Income elasticities and inequality of poverty in urban and rural areas of the Brazilian states: a spatial approach

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Abstract

This study sets out to obtain values for the income elasticities and inequality of poverty in urban and rural areas of the Brazilian states. A panel data methodology capable of capturing spatial effects via a spatial lag model is used to identify whether there are spatial spillovers of poverty in the census situations studied. Changes in growth and inequality lead to spatial spillovers in the proportion of poor people in Brazil's urban areas, but this does not happen at all in rural areas. By demonstrating the existence of spatial spillovers in urban areas, the study shows that anti-poverty measures for these areas should be applied at the national level. In rural areas, the absence of spatial spillovers in the proportion of poor people means that public policies to combat rural poverty can be implemented at both state and national levels.

Keywords

Income, poverty, income distribution, poverty mitigation, rural areas, urban areas, econometric models, economic growth, Brazil

JEL classification

O15, I30, I32

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I. Introduction

Poverty is a persistent phenomenon in practically all countries, differing only in intensity. It exposes the social class suffering from it to a situation of extreme social exclusion, leading to deprivation of basic social rights.

In Brazil, as in most Latin American countries, the number of people living in poverty has historically been high. However, the situation has steadily improved, especially in the 1990s and 2000s. According to Barros (2009), the extremely poor made up almost a quarter of the Brazilian population in the mid-1970s and the situation worsened in the following 10 years. The economic stability of the 1990s, coupled with the growth that began then, resulted in a substantial reduction in the number of poor, so that by 2008 extreme poverty affected only about 8.8% of the population.

The main causes that can be adduced for the decline in the proportion of poor people in Brazil include the pace of economic growth and its impact on the country's socioeconomic dynamics. Barros, Foguel and Ulyssea (2007) show that economic growth was responsible for reducing extreme poverty by 0.7 percentage points annually as of mid-2003, rising to 1.6 percentage points by mid-2006.

Hoffmann (2001) argued that economic growth had considerably reduced poverty in Brazil, but emphasized that in most parts of the country the reduction in inequality had taken the form of an emergency exit from poverty. He also stated that unsustainable growth conjoined with an environment of instability tended to exacerbate inequality, leading to an increase in poverty.

It is a fact that the improvement in Brazilian socioeconomic indicators has been largely driven by economic growth. By way of comparison, income concentration worsened in many developed and developing countries between 1990 and 2000. Drawing on data from the World Bank and the Organization for Economic Cooperation and Development (OECD), Ramos (2015) notes this and points out that while some countries such as China and Sweden recorded high growth rates, these rates were accompanied by an increase in inequality. However, the percentage of poor people fell much more significantly in those countries. In the case of Brazil, the growth rates achieved did bring down poverty across the board, while inequality levels also declined (Ramos, 2015).

However, poverty and inequality display different characteristics when viewed from the perspective of people's census situation. For Ney and Hoffmann (2009), poverty is greater in rural Brazil than in urban areas. The authors point out that factors such as poor distribution of agricultural production resources, low education levels, low pay and ineffective social policies can aggravate poverty in these areas.

Ney and Hoffmann (2009) also show that the heavy concentration of land ownership makes it difficult to earn income from farming. Non-agricultural income can supplement the family income of farmers who have little or no land and provide the inputs they need to maintain crops and cover farming losses.

Thus, the hypothesis formulated in this paper is that urban areas sometimes provide a source of income for lower-income people in rural areas. This being so, any economic shock in urban or rural areas could lead to a change in the socioeconomic dynamics of either or both, as poor people move areas in search of an income source.

In view of these considerations, this study investigates whether there is spatial spillover of poverty in urban and rural areas of the Brazilian states and to what extent economic growth and income inequality affect poverty, taking the proximity of states into account.

The purpose of this research, then, is to obtain values for the income elasticities and inequality of poverty in urban and rural areas of the Brazilian states and ascertain whether there are spatial spillovers of poverty in urban and rural areas of the units of the Brazilian federation. The contribution of this paper to the economic literature on poverty lies in the way elasticities are obtained by a procedure capable of capturing effects from spatial proximity, enabling spatial spillovers of poverty to be quantified from changes in economic growth and income inequality. Data from the National Household Survey (PNAD) published annually by the Brazilian Institute of Geography and Statistics (IBGE) are used for this procedure. Information on urban and rural areas in the 26 Brazilian states and the Federal District for the period 2004–2014 is considered.

The study is divided into five sections, of which this introduction is the first. The second section describes the theoretical basis for the research and the third presents its methodological underpinnings. The fourth section sets out and discusses the results and the fifth and final section presents the conclusions.

II. Literature review

This section sets out the main approaches to poverty on which the present study is based and describes the theoretical framework of the economic literature on spatial spillovers.

1. A triangular relationship: poverty, growth and inequality

The literature explores the existence of a relationship between poverty, economic growth and income inequality to account for changes that have arisen in different areas of the socioeconomic environment. This concept is used, for example, in the studies of Ravallion (2001 and 2005) and Dollar and Kraay (2001). These authors and Adams (2004) demonstrate that absolute poverty relates positively to income inequality and negatively to economic growth, with this constituting the so-called triangular relationship.

Setting out from a study of the interconnections between poverty and inequality at the global level, Ravallion and Chen (1997) concluded that poverty levels were highly sensitive to growth in countries with lower income inequality. In countries with higher levels of inequality, however, economic growth has little impact on poverty. The latter proposition has been tested in some studies on poverty in Brazil, including analyses by Hoffmann (2005) and Tabosa, Irffi and Guimarães (2014).

More recently, Fosu (2015) used this concept in a study on progress with poverty reduction in sub-Saharan Africa. This author also examined the triangular relationship between poverty, growth and inequality in a study on poverty reduction and economic development at the global level (Fosu, 2010). This relationship was likewise addressed in the study by Taques and Mazzutti (2010), who found that the evolution of economic growth and the reduction of inequalities were directly related to the socioeconomic performance of a given society.

According to Ravallion (2016), there is a great debate in the economic literature on the issues linking economic growth with income inequality and poverty, and this ties in with doubts about whether globalized economic growth can facilitate progress in reducing poverty and inequality. According to Ravallion (2016), these doubts are due to a still current classical view that economic growth in a capitalist economy is necessarily unequal.

Bourguignon (2003) and Marinho and Araújo (2012) addressed the triangular relationship between poverty, economic growth and income inequality as a factor of interaction, so that economic growth was measured in these studies by people’s per capita income levels. Thus, in addition to other factors, what are meant by changes in poverty levels are both income movements and changes in the distribution of resources. These interactions are responsible for shaping the socioeconomic dynamics of a given region over time.

While it is clear from the literature that there is interaction between poverty, economic growth and income inequality, Datt, Ravallion and Murgai (2016) conduct a study on the effects of disparities and economic growth on poverty in India, taking into account the effects of urbanization in that country. The study stresses that the interactions of these phenomena have similar causes when analysed separately in urban and rural areas. With this procedure, however, the incidence of economic growth and income inequality on poverty is different in each of the environments described.

The relationship between economic growth and income inequality operates in different ways in Brazil, depending on the region. Although the 2000s witnessed rising rates of economic growth, this failed to eliminate disparities and heterogeneity between the Brazilian states and regions. The north and north-east regions stand out for having the highest indicators of inequality during the period under review, combined with high levels of poverty and low rates of economic growth (Moreira, Braga and Toyoshima, 2010).

In the economic literature, income inequality is characterized as one of the main determinants of poverty, meaning that these phenomena are directly related to each other, as pointed out in the studies by Coelho (2009), Hoffmann (2005) and Annegues and others (2015). It should be noted that poverty in developing countries tends to be highly sensitive to changes in disparities. In other words, the distribution effect is a major determinant of poverty in those countries, and that effect, coupled with the growth effect, is responsible for much of the dynamics of income shortfalls in those areas (Bourguignon, 2003).

Ravallion (2014) conducted a study on income inequality in developing countries. Among the results, the author showed that in most of these countries it was common for increases in growth to be accompanied by increases in inequality. The positive relationship between inequality and growth can also have a direct influence on poverty.

Studies on poverty in Brazil show that public policies to combat it need to focus more on reducing income inequality. Using a dynamic panel data model, Castelar, Tabosa and Irffi (2013) concluded that public policies involving the reduction of inequalities had a greater impact on poverty reduction than measures that only dealt with economic growth.

The relationship between poverty and economic growth is presented as a complex issue in the economic literature, and it is addressed in a number of studies formulated on the basis of various approaches that seek to explain these interactions.

The pro-poor growth approach, for example, seeks to ascertain whether economic growth benefits the poorest social classes. Studies by Kakwani, Neri and Son (2010) and Netto Jr. and Figueiredo (2014) have explored this approach, whose economic rationale divides into three schools of thought. According to the first, growth is pro-poor if the average income of the population deemed poor grows faster than that of the non-poor population. According to the second, growth is pro-poor if the increase in the average income of those deemed poor is proportional to the growth of the poor population. The third determines whether growth is pro-poor by comparing changes in the number of poor people given constant income inequality (Netto Jr. and Figueiredo, 2014).

The Ravallion (2004) approach followed by Silveira Neto (2014) adopts the pro-poor growth perspective formalized both in poverty reduction as measured by an absolute indicator associated with income dynamics and in the stipulation that those deemed poor have greater variations in income than those deemed non-poor.

The pro-poor approach to growth was tested for Brazil by Pinto and Oliveira (2010). The authors found that this type of growth contributed little to poverty reduction in the country's states. However, Silveira Neto (2014) argues that, given the nature of pro-poor growth through income dynamics, results in terms of poverty reduction were better in the 2000s than in earlier periods.

In a theoretical approach, Barreto (2005) affirms that growth is a key factor in reducing the incidence of poverty and that its effects on the poorest are greatest when it is accompanied by redistributive policies. This establishes inequality as a determinant of poverty, which in turn is related to growth.

According to Chu (2003), for developing countries to be able to reach a state of growth in which poverty can be reduced at the same time, measures are needed to reduce inefficiencies related to production incentives, especially for people with lower incomes.

Araújo, Figueirêdo and Salvato (2009) analyse the relationship between poverty and growth in Brazil, carrying out a time decomposition of poverty to measure the impact of growth, as given by income, and of income concentration on poverty levels. The study shows that poverty expresses changes resulting from shifts in average income and in income inequality.

2. Spatial spillovers

Anselin, Varga and Acs (1997) describe the spillover effect as an instrument that makes it possible to identify spatial spillovers of a given variable from changes in that same variable or in other factors that have an explanatory interconnection with the phenomenon studied. This technique serves to establish spatial movements derived from changes in fixed periods or over time and can be useful for determining the space in which a given policy or measure will be applied.

Spatial econometric techniques for identifying spillovers are generally used to analyse the behaviour of a given variable or measure in places close to where the measure was implemented or where the variable fluctuated. A good example is the study by Yu and others (2013) investigating the spillover effects of the transport system infrastructure in China by applying a contiguity matrix of order 1 to the 29 Chinese provinces.

A spillover analysis was also carried out in the study by Anselin, Varga and Acs (2000), using spatial methodology applied to a cross-sectional database of university research projects. This study found that places with greater scientific coverage attracted more investments in sectors associated with the research being carried out. Accordingly, it was concluded that attracting investment affects not only the places where universities are located but also neighbouring areas, meaning that there are spatial spillovers from scientific research.

The study by Álvarez, Arias and Orea (2006) sought to ascertain the spatial spillovers deriving from the productivity of public capital in Spain. Their research showed that, taking the closest neighbours, the productivity of public capital in the country did not present spatial spillovers and had effects only in the places where the productivity applied.

Using a database with information structured into panel data, Uchôa and Menezes (2014) used a maximum likelihood estimate to ascertain the spatial spillover effects of crime in units of the Brazilian federation. A spatial lag model was used for this purpose. According to Almeida (2012), this model is capable of revealing the existence (or non-existence) of spatial spillovers when the spatially lagged dependent variable is inserted into the explanatory set of the model.

From the perspective described by LeSage and Pace (2011), it is extremely important to realize that the spillover effects encountered in a spatial econometric process are local in nature, as opposed to global autocorrelation. Likewise, according to the authors, confirming spatial spillover effects in relation to a given variable can provide information on the migration conditions of nearby residents. However, this is not explicitly demonstrated. LeSage and Pace (2011) also point out that one of the advantages of using a spatial lag model with panel data is that spatial spillover effects are also determined by means of the direct and indirect effects obtained with the estimates. In fact, it is possible to determine whether the dependent variable changes in a given region and its neighbours if there is a change in an explanatory variable in a particular area.

The spatial econometric literature has developed models capable of determining three types of effects involving the interactions of spatial units. The first effect concerns endogenous relationships associated with the dependent variable and is obtained by estimating a spatial autoregressive model

(SARM). The second type of effect concerns exogenous relationships between the explanatory variables used and is obtained by estimating a spatial autocorrelation model (SACM). The third effect concerns interactions relating to the error term and is obtained by estimating a spatial error model (SEM) (Vega and Elhorst, 2013).

III. Methodology

This section presents the methods and instruments used to address the issues raised in this paper. It also indicates the data used, their sources and the processing applied to them before going on to explain the statistical procedures followed.

1. A stationarity test for panel data

The non-stationarity or unit root problem is a characteristic of data with distributions in periods. According to Bueno (2008), stationarity occurs when a series fluctuates around a fixed mean and the variance of that series is constant over time. In addition, Bueno (2008) points out that it is essential to check for stationarity in order to proceed to statistical inferences on the parameters estimated by performing a stochastic process. Thus, before carrying out any statistical procedure, it is necessary to check the data for stationarity. This procedure can be carried out by means of an autoregressive procedure of the type:

$$Y_t = \rho Y_{t-1} + u_t \tag{1}$$

where u_t is the stochastic error term known as white noise when it has a mean of zero and constant variance and is not autocorrelated. Thus, in a situation where $\rho = 1$ there will be a unit root problem. This study uses the Levin-Lin-Chu stationarity test to detect this characteristic, so that if the null hypothesis of the test is rejected, the data used are stationary.

2. The proximity matrix

The proximity matrix is a spatial data clustering tool that serves to delimit neighbours in an area by proximity, number or contiguity. Using this concept, Almeida (2012) indicates that a matrix of spatial weights W presents the following structure:

$$W_{ij} = \begin{cases} 1 \text{ if } i \text{ and } j \text{ are neighbours} \\ 0 \text{ if } i \text{ and } j \text{ are not neighbours} \end{cases} \tag{2}$$

The matrix is constituted as a support in the set of n areas $\{A_1, ..., A_n\}$ giving a matrix $W^{(1)}$ $(n \times n)$ in which each of the elements W_{ij} represents the measure of proximity between A_i and A_j.

This experiment uses a normalized queen type spatial proximity matrix.[1] The particularity of the matrix is that its structure is similar to the way the queen moves on a chess board. The normalized matrix is established as a support in the original (unnormalized) matrix, dividing all the elements of each line by the sum of the line. Therefore, all the lines of the matrix have a sum equal to 1.

[1] Besides the contiguous queen matrix, neighbouring K-type matrices were tried with $k = 3$; $k = 4$; $k = 5$; $k = 8$ and $k = 10$. The matrix used was the one presenting the greatest spatial autocorrelation of the model residuals, without spatial effects.

3. The econometric model

To address the issues described in the first section, this study uses a methodology that encompasses data arranged in units of space and time, considering the spatial effects inserted in the variables. For this purpose, use is made of the method proposed by Elhorst (2014), in which a general model with panel data containing N observations of space arranged in t observations of time encompassing spatial effects is described as follows:

$$Y_t = \delta WT_t + \alpha i_N + X_t\beta + WX_t\theta + u_t \quad \text{with} \quad u_t = \lambda Wu_t + u_t \tag{3}$$

where Y represents the proportion of poor people, t is time, N is the number of observations, WY_t are endogenous interactions on the dependent variable, X_t is the matrix of dependent variables with the natural logarithm of the Gini coefficient and the natural logarithm of per capita income, W represents the matrix of spatial weights, δ and λ are spatial correlation parameters and u_t is the specific effect of the particular omitted variables of each unit of space over time.

Elhorst (2014) recommended using the term ξ_t, a control factor for variables covering all units of space whose omission could lead to biases in the estimates.

$$Y_t = \rho WT_t + \alpha_{iN} + X_t\beta + WX_t\theta + u + \xi_t i_N + u_t \quad \text{with} \quad u_t = \lambda Wu_t + \varepsilon_t \quad \text{and} \quad u = (\mu_t, \ldots, \mu_N) \tag{4}$$

Thus, the model used to capture the existence of spatial spillover effects on poverty in the units of the Brazilian federation is the spatial lag model, which is formulated on the hypothesis that the dependent variable used (the proportion of poor people) for a given region depends over time on the characteristics of the dependent variable for its neighbours. According to Elhorst (2014), this dependence arises from the inclusion of the spatially lagged dependent variable ($W_{ij}Y_{it}$) in the set of explanatory variables of the model, as follows:

$$y_{it} = \delta \sum_{j=1}^{n} W_{ij}y_{it} + x_{it}\beta + \mu_i + \varepsilon_{it} \tag{5}$$

where δ is the spatial autoregressive term and W_{ij} is a component of the matrix of spatial weights W.

4. The spatial fixed effects model

Setting out from a general panel data model with spatial effects, in the event of the effects determined being fixed ones, Elhorst (2014) and Lee and Yu (2010) showed that the model parameters were estimated in three stages. First, the u_i effects are removed from the regression equation to make way for the y and x variables. This transformation is given by:

$$y^*_{it} = y_{it} - \frac{1}{T}\sum_{t=1}^{T} y_{it} \quad and \quad x^*_{it} = x_{it} - \frac{1}{T}\sum_{t=1}^{T} x_{it} \tag{6}$$

where T is the amount of information for each cross-sectional unit used. In the second step, the transformed regression equation, $y^*_{it} = x^*_{it} + \varepsilon^*_{it}$, is estimated using the ordinary least squares process, where $\beta = \left(X^{*T}X^*\right)^{-1}X^{*T}Y^*$ and $\sigma^2 = \left(Y^* - X^*\beta\right)^T\left(Y^* - X^*\beta\right)/\left(NT - N - K\right)$, with K being the number of explanatory variables. The advantage of this process is that it means the calculation of β can include the inversion of a matrix K x K by a matrix $(K+N)$ x $(K+N)$. In this case, estimation is carried out using ordinary least squares with dummy variables (Elhorst, 2014).

Thus, estimation is carried out using the maximum likelihood procedure and the log-likelihood function is given by:

$$logL = -\frac{nT}{2}log\left(2\pi\sigma^2\right) - \frac{1}{2\sigma^2}\sum_{i=1}^{n}\sum_{t=1}^{T}\left(y^*_{it} - x^*_{it}\beta\right)^2 \tag{7}$$

The maximum likelihood estimators β and σ^2 are $\beta = (X^{*T}X^*)^{-1}X^{*T}Y^*$ and $\sigma^2 = (Y^* - X^*\beta)^T(Y^* - X^*\beta)/NT$, respectively. The asymptotic variance matrix of the parameters is given by Greene (2008) as follows:

$$ASY.VAR\left(\beta,\alpha^2\right) = \begin{bmatrix} \frac{1}{\sigma^2}X^{*T}X^* & 0 \\ 0 & \frac{NT}{2\sigma^2} \end{bmatrix}^{-1} \tag{8}$$

Thus, the fixed effects can be described in general as:

$$\mu_i = \frac{1}{T}\sum_{t=1}^{T}\left(y_{it} - x_{it}\beta\right), \qquad i = 1,\ldots,N \tag{9}$$

5. Estimating the spatial lag model with fixed effects

Formulating a fixed effects spatial lag model presents two complications. First, the endogeneity of $\sum_j W_{ij}Y_{jt}$ breaks the standard regression model assumption that $\left[\left(\sum_j W_{ij}Y_{jt}\right)\varepsilon_{it}\right] = 0$. Second, the spatial dependence of the variables in each period can affect the fixed effects estimation. Accordingly, the maximum likelihood estimation recommended by Elhorst (2014) is carried out to include the endogeneity of $\sum_j W_{ij}Y_{jt}$. The log-likelihood function of this process is:

$$logL = -\frac{NT}{2}log\left(2\pi\sigma^2\right) + T log\mid I_N - \delta W\mid - \frac{1}{\sigma^2}\sum_{i=1}^{N}\sum_{t=1}^{T}\left(Y^*_{it} - \delta\sum_{j=1}^{n}W_{ij}Y_{jt} - x_{it}\beta - \mu_i\right)^2 \tag{10}$$

where $Tlog\mid I_N - \delta W\mid$ represents the Jacobian term of the transformation of ε into y bearing in mind the endogeneity of $W_{ij}Y_{jt}$. According to Elhorst (2014), the value of μ_i is obtained by calculating the partial derivative of $\log L$ in relation to μ_i so that:

$$\mu_i = \frac{1}{T}\sum_{t=1}^{t}\left(Y^*_{it} - \delta\sum_{j=1}^{n}W_{ij}Y_{jt} - x_{it}\beta\right), \; i = 1,\ldots,N \tag{11}$$

This equation denotes the formulation of the spatial fixed effects of a spatial lag model. Substituting the value of μ_i into the log-likelihood function and rearranging the terms, the log-likelihood function concentrated with respect to β, δ and σ^2, we get:

$$\begin{aligned} logL = -\frac{NT}{2}log\left(2\pi\sigma^2\right) + T log\ |I_N - \delta W| \\ -\frac{1}{\sigma^2}\sum_{i=1}^{N}\sum_{t=1}^{T}\left(Y_{it}^{*} - \delta\left[\sum_{j=1}^{N} W_{ij}Y_{jt}\right]^{*} - x_{it}^{*}\beta\right)^2 \end{aligned} \tag{12}$$

According to Elhorst (2014) and Lee and Yu (2010), when the variables are distributed into $t = 1, \ldots, T$ time observations, a vector $NT\ x\ 1$ is obtained for Y^* and $(IT \otimes W)Y^*$ and a matrix $NT\ x\ K$ for X^*. The δ estimator of the maximum likelihood procedure is thus obtained by maximizing the concentrated log-likelihood function. Thus, β and σ are estimated by considering the value of σ, so that:

$$\begin{gathered} \beta = b_0 + \delta b_1 = \left(X^{*T}X^{*}\right)^{-1}X^{*T}\left[Y^{*} - \delta\left(I_T \otimes W\right)Y^{*}\right] \\ \text{and} \\ \sigma^2 = \frac{1}{NT}\left(e_0^{*}\delta e_1^{*}\right)^T\left(e_0^{*}\delta e_1^{*}\right) \end{gathered} \tag{13}$$

With this, Elhorst and Fréret (2009) calculate the asymptotic matrix of the parameters, which has a symmetrical form, as follows:

$$\begin{bmatrix} \frac{1}{\sigma^2}x^{*\prime}x^{*} & & \\ \frac{2}{\sigma^2}x^{*\prime}\left(I_T \otimes \tilde{W}\right)x^{*}\beta & T^{*}tr\left(\tilde{W}\tilde{W} + \tilde{W}'\tilde{W}\right) + \frac{1}{\sigma^2}\beta' x^{*\prime}\left(I_T \otimes \tilde{W}'\tilde{W}\right)x^{*}\beta & \\ 0 & \frac{T}{\sigma^2}tr\left(\tilde{W}\right) & \frac{NT}{2\sigma^4} \end{bmatrix}^{-1} \tag{14}$$

where $\tilde{W} = W\left(I_N - \delta W\right)^{-1}$ and tr represents the trace of the matrix. An important feature of the spatial lag model is that the inclusion of the spatially lagged dependent variable in the set of explanatory variables allows the direct and indirect effects of each explanatory variable used to be calculated. According to Uchôa and Menezes (2014), direct effects indicate how much the independent variable changes, taking into consideration what is known as the feedback effect, meaning the repercussions that pass through to nearby spatial units over time and then back to the unit where the change originated. Indirect effects indicate the change in the dependent variable resulting from alterations in the variables in relation to all the spatial units used.

6. A spatial model with random effects

According to Elhorst (2014), to obtain the maximum likelihood parameters, estimation by random effects is carried out in two stages. The log-likelihood function of the random effects will be given by:

$$log L = -\frac{NT}{2}log\left(2\pi\sigma^2\right) + \frac{N}{2}log\phi^2 - \frac{1}{2\sigma^2}\sum_{i=1}^{N}\sum_{t=1}^{T}\left(y_{it}^{*} - x_{it}^{*}\right)^2 \tag{15}$$

where ϕ represents the spatial weights for each unit of space such that $0 \leq \phi^2 = \sigma^2 / \left(T\sigma_\mu^2 + \sigma^2\right) \leq 1$ and the symbol (•) represents the transformation of the dependent variables into ϕ. Thus, we get:

$$y_{it}^* = y_{it} - (1-\phi)\frac{1}{T}\sum_{t=1}^{T} y_{it} \quad \textit{and} \quad x_{it}^* = x_{it} - (1-\phi)\frac{1}{T}\sum_{t=1}^{T} x_{it} \tag{16}$$

If the value of ϕ is zero, then, the estimate will be identified as a fixed effect. Thus, Lee and Yu (2010) and Parent and LeSage (2012) determine that the values of ϕ, β and σ^2 can be ascertained on the basis of second-order conditions of the maximization problem used, with $\beta = (X^{\bullet T} X)^{-1}$ and $\sigma^2 = (Y^\bullet - X^\bullet \beta)^T (Y^\bullet - X^\bullet \beta)/NT$. Consequently, ϕ will be estimated by maximizing the concentrated log-likelihood function in respect of ϕ, given β and σ^2.

7. Estimating the spatial lag model with random effects

According to Elhorst (2014), if the spatial effects assumed are random, the log-likelihood function of the model is given by:

$$\begin{aligned} \log L = & -\frac{NT}{2}\log\left(2\pi\sigma^2\right) \\ & + T\log|I_N - \delta W| + \frac{N}{2}\log\phi^2 - \frac{1}{2\sigma^2}\sum_{i=1}^{N}\sum_{t=1}^{T}\left(y_{it}^* - \delta\left[\sum_{j=1}^{N} W_{ij} y_{it}\right]^*\right)^2 \end{aligned} \tag{17}$$

Thus, β, δ and σ^2 can be found by maximizing the log-likelihood function in respect of ϕ such that:

$$\log L = -\frac{NT}{2}\log\left[e(\phi)^T e(\phi)\right] + \frac{N}{2}\log\sigma^2 \tag{18}$$

where the typical element specified by $e(\phi)$ is:

$$\begin{aligned} e(\phi)_{it} = y_{it} - (1-\phi)\frac{1}{T}\sum_{t=1}^{T} y_{it} - \delta\left[\sum_{j=1}^{N} W_{ij} y_{it} - (1-\phi)\frac{1}{T}\sum_{t=1}^{T}\sum_{j=1}^{N} W_{ij} y_{it}\right] \\ - \left[x_{it} - (1-\phi)\frac{1}{T}\sum_{t=1}^{T} x_{it}\right]\beta \end{aligned} \tag{19}$$

The equation represents interactions used when the set of parameters is alternatively estimated until a situation of convergence is reached. This procedure includes estimation methods used to find the parameters of the fixed effects spatial lag model and the non-spatial random effects model. Thus, the asymptotic variance matrix of the parameters is given by:

$$Asy.Var\left(\beta, \delta, \theta, \sigma^2\right) = \begin{bmatrix} \frac{1}{\sigma^2} X^{*T} X^* & & & \\ \frac{1}{\sigma^2} X^{*T}\left(I_T \otimes \tilde{W}\right) X^* \beta & T * tr\left(\tilde{W}\tilde{W} + \tilde{W}^T \tilde{W}\right) + \frac{1}{\sigma^2}\beta^T X^{*T}\left(I_T \otimes W^T \tilde{W}\right) X^* \beta & & \\ 0 & \frac{1}{\sigma^2} tr\left(\tilde{W}\right) & N\left(T + \frac{1}{\sigma^2}\right) & \\ 0 & \frac{T}{\sigma^2} tr\left(\tilde{W}\right) & -\frac{N}{\sigma^2} & \frac{NT}{2\sigma^4} \end{bmatrix} \tag{20}$$

8. The database

The data used in this study were obtained from the National Household Survey (PNAD) published annually by the Brazilian Institute of Geography and Statistics (IBGE). The Foster, Greer and Thorbecke (1984) index is used to obtain the proportion of people deemed poor ($P0$):

$$P0 = \frac{q}{n} \tag{21}$$

where $P0$ is the proportion of people who are poor, q is the number of poor people and n is the number of people. For the purposes of this index, people with incomes below the poverty line are considered poor. The poverty line used is that of the Institute for Labour and Society Studies (IETS), which sets a reference value for each unit in the federation, considering the year and census situation. Income was obtained by dividing monthly household income by the number of residents per household, and all values were updated to 2015 using the national consumer price index (INPC).

The income inequality used was obtained by calculating the Gini concentration index, described in Hoffmann (1998) as $G = \frac{\alpha}{\alpha + \beta}$, where β represents the area between the Lorenz curve and the abscissa axis and α represents the area between perfect income equality and the Lorenz curve. The variables used are given logarithmically so that the elasticity values can be ascertained, considering the spatial effects encompassed.

The data cover a period of 11 years from 2004 to 2014.[2] This period was chosen because data on rural areas were available for all units of the federation studied. The analyses were conducted for the rural areas and urban areas delimited by the PNAD in each of the 26 units of the federation and the Federal District.

IV. Results and discussion

The initial aim is to determine whether the data used are stationary. For Bueno (2008) and Baltagi (2005), when data are expressed in time series, non-stationarity can lead to mistaken conclusions and biased results. Table 1 shows the results of the Levin-Lin-Chu stationarity test for data from urban and rural areas.

The null hypothesis is rejected in both cases at a 95% confidence level, indicating that the data used are stationary.

Table 1
Stationarity test for the data

Urban areas		Rural areas	
Test	P-value	Test	P-value
-15.0293	0.0000	-17.3862	0.0000

Source: Prepared by the authors.

To ascertain the income elasticities and inequality of poverty during the period studied in urban and rural areas and check whether spatial effects should be incorporated, a panel data model without spatial effects was estimated. The results of this estimation are presented in table 2.

[2] Since the IBGE did not release the 2010 PNAD, the variables used for that year are averages of the 2009 and 2011 values.

Table 2
Results of the estimates for urban and rural areas without spatial effects

Urban areas					
	Fixed effect			Random effect	
	Coefficient	T-statistic		Coefficient	T-statistic
Intercept	10.2184***	41.06	Intercept	10.1042***	40.95
Ln*income*	-1.4848***	-35.22	Ln*income*	-1.4605***	-35.59
Ln*gini*	2.7264***	19.25	Ln*gini*	2.8055***	20.06
Rural areas					
	Fixed effect			Random effect	
	Coefficient	T-statistic		Coefficient	T-statistic
Intercept	9.4247***	28.91	Intercept	9.21***	30.68
Ln*income*	-1.5349***	-29.23	Ln*income*	-1.5003***	-31.58
Ln*gini*	2.2829***	13.92	Ln*gini*	2.2785***	14.25

Source: Prepared by the authors.
Note: The symbols (***) and (**) indicate significance levels of 1% and 5%, respectively.
Urban areas: (Breusch Pagan = 913.78***; Hausman = 7.24***).
Rural areas: (Breusch Pagan = 357.64***; Hausman = 2.61).

For these estimates, rejection of the null hypothesis of the Breusch Pagan test indicates that a model with panel data is preferable to a pooled ordinary least squares model. At the same time, the Hausman test indicates that fixed effects estimation is more suitable for urban areas, while the best estimates for rural areas are obtained by using random effects.

Table 2 shows that, where urban areas were concerned, all variables were statistically significant and had the expected sign. It can be seen that for each one percentage unit increase in per capita income, the proportion of poor people will fall by 1.48%. With respect to income inequality, an increase of one percentage unit in the Gini coefficient will lead to an increase of 2.72% in the proportion of poor people.

For rural areas, the income elasticity estimated (-1.5003) indicates that an increase of one percentage unit in per capita income reduces the proportion of poor people by 1.5%. When inequality elasticity is taken (2.2785), it can be stated that an increase of one percentage unit in the Gini coefficient increases the proportion of poor people by 2.28%.

These results are consistent with studies by França (2010), Pinto and Oliveira (2010), Coelho (2009) and Hoffmann (2005) showing that policies aimed at reducing inequalities bring down poverty more effectively than higher growth does.

However, questions are raised in the literature about the measurement of the spatial dependence of the models estimated in table 2. To check this, the present study applies the criterion indicated by Almeida (2012), which establishes the need to check for spatial autocorrelation in the residuals of the estimation chosen in the model without spatial effects. This procedure is carried out by applying the global Moran index to the residuals of the models indicated by the Hausman test for each unit of time. The results are shown in annex A1. Rejection of the null hypothesis for the global Moran index indicates the existence of spatial autocorrelation in the residuals of the chosen model, while acceptance of the null hypothesis indicates the absence of spatial autocorrelation.

The procedure suggested by Almeida (2012) establishes that, in the presence of spatial autocorrelation in the residuals of the estimated model, an estimate including spatial effects should be considered. If spatial autocorrelation is not observed in the residuals, a model without spatial effects will be more appropriate. Given that the results presented in annex A1 indicate spatial autocorrelation in the residuals of the models yielded by the Hausman test in table 2, it can be stated that a spatial model with panel data is preferable to the estimates made previously.

Table 3 presents the results of the estimates of the spatial lag model for fixed and random effects, including the spatially lagged dependent variable as an explanatory variable. The results obtained with the Hausman test revealed that the fixed effects could not be considered valid in the two census situations studied. Furthermore, non-rejection of the null hypothesis regarding the Breusch Pagan test indicates that, in this case, a spatial pooled model would be inconsistent.

Table 3
Results of the estimates for urban and rural areas with spatial effects

Urban areas					
	Fixed effect			Random effect	
	Coefficient	T-statistic		Coefficient	T-statistic
Intercept	-	-	Intercept	8.6257***	36.094
ρ	0.0147***	4.2538	ρ	0.0118***	3.7917
Ln*income*	-1.1918***	-14.789	Ln*income*	-1.2422***	-31.382
Ln*gini*	2.2816***	14.436	Ln*gini*	2.4168***	18.067
Rural areas					
	Fixed effect			Random effect	
	Coefficient	T-statistic		Coefficient	T-statistic
Intercept	-	-	Intercept	9.4062***	31.48
ρ	-0.0103**	-2.0763	ρ	-0.0022	-0.599
Ln*income*	-1.7251***	-16.571	Ln*income*	-1.5358***	-32.484
Ln*gini*	2.4789***	13.732	Ln*gini*	2.3176***	14.613

Source: Prepared by the authors.
Note: The symbols (***) and (**) indicate significance levels of 1% and 5%, respectively.
Urban areas: (Breusch Pagan = 18.445***; Hausman = 2.3906).
Rural areas: (Breusch Pagan = 8.3803***; Hausman = 3.4637).

According to the results presented in table 3, the values for the spatially lagged dependent variable (ρ) indicate the existence of positive spatial autocorrelation as regards the proportion of poor people in urban areas of the Brazilian states. As for rural areas, the spatial autocorrelation parameter was not statistically significant. This direct relationship between the dependent variable and the spatially lagged dependent variable indicates the existence of regional clusters of high or low values associated with urban areas in the states analysed.

The existence of spatial clusters, denoted by (ρ), affects the dynamics of urban poverty in the Brazilian states, with the positive value found for spatial autocorrelation indicating that poverty levels in the urban areas of a given state are similar to those in its neighbours'. A shift in poverty in a particular state's urban areas may present similar effects in neighbouring states.

As in the model without spatial effects, the value for the income elasticity of poverty in urban and rural areas was lower in absolute terms than inequality elasticity. These considerations reinforce the assertion that poverty reduction in the areas studied is most effective when associated with distributive measures.

An analysis of the value for income elasticity in urban areas (-1.2422) shows that, if the other variables remained constant, an increase of one percentage unit in income would reduce the proportion of poor people by 1.2422%. With respect to inequality elasticity, it is observed that a 1% increase in income inequality would increase the proportion of poor people in urban areas by 2.4168%, assuming the other variables remained unchanged.

In relation to rural areas, the elasticities reveal that a rise of one percentage unit in per capita income would lead to a 1.5358% reduction in the proportion of poor people, while a rise of one percentage unit in income inequality would increase it by 2.3176%.

By comparing the elasticities found in the spatial lag model, it is possible to affirm that poverty levels are more sensitive to changes in growth in rural areas of Brazil than in urban areas. On the other hand, urban areas in the Brazilian states are more sensitive to changes in inequality levels than rural areas. This being so, a policy of combating poverty by increasing economic growth would have greater effects in rural areas. On the other hand, anti-poverty measures based on the reduction of inequalities would be more effective if applied in urban areas.

These results were also observed for urban and rural areas of the north-east region of Brazil in the study conducted by Araújo, Tabosa and Khan (2012), which estimated the values of income elasticities and poverty inequality in that region in the period from 1995 to 2009.

Setting out from the results obtained with the earlier estimates, the aim is to verify the direct and indirect effects of the variables used. According to Elhorst (2012) and LeSage and Pace (2009), direct and indirect effects can provide information on alterations in the dependent variable in different spaces when a particular explanatory variable changes.

According to the results presented in table 4 on urban areas, the direct, indirect and total effects were statistically significant. Although the coefficients of the direct effects are very similar to those obtained in table 3, they express a small change. This arises via the feedback effect, which denotes fluctuations in the poverty of a state that are passed on to its neighbours and eventually return to the unit of the federation where the change originated.

Table 4
Direct, indirect and total effects for the models chosen

	Urban areas		
	Direct effects	Indirect effects	Total effects
Ln*income*	-1.2427***	-0.0144***	-1.2571***
Ln*gini*	2.4178***	0.028***	2.4458***
	Rural areas		
Ln*income*	-1.5357***	0.0032	-1.5325***
Ln*gini*	2.3174***	-0.0048	2.3125***

Source: Prepared by the authors.
Note: The symbols (***) and (**) indicate significance levels of 1% and 5%, respectively.

The direct effects obtained for urban areas indicate that if the urban per capita income of a given state increases by 1%, the proportion of poor people in urban areas of that state will decrease by 1.2427%. Furthermore, a one percentage unit increase in income inequality in a state's urban areas will result in a 2.4178% increase in the proportion of poor people in those same areas. In the case of rural areas, the direct effects differ little from the estimates presented in table 3 and come to have virtually the same coefficients. This is due to the non-significance of the spatial autocorrelation term (ρ), indicating that there are no spatial spillovers in these areas.

Considering that indirect effects denote the change in the dependent variable in neighbouring states resulting from a change in an independent variable in a given area (LeSage and Pace, 2011), the statistical non-significance of the spatial autocorrelation parameter (ρ) means that indirect effects for rural areas in Brazil are insignificant. This result indicates that a poverty reduction measure targeting the rural areas of a given state, whether through changes in growth or income inequality, will not lead to changes in poverty levels in rural areas of neighbouring states.

The results obtained with the indirect effects also indicate that, if income inequality remains constant, a 1% increase in urban economic growth in a given state will reduce urban poverty in neighbouring states by 0.0144%. Likewise, if growth remains constant, every one percentage unit increase in urban income inequality in a given unit of the federation will be matched by a 0.028% increase in income inequality in the urban areas of neighbouring states. These results demonstrate the impact of spatial spillovers on urban poverty in the Brazilian states. Thus, it can be affirmed that a policy to combat poverty in urban areas, whether through changes in income or in inequality, will be more effective if applied at the national level, since applying a measure of this type locally would result in a spatial spillover of the proportion of poor people.

LeSage and Pace (2011) define total effects as the total impact on the dependent variable resulting from a change in an explanatory variable throughout the area studied. Thus, it is found that a 1% increase in economic growth will bring about a 1.2571% reduction in urban poverty in the Brazilian states if income inequality remains unchanged, with 1.2427% of this total coming from local effects and the remaining 0.0144% from the spatial overspill of the proportion of poor people.

Given the non-existence of spatial spillovers of the proportion of poor people in rural areas, the indirect effects found for those areas derive from changes at the state level. It is found that a 1% increase in rural economic growth in the Brazilian states will lead to a 1.5325% reduction in the rural proportion of poor if income inequality remains unchanged. This impact derives from direct effects. In addition, given unchanged growth, a 1% increase in income inequality in rural areas will generate a 2.3125% increase in the rural proportion of poor people, this impact likewise being caused by direct effects.

When the value of the coefficients found is analysed in the light of the indirect effects, it is observed that the income inequality effects obtained in the two types of area studied exceed economic growth in absolute terms. This reinforces the conclusion reached in the studies by França (2010), Pinto and Oliveira (2010), Coelho (2009) and Hoffmann (2005), which showed that measures aimed at reducing poverty in Brazil have a greater impact when associated with the reduction of disparities.

V. Final considerations

The present study has sought to ascertain the existence of spatial poverty spillovers in urban and rural areas of the units of the Brazilian federation. It has also sought to determine how sensitive poverty is to changes in levels of economic growth and income inequality in urban and rural areas, considering spatial effects. A panel data methodology capable of encompassing the proximity characteristics of the areas studied was employed for this purpose.

Analysis of the endogenous spatial interactions of the proportion of poor people revealed the existence of spatial poverty spillovers in urban areas and their absence in rural areas. This result indicates that any anti-poverty measure aimed at urban areas should be applied at the national level, since doing so locally may cause a spillover effect and draw in poor people from areas close to the place where the measure originated.

By comparing the endogenous spatial interactions of the proportion of poor people in urban areas and the direct and indirect effects found, the existence of a so-called feedback effect was identified for these areas. This result shows that changes in growth and income inequality in the urban areas of the Brazilian states lead to alterations in the proportion of poor people in nearby areas that eventually produce shifts in the proportion of poor people in the region where the change originated.

Analysis of the elasticities found and the estimated total effects revealed that poverty levels were more sensitive to changes in growth in rural areas of Brazil than in urban areas. It was also concluded that urban areas in Brazilian states were more sensitive than rural areas to changes in inequality.

It is concluded that, in both urban and rural areas of the Brazilian states, poverty reduction measures will be more effective if coupled with the reduction of disparities.

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Annex A1

Table A1.1
Spatial autocorrelation of the residuals of the table 2 estimates using the normalized queen matrix

Year	Urban areas		Rural areas	
	Moran	P-value	Moran	P-value
2004	0.4348	0.003	0.5483	0.001
2005	0.3895	0.006	0.4713	0.001
2006	0.3994	0.004	0.4208	0.002
2007	0.3391	0.006	0.3268	0.008
2008	0.3839	0.003	0.04	0.27
2009	-9.13	0.397	0.1766	0.07
2010	0.3466	0.013	0.3146	0.007
2011	0.0636	0.24	0.5087	0.001
2012	0.2252	0.036	0.572	0.001
2013	0.5841	0.001	0.1195	0.144
2014	-0.1483	0.209	0.516	0.001

Source: Prepared by the authors.