Poverty convergence in Brazilian municipalities

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Abstract

This paper aims to analyze poverty convergence in Brazil. Following Ravallion (2012), we study the effects of the initial poverty incidence on average per capita income growth and poverty reduction. Using a dataset from 1991 to 2010, we find that per capita income growth decreases poverty in Brazil. Also, there is absolute income convergence across the Brazilian municipalities. However, these effects are counterbalanced by the initial poverty incidence on income growth and poverty reduction since we do not find poverty convergence across the Brazilian municipalities.

Keywords: Poverty Incidence; Economic Growth; Brazilian Municipalities.

ANPEC Area: Area 6

JEL Classification: O11;O47;I32

Resumo

O objetivo deste artigo é analisar porque não observamos convergência da pobreza nos municípios brasileiros. Seguindo Ravallion (2012), estudamos os efeitos da incidência de pobreza inicial sobre o crescimento da renda per capita média e sobre a redução da própria pobreza. Os resultados encontrados sugerem que a própria pobreza pode estar prejudicando a convergência da pobreza. Encontramos que o crescimento da renda per capita média reduz pobreza e a presença da convergência da renda no Brasil. Entretanto, esses efeitos são contrabalanceados pela incidência de pobreza inicial no crescimento da renda e na redução da pobreza.

Palavras-chaves: Pobreza; Crescimento Econômico; Municípios Brasileiros.

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1 Introduction

Poverty incidence is a relevant research topic in economic growth and development since people subjective well-being is negatively correlated to poverty regional rate, suggesting that poverty is a public bad (Welsch and Biermann, 2019). Also, poverty may influence the criminality rates. Pare and Felson (2014) find that individuals living in countries with a higher poverty incidence are more likely to be a victim of homicide, robbery, burglary, and other crimes of theft. Mehlum et al. (2006) also find a positive relationship between poverty and property crimes. Finally, poverty may hamper economic growth and development (Ravallion, 2012).

Following Ravallion (2012), two stylized facts are highlighted in the economic growth and development literature when comparing countries with different economic development levels: 1) the advantage of backwardness; and 2) the advantage of growth. The first fact states that when comparing two similar countries, the one with lower initial average income will experience higher economic growth. The second suggests that countries with higher economic growth have a more substantial poverty reduction. Therefore, we can infer that countries with lower initial income – those usually having higher poverty incidence – experience higher economic growth. Consequently, they have a more significant poverty reduction.

However, considering the Brazilian municipalities, the ones with the lowest average income are not those experiencing the most relevant poverty reduction from 1991 to 2010, i.e., there is no sign of poverty convergence in Brazil, which is in line with the results of Ravallion (2012) for countries. Ouyang et al. (2019) also find a lack of "poverty convergence" across the Less Developed Countries (LDCs) using the the same data source as Ravallion (2012), but for an extended period (1980-2014) [1]. This enigma points out that we are missing something important. Benfica and Henderson (2021) highlight the relevance of the initial conditions, such as economic inequality and the level of development, in modifying the relationship between economic growth and poverty. Ravallion (2012) considers that the initial poverty incidence may influence income growth and poverty reduction in ways that cancel out the previously cited advantages.

Lopez and Servén (2006) introduce a minimum subsistence consumption level to Aghion et al. (1999)'s model and find that high poverty incidence implies a lower growth rate. Poverty trap models based on impatience to consume (high time preference associated with low life expectancy) indicate that poverty reduces savings and investment rates (Azariadis, 2006; Kraay and Raddatz, 2005). Another way in which poverty affects income performance is via nutrition and health. The individuals in adulthood will be able to perform work fully only when nutrition is sufficient to cover the basal metabolic rate in childhood. In addition, other aspects of children's development, such as learning and cognitive skills development, can be affected by poverty, reducing their future earnings (Aber et al., 1997; Engle and Black, 2008; Hanson et al., 2013). Therefore, high poverty incidence hurts economic performance.

The present paper follows Ravallion (2012)'s analysis, but for the Brazilian municipalities. It is crucial to check if his results hold for regions of the same country since many important variables

[1] For the Sub-Saharan Africa countries, Ouyang et al. (2019) find poverty convergence because the income convergence effect is stronger than that found across LDCs.

affecting income performance and poverty incidence, as the institutional setting and macroeconomic policies, are more similar than across countries. Because we are using a municipal dataset, the number of observations is higher than in cross-country studies. As a consequence, the estimated parameters are more reliable. While Ravallion (2012) employs samples consisting of a maximum of 90 countries, the sample size of our study is composed of 4,491 municipalities.

In addition, since poverty is high in many Brazilian municipalities, it is relevant to understand its impacts on economic performance to foster public policies to fight poverty. Considering the households with monthly per capita income thresholds of R$ 140.00 [2], the municipalities in the bottom one-quarter of the poverty incidence distribution had a 36.6% poverty rate or below, while in the upper one-quarter, it was above 76.9%, in 1991. Also, we consider other variables that may influence income or poverty variations, such as income distribution and middle-class size.

Many theoretical studies have pointed to the importance of initial income distribution on economic growth. High inequality can reduce physical and human capital investments when credit constraints exist (Galor and Zeira, 1993; Perotti, 1996; Aghion and Bolton, 1997). Moreover, high inequality can distort policy responses or restrict efficiency-promoting cooperation so that essential public goods are underprovided or efficiency-enhancing reforms are blocked (Bardhan et al., 2000). Thus, many papers include income inequality measures as an explanatory variable for economic growth, and they find adverse effects of income inequality on growth (Li and Zou, 1998; Barro, 2000; Forbes, 2000). In addition, Fosu (2017) shows that the relationship between income growth and poverty reduction depends on the income inequality level, indicating the presence of an interaction effect among them.

The above arguments suggest that poverty is crucial in explaining income growth. There is also evidence that income inequality is relevant to economic performance. Therefore, we include both variables in the empirical analysis as regressors to check which of them is more relevant in the economic process.

Since the variables in the present study are likely to be influenced by public policies and other macroeconomic events that are broader in space than the limits of a municipality, we have considered the potential spatial correlation on our estimates. For example, this spatial dependence may be due to economies of agglomeration and regional dynamics of labor attraction (Kalenkoski and Lacombe, 2008). When there is a spatial correlation in the data, but it is ignored, the OLS and GMM estimation methods are biased (Arbia, 2014).

In general, our results align with those of Ravallion (2012). They indicate the presence of the advantages of backwardness and growth, but no poverty convergence across the Brazilian municipalities due to the influence of the initial poverty incidence reducing both effects (backwardness and growth). The data shows a nonlinear relationship between initial poverty incidence and subsequent poverty reduction. Municipalities with a high poverty incidence in 1991 experienced a more expressive poverty reduction from 1991 to 2010 up to a threshold point. After this point, higher initial poverty is related to a lower subsequent poverty contraction.

Besides this introduction, the following section brings the methodology, data, and tests to check for spatial correlation across the municipalities. The following one brings the empirical analysis, testing

[2] In 2010 prices.

for the advantages of backwardness and growth, besides "poverty convergence". The last section concludes.

2 Methodology and data

2.1 Data and Descriptive Statistics

Most data are from the Human Development Atlas (PNUD). PNUD uses the Brazilian Demographic Censuses (IBGE) to construct its dataset. All variables values are in prices of 2010. The dataset is for 1991, 2000, and 2010. The 2020 Brazilian Census has been postponed, and its dataset is not available yet. Since the data for the variables are from the same surveys, the comparability problems are minor compared to countries' datasets.

Given the most recent survey for date (t) in municipality i and the earliest available survey for data $(t-\tau)$, the growth rate for variable x is

$$g_i(x_{i,t}) = (x_{i,t} - x_{i,t-\tau})/(\tau x_{i,t-\tau}). \tag{1}$$

The headcount index measures the proportion of the poor population $(P_{i,t})$. It is calculated as the proportion of the population living in households with income per capita below a poverty line. There are three standard poverty lines in Brazil: extreme poverty; poverty; and vulnerability to poverty. The monthly income thresholds are R$ 70.00, R$ 140.00, and R$ 255.00, in 2010 prices. These income thresholds are used as references to assessment poverty programs. In this paper, we focus on the R$ 140.00 threshold as the poverty line $P_{i,t}$. Table 1 brings the descriptive statistics. For 1991, the poverty incidence ranges from 0.44% (Fernando de Noronha – PE) to 97% (São Sebastião de Uatumá – AM). In the bottom one-quarter of the sample, the poverty incidence P_{1991} was below 36.6%, while in the upper one-quarter, it was above 76.9 %, showing that poverty is a relevant problem in Brazil.

In relation to the income inequality measures, the literature has focused mainly on the Gini index (Voitchovsky, 2005). Also, the middle-class size has been used to measure the income distribution influence on income performance. The increase in the middle-class can foster entrepreneurship, consumer demand, growth-promoting policy reforms, and good institutions (Doepke and Zilibotti, 2005; Sridharan, 2004; Easterly, 2001; Birdsall et al., 2000; Acemoglu and Zilibotti, 1997; Murphy et al., 1989).

The Gini index measures income inequality $(G_{i,t})$. It ranges from 0 (most equal income distribution) to 100 (most unequal income distribution). In 1991, the income distribution measure ranged from 32 (Areiopolis – SP) to 92 (Santa Helena – PB). About one-quarter of the sample had a Gini index below 49, while one-quarter had it above 57. The average Gini index was 53.1, in 1991, and 49.5, in 2010.

In addition, we use three measures of the middle-class size as indicators of income inequality. As in Paes de Barros and Grosner (2012)[3], the first is the share of the population living in households with income between R$ 1,540.00 and R$ 2,813.00, in 2012 prices. Following Easterly (2001), the second measure is the income share of the households in the middle three quintiles of the income distribution

[3]This is the middle class criterion adopted by the Brazilian Bureau of Strategic Affairs (SAE).

($MQ_{i,t}$). Finally, the "miser index" proposed by Lind and Moene (2011) is an inverse measure of the middle class. $P_{i,t}(y_{i,t} - y^P_{i,t})$ is the "miser index", where $P_{i,t}$ is the proportion of the population living below the poverty line, $y_{i,t}$ is the average income, and $y^P_{i,t}$ is the average income of those living below the poverty line.

Table 1: Descriptive Statistics

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
y	4,491	244.704	145.955	43.700	125.155	327.730	1,185.280
y^P	4,491	73.377	14.902	0.000	62.140	85.331	124.820
P	4,491	55.348	23.593	0.440	36.581	76.895	97.020
G	4,491	53.058	6.578	32.000	49.000	57.000	92.000
MC	4,491	22.086	11.680	0.000	12.336	30.273	60.399
MQ	4,491	37.989	5.243	1.920	34.665	41.630	53.450
$miser$	4,491	6,643.590	2,833.751	200.882	4,391.596	8,546.213	23,695.700
$g(y)$	4,491	6.521	3.162	−0.233	4.427	8.110	30.967
$g(P)$	4,491	−3.362	1.055	−5.216	−4.185	−2.602	21.053
LF	4,491	63.851	4.660	50.970	60.320	67.650	73.610
SA	4,491	70.254	13.398	10.590	62.963	80.015	99.250

Notes: **y** is the average per capita income. $\mathbf{y^P}$ is the average per capita income of the poor. **P** is the proportion of people below the poverty line (headcount index). **G** is the Gini inequality index. **LF** is the life expectation index. **SA** is the school attendance rate. **MC** is the middle class size (SAE definition). **MQ** is the income share commanded by the middle three quintiles. **miser** is the miser index. **g** is the rate of growth given by equation (1) from 1991 to 2010.

Table 2 shows the correlation coefficients in 1991. We find a relevant negative correlation between the Gini index (G_{1991}) and the income share of the households in the middle three quintiles (MQ_{1991}) (-0.97), indicating that both measures similarly capture income inequality. There is also a large negative correlation between poverty incidence ($P_{i,t}$) and average income (y_{1991}) (-0.92), and poverty incidence ($P_{i,t}$) and y^P_{1991} (-0.90), indicating that regions with high income have low poverty incidence in Brazil. The SAE measure of middle-class size (MC_{1991}) is highly correlated with the poverty measure (-0.95), average income (y_{1991}) (0.86), and average income of the poor (y^P_{1991}) (0,87). Therefore, the data indicate meaningful interactions among average income, poverty incidence, and income inequality.

Figure 1 brings the spatial correlations of the main variables of the present study for 1991. Panel (a) shows the poverty headcount index (P_{1991}), which shows a concentration of high poverty incidence in the municipalities of the North and Northeast of the country. In panels (b) and (c), we have the average per capita income (y_{1991}) and the size of the middle class (MC_{1991}), which shows higher values in the municipalities of the South and Southeast of Brazil. Finally, panel (d) brings the income distribution measured by the Gini index (G_{1991}). The income distribution is better in the country's South and Southeast municipalities, but many in the Northeast have good income distribution.

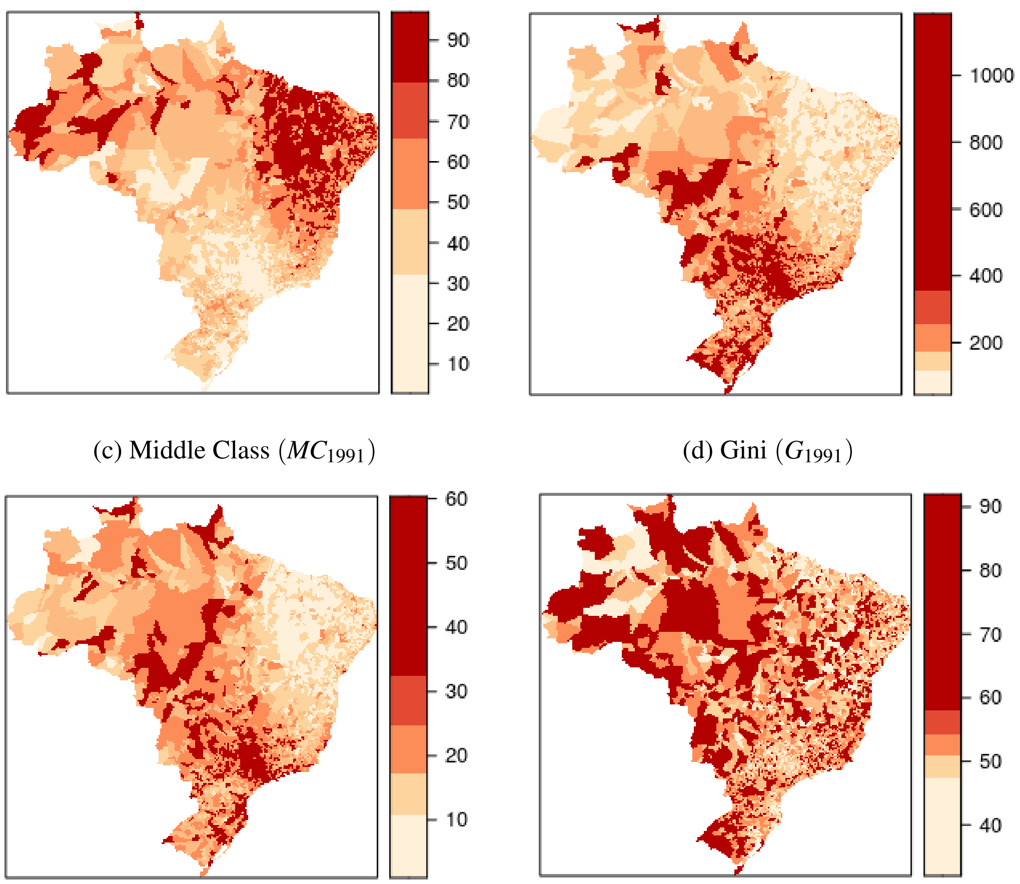
In Table 3, we have the Moran's I Global Statistics for the variables of Figure 1. The Moran's I Statistics is a correlation coefficient that measures the spatial autocorrelation of the variables across the neighboring municipalities, and it ranges from -1 to 1. The tests' results indicate the presence of spatial autocorrelation with the most used neighbors' spatial weight matrices, and the spatial correlation coefficients are similar in all of them. The poverty measure and income per capita have the two highest

Table 2: Correlations

	y	yP	P	G	MC	MQ	miser	gy	gP
y	1								
yP	0.706	1							
P	-0.874	-0.82	1						
G	-0.216	-0.45	0.39	1					
MC	0.808	0.76	-0.947	-0.456	1				
MQ	0.066	0.213	-0.264	-0.926	0.352	1			
miser	-0.132	-0.121	0.072	0.704	-0.146	-0.649	1		
gy	-0.506	-0.479	0.463	-0.141	-0.469	0.208	-0.36	1	
gP	-0.447	-0.569	0.541	-0.062	-0.458	0.1	-0.474	-0.13	1

Notes: **y** is the average per capita income. $\mathbf{y^P}$ is the average per capita income of the poor. **P** is the proportion of people below the poverty line (headcount index). **G** is the Gini inequality index. **MC** is the middle class size (SAE definition). **MQ** is the income share commanded by the middle three quintiles. **miser** is the miser index. **g** variables are the growth rate of the per capita income and the poverty index by the percentual difference.

Figure 1: Spatial distributions



(a) Poverty (P_{1991}) (b) Per Capita Income (y_{1991}) (c) Middle Class (MC_{1991}) (d) Gini (G_{1991})

spatial correlations.

Table 3: Global Moran's I Statistics

	P_{1991}	y_{1991}	MC_{1991}	G_{1991}
Queen	0.853***	0.734***	0.79***	0.217***
Rook	0.853***	0.735***	0.789***	0.217***
Dist (30 km)	0.742***	0.62***	0.712***	0.173***
K-5	0.857***	0.706***	0.806***	0.229***
K-10	0.847***	0.701***	0.792***	0.216***

Note: * Significant at 10%; ** Significant at 5%; *** Significant at 1%.

2.2 The choice of the spatial model

According to Vega and Elhorst (2015), unless we have sound theoretical reasoning for modeling spatial dependence, the SLX model with a parametric spatial matrix based on the inverse distance [4] is the most suitable model to start the analysis. The SLX model takes the form:

$$\mathbf{Y} = \alpha \mathbf{i_N} + \mathbf{X}\beta + \mathbf{WX}\theta + \varepsilon \tag{2}$$

where $\mathbf{Y}$ represents an $N \times 1$ vector consisting of one observation on the dependent variable for every unit in the sample, $\mathbf{i_N}$ is an $N \times 1$ vector of ones associated with the constant term α, $\mathbf{X}$ is an $N \times K$ matrix of explanatory variables related to the $K \times 1$ parameter vector β, $\mathbf{W}$ is a positive $N \times N$ spatial weight matrix so that $\mathbf{WX}$ represents the exogenous interaction effects among the explanatory variables associated with the $K \times 1$ parameter vector θ and ε is a vector of iid disturbance with zero mean and variance σ^2.

Following Vega and Elhorst (2015), we use a parameterized spatial weight matrix which has the form

$$W = (w_{i,j}) \in \mathbb{R}^{N \times N}; \quad w_{i,j} = \begin{cases} 0, & \text{if} \quad i = j \quad \text{or} \quad d_{i,j} > \bar{c} \\ \dfrac{1}{d_{i,j}^{\gamma}}, & \text{if} \quad i \neq j \quad \text{and} \quad d_{i,j} \leq \bar{c} \end{cases} \tag{3}$$

where N is the number of municipalities, $d_{i,j}$ is the distance between regions i and j, γ[5]. is the estimated decay parameter, and $\bar{c}$ is a cut-off distance[6].

Amongst the advantages of this approach is that the SLX model does not impose a prior restriction on the ratio between the direct and spillover effects as the SAC and SAR models (Vega and Elhorst, 2015). Also, LeSage (2014) emphasizes that most spatial spillovers are local. Thus the preferred models would be the SLX and SDEM.

In the present study, the LM tests, the AIC and BIC criteria and the Moran's I statistics on the

[4] The parametric elements of the spatial matrix can be estimated following $w_{i,j} = 1/d_{i,j}$, where $d_{i,j}$ denotes the distance between observations i and j, and γ is the distance decay parameter to be estimated alongside the model. The advantage of using this parametric spatial matrix is that more information is used to evaluate the spatial effects compared to pre-defined matrices (Vega and Elhorst, 2015).

[5] The algorithms to estimate the decay parameter (γ) can be obtained upon request.

[6] In the present paper, the cut-off is the minimum distance as such all the municipalities have at least one neighbor. The cut-off distance is 260km.

residuals supports the SDEM model as the preferred one, which has the form:

$$\begin{aligned} \mathbf{Y} &= \alpha \mathbf{i_N} + \mathbf{X}\beta + \mathbf{WX}\theta + \mathbf{u} \\ \mathbf{u} &= \lambda W \mathbf{u} + \varepsilon \end{aligned} \tag{4}$$

3 Empirical results

3.1 Testing for Convergence in average income and poverty

The two stylized facts of income convergence and income growth reducing poverty should imply poverty convergence. According to Ravallion (2012), in the standard log-linear growth models, the speed of convergence is the same for the average income and poverty incidence [7]. To show this, consider the most common growth specification (consider $\tau = 1$):

$$\Delta \ln y_{i,t} = \alpha_1 + \alpha_2 \ln y_{i,t-1} + \varepsilon_{i,t} \tag{5}$$

where α_i is a municipal-specific effect, β_i is a municipal-specific convergence parameter, and $\varepsilon_{i,t}$ is a zero-mean error term.

Now consider the most simple specification for poverty as a function of average income per capita:

$$\ln P_{i,t} = \eta_1 + \eta_2 \ln y_{i,t} + v_{i,t} \tag{6}$$

Where δ_i is a municipal-specific effect, η_i is the elasticity of poverty to income, and $v_{i,t}$ is a zero-mean error term. From equation (6), we obtain:

$$\ln P_{i,t} - \ln P_{i,t-1} = \eta_2(\ln y_{i,t} - \ln y_{i,t-1}) + \mu_{i,t} \tag{7}$$

where $\mu_{i,t} = v_{i,t} - v_{i,t-1}$. Using equation (6) in $t-1$ in (5), the variation in average income is given by

$$\ln y_{i,t} - \ln y_{i,t-1} = \alpha_1 + (\alpha_2/\eta_2)(\ln P_{i,t-1} - \eta_1 - v_{i,t-1}) + \varepsilon_{i,t} \tag{8}$$

From equations (7) and (8), the implied equation for poverty variation is

$$\Delta \ln P_{i,t} = \tilde{\alpha}_1 + \tilde{\alpha}_2 \ln P_{i,t-\tau} + \tilde{\varepsilon}_{i,t}, \tag{9}$$

where $\tilde{\alpha}_1 = \alpha_1\eta_2 - \alpha_2\eta_1$, $\tilde{\alpha}_2 = \alpha_2$ and $\tilde{\varepsilon}_{i,t} = \varepsilon_{i,t}\eta_2 + v_{i,t} - (1+\alpha_2)v_{i,t-\tau}$. Comparing (5) and (9), we see that the "speed of poverty convergence", $\partial \Delta P_{i,t}/\partial \ln P_{i,t-\tau} = \alpha_2$, is the same as that for income per capita, $\partial \Delta \ln y_{i,t}/\partial \ln y_{i,t-\tau} = \alpha_2$. We would expect this result since there is a direct relationship between $\Delta \ln P_{i,t}$ and $\Delta \ln y_{i,t}$ according to equation (7).

[7] In this section, we follow closely Ravallion (2012), but instead of average consumption, we use average income because of data availability.

In columns (1) and (2) of Table 4, we have the results for income convergence based on the following equation:

$$g(y_{i,1991\text{-}2010}) = \beta_1 + \beta_2 \ln y_{i,1991} + \beta_3 X_{i,1991} + \varepsilon_{i,2010} \tag{10}$$

Where X denotes a vector of controls comprising school attendance and life expectancy at birth. The results of Table 4 support the income convergence hypothesis since the estimated β_2 coefficient is -2.86 (column 1) without the controls variables, and -6.00 (column 3) with them. The results are robust when considering the spatial correlation, with the results in columns (2) and (4). Without the control variables, the direct effect is -4.03, and the spillover effect is 0.83. With them, the direct effect is -5.81, and the spillover effect is considerably higher: 2.88 [8]. The decay parameter is significant and near 1 in column (2) and 0.11 in column (4), suggesting that the additional controls raise the spillover effects of more distant neighbors. The Moran's I Statistics suggest that the SDEM model considerably reduces the residual spatial correlation.

Table 4: Testing advantage of backwardness

	$g(y)$			
	OLS	*SDEM*	*OLS*	*SDEM*
	(1)	(2)	(3)	(4)
$\ln y$	-2.865 t = -42.355^{***}	-4.028 t = -46.025^{***}	-6.000 t = -58.494^{***}	-5.814 t = -52.394^{***}
Lag $\ln y$		0.825 t = 12.375^{***}		2.883 t = 4.135^{***}
Constant	21.791 t = 60.075^{***}	26.164 t = 56.440^{***}	-72.771 t = -25.649^{***}	-37.003 t = -10.346^{***}
λ		1***		0.992***
γ		0.96		0.11
AIC	21576.1	20014.3	20354.5	19685.8
BIC	21595.3	20046.4	20386.5	19685.8
Moran's I Stat.	0.28***	0.05***	0.13***	0.02***
Observations	4,490	4,490	4,490	4,490

Notes: * Significant at 10%; ** Significant at 5%; *** Significant at 1%. Columns (1) and (2) show the estimation of the expression 10. Columns (3) and (4) show the estimation of expression 10 with additional controls (ln school frequency and ln life expectancy). λ is the scalar spatial autoregressive disturbance parameter. γ is the distance decay parameter. AIC and BIC are the Akaike and Bayesian information criterion. Moran's I Stat is the the spatial correlation test on the regression residuals.

Table 5 brings the results to measure the influence of income growth on poverty reduction based on the following equation:

[8] The SDEM's total effects have been ommited to save space, but the results are significant and can be obtained upon request.

$$g(P_{i,1991\text{-}2010}) = \delta_1 + \delta_2 g(y_{i,1991\text{-}2010}) + \delta_3 X_{i,1991} + \nu_{i,2010} \tag{11}$$

where X denotes the same matrix of controls. In column (1) of Table 5, the significant coefficient of -0.043 suggests that a rise in income per capita reduces poverty. Considering the estimation with the control variables, the income influence on poverty reduction duplicates (see column (3)). When considering the spatial correlation, the direct effect of income growth on poverty reduction is also negative, with the results in columns (2) and (4). With the control variables, the total effect is positive due to the spillovers, indicating that the average income growth of the neighbors raises poverty incidence. The results suggest the presence of the advantage of growth effect, i.e., that economic growth is associated with a reduction in poverty incidence. This result is supported by other studies as Benfica and Henderson (2021), Datt et al. (2016), Banerjee et al. (2015) and Adams Jr (2004).

Table 5: Testing advantage of growth

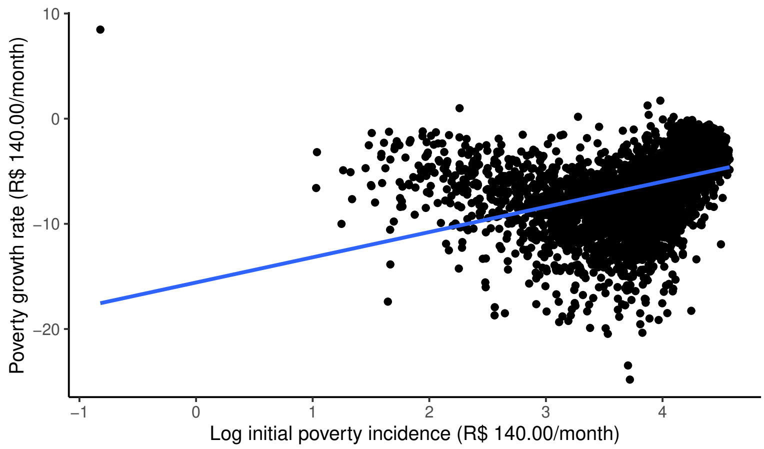
	$g(P)$			
	OLS	*SDEM*	*OLS*	*SDEM*
	(1)	(2)	(3)	(4)
$g(y)$	-0.043	-0.060	-0.092	-0.079
	t = -9.387^{***}	t = -16.849^{***}	t = -31.033^{***}	t = -26.807^{***}
Lag $g(y)$		-0.129		0.130
		t = -10.210^{***}		t = 4.286^{***}
Constant	-3.084	-2.322	34.438	21.816
	t = -91.900^{***}	t = -69.904^{***}	t = 62.315^{***}	t = 27.309^{***}
λ		0.999***		0.997***
γ		0		0
AIC	12573.9	9040	8362.1	7228
BIC	12593.2	9072.1	8394.2	7228
Moran's I Stat.	0.59***	0.13***	0.13***	0.05***
Observations	4,490	4,490	4,490	4,490

Notes: * Significant at 10%; ** Significant at 5%; *** Significant at 1%. Columns (1) and (2) show the estimation of the expression 11. Columns (3) and (4) show the estimation of expression 11 with additional controls (ln school frequency and ln life expectancy). λ is the scalar spatial autoregressive disturbance parameter. γ is the distance decay parameter. AIC and BIC are the Akaike and Bayesian information criterion. Moran's I Stat is the the spatial correlation test on the regression residuals.

However, as shown in Figure 2, poverty convergence does not seem to occur. We would expect a negative relationship, meaning that the municipalities with high initial poverty incidence would have a low - possible negative - poverty growth rate. In Figure 2, the relationship between the two variables seems not linear, with a negative relation up to a threshold and then a positive one. Therefore, after a threshold, a higher initial poverty incidence leads to less poverty reduction.

The other two measures of poverty incidence leads to a similar conclusion, i.e, they point to the absence of poverty convergence in the Brazilian Municipalities from 1991 to 2010. With the extreme poverty measure, the regression line has an almost horizontal inclination, and with the vulnerability to poverty measure, it is slightly positive. The figures with the later relationships are not presented for the sake of brevity.

Figure 2: Poverty variation and initial poverty



In summary, similar to what Ravallion (2012) find for countries, our results support the existence of the advantages of growth and backwardness effects. However, there are no poverty convergence in the Brazilian municipalities.

3.2 Initial poverty incidence and income growth

This subsection begins with the specification in equation (12) to test the importance of initial poverty incidence on economic performance. The results of the estimations using equation (12) are presented in Table 6.

$$g(y_{i,1991\text{-}2010}) = \lambda_1 + \lambda_2 \ln y_{i,1991} + \lambda_3 \ln P_{i,1991} + \varepsilon_{i,2010} \quad (12)$$

In column (1) of Table 6, the OLS results show that the estimated coefficients of the initial poverty incidence are negative and significant, indicating that the initial poverty incidence negatively impacts economic performance. A 1% increase in initial poverty incidence (P_{1991}) is associated with an annual income growth decline of almost 0.5 p.p. from 1991 to 2010.

We have considered several alternative specifications to examine the robustness of the results. Column (2) of Table 6 brings the SDEM estimation results instead of the OLS ones. In all specifications, the initial poverty incidence has adverse direct and spillover effects, but the spillover effects are not significant in column (3), and the direct effect is not significant in column (4).

The negative spillover effects of poverty incidence on income growth suggests that poverty and per capita income growth are determined at a broader level than the municipalities' borders. One possible explanation is that when the neighboring municipalities' poverty incidence is high, the incentives to engage in productive activities reduce because the average purchasing power of their citizens is low, reducing the demand for goods and services. Also, when poverty is high in the neighboring municipalities, their economy may be less dynamic, reducing the interaction among the municipalities' productive sectors and the efficiency in resource allocation and, consequently, the municipal economic growth.

Another robustness check uses the three available surveys (1991, 2000, and 2010) to reduce measurement error and smooth short-term variation of the variables using their average of the previous two periods. Equation (12) can be rewritten as

$$g(y_{i,2000\text{-}2010}) = \theta_1 + \theta_2 \ln \bar{y}_{i,1991\text{-}2000} + \theta_3 \ln \bar{P}_{i,1991\text{-}2000} + \varepsilon_{i,2010}, \tag{13}$$

where $\bar{y}_{i,1991\text{-}2000}$ is the income per capita average of 1991 and 2000, and $\bar{P}_{i,1991\text{-}2000}$ is the poverty incidence average of 1991 and 2000. Column (3) of Table 6 brings the results, which are robust to this change in the initial year.

Table 6: Regressions of Growth Rates on Initial Mean and Initial Headcount Index of Poverty

	$g(y)$			
	Two years (1991 and 2010)		Three years (1991, 2000 and 2010)	
	OLS	*SDEM*	*1991-2000 means as initial conditions - SDEM*	*Using IV's from 1991 - SDEM*
	(1)	(2)	(3)	(4)
$\ln y$	-3.297 t = -23.276^{***}	-4.979 t = -35.149^{***}	-2.743 t = -25.605^{***}	-3.848 t = -9.450^{***}
$\ln P$	-0.493 t = -3.470^{***}	-0.969 t = -5.850^{***}	-0.697 t = -5.725^{***}	-0.520 t = -1.353
Lag $\ln y$		2.023 t = 9.037^{***}	0.420 t = 3.682^{***}	0.784 t = 3.659^{***}
Lag $\ln P$		-1.764 t = -5.865^{***}	-0.087 t = -0.500	-0.548 t = -1.662^{*}
λ		0.997***	0.997***	1***
γ		1.11	1.6	0
AIC	21566.1	19901.9	17090.8	
BIC	21591.7	19946.8	17116.4	
Moran's I Stat.	0.3***	0.06***	0.05***	0.26***
Observations	4,490	4,490	4,490	4,490

Notes: * Significant at 10%; ** Significant at 5%; *** Significant at 1%. The Table shows the estimation of the expression 12. Column (1) is the OLS estimation and the others are robustness test for spatial dependence (2), possible measurement errors (3) and endogeneity (4). λ is the scalar spatial autoregressive disturbance parameter. γ is the distance decay parameter. AIC and BIC are the Akaike and Bayesian information criterion. Moran's I Stat is the the spatial correlation test on the regression residuals.

In addition, we can use the 1991 dataset as instruments for the variables of 2000. Therefore, the estimated equation is

$$g(y_{i,2000\text{-}2010}) = \zeta_1 + \zeta_2 \log \hat{y}_{i,2000} + \zeta_3 \log \hat{P}_{i,2000} + \varepsilon_{i,2010}, \tag{14}$$

Where $\ln \hat{y}_{i,2000}$ and $\ln \hat{P}_{i,2000}$ are the initial poverty incidence and income per capita – values of 2000 – instrumentalized by the values of the variables in 1991. Column (4) of Table 6 reports the Generalized Methods of Moments estimates using $\ln \hat{y}_{i,2000}$ and $\ln \hat{P}_{i,2000}$ as regressors. The poverty total effects are negative. However, the direct effect of poverty on income growth is not statistically different from zero, and the spillover effects are significant only at the 10% level.

The initial poverty incidence may capture the influence of other variables on subsequent income growth. Therefore, we have added regressors such as income inequality, the income share of the households in the middle three quintiles of the income distribution, the share of the middle class, the miser index, primary school frequency, and life expectancy at birth. Table 7 brings the estimations with these additional control variables.

In Table 7, we see that the initial poverty incidence is a relevant predictor of income growth in the OLS regression. The SDEM direct effect of poverty incidence on income growth is similar to the OLS estimated coefficient but somewhat smaller. The spillover effects are significant and higher than the direct ones. The Gini index (G) coefficients are significant with both estimation methods, but they are positive, contrary to expected. The estimated coefficients of the middle-class size measured by the population living in households with income between R\$ 1,540.00 and R\$ 2,813.00 (MC), in 2012 prices, via OLS and SDEM (direct effect) are negative, although the total effect via SDEM is not statistically different from zero. The income share of the households in the middle three quintiles of the income distribution (MQ) positively and significantly influences income performance. Contrary to expected, the "miser index" positively influences subsequent income growth. The variables related to human capital, such as school frequency and life expectancy, have a positive direct effect on per capita income growth. In summary, Table 7 suggests that poverty is a better predictor of economic performance than income inequality and the middle-class measured by the "miser index" and MC.

3.3 Initial poverty and the growth elasticity of poverty reduction

In Section 3.2, we saw that municipalities with a higher poverty incidence have a lower income growth rate given the initial per capita income. Following Ravallion (2012), we analyze the relationship of the initial poverty incidence, income growth, and poverty reduction in this section.

To test this effect, we use the following equation:

$$g(P_{i,1991\text{-}2010}) = \gamma_1 + \gamma_2 g(y_{i,1991\text{-}2010}) + \gamma_3 \ln P_{i,1991} + \gamma_4[g(y_{i,1991\text{-}2010}) \cdot P_{i,1991}] + \varepsilon_{i,2010} \tag{15}$$

where $g_i(P_{i,1991-2010})$ is the poverty annualized growth rate between 1991 and 2010. Poverty converge would imply $\gamma_3 < 0$. The interaction effect between the initial poverty incidence and income growth (γ_4) tests if a higher incidence of initial poverty reduces the influence of income growth on poverty

Table 7: Regression for per capita income growth rates on the initial poverty rate augmented with extra control variables

	$g(y)$		
	OLS	*SDEM - Direct Effects*	*SDEM - Spillover Effects*
	(1)	(2)	(3)
$\ln y$	-11.189	-9.563	-19.960
	t = -22.047^{***}	t = -19.620^{***}	t = -3.521^{***}
$\ln P$	-4.988	-4.190	-14.226
	t = -13.087^{***}	t = -11.370^{***}	t = -3.096^{***}
$\ln G$	3.330	3.034	38.266
	t = 4.525^{***}	t = 4.412^{***}	t = 4.667^{***}
$\ln MQ$	6.276	4.553	19.566
	t = 11.111^{***}	t = 8.693^{***}	t = 2.336^{**}
MC	-0.059	-0.048	0.263
	t = -6.497^{***}	t = -5.521^{***}	t = 1.409
miser	0.001	0.0004	0.003
	t = 11.663^{***}	t = 7.197^{***}	t = 4.627^{***}
ln School att.	3.045	2.465	-1.428
	t = 15.736^{***}	t = 12.828^{***}	t = -0.530
ln Life expec.	23.250	13.355	-19.248
	t = 29.275^{***}	t = 14.027^{***}	t = -1.769^{*}
Constant	-63.099	-23.294	-23.294
	t = -9.422^{***}	t = -3.554^{***}	t = -3.554^{***}
λ		0.991***	0.991***
γ		0.64	0.64
AIC	20097.9	19199.7	19199.7
BIC	20162	19321.5	19321.5
Moran's I Stat.	0.13***	0.02***	0.02***
Observations	4,490	4,490	4,490

Notes: * Significant at 10%; ** Significant at 5%; *** Significant at 1%. Columns (1) show the estimation of the expression 12 with additional controls. Columns (2) and (3) show the SDEM estimation of expression 12 with additional controls. λ is the scalar spatial autoregressive disturbance parameter. γ is the distance decay parameter. AIC and BIC are the Akaike and Bayesian information criterion. Moran's I Stat is the the spatial correlation test on the regression residuals.

reduction (if $\gamma_4 > 0$). We can represent equation (15) as

$$g(P_{i,1991\text{-}2010}) = \gamma_1 + \gamma_3 \ln P_{i,1991} + (\gamma_2 + \gamma_4 P_{i,1991}) \cdot g(y_{i,1991\text{-}2010}) + \varepsilon_{i,2010} \tag{16}$$

In equation (16), we see that the influence of income growth rate on poverty reduction depends on the initial poverty incidence. If γ_4 is positive, a higher initial poverty incidence reduces the effect of income growth on poverty reduction. Another way to estimate the interaction effect between the initial poverty incidence and income growth is through the following equation:

$$g(P_{i,1991\text{-}2010}) = \tau_1 + \tau_2 \ln P_{i,1991} + \tau_3 (1 - P_{i,1991}) \cdot g(y_{i,1991\text{-}2010}) + \varepsilon_{i,2010} \tag{17}$$

If the initial poverty incidence reduces the economic growth influence on poverty reduction, the coefficient τ_3 should be negative ($\tau_3 < 0$). In equation (17), we assume that $\tau_3 = \gamma_2 = -\gamma_4$ (restrict equation). This specification makes the interpretation of the interaction effect more straightforward.

Table 8 presents the OLS and SDEM estimation results using equations (16) and (17). In columns (1) and (2), we see that the municipalities with a higher initial poverty rate have a lower income growth effect on poverty reduction since the estimated coefficient of the interaction between the income growth rate and initial poverty incidence is positive ($\gamma_4 > 0$). For both the OLS and SDEM estimation methods, there is no conditional poverty convergence.

Since there is no evidence of poverty converge, we exclude the initial poverty incidence as a regressor in the results of columns (3) and (4) of Table 8. The results are close to those of columns (1) and (2). Then in columns (5) and (6), we adopt the most parsimonious model (equation (17) – restricted model). The results indicate that the municipalities with a high initial poverty incidence experiment a low influence of income growth on poverty reduction. At an initial poverty incidence of 22 percent (about one standard deviation below the average), the expression $\tau_3(1 - \ln P_{i,t-1})$ is near -0.4. It falls to -0.16 at a poverty incidence of 65 percent (about one standard deviation above the average), indicating the relevance of poverty incidence in downsizing the influence of income growth on poverty reduction.

3.4 The reasons we do not see poverty convergence

Following Ravallion (2012), we find income convergence in the Brazilian municipalities and that income growth reduces poverty incidence (section 3.1). We also find an initial poverty incidence adverse influence on income growth and poverty reduction (sections 3.2 and 3.3). Putting together these effects, we test poverty convergence using Ravallion (2012) empirical model:

$$g(P_{i,1991\text{-}2010}) = \eta(1 - P_{i,1991}) g(y_{i,1991\text{-}2010}) + \nu_{i,2010} \tag{18}$$

$$g(y_{i,1991\text{-}2010}) = \alpha + \beta \ln(y_{i,1991}) + \delta \ln P_{i,1991} + \varepsilon_{i,2010} \tag{19}$$

Using (18) and (19), we can derive the following decomposition of the poverty convergence

Table 8: Regressions for proportionate change in poverty rate as a function of the growth rate and initial poverty rate

	$g(P)$ from 1991 to 2010					
	Complete		Dropping initial poverty		Imposing Homogeneity	
	OLS	*SDEM*	*OLS*	*SDEM*	*OLS*	*SDEM*
	(1)	(2)	(3)	(4)	(5)	(6)
$\ln P$	0.190^{***}	-0.006				
	t = 7.543	t = -0.226				
$g(y)$	-0.464^{***}	-0.312^{***}	-0.489^{***}	-0.314^{***}		
	t = -63.335	t = -38.221	t = -75.034	t = -40.606		
$g(y) \cdot P$	0.005^{***}	0.003^{***}	0.005^{***}	0.003^{***}		
	t = 50.867	t = 30.178	t = 77.238	t = 34.366		
Lag $\ln P$		-0.026				
		t = -0.360				
Lag $g(y)$		-0.556^{***}		-0.557^{***}		
		t = -12.718		t = -18.790		
Lag $g(y) \cdot P$		0.007^{***}		0.007^{***}		
		t = 15.385		t = 15.291		
$g(y) \cdot (1-P)$					-0.005^{***}	-0.003^{***}
					t = -75.291	t = -43.768
Lag $g(y) \cdot (1-P)$						-0.005^{***}
						t = -18.818
Constant	-3.009^{***}	-2.022^{***}	-2.304^{***}	-2.051^{***}	-2.085^{***}	-1.966^{***}
	t = -31.191	t = -18.382	t = -95.237	t = -73.271	t = -105.993	t = -82.073
λ		0.997***		0.997***		0.997***
γ		0.16		0.09		0
AIC	8724.3	7169.6	8778.8	7185.9	8994.1	7246.1
BIC	8756.3	7227.3	8804.5	7230.8	9013.4	7278.2
Moran's I Stat.	0.17***	0.05***	0.18***	0.05***	0.23***	0.05***
Observations	4,490	4,490	4,490	4,490	4,490	4,490

Notes: * Significant at 10%; ** Significant at 5%; *** Significant at 1%. Columns (1) and (2) show the estimation of the expression 15. λ is the scalar spatial autoregressive disturbance parameter. γ is the distance decay parameter. AIC and BIC are the Akaike and Bayesian information criterion. Moran's I Stat is the the spatial correlation test on the regression residuals.

(dropping the subscripts for clarity):

$$\frac{\partial g(P)}{\partial \ln P} = \eta[-Pg(y) + \frac{\partial g(y)}{\partial \ln P} \cdot (1-P)] \tag{20}$$

From equation (12), we have

$$\frac{\partial g(y)}{\partial \ln P} = \lambda_2 \frac{\partial \ln y}{\partial \ln P} + \lambda_3 \tag{21}$$

Using equation (21) into (20):

$$\frac{\partial g(P)}{\partial \ln P} = -\eta P g(y) + \eta(1-P)\left[\lambda_2 \frac{\partial \ln y}{\partial \ln P} + \lambda_3\right] \tag{22}$$

Rearranging:

$$\frac{\partial g(P_{i,t})}{\partial \ln P_{i,t-\tau}} = \underbrace{\eta\lambda_2(1-P_{i,t-\tau})\left(\frac{\partial \ln P_{i,t-\tau}}{\partial \ln y_{i,t-\tau}}\right)^{-1}}_{\text{(mean convergence effect)}} + \underbrace{\eta\lambda_3(1-P_{i,t-\tau})}_{\text{(direct effect of poverty)}} - \underbrace{\eta g(y_{i,t})P_{i,t-\tau}}_{\text{(poverty elasticity effect)}} \tag{23}$$

We can calculate the convergence poverty elasticity decomposition by evaluating all variables at the sample average values and using the estimates in the previous sections. Substituting the values in equation (23), we obtain:

$$\begin{aligned}\frac{\partial g(P_{i,t})}{\partial \ln P_{i,t-\tau}} &= (-0.005)\times(-11.19)\times 44.6\times(-0.88)^{-1} + (-0.005)\times(-4.99)\times 44.6 - (-0.005)\times 6.52\times 55.4 \\ &= -2.838 + 1.113 + 1.806 \\ &= 0.081 \end{aligned} \tag{24}$$

where -0.88 is the OLS elasticity of the initial poverty index P_{1991} with respect to the initial per capita income. The mean convergence effect is -2.838, while the direct effect of poverty is 1.113, and the poverty elasticity is 1.806. Therefore, the direct effect of poverty and the poverty elasticity are in the opposite direction of the mean convergence effect. As Ravallion (2012) finds for countries, the net effect is near zero. Using the SDEM direct effects[9], the calculations in (24) is -0.051, an almost zero convergence effect.

4 Conclusions

In the present paper, we analyze the influence of poverty on economic performance and poverty reduction in the Brazilian municipalities. We use the same analytical framework as Ravallion (2012). The consequences of poverty on economic performance are still not well understood in the economic growth and development literature, and we take a step to shed some light on this subject with our empirical results.

[9] The calculation with the total effect can be distorcive given the high spillover effects of Table 7.

Ravallion (2012) highlights that the advantages of backwardness and growth imply that we should see poverty convergence. Our results indicate the presence of the advantage of backwardness since they indicate income convergence across the Brazilian municipalities from 1991 to 2010, i.e., those with lower initial average income tend to have a higher income growth rate. In addition, the municipalities with higher income growth tend to accomplish more poverty reduction (advantage of growth). Therefore, we should see poverty convergence.

However, as Figure 2 shows, this is not the case for the Brazilian municipalities. Our empirical findings suggest that high initial poverty incidence affects both advantages of backwardness and growth, leading to the absence of poverty convergence in the Brazilian municipalities. Regions with greater poverty incidence endure a weaker income convergence process and a smaller influence of economic growth on poverty reduction.

The results are robust to including variables capturing income inequality, middle-class size, human capital, the initial year, and spatial correlation via the SDEM estimation method, indicating that poverty incidence is one relevant variable affecting economic performance and poverty reduction. Therefore, public policies to fight poverty are essential to improve the well-being of those living in this condition and foment economic growth.

A relevant study topic in this research agenda is to understand better the channels in which the initial poverty incidence influences subsequent income growth and poverty reduction. The relationships among poverty, human capital accumulation, and resources allocation are possibilities.

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