from the IBGE censuses. Brazilian economic historians argue that after slavery, the Brazilian society was not able or willing to integrated the black population in the economy and give them access to land and the same job opportunities in relation to white population (GRADÍN, 2009; ARAÚJO, 2000). Fernandes (1968 cited in Lima, 2002)[6] presented evidence from São Paulo municipality that in 1893 (five years after abolition), the good job opportunities were filled basically 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 the African Brazilian community, the poverty is higher among them even nowadays. Based on 2005 Pnad/IBGE dataset, Gradín (2009) offered evidence pointing that while the African Brazilians accounted for almost half of the population, about 33% of them lived in poor households (whose incomes were below 50% of the median Brazilian income) while 14% of whites were in the same situation. The author points to discrimination in the labor market and to the lower quality of education faced by the African Brazilians as important elements to understand this situation.

To calculate Total Factor Productivity (TFP) for the Brazilian States, we have used Hall and Jones (1999)'s methodology. This accounting method decomposes differences in output per worker into differences in capital-output ratio rather than in capital-labor ratio. Following the Solow Model (theoretical reference of this development account exercise), capital-output intensification is

[6] FERNANDES, Florestan (1968), "Relações de Raça no Brasil: Realidade e Mito". In: Celso Furtado: Brasil: Tempos Modernos. Pp.111:137. Rio de janeiro: Paz e terra.

associated to transitional periods, i.e., those in which the economy product grows at higher rates than productivity. In the long term, capital-output ratio stability is expected since both variables grow at the same pace.

Hall and Jones (1999) highlight two reasons for working with the capital-output ratio decomposition: i) since, in the steady state, K and Y grow at the same rate, we can infer that the economy is in its steady state when its growth rate are due to technological and labor evolution; and ii) if there is an exogenous growth in productivity without changing the investment rate, the K/L ratio will grow over time because of a productivity increase. In this case, part of the capital-labor ratio growth reflects productivity progress which would be attributed to physical capital accumulation, while in Hall and Jones (1999) decomposition this effect is captured only in the TFP term.

The development decomposition departs from the following specification of the Cobb-Douglas production function with constant returns to scale:

$$(15) \qquad Y_{i,t} = K_{i,t}^{\alpha}\left(A_{i,t}H_{i,t}\right)^{1-\alpha}$$

in which *Y*, *A*, *K*, *H* denote, respectively, output, Harrod-Neutral productivity, physical capital stock, and human capital stock. Dividing both sides of equation (15) by ($L^{1-\alpha}\ Y^{\alpha}$), the production function is expressed in terms of output per worker:

$$(16) \qquad y_{i,t} = \left(\frac{K_{i,t}}{Y_{i,t}}\right)^{\alpha/(1-\alpha)} A_{i,t}h_{i,t}$$

in which $y_{i,t} \equiv \frac{Y_{i,t}}{L_{i,t}}$; $k_{i,t} \equiv \frac{K_{i,t}}{L_{i,t}}$; $h_{i,t} \equiv \frac{H_{i,t}}{L_{i,t}}$. Thus,

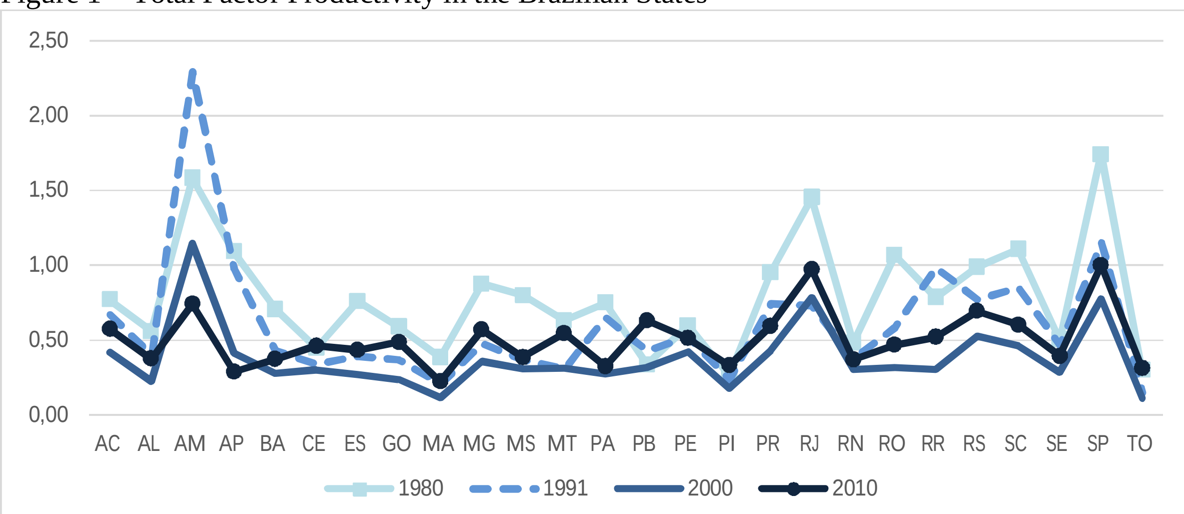
$$(17) \qquad A_{i,t} = \frac{y_{i,t}}{\kappa_{i,t}^{\alpha/(1-\alpha)}h_{i,t}}$$

in which $\kappa_{i,t} = \frac{K_{i,t}}{Y_{i,t}}$. Equation (17) is the base to calculate the Brazilian States TFP.

The estimated TFP of the Brazilian States (Sao Paulo PTF in 2010 = 1) with *h1* as the human capital *proxy* is presented in Figure 1. In almost all cases, TFP has dropped from 1980 to 1990 and from 1990 to 2000. These two decades (from 1980 to 2000) was a very difficult period in the Brazilian economy and the TFP behavior reflects it. With a better dynamism from 2000 to 2010, almost all the Brazilian state have experimented an improvement in TFP. However, for many states, it was just enough to return to the 1990 level, which still was well below in relation to the 1980 level.

Sao Paulo State had the lead in 1980 TFP ranking and it was in the same position in 2010, even with a decrease in TFP of 42.5% in this time span. The estimated TFP decrease from 1980 to 2000 is in line with others studies measuring the evolution of the TFP in the national level as in Ferreira, Ellery and Gomes (2008), Bacha and Bonelli (2005), Gomes, Pessôa and Veloso (2003). Nevertheless, some of them find a slightly improvement in TFP from 1990 to 2000, mainly after 1994, as Ferreira, Ellery and Gomes (2008), and Bacha and Bonelli (2005). Bonelli and Levy (2010) estimated the TFP growth rate for the Brazilians States from 1970 to 2005, but their results are driven by the significant rise in TFP from 1970 to 1980.

Figure 1 – Total Factor Productivity in the Brazilian States

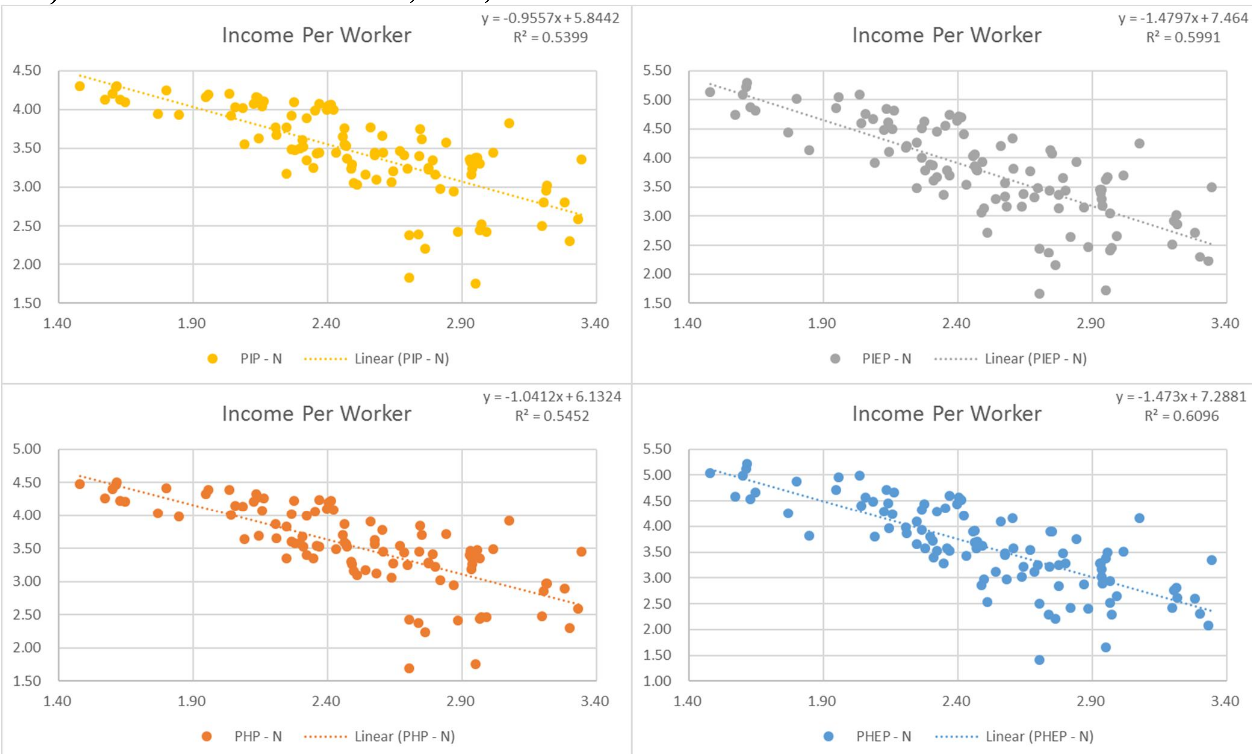


Source: own elaboration based on IPEA and IBGE data.

5. Preliminary Results

In Figure 2, each scatter plot relates the natural logarithm (log) of income per worker (horizontal axis) and the natural logarithm (log) of the poverty indicators (vertical axis) in the Brazilian States for all the years that the data is available: 1980; 1991; 2000; and 2010. In the scatter plots it is possible to identify the strong and negative relationship between them. It seems to be stronger in the case of the extreme poverty indexes, with the simple OLS estimated coefficients of determination being close to 0.6.

Figure 2 – Relationship between log income per worker (vertical axis) and log poverty (horizontal axis) in the Brazilian States: 1980, 1991, 2000 and 2010.

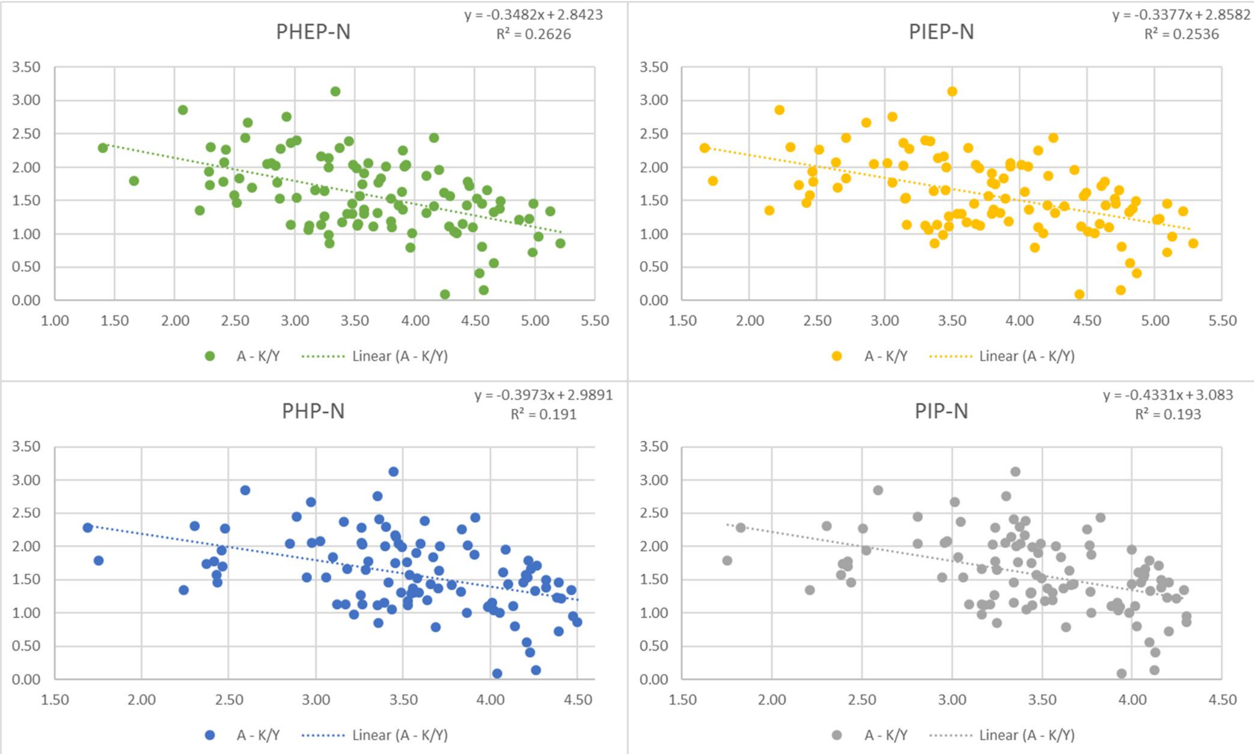


Source: own elaboration based on data from IPEA and IBGE.
Notes: PIP – Proportion of individuals in poverty- required calories (%); PIEP – Proportion of individuals in extreme poverty - required calories (%); PHP - Proportion of households in poverty (%); PHEP – Proportion of households in extreme poverty (%).

In Figure 3, the relationships are between TFP and the poverty indexes. The Brazilian States with higher proportions of poverty are the same with lower TFP and the correlations are higher with the extreme poverty indexes. Here, the correlations are not so strong as with income per worker, but they still are negative. The simple OLS estimated coefficients of determination are next to 0.25. Therefore, part of the negative effect of poverty on income appears to be driven by productivity reduction with is in line with the hypothesis that poverty increases resources misallocations and, in this way, to a decline in productivity.

However, the scatter plots in Figures 2 and 3 point to simple correlations between the variables without any indication of causation or omitted variable leading to the correlation between them. In the next section, we estimate equation (10) with different methods, and we also address the causality problem via Dynamic Panel Model and the use of instrumental variable.

Figure 3 – Relationship between log TFP (vertical axis) and log poverty (horizontal axis) in the Brazilian States: 1980, 1991, 2000 and 2010.

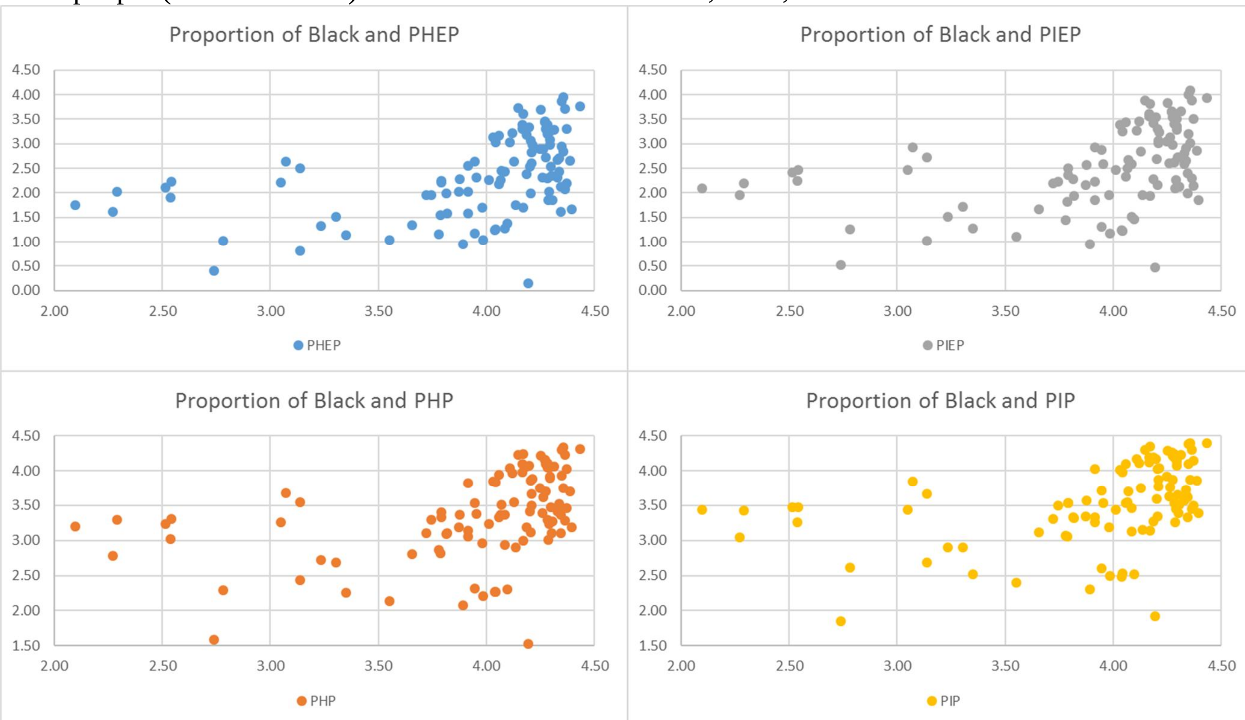


Source: own elaboration based on data from IPEA and IBGE.
Notes: PIP – Proportion of individuals in poverty- required calories (%); PIEP – Proportion of individuals in extreme poverty - required calories (%); PHP - Proportion of households in poverty (%); PHEP – Proportion of households in extreme poverty (%).

In Figure 4, it is possible to perceive the positive relationship between the log proportion of black people and the log poverty in the Brazilian States. However, it is clearly positive only for the states with higher proportion of black population: upper to 3.5, which correspond to a black population of 35% or more. Below this threshold, the relationship is not clear due to the Southern States of Brazil that had low proportions of black people with relatively high poverty rates in 1980, 1990 and 2000.

In Figure 4's scatter plots, the relationship between the log proportion of black people and log poverty in the Brazilian States does not look linear. It is closer to a quadratic relationship than a linear one. Therefore, we have also included the square of the log proportion of black people as an instrument for the poverty indicators in the Dynamic Panel estimations.

Figure 4 – Relationship between log proportion of poverty (vertical axis) and log proportion of black people (horizontal axis) in the Brazilian States: 1980, 1991, 2000 and 2010.



Source: own elaboration based on data from IPEA and IBGE.
Notes: PIP – Proportion of individuals in poverty- required calories (%); PIEP – Proportion of individuals in extreme poverty - required calories (%); PHP - Proportion of households in poverty (%); PHEP – Proportion of households in extreme poverty (%).

6. Estimation Results

6.1. Fixed Effects and Random Effects

As suggested by the specification in equation (10), all variables have been transformed into their natural logarithmic. Therefore, the estimated coefficients should be interpreted as elasticities. In Table 1 are the estimations results based on equations (10) and (11) with the poverty indicators PHEP and PHP as regressors. The regression methods are Fixed Effect (FE) and Random Effects (RE). There are four estimations results for each poverty indicator since there are two estimation methods (FE and RE) and two different human capital *proxies*. The first one (h1) considers only human capital quantitative aspects while the second one (h2) incorporates its qualitative aspects as explained previously.

In Table 1, the results indicate the importance of poverty into the determination of income per worker. Even controlling for human capital, investment in physical capital and for the effective depreciation of capital, a 10% increase in poverty has a negative impact on income per worker from 1.7% to 3.3% depending on the estimation method and the poverty indicator. In all specifications, the estimated poverty coefficients are significant different from zero at the 1% level.

Investment in physical capital has a positive influence on income per worker, but its estimated coefficients are not significant with the FE method and PHEP as the poverty indicator. With the RE method, its coefficients are positive and significant, but the Hausman specification test indicates that this method is inconsistent in the current estimations. With the FE estimated coefficients, a 10% increase in physical capital investment would have a positive impact on income per worker from 0.36% to 0.57%.

The human capital *proxies* have a positive and important consequence on income per worker and their coefficients are statistically different from zero in all estimations. Considering its quality slightly changes the results, with is an evidence that the effects of poverty on income per worker are not driven by human capital quality. A 10% upturn in human capital would have a positive impact on the regressand of about 2.2% with the FE method and of about 3.5% with the RE method. The effective depreciation of capital has the expected sign, but its estimated coefficients are not statistically different from zero.

The R^2 indicates that the four regressors explain more than 60% of the income per worker across Brazilian States and that it is mainly due to the R^2 between. The F (4, 74) test also points toward the importance of the regressors, while the F (25, 74) indicates that at least one estimated coefficient of the *dummies* that capture each states time constant singularities is statistically different from zero, with gives support to the use of the FE method instead of OLS. The intraclass correlation estimate (rho) [7] shows that more than 80% of the variance is due to differences across panels in the FE estimations.

The modified Wald test for groupwise heteroscedasticity and the Wooldridge test for autocorrelation in panel data indicates the presence of both problems and that heteroscedasticity is more severe, as expected, since the number of observations in each period is larger than the number of periods. Therefore, we should take care of them when estimating the effects of the regressors on income per worker.

[7] $Rho = \frac{(sigma\_u)^2}{(sigma\_u)^2+(sigma\_e)^2}$

Table 1 – Panel Data Estimations – PHEP and PHP as the indicators for poverty

	Dependent Variable – ln GDP per worker							
	Poverty Indicators – PHEP and PHP							
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
	PHEP				**PHP**			
	FE	**RE**	**FE**	**RE**	**FE**	**RE**	**FE**	**RE**
Poverty Indicator	-0.1723 (0.0359)***	-0.2568 (0.0373)***	-0.1720 (0.0359)***	-0.2187 (0.0366)***	-0.2233 (0.0538)***	-0.3356 (0.0562)***	-0.2228 (0.0538)***	-0.2730 (0.0542)***
s	0.0363 (0.0359)	0.0955 (0.0387)**	0.0366 (0.0359)	0.0884 (0.0340)***	0.0573 (0.0387)	0.1297 (0.0415)***	0.0577 (0.0387)	0.1109 (0.0362)***
h1	0.2236 (0.1128)**	0.3506 (0.1232)***			0.2136 (0.1178)*	0.3449 (0.1311)***		
h2			0.2240 (0.1125)**	0.3705 (0.1056)***			0.2148 (0.1175)*	0.3574 (0.1109)***
n	-0.0179 (0.0490)	-0.0235 (0.0504)	-0.0173 (0.0491)	-0.0065 (0.0477)	-0.0007 (0.0499)	-0.0002 (0.0520)	-0.0000 (0.0500)	0.0163 (0.0483)
c	2.6857 (0.2103)***	2.6690 (0.2326)***	2.4152 (0.3368)***	2.1158 (0.3291)***	2.9731 (0.2693)***	3.0966 (0.3034)***	2.7118 (0.3936)***	2.4692 (0.3955)***
Obser.	104	104	104	104	104	104	104	104
R^{2w}	0.4153	0.4063	0.4156	0.4082	0.3785	0.3694	0.3789	0.3720
R^{2b}	0.7906	0.7788	0.7536	0.7390	0.7282	0.7157	0.6993	0.6878
R^{2o}	0.6595	0.6674	0.6651	0.6674	0.6039	0.6119	0.6146	0.6193
F(4,74)	13.14***		13.15***		11.27***		11.29***	
F(25, 74)	11.09***		11.11***		12.37***		12.20***	
sig_u	0.2964	0.1593	0.2818	0.19228	0.3090	0.1636	0.2949	0.2185
sig_e	0.1345	0.1345	0.1345	0.1345	0.1387	0.1387	0.1386	0.1386
Rho	0 .8291	0.5837	0.8143	0.6713	0.8322	0.5819	0.8189	0.7129
Wald χ^2		99.53***		99.67***		83.67***		81.09***
Hausm χ^2		29.13***		16.94***		30.89***		13.77***
Wald Het.	2468.9***		2680.5***		2731.7***		2885.3***	
Autocorr	8.548***		8.410***		6.223**		6.154**	

Notes: standard deviations are in parentheses. ***** Significant at 10%; ****** significant at 5%; ******* significant at 1%. The dependent variable is income per worker, **s** is the average growth rate of physical capital per worker, **h1** is years of schooling, **h2** is years of schooling times IDEB, **n** is each State population growth rate, **c** is a constant term. **PHEP** is the proportion of households living in extreme poverty, and **PHP** is the proportion of households living in poverty. **Observ**. 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 overall effect of the regressors. **F (4,74)** is the test to check whether all the coefficients in the model are equal to zero, **F (25,74)** is to test the hypothesis that the dummy coefficients are all equal to zero, and **rho** is the intraclass correlation. **Wald χ^2** is to test if all the coefficients in the model are equal to zero in the Random Effects estimates, and **Hausm χ^2** is Hausman test for Fixed vs. Random Effect. **Wald Het.** is the Modified Wald test for groupwise heteroscedasticity and **Autocorr** is the Wooldridge test for autocorrelation in panel data.

In Table 2, the specifications and methods are the same. The only difference are the poverty indicators. Instead of PHEP and PHP as the poverty indicators, we have used PIEP and PIP to check if the results are robust with measures of poverty for individuals rather than for households. Comparing both tables results, the impact of poverty on income per worker hardly change. With the indicators of extreme poverty, the effects are essentially the same, while with PIP the poverty effects on income per worker increase slightly in relation to the results with PHP. The human and physical capital estimated coefficients rise somewhat.

The tests point to FE method as being the most appropriate in relation to the RE and OLS methods. The modified Wald test for groupwise heteroscedasticity and the Wooldridge test for autocorrelation in panel data also indicates the presence of both problems. As in the previous tests, heteroscedasticity is a central concern.

Table 2 – Panel Data Estimations – PIEP and PIP as the indicators for poverty

	Dependent Variable – ln income per worker							
	Poverty Indicators – PIEP and PIP							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	PIEP				PIP			
	FE	RE	FE	RE	FE	RE	FE	RE
Poverty Indicator	-0.1727 (0.0367)***	-0.2587 (0.0376)***	-0.1724 (0.0367)***	-0.2195 (0.0369)***	-0.2448 (0.0599)***	-0.3697 (0.0614)***	-0.2442 (0.0600)***	-0.3006 (0.0594)***
s	0.0514 (0.0369)	0.1161 (0.0392)***	0.0517 (0.0369)*	0.1051 (0.0345)**	0.0647 (0.0396)*	0.1388 (0.0418)***	0.0652 (0.0396)*	0.1172 (0.0365)***
h1	0.2411 (0.1125)**	0.3674 (0.1226)***			0.2368 (0.1168)**	0.3686 (0.1290)***		
h2			0.2417 (0.1122)**	0.3821 (0.1047)***			0.2381 (0.1164)**	0.3718 (0.1092)***
n	-0.0117 (0.0489)	-0.0200 (0.0503)	-0.0110 (0.0490)	-0.0028 (0.0475)	0.0030 (0.0498)	0.0006 (0.0518)	0.0037 (0.0499)	0.0169 (0.0481)
c	2.6710 (0.2104)***	2.6685 (0.2332)***	2.379 (0.3359)***	2.1025 (0.3277)***	3.0525 (0.2867)***	3.241 (0.3204)***	2.7630 (0.4045)***	2.575 (0.4080)***
N	104	104	104	104	104	104	104	104
R^{2w}	0.4101	0.4014	0.4105	0.4038	0.3745	0.3657	0.3751	0.3691
R^{2b}	0.7777	0.7674	0.7447	0.7325	0.7177	0.7068	0.6900	0.6810
R^{2o}	0.6557	0.6630	0.6627	0.6645	0.6042	0.6114	0.6141	0.6177
F(4,74)	12.86***		12.88***		11.08***		11.10***	
F(25, 74)	11.10***		11.07***		12.27***		12.16***	
sig_u	0.2952	0.1596	0.2796	0.1950	0.3065	0.1643	0.2913	0.2218
sig_e	0.1351	0.1351	0.1351	0.1351	0.1391	0.1391	0.1391	0.1391
Rho	0.8267	0.5824	0.8107	0.6757	0.8290	0.5823	0.8143	0.7178
Wald		99.18***		98.81***		84.44***		81.07***
Hausam χ^2		28.80***		15.92***		30.12***		12.49***
Wald Het.	4637.9***		4675.2***		2870.1***		3112.1***	
Autocorr	6.959**		6.808**		5.579**		5.505**	

Notes: standard deviations are in parentheses. ***** Significant at 10%; ****** significant at 5%; ******* significant at 1%. The dependent variable is income per worker, **s** is the average growth rate of physical capital per worker, **h1** is years of schooling, **h2** is years of schooling times IDEB, **n** is each State population growth rate, **c** is a constant term. **PIEP** is the proportion of individuals living in extreme poverty, and **PIP** is the proportion of individuals living in poverty. **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 overall effect of the regressors. **F (4,74)** is the test to check whether all the coefficients in the model are equal to zero, **F (25,74)** is to test the hypothesis that the dummy coefficients are all equal to zero, and **rho** is the intraclass correlation. **Wald** χ^2 is to test if all the coefficients in the model are equal to zero in the Random Effects estimates, and **Hausm** χ^2 is Hausman test for Fixed vs. Random Effect. **Wald Het.** is the Modified Wald test for groupwise heteroscedasticity and **Autocorr** is the Wooldridge test for autocorrelation in panel data.

In Table 3, the estimated results are those with robust standard errors to cross-sectional heteroskedasticity and within-panel serial correlation. With the robust standard errors, there is a rise in the estimated standard errors. Even though, all the poverty indicators estimated coefficients are still statistically different from zero at the 1% level. The coefficients of physical capital lose their statistical significance in all estimations. Human capital coefficients continue significant, except with PHP as the poverty indicator.

Table 3 – Panel Data Estimations – Fixed Effect with Robust Standard Errors

	Dependent Variable – ln income per worker							
	All poverty indicators – Fixed Effects with Robust Standard Errors							
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
	PHEP		**PHP**		**PIEP**		**PIP**	
Poverty Indicator	-0.1723 (0.0312)***	-0.1720 (0.0312)***	-0.2233 (0.0657)***	-0.2228 (0.0658)***	-0.1727 (0.0340)***	-0.1724 (0.0340)***	-0.2448 (0.0780)***	-0.2442 (0.0781)***
s	0.0363 (0.0370)	0.0366 (0.0364)	0.0573 (0.0402)	0.0577 (0.0398)	0.0514 (0.0386)	0.0517 (0.0380)	0.0647 (0.0418)	0.0652 (0.0414)
h1	0.2236 (0.1247)*		0.2136 (0.1337)		0.2411 (0.1191)**		0.2368 (0.1300)*	
h2		0.2240 (0.1226)*		0.2148 (0.1319)		0.2417 (0.1169)**		0.2381 (0.1280)*
n	-0.0179 (0.0424)	-0.0173 (0.0423)	-0.0007 (0.0457)	-0.0000 (0.0456)	-0.0117 (0.0403)	-0.0110 (0.0402)	0.0030 (0.0442)	0.0037 (0.0440)
c	2.6857 (0.1924)***	2.4152 (0.3244)***	2.9731 (0.2829)***	2.7118 (0.4034)***	2.6710 (0.1796)***	2.379 (0.3022)***	3.0525 (0.3082)***	2.7630 (0.4094)***
N	104	104	104	104	104	104	104	104
R^{2w}	0.4153	0.4156	0.3785	0.3789	0.4101	0.4105	0.3745	0.3751
R^{2b}	0.7906	0.7536	0.7282	0.6993	0.7777	0.7447	0.7177	0.6900
R^{2o}	0.6595	0.6651	0.6039	0.6146	0.6557	0.6627	0.6042	0.6141
F(4,25)	9.02***	8.98***	5.37***	5.37***	8.14***	8.12***	5.12***	5.12***
sig_u	0.2964	0.2818	0.3090	0.2949	0.2952	0.2796	0.3065	0.2913
sig_e	0.1345	0.1345	0.1387	0.1386	0.1351	0.1351	0.1391	0.1391
Rho	0 .8291	0.8143	0.8322	0.8189	0.8267	0.8107	0.8290	0.8143

Notes: robust standard deviations are in parentheses. * Significant at 10%; ** significant at 5%; *** significant at 1%. The dependent variable is income per worker, **s** is the average growth rate of physical capital per worker, **h1** is years of schooling, **h2** is years of schooling times IDEB, **n** is each State population growth rate, **c** is a constant term. **PHEP** is the proportion of households living in extreme poverty, **PHP** is the proportion of households living in poverty, **PIEP** is the proportion of individuals living in extreme poverty, and **PIP** is the proportion of individuals living in poverty. **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 overall effect of the regressors. **F (4,25)** is the test to check whether all the coefficients in the model are equal to zero, and **rho** is the intraclass correlation.

In general, the results indicate that the proportion of poverty is important to understand the difference in income per worker across the Brazilian States. The results of Table 3 are more reliable since they are estimated with the most appropriate method – FE – and they are corrected for heteroscedasticity and autocorrelation. The estimated results indicate that an increase in the proportion of poverty in 10% has a negative impact on the level of income per worker from 1,7% to 2,5% in the Brazilian States, even after controlling for human capital, investment in physical capital e for the effective depreciation of capital.

The problem of this estimation method is that it does not consider the reverse causality problem. Since poverty is likely to be reduced with an improvement in income per worker, as argued in the introduction, the previous estimates may be biased. The Dynamic Panel Model is one way to circumvent this problem.

6.2. Dynamic Panel Data

In Table 4 are presented the Arellano-Bond estimator results with PHEP and PHP as the poverty indicators. The estimations are based on the one-step Arellano-Bond estimator since the two-step is biased downwards[8]. By means of the Monte Carlo simulations, Judson and Owen (1999) show that the one-step GMM estimator outperforms the two-step estimator. For each poverty indicator, the first two columns convey the Arellano-Bond estimator (AB) results, and in the following two columns, the estimated standard errors are correct for heteroscedasticity (AB - R).

In Tables 4 and 5, only the poverty indicators were considered as endogenous regressors. The proportion of black people in each Brazilian State and its square were included in the estimations as exogenous instruments for poverty. The results in Table 4 point toward the importance of one period lagged poverty indicator in income per worker determination. With PHEP indicator, a 10% increase in the proportion of extremely poor households would have a 6.2% negative influence on income per worker, which is a considerable effect. All the estimated coefficients are significant at the 5% level. When PHP is considered as the poverty indicator, its negative impact is even larger, but its estimated coefficients are not significant.

In Table 4, the investment in physical capital have a larger impact in relation to the FE estimates, but its coefficients are statistically different from zero only with PHEP as a regressor and with robust standard errors. In this last case, a 10% upturn in physical investment rate leads to a 1.5% increase in income per worker. Considering the human capital *proxies*, despite the increase in their coefficients in relation to the FE estimates, they are not statistically different from zero in any specification. The negative lagged effect of income per worker was not the expected one. Additionally, with robust standard errors, the estimated coefficients are significant at 5% level.

In Table 4, the Wald tests points to the importance of the regressors, except with PHP and h2 as regressors, and when it is not corrected for heteroscedasticity. The Sargan tests indicate that the instruments are good (not correlated with the residuals) and the Wooldridge tests for autocorrelation do not reject the null of no first order autocorrelation.

[8] The two steps results are in Annex.

Table 4 – Dynamic Panel – Arellano and Bond: PHEP and PHP

	Dependent Variable – ln GDP per worker							
	Poverty Indicators – PHEP and PHP							
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
	PHEP				**PHP**			
	AB		**AB – R**		**AB**		**AB – R**	
Lagged IW	-1.1777	-1.1829	-1.1777	-1.1829	-1.3850	-1.3305	-1.3850	-1.3305
	(0.9594)	(0.9622)	(0.5535)**	(0.5538)**	(1.2687)	(1.2133)	(0.6545)**	(0.6278)**
Poverty Indicator	-0.0871	-0.0863	-0.0871	-0.0863	0.0392	0.0232	0.0392	0.0232
	(0.2131)	(0.2137)	(0.2355)	(0.2376)	(0.3486)	(0.3339)	(0.3446)	(0.3383)
Lagged Poverty Indicator	-0.6196	-0.6193	-0.6196	-0.6193	-1.118	-1.075	-1.118	-1.075
	(0.2990)**	(0.2989)**	(0.28264)**	(0.2860)**	(0.7493)	(0.7096)	(0.7823)	(0.7632)
s	0.1481	0.1489	0.1481	0.1489	0.1325	0.1303	0.1325	0.1303
	(0.1189)	(0.1191)	(0.0707)**	(0.0704)**	(0.1603)	(0.1551)	(0.0975)	(0.0940)
h1	0.7879		0.7879		0.6337		0.6337	
	(0.5826)		(0.7034)		(0.5974)		(0.6933)	
h2		0.7880		0.7880		0.6049		0.6049
		(0.5829)		(0.7049)		(0.5695)		(0.6687)
n	-0.1062	-0.1042	-0.1062	-0.1042	-0.0892	-0.0897	-0.0892	-0.0897
	(0.1645)	(0.1647)	(0.1401)	(0.1392)	(0.2036)	(0.1973)	(0.1754)	(0.1675)
c	6.3557	5.4185	6.3557	5.4185	9.0488	8.1220	9.0488	8.1220
	(2.3976)***	(2.1782)**	(1.4463)***	(1.6279)***	(4.5630)**	(4.1565)**	(2.9361)***	(2.5442)***
N	52	52	52	52	52	52	52	52
N Inst	10	10	10	10	10	10	10	10
N Groups	26	26	26	26	26	26	26	26
Wald	15.06**	15.08**	25.68***	25.45***	7.77	8.22	13.62**	13.96**
Sargan	1.8693	1.873			3.2581	3.5545		
P-Value	(0.6000)	(0.5990)			(0.3535)	(0.3138)		
Autocorr			-1.4255	-1.4206			-1.5865	-1.5836
P-Value			(0.1540)	(0.1554)			(0.1126)	(0.1133)

Notes: standard deviations are in parentheses. ***** Significant at 10%; ****** significant at 5%; ******* significant at 1%. The dependent variable is income per worker, **s** is the average growth rate of physical capital per worker, **h1** is years of schooling, **h2** is years of schooling times IDEB, **n** is each State population growth rate, **c** is a constant term. **PHEP** is the proportion of households living in extreme poverty, and **PHP** is the proportion of households living in poverty. **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. **Wald** is to test if all the coefficients in the model are equal to zero, **Sargan** is the Sargan test of overidentifying restrictions derived by Arellano and Bond (1991), and **Autocorr** is the Wooldridge test for autocorrelation in panel data.

With the poverty indicators for individuals, with the results in Table 5, the poverty effects are somewhat larger in the case of one period lagged extreme poverty (PIEP). In this case, a 10% rise in extreme poverty has a negative impact on income per worker of nearly 6.7%. Considering the poverty indicator (PIP), the estimated coefficients are larger, in absolute value, but they are not significant. Therefore, the results indicate that extreme poverty is more important on income per worker determination than poverty, with is also supported by the Wald tests to check if all the coefficients in the model are equal to zero.

The other results in Table 5 are very similar to those in Table 4. Investment in physical capital has a positive impact on the regressand, but its coefficients are significant only with the extreme poverty indicator and robust standard errors. Human capital is not significant due to the large standard errors. The Sargan and the Wooldridge tests are favourable.

Table 5 - Dynamic Panel – Arellano and Bond: PIEP and PIP

	Dependent Variable – ln income per worker							
	Poverty Indicators – PIEP and PIP							
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
	PIEP				**PIP**			
	AB		**AB (R)**		**AB**		**AB (R)**	
Lagged IW	-1.1563	-1.1531	-1.1563	-1.1531	-1.4559	-1.3142	-1.4559	-1.3142
	(0.9661)	(0.9630)	(0.5246)**	(0.5238)**	(1.5410)	(1.3810)	(0.8944)*	(0.8142)*
Poverty Indicator	-0.0250	-0.02686	-0.0250	-0.02686	0.1449	0.0978	0.1449	0.0978
	(0.2500)	(0.2492)	(0.2570)	(0.2593)	(0.4899)	(0.4398)	(0.4982)	(0.4638)
Lagged Poverty Indicator	-0.6710	-0.6670	-0.6710	-0.6670	-1.3126	-1.1930	-1.3126	-1.1930
	(0.3416)**	(0.3388)**	(0.2958)**	(0.2993)**	(1.0876)	(0.9593)	(1.1492)	(1.062)
s	0.1333	0.1340	0.1333	0.1340	0.0824	0.0802	0.0824	0.0802
	(0.1261)	(0.1257)	(0.0678)**	(0.0671)**	(0.1622)	(0.1506)	(0.0825)	(0.0768)
h1	.8916		.8916		0.6735		0.6735	
	(0.6577)		(0.7609)		(0.6595)		(0.7970)	
h2		0.8843		0.8843		0.6108		0.6108
		(0.6527)		(0.7604)		(0.5890)		(0.7249)
n	-0.0522	-0.0505	-0.0522	-0.0505	-0.0498	-0.0558	-0.0498	-0.0558
	(0.1754)	(0.1749)	(0.1653)	(0.1635)	(0.2174)	(0.2009)	(0.1859)	(0.1692)
c	6.3333	5.2634	6.3333	5.2634	9.7712	8.4786	9.7712	8.4786
	(2.4393)***	(2.1951)**	(1.3355)***	(1.5491)***	(5.9601)*	(5.0282)*	(4.3157)**	(3.3818)**
N	52	52	52	52	52	52	52	52
N Inst	10	10	10	10	10	10	10	10
N Groups	26	26	26	26	26	26	26	26
Wald	13.51**	13.65**	29.19***	28.64***	6.46	7.40	11.67*	12.28*
Sargan	1.92398	1.9580			3.5995	4.3303		
P-Value	(0.5883)	(0.5812)			(0.3081)	(0.2279)		
Autocorr			-1.3416	-1.3366			-1.6072	-1.5892
P-Value			(0.1797)	(0.1814)			(0.1080)	(0.1120)

Notes: standard deviations are in parentheses. ***** Significant at 10%; ****** significant at 5%; ******* significant at 1%. The dependent variable is income per worker, **s** is the average growth rate of physical capital per worker, **h1** is years of schooling, **h2** is years of schooling times IDEB, **n** is each State population growth rate, **c** is a constant term. **PIEP** is the proportion of individuals living in extreme poverty, and **PIP** is the proportion of individuals living in poverty. **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. **Wald** is to test if all the coefficients in the model are equal to zero, **Sargan** is the Sargan test of overidentifying restrictions derived by Arellano and Bond (1991), and **Autocorr** is the Wooldridge test for autocorrelation in panel data.

In general, the previous results point to the importance of the proportion of poverty on income per worker. When taking into consideration the dynamic of the variables and controlling for reverse causality by means of Arellano-Bond estimators, the results indicates that extreme poverty is a central variable to understand income per worker differentials in the Brazilian States. Additionally, the effects are relevant: a 10% increase in extreme poverty leads to a decrease in income per worker from 6.2% to 6.7%

6.3. Poverty and productivity

As discussed previously, one of the channels in which poverty influences income per worker is via productivity. Equation (10), replicated below, gives one way to link both variables. The assumption in equation (17) is that the effect of poverty incidence on income per worker was being captured by the error term in the MRW (1992) extended Solow model:

$$(17) \qquad lnA_{i,t} = a_i + lnp_{i,t} + \varepsilon_{i,t}$$

In this section, the estimations are based on equation (17) to check if poverty is a relevant variable to understand TFP differences across the Brazilian States. Estimations based on equation (17) are also relevant because it involves only one regressor, what makes it easier to circumvent the reverse causality problem.

For example, when estimating equation (11) all the regressors may be endogenous, what makes it more challenging to deal with reverse causality even in the Dynamic Panel Data framework since more instruments are needed and the lagged endogenous regressors may not always be appropriate. The inertia of the variables through time may make it difficult to eliminate the causality problem only with the lagged values as instruments.

In Table 6, the FE estimations[9] with robust standard errors indicate that extreme poverty has a negative and significant impact on the Brazilian States' TFP at the 5% and 1% level. A 10% intensification in the proportion of extreme poverty would have a 1.8% (or 1.7% with PIEP) negative influence on TFP. The proportion of poverty also has a negative influence on TFP, but its estimated coefficients are not statistically different from zero. In addition, the F tests do not reject the null that poverty is not an important regressor, which is expected since the F and t tests leads to the same conclusion with only one regressor.

Table 6 – Panel Data – Fixed Effects: Total Factor Productivity

	Dependent Variable – ln Total Factor Productivity							
	All poverty indicators – Fixed Effect Estimators with and without robust standard errors							
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
	PHEP		**PHP**		**PIEP**		**PIP**	
	FE	**FE (Rob)**	**FE**	**FE (Rob)**	**FE**	**FE (Rob)**	**FE**	**FE (Rob)**
Poverty Indicator	-0.1890 (0.0806)**	-0.1890 (0.0649)***	-0.1011 (0.1028)	-0.1011 (0.0866)	-0.1725 (0.0787)**	-0.1725 (0.0600)***	-0.1207 (0.1131)	-0.1207 (0.0933)
Constant	3.0250 (0.1925)***	3.0250 (0.1520)***	2.9229 (0.3483)***	2.9229 (0.2919)***	3.0244 (0.2052)***	3.0244 (0.1538)***	3.0110 (0.4034)***	3.0110 (0.3316)***
N	104	104	104	104	104	104	104	104
R^{2w}	0.0666	0.0666	0.0124	0.0124	0.0587	0.0587	0.0146	0.0146
R^{2b}	0.4168	0.4168	0.3958	0.3958	0.4147	0.4147	0.3866	0.3866
R^{2o}	0.2612	0.2612	0.1906	0.1906	0.2529	0.2529	0.1920	0.1920
F(1,77)	5.49**	8.48***	0.97	1.36	4.80**	8.25**	1.14	1.67
F(25, 77)	3.48***		3.72***		3.50***		3.72***	
sig_u	0.3781	0.3781	0.4191	0.4191	0.3829	0.3829	0.4166	0.4166
sig_e	0.3797	0.3797	0.3906	0.3906	0 .3813	0 .3813	0.3902	0.3902
rho	0.4978	0.4978	0.5352	0.5352	0.5021	0.5021	0.5326	0.5326

Notes: robust standard deviations are in parentheses. ***** Significant at 10%; ****** significant at 5%; ******* significant at 1%.

[9] We present only the Fixed Effect results in Table 6 since the Hausman tests indicates that this method is more appropriate than Random Effects. The RE estimates are in Annex.

The dependent variable is income per worker, **s** is the average growth rate of physical capital per worker, **h1** is years of schooling, **h2** is years of schooling times IDEB, **n** is each State population growth rate, **c** is a constant term. **PHEP** is the proportion of households living in extreme poverty, **PHP** is the proportion of households living in poverty, **PIEP** is the proportion of individuals living in extreme poverty, and **PIP** is the proportion of individuals living in poverty. **N**. is the sample size, $\mathbf{R^{2w}}$ is the within effect of the regressors, $\mathbf{R^{2b}}$ is the between effect of the regressors, and $\mathbf{R^{2o}}$ is overall effect of the regressors. **F (4,25)** is the test to check whether all the coefficients in the model are equal to zero, and **rho** is the intraclass correlation.

At the bottom of Table 6, the F statistics to test if all the dummies coefficients are zero are rejected. Therefore, the FE method is more appropriate than OLS. The intraclass correlation estimative shows that about half of the variance is due to differences across panels.

Introducing the dynamics among variables through the Arellano-Bond estimator and controlling for the reverse causality problem with lagged endogenous variables and proportion of black in each Brazilian State and its square as instruments in the first stage, the results in Table 7 show the importance of contemporaneous and lagged poverty indicators on TFP determination. In almost all estimations, the poverty contemporaneous coefficients are significant at 5% or 10% of significance, except for PHP.

In Table 7, the difference between its first and second columns' results for each poverty indicator is that in the latter, the Arellano-Bond results are corrected for heteroscedasticity. With PHEP as the regressor, a 10% rise in a Brazilian State proportion of households in extreme poverty would reduce TFP in 5%, which is a considerable amount. Including the effect of the lagged poverty indicator, the reduction in PTF would be twofold, i.e. 10%. But its coefficient is significant only without the robust standard errors estimates.

With PIEP, the extreme poverty contemporaneous effect is similar in relation to the regressions with PHEP, but somewhat smaller. PIP coefficients are significant and their current effect is quite large. In all estimations, summing up the contemporary and lagged estimated coefficients, a 10% increase in poverty would lead to nearly 10% reduction in TPF. However, in almost all estimation, the lagged coefficients are not statistically different from zero.

The Sargan tests indicates a overidentifying problem at the 10% level of significance, but not at 5% when the extreme poverty indicators (PHEP and PIEP) are the regressors. With the poverty indicators (PHP and PIP) as regressors, it is a problem even with the 1% level of significance, casting doubts into the estimated results. Autocorrelation also seems to be a major problem with the poverty indicators (PHP and PIP).

Table 7 - Dynamic Panel – Arellano and Bond: Total Factor Productivity

	Dependent Variable – ln Total Factor Productivity							
	All poverty indicators – Arellano and Bond Estimators with and without robust standard errors							
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
	PHEP		**PHP**		**PIEP**		**PIP**	
	AB	**AB (Rob)**	**AB**	**AB (Rob)**	**AB**	**AB (Rob)**	**AB**	**AB (Rob)**
Lagged TFP	0.5226 (0.3450)	0.5226 (0.2841)*	0.5651 (0.3380)*	0.5651 (0.3416)*	0.4849 (0.3984)	0.4849 (0.3537)	0.7047 (0.2837)**	0.7047 (0.2744)***
Poverty Index	-0.5280 (0.2392)**	-0.5280 (0.2485)**	-0.5324 (0.3566)”	-0.5324 (0.4408)	-0.4629 (0.2599)*	-0.4629 (0.2678)*	-0.8007 (0.3402)**	-0.8007 (0.3823)**
Lagged Poverty Index	-0.5064 (0.3094)*	-0.5064 (0.3679)	-0.5702 (0.6248)	-0.5702 (0.8658)	-0.5181 (0.3867)	-0.5181 (0.4345)	-0.1179 (0.6431)	-0.1179 (0.8223)
Constant	3.6097 (1.1235)***	3.6097 (1.1270)***	4.7720 (1.9299)**	4.7720 (2.5125)*	3.8066 (1.4422)***	3.8066 (1.4805)***	3.8746 (1.9783)**	3.8746 (2.4547)
N	52	52	52	52	52	52	52	52
N Instruments	7	7	7	7	7	7	7	7
N Groups	26	26	26	26				
Wald	27.48***	42.36***	17.55***	15.81***	25.47***	50.42***	22.77***	14.34***
Sargan	6.9114		13.0210		7.7543		18.3774	
P-Value	(0.0748)*		(0.0046)***		(0.0514)*		(0.0004)***	
Autocor		-1.7922		-2.7796		-1.634		-3.173
P-Value		(0.0731)*		(0.0054)***		(0.1023)”		(0.0015)***

Notes: standard deviations are in parentheses. ***** Significant at 10%; ****** significant at 5%; ******* significant at 1%. The dependent variable is total factor productivity. **PHEP** is the proportion of households living in extreme poverty, **PHP** is the proportion of households living in poverty, **PIEP** is the proportion of individuals living in extreme poverty, and **PIP** is the proportion of individuals living in poverty. **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. **Wald** is to test if all the coefficients in the model are equal to zero, **Sargan** is the Sargan test of overidentifying restrictions derived by Arellano and Bond (1991), and **Autocorr** is the Wooldridge test for autocorrelation in panel data.

The results in the last two tables indicate that an important part of poverty effect on income per worker is via TFP. In addition, the empirical results suggest that extreme poverty incidence is the relevant measure of poverty to understand the link between poverty incidence and development level in the Brazilian States.

7. Conclusions

In the present study, our main concern was to examine the effects of poverty on development level of the Brazilian States. There are many studies assessing the relevance of economic growth and development in poverty reduction, but there are almost no one trying to measure the impacts of poverty on economic development.

The empirical results indicate that the incidence of poverty is important in the economic development of the Brazilian States. Poorer Brazilian States also 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 (PHEP and PIEP) on the development level across the Brazilian States in relation to the variables quantifying poverty (PHP and PIP).

In the Fixed Effect (FE) estimates with robust standard errors, all poverty indicators have an adverse influence on income per worker and their coefficients are statistically different from zero at 1% level. With the Arellano-Bond estimators, all poverty indicators impact negatively the economic development level of the Brazilian States, but only the extreme poverty indicators are statistically significant (5% level). A 10% increase in extreme poverty leads to a decrease on income per worker from 6.2% to 6.7%, controlling for human capital stock, investment in physical capital, and effective depreciation of capital.

Some of the effects seem to be driven via productivity. The Brazilian States with higher incidence of poverty are the same with lower Total Factor Productivity (TFP) and this effect holds even when taking into consideration the reverse causality problem. In the FE estimates with robust standard errors, all poverty indicators have a deleterious effect on TFP, but only the extreme poverty incidence indicators had a significant effect on TFP (1% level). With these estimates, a 10% increase in extreme poverty would lead to a reduction on TFP from 1.7% to 1.9%.

In the Arellano-Bond estimates, the extreme poverty indicators have a negative and statistically significant effect on TFP, with the same results holding for the proportion of individuals living in poverty (PIP) as the regressor. However, the Sargan tests indicate that the instruments are not adequate for the poverty incidence indicators (PIP and PHP). With the extreme poverty indicators (PIEP and PHEP), the Sargan tests indicate that the instruments are adequate at 5% level of significance, but no at 10%.

Summarizing, the results point to the importance of extreme poverty incidence indicators in helping to understand the development level differentials across the Brazilian States. With the present study, we hope to foster some attention to studies focusing on the important relationship between poverty and economic development.

8. References

ARAÚJO, U. C. (2000). Reparação moral, responsabilidade pública e direito à igualdade do cidadão negro no Brasil. Seminário "Racismo, Xenofobia e Intolerância", Hotel Bahia Othon, Salvador, 20 de novembro de 2000.

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: 277-297.

ASHRAF, Q. H.; WEIL, D. N.; WILDE, J. (2013). The Effect of Fertility Reduction on Economic Growth. *Population and Development Review*, 39 (1): 97–130.

BACHA, E. L.; BONELLI, R. (2005). Uma Interpretação das Causas da Desaceleração Econômica do Brasil. *Revista de Economia Política*, 25 (3): 163-189.

BANERJEE, A. N.; BANIK, N.; MUKHOPADHYAY, J. P. (2015). The Dynamics of Income Growth and Poverty: Evidence from Districts in India. *Development Policy Review*, 33 (3): 293-312.

BARBOSA FILHO, F. H.; PESSÔA, S. A.; VELOSO, F. A. (2010). Evolução da produtividade total dos fatores na economia brasileira com ênfase no capital humano - 1992-2007. *Revista Brasileira de Economia*, 64 (2): 91–113.

BONELLI, R.; LEVY, P. M. (2010). Determinantes do crescimento econômico do Espírito Santo: uma análise de longo prazo. In Espírito Santo: instituições, desenvolvimento e inclusão social - Chapter 2.

COELHO, R. L. P. (2006). Dois Ensaios sobre a Desigualdade de Renda nos Municípios Brasileiros. *Dissertação de Mestrado*, CEDEPLAR/UFMG.

COELHO, R. L. P.; FIGUEIREDO, L. (2007). Uma análise da hipótese da convergência para os municípios brasileiros. *Revista Brasileira de Economia*, 61 (3): 331-352.

CHEN, S.; RAVALLION, M. (2013). More Relatively-Poor People in a Less Absolutely-Poor World. Review of Income and Wealth, 59 (1): 1-28.

DATT, G.; RAVALLION, M.; MURGAI, R. (2016). Growth, Urbanization and Poverty Reduction in India. *NBER Working Paper Series*, Working Paper 21983. 45 pages.

DEATON, A.; KOZEL, V. (2005). Data and Dogma: The Great Indian Poverty Debate. *The World Bank Researcher Observer*, 20 (02): 177- 199.

FERREIRA, P. C., ELLERY, R. JR.; GOMES. V. (2008). Produtividade agregada brasileira (1970-2000): declínio robusto e fraca recuperação. *Estudos Econômicos*, 38 (1): 31-53.

FIGUEIREDO, L.; NAKABASHI, L. (2016). The relative importance of total factor productivity and factors of production in income per worker: evidence from the Brazilian States. *Economia*. Forthcoming.

FOSU, A. K. (2015). Growth, Inequality and Poverty in Sub-Saharan Africa: Recent Progress in a Global Context. *Oxford Development Studies*, 43 (1): 44–59.

GALSTER, G.C.; CUTSINGER, J.; MALEGA, R. (2008). The costs of concentrated poverty: Neighborhood property markets and the dynamics of decline. In N. Retsinas and E. Belsky (Eds.)

Revisiting Rental Housing (93-113). Washington, D.C.: Brookings Institution Press.

GOMES, V., PESSÔA, S., VELOSO, F. (2003). Evolução da Produtividade Total dos Fatores na Economia Brasileira: Uma Análise Comparativa. *Pesquisa e Planejamento Econômico*, 33 (3): 389-434.

GRADIN, C. (2009). Why is Poverty So High Among Afro-Brazilians? A Decomposition Analysis of the Racial Poverty Gap. *The Journal of Development Studies*, 45 (09): 1426-1452.

HALL, R. E.; JONES, C. I. (1999). Why do some countries produce so much more output per worker than others? *Quarterly Journal of Economics*, 114 (1): 83-116.

HANSON, J. L.; HAIR, N.; SHEN, D. G.; SHI, F.; GILMORE, J. H.; WOLFE, B. L.; POLLAK, S. D. (2013). Family Poverty Affects the Rate of Human Infant Brain Growth. *PLOS ONE*, 8 (12): 1-9.

ISLAM, N. (1995). Growth Empirics: A Panel Data Approach. *The Quarterly Journal of Economics*, 110 (4): 1127-1170.

JUDSON, R.A.; OWEN, A.L. (1999). Estimating dynamic panel data models: a guide for macroeconomists. *Economic Letters*, 65 (1): 9–15.

LIMA, M. C. (2002). Raízes da miséria no Brasil: da senzala à favela. In Extrema Pobreza no Brasil: a situação do direito à alimentação e moradia adequada.

LOUREIRO, P.R.A.; CARNEIRO, F.G. (2001). Discriminação no mercado de trabalho: Uma análise dos setores rural e urbano no Brasil. *Economia Aplicada*, 5 (3): 519-545.

LUCAS, R. E. JR. (1988). On the Mechanics of Economic Development. *Journal of Monetary Economics*, 22 (1): 3-42.

MANKIW, N.G.; ROMER, D.; WEIL, D. (1992). *A contribution to the Empirics of Economic Growth*. The Quarterly Journal of Economics, 107 (2): 407- 437.

MINCER, J. (1974). Schooling, experience, and earnings. National Bureau of Economic Research, New York: Columbia University Press.

PEREIRA, A.E.G. (2012). Dois Ensaios sobre Instituições e Desenvolvimento Econômico no Brasil. Dissertação de Mestrado do Programa de Pós-Graduação em Desenvolvimento Econômico, UFPR.

NAKABASHI, L; SALVATO, M.A. (2007). Human Capital Quality in the Brazilian States. *Economia*, 8, (2): 211–229.

RAVALLION, M. Why Don't We See Poverty Convergence? *American Economic Review*, 102 (1): 504-523.

REIS, E.; MAGALHAES, K.; PIMENTEL, M.; MEDINA, M. (2005). Estoque de capital privado nos municípios brasileiros, 1970-1985. 64p.

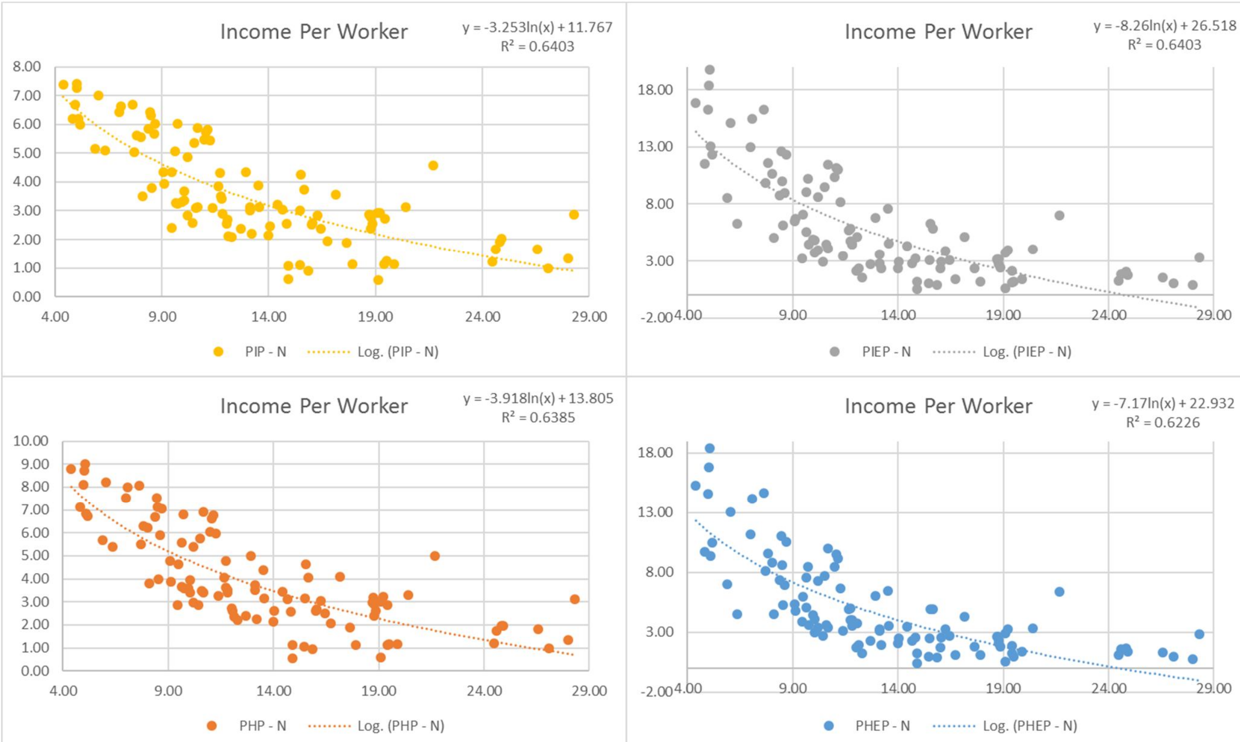
RESENDE, M.; WYLLIE, R. (2006). Retornos para educação no Brasil: evidências empíricas adicionais. *Economia Aplicada*, 10 (3): 349-365.

SACHSIDA, A.; LOUREIRO, P. R. A; MENDONÇA, M. J. C. (2004). Um Estudo Sobre Retorno em Escolaridade no Brasil. *Revista Brasileira de Economia*, 58 (2): 249-265.

SINDING, S. W. (2009). Population, poverty and economic development. *Philosophical Transactions of the Royal Society*, 364: 3023–3030.

Annex A – relationship between poverty indicators with income, total factor productivity and black population – variables in level (not in log).

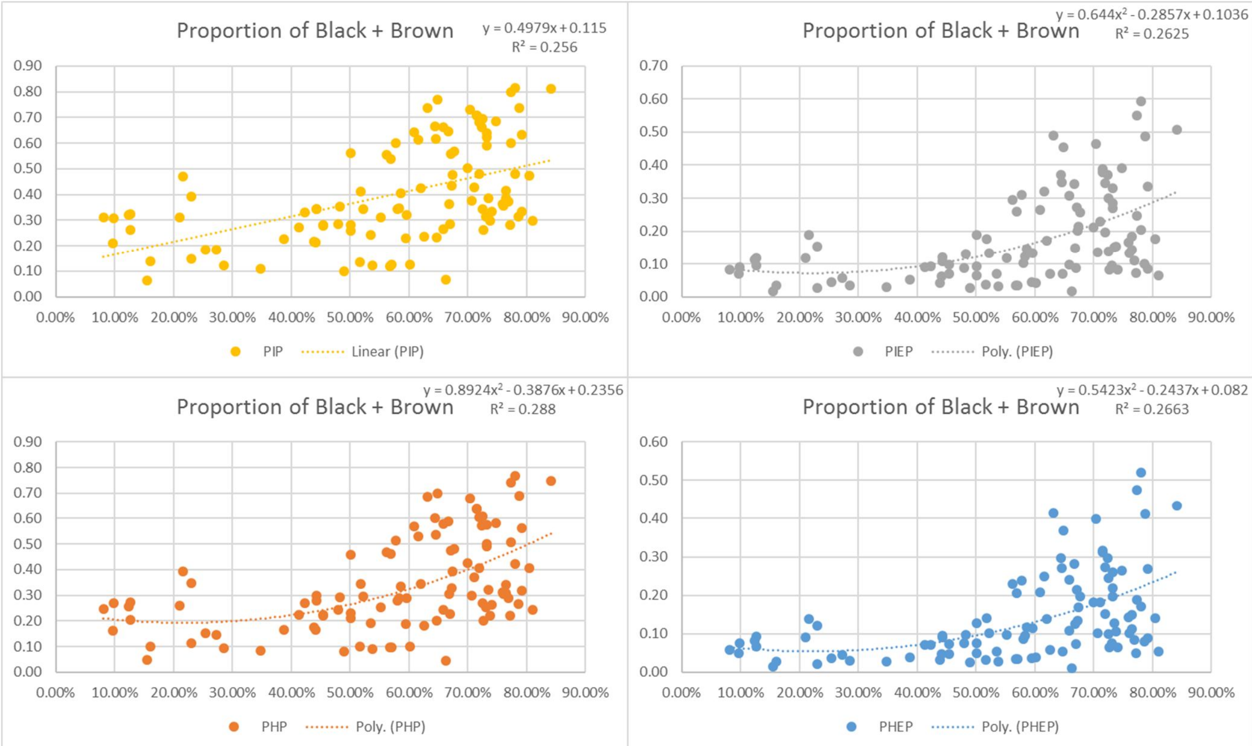
Figure A.1 – Relationship between income per worker and poverty in the Brazilian States: 1980, 1991, 2000 and 2010.



Source: own elaboration based on data from IPEA and IBGE.

Notes: PIP – Proportion of individuals in poverty- required calories (%); PIEP – Proportion of individuals in extreme poverty - required calories (%); PHP - Proportion of households in poverty (%); PHEP – Proportion of households in extreme poverty (%).

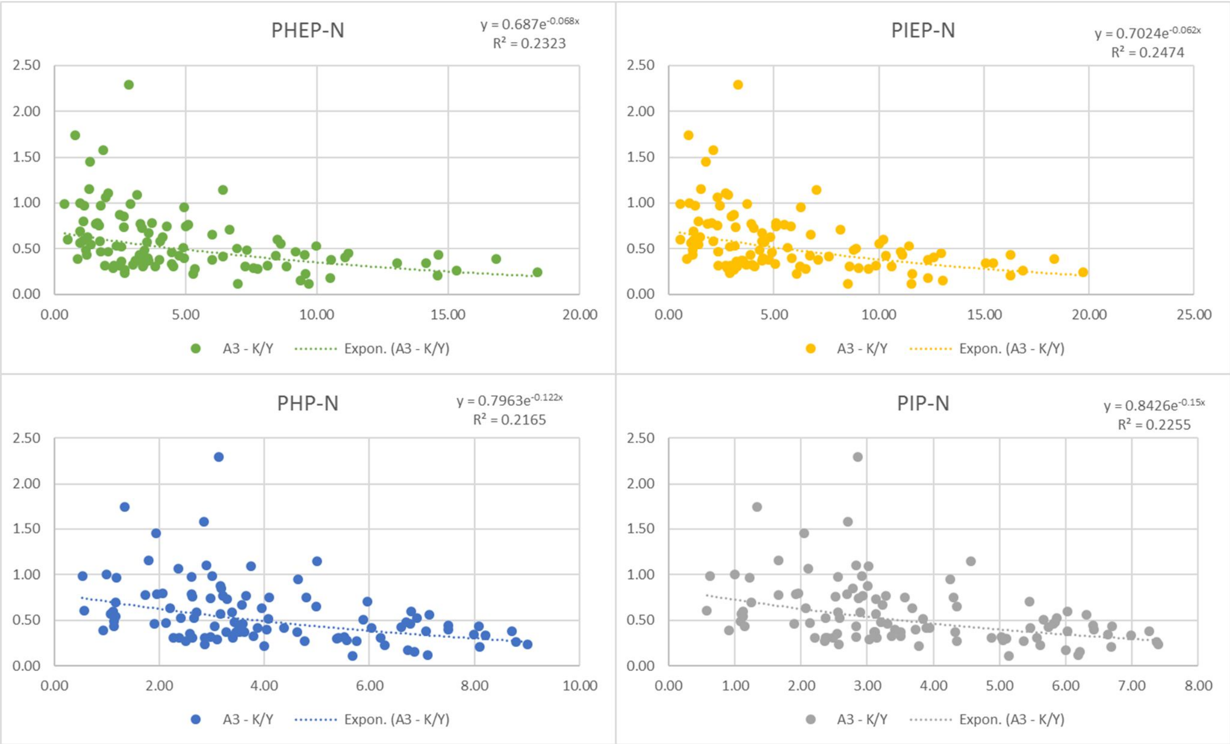
Figure A.2 – Relationship between black people and poverty in the Brazilian States: 1980, 1991, 2000 and 2010



Source: own elaboration based on data from IPEA and IBGE.

Notes: PIP – Proportion of individuals in poverty- required calories (%); PIEP – Proportion of individuals in extreme poverty - required calories (%); PHP - Proportion of households in poverty (%); PHEP – Proportion of households in extreme poverty (%).

Figure A.3 – Relationship between poverty indexes and TFP in the Brazilian States: 1980, 1991, 2000 and 2010



Source: own elaboration based on data from IPEA and IBGE.

Notes: PIP – Proportion of individuals in poverty- required calories (%); PIEP – Proportion of individuals in extreme poverty - required calories (%); PHP - Proportion of households in poverty (%); PHEP – Proportion of households in extreme poverty (%).

Annex B – Estimation Results

Table B.1 – Dynamic Panel – Arellano and Bond Two Step Estimations: PHEP and PHP

	Dependent Variable – ln GDP per worker							
	Poverty Indicators – PHEP and PHP							
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
	PHEP				**PHP**			
	AB		**AB – R**		**AB**		**AB – R**	
Lagged IW	-1.1036	-1.1251	-1.1036	-1.1251	-1.1276	-1.0744	-1.1276	-1.0744
	(0.5243)**	(0.5256)**	(0.6357)*	(0.6174)*	(0.6250)*	(0.5979)*	(0.8824)	(0.8880)
Poverty Indicator	0.0278	0.04135	0.0278	0.04135	0.1080	0.0939	0.1080	0.0939
	(0.2076)	(0.2107)	(0.2926)	(0.3011)	(0.2202)	(0.2206)	(0.3046)	(0.3212)
Lagged Poverty Indicator	-0.7785	-0.7958	-0.7785	-0.7958	-1.4484	-1.3914	-1.4484	-1.3914
	(0.2134)***	(0.2178)***	(0.2564)***	(0.2592)***	(0.5515)***	(0.5382)***	(0.9050)	(0.9510)
s	0.2033	0.2043	0.2033	0.2043	0.1912	0.1813	0.1912	0.1813
	(0.0584)***	(0.0586)***	(0.0652)***	(0.0644)***	(0.0830)**	(0.0801)**	(0.1361)	(0.1378)
h1	1.2215		1.2215		0.8750		0.8750	
	(0.5559)**		(0.8132)"		(0.3947)**		(0.6740)**	
h2		1.2495		1.2495		0.8201		0.8201
		(0.5650)**		(0.8285)"		(0.3849)**		(0.7042)**
n	-0.1474	-0.1527	-0.1474	-0.1527	-0.2279	-0.2259	-0.2279	-0.2259
	(0.0901)*	(0.0916)*	(0.1059)	(0.1077)"	(0.0924)**	(0.0903)***	(0.1138)**	(0.1215)*
c	5.9140	4.4658	5.9140	4.4658	9.2459	8.052	9.2459	8.052
	(1.3497)***	(1.4401)***	(1.7472)***	(2.0369)**	(2.7378)***	(2.5097)***	(4.2304)**	(3.9141)**
N	52	52	52	52	52	52	52	52
N Inst	10	10	10	10	10	10	10	10
N Groups	26	26	26	26	26	26	26	26
Wald	58.93***	58.44***	35.65***	37.46***	22.38***	22.13***	10.14	9.08
Sargan	2.6435	2.5916			4.7125	5.1896		
P-Value	(0.4499)	(0.4590)			(0.1941)	(0.1584)		
Autocorr	-1.1033	-1.1073	-1.0854	-1.0907	-1.0513	-1.0548	-0.9783	-0.9632
P-Value	(0.2699)	(0.2682)	(0.2777)	(0.2754)	(0.2931)	(0.2915)	(0.3279)	(0.3354)

Notes: standard deviations are in parentheses. ***** Significant at 10%; ****** significant at 5%; ******* significant at 1%. The dependent variable is income per worker, **s** is the average growth rate of physical capital per worker, **h1** is years of schooling, **h2** is years of schooling times IDEB, **n** is each State population growth rate, **c** is a constant term. **PHEP** is the proportion of households living in extreme poverty, and **PHP** is the proportion of households living in poverty. **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. **Wald** is to test if all the coefficients in the model are equal to zero, **Sargan** is the Sargan test of overidentifying restrictions derived by Arellano and Bond (1991), and **Autocorr** is the Wooldridge test for autocorrelation in panel data.

Table B.2 - Dynamic Panel – Arellano and Bond Two Step Estimations: PIEP and PIP

	Dependent Variable – ln income per worker							
	Poverty Indicators – PIEP and PIP							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	PIEP				PIP			
	AB		AB (R)		AB		AB (R)	
Lagged IW	-1.0914	-1.1087	-1.0914	-1.1087	-1.1509	-0.9983	-1.1509	-0.9983
	(0.5009)**	(0.5003)**	(0.6641)*	(0.6584)*	(0.7164)*	(0.6523)	(1.1065)	(1.0610)
Poverty Indicator	0.0827	0.0960	0.0827	0.0960	0.2252	.1719	0.2252	0.1719
	(0.1921)	(0.1961)	(0.2280)	(0.2275)	(0.3029)	(0.2907)	(0.4341)	(0.4353)
Lagged Poverty Indicator	-0.8520	-0.8673	-0.8520	-0.8673	-1.5526	-1.3846	-1.5526	-1.3846
	(0.2152)***	(0.2193)***	(0.2660)***	(0.2686)***	(0.7489)**	(0.6932)**	(1.2381)	(1.2331)
s	0.1894	0.1878	0.1894	0.1878	0.1311	0.1144	0.1311	0.1144
	(0.0558)***	(0.0556)***	(0.0601)***	(0.0616)***	(0.0674)**	(0.0623)*	(0.1294)	(0.1227)
h1	1.419		1.419		0.9294		0.9294	
	(0.514)***		(0.7132)**		(0.4388)**		(0.8421)	
h2		1.4399		1.4399		0.80490		0.80490
		(0.5238)***		(0.7112)**		(0.4056)**		(0.8301)
n	-0.1302	-0.13457	-0.1302	-0.13457	-0.1977	-0.1990	-0.1977	-0.1990
	(0.0995)	(0.1011)	(0.0999)	(0.1008)	(0.1166)*	(0.1082)*	(0.1396)	(0.1449)*
c	5.9587	4.2824	5.9587	4.2824	9.5920	7.9691	9.5920	7.9691
	(1.2681)***	(1.3113)***	(1.5787)***	(1.5246)***	(3.3512)***	(2.8418)***	(5.3565)**	(4.5852)*
N	52	52	52	52	52	52	52	52
N Inst	10	10	10	10	10	10	10	10
N Groups	26	26	26	26	26	26	26	26
Wald	53.24***	52.59***	38.63***	40.34***	16.90***	17.29***	7.32	6.63
Sargan	-1.0673	2.4109			5.4986	6.3386		
P-Value	(0.2859)	(0.4916)			(0.1387)	(0.0962)		
Autocorr	2.3772	-1.0698	-1.0659	-1.0692	-1.0748	-1.0823	-0.9751	-0.9589
P-Value	(0.4979)	(0.2847)	(0.2865)	(0.2850)	(0.2825)	(0.2791)	(0.3295)	(0.3376)

Notes: standard deviations are in parentheses. ***** Significant at 10%; ****** significant at 5%; ******* significant at 1%. The dependent variable is income per worker, **s** is the average growth rate of physical capital per worker, **h1** is years of schooling, **h2** is years of schooling times IDEB, **n** is each State population growth rate, **c** is a constant term. **PIEP** is the proportion of individuals living in extreme poverty, and **PIP** is the proportion of individuals living in poverty. **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. **Wald** is to test if all the coefficients in the model are equal to zero, **Sargan** is the Sargan test of overidentifying restrictions derived by Arellano and Bond (1991), and **Autocorr** is the Wooldridge test for autocorrelation in panel data.

Table B.3 – Panel Data – Random Effects: Total Factor Productivity

	Dependent Variable – ln Total Factor Productivity							
	All poverty indicators – Fixed Effect Estimators with and without robust standard errors							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	PHEP		PHP		PIEP		PIP	
	RE	RE (Rob)	RE	RE (Rob)	RE	RE (Rob)	RE	RE (Rob)
Poverty Indicator	-0.2788 (0.0639)***	-0.2788 (0.0495)***	-0.2597 (0.0862)***	-0.2597 (0.0862)***	-0.2649 (0.0630)***	-0.2649 (0.0516)***	-0.2881 (0.0940)***	-0.2881 (0.0867)***
Constant	3.2351 (0.1649)***	3.2351 (0.1302)***	3.4569 (0.2990)***	3.4569 (0.2990)***	3.2611 (0.1757)***	3.2611 (0.1460)***	3.6056 (0.3417)***	3.6056 (0.3048)***
N	104	104	104	104	104	104	104	104
R^{2w}	0.0666	0.0666	0.0124	0.0124	0.0587	0.0587	0.0146	0.0146
R^{2b}	0.4168	0.4168	0.3958	0.3958	0.4147	0.4147	0.3866	0.3866
R^{2o}	0.2612	0.2612	0.1906	0.1906	0.2529	0.2529	0.1920	0.1920
sig_u	0.2937	0.2937	0.2976	0.2976	0.2939	0.2939	0.3010	0.3010
sig_e	0.3797	0.3797	0.3906	0.3906	0.3813	0.3813	0.3902	0.3902
rho	0.3743	0.3743	0.3673	0.3673	0.3727	0.3727	0.3730	0.3730
Wald	19.02***	31.63***	9.08***	11.14***	17.69***	26.27***	9.38***	11.03***
Hausman (χ^2)	3.14*		6.68***		3.57*		6.07**	
P-Value	(0.0763)		(0.0098)		(0.0590)		(0.0138)	

Notes: robust standard deviations are in parentheses. **”** Significant at 15%; ***** Significant at 10%; ****** significant at 5%; ******* significant at 1%. The dependent variable is income per worker, **s** is the average growth rate of physical capital per worker, **h1** is years of schooling, **h2** is years of schooling times IDEB, **n** is each State population growth rate, **c** is a constant term. **PHEP** is the proportion of households living in extreme poverty, **PHP** is the proportion of households living in poverty, **PIEP** is the proportion of individuals living in extreme poverty, and **PIP** is the proportion of individuals living in poverty. **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 overall effect of the regressors. **$F_{(4,25)}$** is the test to check whether all the coefficients in the model are equal to zero, and **rho** is the intraclass correlation.

Table B.4 – Summary Statistics

Variable	*Obs.*	*Mean*	*Std. Dev.*	*Min*	*Max*
state	104	13.50	7.54	1.00	26.00
year	104	1995	11	1980	2010
iw	104	2.50	0.43	1.48	3.34
s	104	2.20	0.66	-0.13	3.46
k3	104	10.53	0.46	9.36	11.93
h1	104	0.72	0.26	0.24	1.29
h2	104	1.92	0.34	1.24	2.70
n	104	1.28	0.54	0.28	3.71
phep	104	2.34	0.82	0.14	3.95
php	104	3.37	0.61	1.53	4.34
piep	104	2.56	0.83	0.47	4.08
pip	104	3.55	0.57	1.85	4.40
TFP	104	2.58	0.56	1.09	4.13
black	104	3.95	0.53	2.10	4.43
blacksquare	104	15.86	3.66	4.41	19.62
lagiw	103	2.50	0.44	1.48	3.34

Iw is income per worker, **s** is the average growth rate of physical capital per worker, **h1** is years of schooling, **h2** is years of schooling times IDEB, **n** is each State population growth rate. **PHEP** is the proportion of households living in extreme poverty, **PHP** is the proportion of households living in poverty, **PIEP** is the proportion of individuals living in extreme poverty, and **PIP** is the proportion of individuals living in poverty. **TFP** is the estimated total factor productivity