Urban and rural population growth in a spatial panel of municipalities

Costa da Silva, Diego Firmino; Elhorst, Paul; Silveira Neto, Raul da Mota

Published in:
Regional Studies

DOI:
10.1080/00343404.2016.1144922

Publication date:
2017

Urban and Rural Population Growth in a Spatial Panel of Municipalities*

Diego Firmino Costa da Silva

Rural Federal University of Pernambuco and University of Groningen. Address: Rua Dr. Odilon Lima, 44/02, 50850-010, Afogados, Recife, PE, Brazil. E-mail: diegofirmino@gmail.com, Phone: +55 (81) 32711196

J. Paul Elhorst (corresponding author)

University of Groningen. Address: P.O. Box 800, 9700 AV, Groningen, the Netherlands. E-mail: j.p.elhorst@rug.nl, Phone: +31503633893

Raul da Mota Silveira Neto

Federal University of Pernambuco. Address: Av. Prof. Moraes Rego, 1235, Recife, PE, 50670-901, Brazil. E-mail: rau.silveira@uol.com.br, Phones: +55 (81) 21268381 r. 224, + 55 (81) 91381357

Abstract

Using Bayesian posterior model probabilities and data pertaining to 3659 Brazilian Minimum Comparable Areas (MCA) over the period 1970-2010, two theoretical settings of population growth dynamics resulting in two spatial econometric specifications in combination with a wide range of potential neighborhood matrices are tested against each other. The best performing combination counts five determinants producing significant long-term spatial spillover effects. Ignoring these spillovers, as many previous population growth studies have done, is shown to underestimate their impact and thus the effectiveness of policy measures acting on these determinants.

JEL Classification: C23, R23

Keywords: Population growth, regions, spatial interaction, dynamic spatial panel models, spillover effects

INTRODUCTION

Brazilian urbanization represents a highly significant, robust social phenomenon; the percentage of people living in urban centers in Brazil increased from 55.9% in 1970 to 84.4% in 2010 (IBGE, 2011). This process resulted largely from improved economic and social prospects in cities (DA MATA *et al.*, 2007; HENDERSON, 1988; YAP, 1976). Despite these studies, relatively little is known about how these specific factors condition population growth of Brazilian Cities. HENDERSON (1988) shows that the population growth of Brazilian cities between 1960 and 1970 related positively to initial increases in levels of education. Reviewing growth between 1970 and 2000, DA MATA *et al*. (2007) reveal that favorable supply and demand conditions, including market potential variables, better schooling, and limited opportunities in the agricultural sector, favored the growth of Brazilian cities. However, these studies are limited in two aspects. First, by considering only a subset of Brazilian cities, they provide no complete picture of the conditions of growth. Second, they do not account for spatial dependence, i.e., their theoretical and empirical treatments consider cities as independent entities.

Extending the analysis of urban population growth in Brazil to include all of its areas is fundamental for understanding the dynamics of the process. Population growth in one area implies population decline in another area. Overall, urban areas may growth at the expense of rural areas. By considering both urban and rural areas and both population growth and decline, more information might be obtained about the impact of certain determinants. DA

MATA *et al*. (2007), the most comprehensive study about growth of Brazilian cities, focus on municipalities with more than 75,000 inhabitants, or only about 75% of Brazil’s urban population. Furthermore, it does not consider urban dynamics after 2000, a period of price stability, as well as income convergence, among the Brazilian states (SILVEIRA NETO and AZZONI, 2012). Substantial increases in the production of commodities and agricultural goods during this period had positive impacts on opportunities available in towns further distant from large urban centers.

Spatial dependence is known to particularly severe for small spatial units, such as municipalities (BOARNET *et al*., 2005). In analyzing income dynamics at different levels of spatial aggregation, RESENDE (2013) confirms the importance of spatial dependence for Brazilian minimum comparable areas (MCA).[1] Indeed, in the context of Brazilian urban dynamics, institutional factors, local well-being characteristics, and technological spillovers tend to make municipal population growth dependent on the population dynamics of neighboring municipalities. The small size of municipalities also implies that local factors affecting well-being, such as crime and pollution, tend to affect population dynamics of neighboring cities. SCORZAFAVE and SOARES (2009), for example, find strong spatial dependence of pecuniary crimes among the municipalities in the state of São Paulo. Furthermore, spatial technological spillovers (ERTUR and KOCH, 2007) may be more prevalent among small, neighboring urban centers than among large ones. In their recent study of Brazilian micro-region income dynamics, LIMA and SILVEIRA NETO (2015) provide robust evidence of spatial spillovers of both physical and human capital.

Because it is asserted that all of these factors might induce spatial dependence on the population growth dynamics of Brazilian cities and its determinants, this article seeks to model spatial dependence among spatial units explicitly. The central objective is to present the population growth dynamics of Brazilian MCAs and thereby assess the determinants of the population growth of these units between 1970 and 2010, as well as examine the existence and magnitude of spatial interaction and spatial spillover effects associated with these determinants. To model the population growth dynamics of Brazilian cities, an economic–theoretical model is constructed that includes spatial interaction effects, and then its reduced-form solution is estimated taking the form of a dynamic spatial panel model with controls for spatial and time-specific effects. Accordingly, the magnitude and significance levels of spatial spillover effects can be determined, as a result which any support for these effects is not simply an artifact of ignoring time-specific effects that areas have in common.

This paper's investigation is motivated by first presenting a spatial extension of the city population growth model developed by GLAESER *et al*. (1995). This extension accounts for spatial interaction effects among productivity and city amenities and is shown to imply an empirical specification for population growth dynamics that consists of spatial interaction effects in the dependent and independent variables. Next, the econometric methodology underlying the empirical investigation is presented, as well as the definition of spatial spillover effects. After detailing the data, the results of the empirical analysis are presented and discussed, including a robustness check distinguishing metropolitan and non-metropolitan municipalities. Finally, the main findings and draw conclusions are summarized.

SPATIAL EXTENSION OF GLAESER'S POPULATION GROWTH MODEL

The theoretical framework of population growth across Brazil builds on previous work by GLAESER *et al*. (1995), which is taken as point of departure, and by BRUECKNER (2003) and ERTUR and KOCH (2007), which are used to extend the model. In the urban growth model developed by GLAESER *et al*. (1995),[2] cities are treated as independent economies that share common pools of labor and capital and differ in their level of productivity (A_{it}) and quality of life (Q_{it}), whose growth rates depend on factors such as crime, housing prices, and traffic congestion. The total output of an economy is the product of the productivity level and a Cobb-Douglas production function that depends on population size and the population growth rate. The first-order condition with respect to population in its role as labor determines the wage rate. The level of utility of a resident or of a potential migrant to this economy is the product of this wage rate and the quality of life, a measure which is assumed to decrease with population size. The reduced form result of combining these two functional forms of production and consumption is a population growth regression containing several factors that determine productivity growth and quality of life, among which the aforementioned factors, and population growth lagged in time.

An objection to this theoretical framework is that it ignores spatial interaction effects among economies, especially between a locality and its surroundings. To address this problem, these spatial interaction effects are modeled explicitly. Suppose the total output of an economy is given by

$$Y_{it} = A_{it} P_{it}^{\beta} K_{it}^{\gamma} \overline{Z}_i^{1-\beta-\gamma} , \tag{1}$$

where P_{it} represents the population size in economy i at time t in their role of workers, K_{it} denotes traded capital, and $\overline{Z}_i$ is fixed non-traded capital. Then, the first extension includes productivity interaction effects among economies. ERTUR and KOCH (2007) argue that knowledge accumulated in one economy depends on knowledge accumulated in other economies, though with diminished intensity due to frictions caused by socio-economic and institutional dissimilarities, which in turn can be captured by geographical distance or border effects. More formally,

$$A_{it} = a_{it} \prod_{j \neq i}^{N} a_{jt}^{\rho w_{ij}} \ , \tag{2}$$

where the productivity level of an economy A_{it} depends on urban differences in the productivity of labor related to social, technological, and political sources in the own economy (i) a_{it}, as well as those in neighboring economies ($j \neq i$) a_{jt}; N is the number of economies. The parameter ρ reflects the degree of interdependence among economies, with $0 < \rho < 1$. Although this parameter is assumed to be identical for all economies, the impact of the interaction effects on economy i depends on its relative location, reflecting the effect of being located closer to or further away from other economies. This relative location can be represented by the exogenous term w_{ij}, which is assumed to be non-negative, non-stochastic, and finite, establishing an $N \times N$ neighborhood matrix **W** in which $0 \leq w_{ij} \leq 1$ and $w_{ij} = 0$ if i = j. Substituting (2) into (1) represents total output of an economy, whose first-order conditions for capital and labor, that is, capital income (normalized price = 1) and the wage rate (denoted S_{it}) are equal to their marginal products, yield the following labor demand equation, after the optimal solution for capital is substituted in the condition for labor:

$$S_{it} = \beta \gamma^{\frac{\gamma}{1-\gamma}} \left(a_{it} \prod_{j \neq i}^{N} a_{jt}^{\rho w_{ij}} \right)^{\frac{1}{1-\gamma}} P_{it}^{\frac{\beta+\gamma-1}{1-\gamma}} \overline{Z}_{i}^{\frac{1-\beta-\gamma}{1-\gamma}} \ . \tag{3}$$

As this labor demand equation shows, higher wages reflect higher productivity and fewer population in their role of workers.

Population in their role of consumers have Cobb-Douglas utility functions for tradable goods and housing, denoted by C_{it} and H_{it}, respectively. It is assumed that utility is due to the (dis)amenities of the local economy Θ_{it}; they might interfere negatively or positively with a resident's utility, and they can be either natural (e.g., climate, beaches, vegetation) or generated by humans (e.g., violence, entertainment, traffic, pollution). Formally,

$$U_{it} = C_{it}^{1-\alpha} H_{it}^{\alpha} \Theta_{it} , \tag{4}$$

where α is a constant. The price of tradable goods is normalized to 1; the housing price is p_{Hit}. Consumers maximize their utility, subject to a budget constraint,

$$C_{it} + p_{Hit} H_{it} = S_{it} , \tag{5}$$

by choosing C_{it} and H_{it}.

The second extension includes amenity interaction effects across economies. Some (dis)amenities may (dis)benefit people living in other economies (BRUECKNER, 2003). In mathematical terms,

$$\Theta_{it} = \left(\theta_{it} \prod_{j \neq i}^{N} \theta_{jt}^{\eta w_{ij}} \right), \tag{6}$$

where the overall amenities of an economy Θ_{it} depend on local amenities θ_{it} and those in neighboring economies θ_{jt}, and the impact of the latter decreases with geographical distance. The parameter η measures the degree of interdependence among economies, with $0 < \eta < 1$. According to GLAESER *et al*. (1995), many potential (dis)amenities can be reflected by the level of population and the population growth rate; the greater the size of a city, the lower the quality of life. The costs of migration rise with the number of immigrants, and if the population size increases rapidly, expansions in public goods, infrastructure, and housing might not be able to keep pace. Therefore, residents of quickly growing cities suffer in terms of quality of life, yielding the utility function

$$U_{it} = C_{it}^{1-\alpha} H_{it}^{\alpha} \left(\theta_{it} \prod_{j \neq i}^{N} \theta_{jt}^{\eta w_{ij}} \right) P_{it}^{-\varphi} \left(\frac{P_{it}}{P_{it-1}} \right)^{-\tau}, \tag{7}$$

where $\varphi > 0$ and $\tau > 0$. In addition, total city demand for housing is given by

$$H_{it} = P_{it} \frac{\alpha S_{it}}{p_{Hit}}. \tag{8}$$

According to GLAESER and GOTTLIEB (2009), the spatial equilibrium condition is a primary theoretical tool for urban economists, as exemplified in pioneering work by MILLS (1967), ROSEN (1979), and ROBACK (1982) on population changes within a country. This condition states that utility equalizes across space, provided that labor is mobile; higher wages in urban areas get offset by negative urban attributes, such as higher prices and negative amenities. If the common utility level at a particular point in time is denoted by $\overline{V}_t$, application of the spatial equilibrium condition produces the following results when substituting the demand equation for housing derived in (8) into (7), such that it yields the indirect utility function in (9), equal to $\overline{V}_t$:

$$V(S_{it}, p_{Hit}) = \alpha (1-\alpha)^{1-\alpha} \left(\theta_{it} \prod_{j \neq i}^{N} \theta_{jt}^{\eta w_{ij}} \right) S_{it} \, p_{Hit}^{-\alpha} P_{it}^{-\varphi} \left(\frac{P_{it}}{P_{it-1}} \right)^{-\tau} = \overline{V}_t. \tag{9}$$

Following GLAESER (2008), housing floor space is produced competitively, either by land (L) or by height (h). If the supply of land at a particular location is fixed, or comes available only gradually, the prices of land (p_L) and housing (p_H) are endogenous, as a result of which the cost of producing hL units of structure on top of L units of land is given by $c_0 h^{\delta} L$, where $\delta > 1$. The developer then maximizes profits,

$$\pi = p_{Hit} hL - c_0 h^{\delta} L - p_L L \ . \tag{10}$$

Differentiating this profit function with respect to height (h) and solving the resulting first-order condition, yields $h = \left(p_H / \delta c_0\right)^{\frac{1}{\delta - 1}}$, which implies that total housing supply is given by

$$h\overline{L} = \left(p_{Hit} / \delta c_0\right)^{\frac{1}{\delta - 1}} \overline{L} \ . \tag{11}$$

By comparing housing demand in (8) with housing supply in (11), the housing price equation is obtained:

$$p_{Hit} = \left(\frac{P_{it} \alpha S_{it}}{\overline{L}}\right)^{\frac{\delta - 1}{\delta}} \left(\delta c_0\right)^{\frac{1}{\delta}} . \tag{12}$$

Labor demand in (3), indirect utility in (9), and housing prices in (12) then form a system, with three unknown variables (P_{it}, S_{it}, and p_{Hit}). Solving this system for the population P_{it} yields

$$\log P_{it} = D_N + \psi\left\{\log\theta_{it} + \left(\eta\sum_{j\neq i}^{N} w_{ij}\log\theta_{jt}\right) + \left(\frac{\delta-\alpha\delta-\alpha}{\delta}\right)\left(\log a_{it} + \rho\sum_{j\neq i}^{N} w_{ij}\log a_{jt}\right)\right. \qquad (13)$$
$$\left. + \tau\log P_{it-1} + \log\overline{V}_t\right\},$$

where D_N and ψ are detailed in appendix A. According to GLAESER and GOTTLIEB (2009), the spatial equilibrium condition means that in a dynamic model, only lifetime utility levels get equalized across space. However, as long as housing prices or rents can change quickly, or to a reasonable extent within the observation periods being considered— which is 10 years for the present study[3]—a price adjustment is enough to maintain the spatial equilibrium. Then the change in utility between times t and $t+1$ is the same across space, $\overline{V}_{t+1}/\overline{V}_t$, and (13) can be rewritten as

$$\log\left(\frac{P_{it+1}}{P_{it}}\right) = \psi\left(\log\left(\frac{\theta_{it+1}}{\theta_{it}}\right) + \left(\eta\sum_{j\neq i}^{N} w_{ij}\log\left(\frac{\theta_{jt+1}}{\theta_{jt}}\right)\right) + \left(\frac{\delta-\alpha\delta-\alpha}{\delta}\right)\left(\log\left(\frac{a_{it+1}}{a_{it}}\right) + \rho\sum_{j\neq i}^{N} w_{ij}\log\left(\frac{a_{jt+1}}{a_{jt}}\right)\right)\right. \qquad (14)$$
$$\left. + \tau\log\left(\frac{P_{it}}{P_{it-1}}\right) + \log\left(\frac{\overline{V}_{t+1}}{\overline{V}_t}\right)\right).$$

Following GLAESER *et al*. (1995), X_{it} is assumed to be a vector of city characteristics at time t that determine both the growth of city-specific productivity denoted by a and city-specific amenity growth denoted by θ:

$$\log\left(\frac{a_{it+1}}{a_{it}}\right) = X'_{it}\lambda_a + \xi_{it+1}\text{, and} \qquad (15a)$$

$$\log\left(\frac{\theta_{it+1}}{\theta_{it}}\right) = X'_{it}\lambda_\theta + \varepsilon_{it+1}. \qquad (15b)$$

Combining (14) and (15) yields the dynamic spatial population growth equation:

$$\log\left(\frac{P_{it+1}}{P_{it}}\right)=\psi\left(\tau\log\left(\frac{P_{it}}{P_{it-1}}\right)+\left(1+\frac{(\delta-\alpha\delta+\alpha)}{\delta}\right)X'_{it}(\lambda_a+\lambda_\theta)\right.$$
$$+\left(\eta+\rho\frac{(\delta-\alpha\delta+\alpha)}{\delta}\right)\sum_{j\neq i}^{N}w_{ij}X'_{jt}(\lambda_a+\lambda_\theta)\Bigg) \tag{16}$$
$$+\psi\left(\log\left(\frac{\overline{V}_{t+1}}{\overline{V}_t}\right)+\eta\sum_{j\neq i}^{N}w_{ij}\varepsilon_{jt+1}+\rho\frac{(\delta-\alpha\delta+\alpha)}{\delta}\sum_{j\neq i}^{N}w_{ij}\xi_{jt+1}+\varepsilon_{it+1}+\xi_{it+1}\right),$$

which contains spatial interaction effects among both the explanatory variables and the error terms. In spatial econometrics literature, such a model specification is known as the spatial Durbin error model (SDEM; see LESAGE and PACE, 2009). Since the right-hand side of this model also contains the dependent variable, lagged one period, it also could be labeled a dynamic SDEM model.

The utility function specified in (8) assumes that its function value for potential migrants declines with both the level and the growth rate of the population. However, just as knowledge and amenities in one economy interact with knowledge and amenities in others, so might the level and growth rate of population depend on these values in neighboring economies. If residents of quickly growing cities suffer in terms of quality of life, they might move to neighboring areas. Therefore, assuming individual utility correlates negatively with the level of population (population size) and the population growth rate of neighbors, the utility function may take the more complicated form

$$U_{it}=C_{it}^{1-\alpha}H_{it}^{\alpha}\left(\theta_{it}\prod_{j\neq i}^{N}\theta_{jt}^{\eta w_{ij}}\right)P_{it}^{-\varphi}\left(\frac{P_{it}}{P_{it-1}}\right)^{-\tau}\left(\prod_{j\neq i}^{N}P_{jt}^{-\nu w_{ij}}\right)\left(\prod_{j\neq i}^{N}\left(\frac{P_{jt}}{P_{jt-1}}\right)^{-\sigma w_{ij}}\right), \tag{17}$$

where $\nu>0$ and $\sigma>0$. Solving the system for the population P_{it} with this alternative specification of the utility function, applying the same steps set out above, yields a population growth equation whose right-hand side also includes the terms

$$\ldots = \psi\left(-(\nu+\sigma)\left(\sum_{j\neq i}^{N} w_{ij} \log \frac{P_{jt+1}}{P_{jt}} \right) + \sigma \left(\sum_{j\neq i}^{N} w_{ij} \log \frac{P_{jt}}{P_{jt-1}} \right) \right) + \ldots \tag{18}$$

In addition to spatial interaction effects among the explanatory variables and the error terms, this extended model specification contains spatial interaction effects for the dependent variable. In the spatial econometrics literature, such a specification is known as a general nesting spatial (GNS) model (ELHORST, 2014a), and when accounting for the dependent variable lagged one period, as a dynamic GNS model.

Apart from dynamic effects in both space and time, the population growth rate depends on factors determining its productivity and amenities and that of its neighbors. Three productivity and two amenity-related variables that will be introduced later turn out to produce significant spatial interaction effects, demonstrating the relevance of this theoretical extension. However, the econometric strategy used in this paper to discriminate between the spatial population growth equations in (16) and (18) and technical issues that arise when estimating the parameters of the model using panel data will be presented first.

ECONOMETRIC METHODOLOGY

The econometric counterpart of the dynamic spatial GNS model, which is the final equation implied by the theoretical model presented in the previous section, reads, in vector form, as

$$\mathbf{Y}_t = \tau\mathbf{Y}_{t-1} + \delta\mathbf{W}\mathbf{Y}_t + \eta\mathbf{W}\mathbf{Y}_{t-1} + \mathbf{X}_t\boldsymbol{\beta} + \mathbf{W}\mathbf{X}_t\boldsymbol{\theta} + \boldsymbol{\mu} + \lambda_t\boldsymbol{\iota}_N + \mathbf{v}_t, \quad \mathbf{v}_t = \lambda\mathbf{W}\mathbf{v}_t + \boldsymbol{\varepsilon}_t, \tag{19}$$

where $\mathbf{Y}_t$ denotes an $N \times 1$ vector that consists of one observation of the dependent variable for every economy (i = 1, ..., N) in the sample at time t (t = 1, ..., T), which for this study is the population growth rate, $\log(P_{it+1}/P_{it})$; and $\mathbf{X}_t$ is an $N \times K$ matrix of exogenous or predetermined explanatory variables, observed at the start of each observation period and associated to the determinants of local productivity and amenities. Table 1 provides a detailed description between the theoretical and econometric model equations. Although it was tried to maintain consistent symbols, the limited supply of Greek letters mandated that many of the parameters in the econometric model relied on a different interpretation than those used in the theoretical model. A vector or matrix with subscript t–1 in (19) denotes its time lagged value, whereas a vector or matrix premultiplied by **W** denotes the spatially lagged value. The $N \times N$ matrix **W** is a non-negative matrix of known constants that describe the spatial arrangement of the economies in the sample, as introduced in the previous section. The parameters τ, δ, and η are the response parameters of, respectively, the dependent variable lagged in time $\mathbf{Y}_{t-1}$, the dependent variable lagged in space $\mathbf{WY}_t$, and the dependent variable lagged in both space and time $\mathbf{WY}_{t-1}$. The symbols $\boldsymbol{\beta}$ and $\boldsymbol{\theta}$ represent $K \times 1$ vectors of the response parameters of the exogenous explanatory variables. The error term specification consists of different components: the vector $\mathbf{v}_t$ that is assumed to be spatially correlated with autocorrelation coefficient λ; the $N \times 1$ vector $\boldsymbol{\varepsilon}_t = (\varepsilon_{1t}, \ldots, \varepsilon_{Nt})^T$ that consists of i.i.d. disturbance terms, which have zero mean and finite variance σ^2; the $N \times 1$ vector $\boldsymbol{\mu} = (\mu_1, \ldots, \mu_N)^T$ that contains spatial specific effects μ_i and is meant to control for all spatial-specific, time-invariant variables whose omission could bias the estimates in a typical cross-sectional study; and the time-specific effects λ_t (t = 1, …, T), where $\boldsymbol{\iota}_N$ is a $N \times 1$ vector of ones, meant to control for all time-specific, unit-invariant variables whose omission could bias the estimates in a typical time-series study.

<< Table 1 around here >>

Spatial- and time period–specific effects can be treated as fixed or random effects. A random effects model would make sense if a limited number of MCAs were being drawn randomly from Brazil, but in that case the elements of the neighborhood matrix could not be defined, and the impact of spatial interaction effects could not be estimated consistently. Only when neighboring units are part of the sample is it possible to measure the impact of neighboring units. Therefore, this study is distinct from urban studies that seek to explain economic growth in cities, such as those by GLAESER *et al.* (1995) and DA MATA *et al.* (2007). To cover the whole country and model the interactions, both urban and rural regions are included, whereas previous studies ignore the potential interaction effects with surroundings and treat cities as independent entities.

Direct interpretation of the coefficients in the dynamic GNS model is difficult, because they do not represent true partial derivatives (LESAGE and PACE, 2009). ELHORST (2012) shows that the matrix of (true) partial derivatives of the expected value of the dependent variable with respect to the k^{th} independent variable for $i = 1, \ldots, N$ in year t for the long term is given by the N by N matrix

$$\left[\frac{\partial E(\mathbf{Y})}{\partial x_{1k}} \quad \cdots \quad \frac{\partial E(\mathbf{Y})}{\partial x_{Nk}}\right] = [(1-\tau)\mathbf{I} - (\delta+\eta)\mathbf{W}]^{-1}[\beta_k \mathbf{I}_N + \theta_k \mathbf{W}]. \tag{20}$$

whose average diagonal element can be used as a summary indicator for the direct effect, and average row sum of off-diagonal elements as a summary indicator of the spillover effect. These summary indicators reflect the impact on the dependent variable that result from a change in the k^{th} regressor x_k respectively in the own economy and in other economies.

One problem with the dynamic GNS model is that its parameters are not identified, as acknowledged by ANSELIN *et al*. (2008) and ELHORST (2014a). The interaction effects among the dependent variable and the error terms cannot be distinguished formally, as long as the interaction effects among the explanatory variables are also included. Therefore, one of the two spatial interaction effects should be excluded. If the spatial interaction effects for the dependent variable are excluded ($\delta = \eta = 0$), the dynamic SDEM specification results, consistent with the utility function specified in (7), while the spatial multiplier matrix $[(1 - \tau)\mathbf{I} - (\delta + \eta)\mathbf{W}]^{-1}$ in (20) reduces to $1/(1 - \tau)\mathbf{I}$. If the spatial interaction effects among the error terms is left aside ($\lambda = 0$), a dynamic spatial Durbin model (SDM) results. This model specification is consistent with the utility function specified in (17). Although the specification does not account for interaction effects among the error terms, which reduces the efficiency of the parameter estimates, it does not affect the consistency of the parameter estimates. Furthermore, it also does not influence the direct or spillover effects derived from (20).

Another important difference between the SDEM and SDM specifications is that the spillover effects in the first model are local, whereas in the second model, they are global in nature. Local spillovers occur at other locations only if they according to **W** are connected to each other, whereas global spillovers gets transmitted to all other locations even if the two locations are unconnected according to **W**. This requires that $\delta \neq 0$.

To choose between SDM and SDEM, and thus respectively between a global or local spillover model and the utility functions specified in (7) or (17), as well as to choose between different potential specifications of the neighborhood matrix **W**, a Bayesian comparison approach is applied. This approach determines the Bayesian posterior model probabilities of the SDM and SDEM specifications given a particular neighborhood matrix, as well as the Bayesian posterior model probabilities of different neighborhood matrices given a particular model specification. These probabilities are based on the log marginal likelihood of a model obtained by integrating out all parameters of the model over the entire parameter space on which they are defined. If the log marginal likelihood value of one model or of one **W** is higher than that of another model or another **W**, the Bayesian posterior model probability is also higher. It should be stressed that the model parameters are not estimated and so cannot be reported when applying the Bayesian comparison approach. Whereas the popular likelihood ratio, Wald and/or Lagrange multiplier statistics compare the performance of one model against another model based on specific parameter estimates within the parameter space, the Bayesian approach compares the performance of one model against another model, in this case SDM against SDEM, on their entire parameter space. This is the main strength of this approach. Inferences drawn on the log marginal likelihood function values for the SDM and SDEM model are further justified because they have the same set of explanatory variables, $\mathbf{X}_t$ and $\mathbf{WX}_t$, and are based on the same uniform prior for δ and λ. This prior takes the form $p(\delta)=p(\lambda)=1/D$, where $D=1/\omega_{max}-1/\omega_{min}$ and ω_{max} and ω_{min} represent respectively the largest and the smallest (negative) eigenvalue of the neighborhood matrix **W**. This prior requires no subjective information on the part of the practitioner as it relies on the parameter space $(1/\omega_{min}, 1/\omega_{max})$ on which δ and λ are defined, where $\omega_{max}=1$ if **W** is row-normalized. Full details regarding the choice of model can be found in LESAGE (2014) and regarding the choice of **W** in LESAGE and PACE (2009, Chs. 5 and 6). Depending on the outcomes of the Bayesian comparison approach, either the SDM or the SDEM specification is estimated, using maximum likelihood (ML).

DATA IMPLEMENTATION

Data are taken from the Brazilian Demographic Census for the years 1970, 1980, 1991, 2000, and 2010, as conducted by the Brazilian Institute of Geography and Statistics (IBGE), complemented by data collected by the Brazilian Institute for Applied Economic Research (IPEA).

The municipality constitutes the lowest administrative level in Brazil for which economic and demographic data are available. During 1970–2000, the number of municipalities increased from 3,952 to 5,565. Such ongoing changes in the number, area, and borders of municipalities mean that a consistent comparison over time is possible only if the municipalities are aggregated into broader geographical areas, or MCAs. Using the aggregation of municipalities developed by IPEA (REIS *et al.*, 2010), a spatial panel is obtained of 3,659 MCAs during 1970–2010 (see also DA MATA *et al.*, 2007). A geographical delineation of these MCAs is taken up in appendix B.

The dependent variable Y_{it} is measured by the rate of population growth in one particular MCA over a decade (t – 1, t), where i runs from 1 to 3,659, t spans from 1980 to 2010, in correspondence with (19), and the number 1 represents a decade. This population growth rate depends on the population growth rate in the previous decade; when the dynamic spatial Durbin model is used, it also depends on the population growth rate in neighboring units in contemporaneous and previous decades. Based on the theoretical model and data availability, the influences of 13 explanatory variables associated with local productivity and amenities are considered. This selection reflects mainly the recent review by DURANTON and PUGA (2013) and previous studies by GLAESER *et al*. (1995), DA MATA *et al*. (2007), GLAESER (2008), and CHI and VOSS (2011). Table 2 provides a systematic overview of the explanatory variables and their data sources.

<< Table 2 about here >>

In particular, DURANTON and PUGA (2013) discuss key theories from urban growth research and their implications in terms of population, surface area, and income per person. They provide empirical evidence of the main drivers of city growth, drawn primarily from the Unites States and other developed countries. Although Brazil is an emerging economy, and population growth in both urban and rural areas are considered to be able to model spatial interaction effects, the explanations put forward in their overview remain helpful for selecting explanatory variables for the present study. However, the variables selected must be revised for the different context. For example, whereas DURANTON and PUGA (2013) observe a tendency to measure human capital by the share of university graduates, this article focuses on the share of people aged 25 years and over who are literate, a measure that is more meaningful in Brazil and that increased from 48% in 1970 to 82% in 2010. The contributions of GLAESER *et al*. (1995) and GLAESER (2008) are integrated to this, considering that their work provided the theoretical basis for the spatial extension in the previous sections. DA MATA *et al*. (2007) is valued for its empirical focus on population growth in Brazil, though it includes only 123 Brazilian agglomerations and does not span the whole country. Both GLAESER *et al*. and DA MATA *et al*. ignore spatial interaction effects, such as those between an agglomeration and its surroundings or between a city and its suburbs within an agglomeration. Finally, CHI and VOSS (2011) is relied on, because it estimates a dynamic spatial panel data model, though without providing a theoretical motivation for this model specification. More detailed motivations behind each variable and their expected signs are provided in appendix C.

EMPIRICAL ANALYSIS

The estimation results of the parameters of (19) are in Table 3. The first column reports the estimation results of a standard linear panel data model, extended to include spatial and time-period fixed effects, but without any spatial interaction effects. The second column reports the results when including spatial interaction effects for the model that came out as the best performing one from the Bayesian comparison approach. However, this article first discusses the results in the first column and this comparison approach and then turns to the results in the second column.

<< Table 3 around here >>

SPATIAL DEPENDENCE

To investigate the (null) hypothesis that the spatial fixed effects are jointly insignificant, a likelihood ratio (LR) test is performed. The results (8674.34, with 3658 degrees of freedom [df], $p < 0.01$) reject this hypothesis. Similarly, the hypothesis that the time-period fixed effects are jointly insignificant can be rejected (789.06, 3 df, $p < 0.01$). These results justify the extension of the model with spatial and time period fixed effects. Appendix E reports the correlation coefficients for the explanatory variables, which indicate that multicollinearity is not a problem.

To test whether the non-spatial model with spatial and time period fixed effects should be extended with spatial interaction effects for the dependent variable (SAR specification) or for the error terms (SEM specification), LM tests are used, applied to a first-order, binary, contiguity neighborhood matrix that is row-normalized to ensure row sums equal to 1. These LM tests follow a chi-squared distribution with one degree of freedom and reach a critical value of 3.84 at 5% significance or 2.71 at 10% significance. In classic LM tests, the hypotheses of both no spatially lagged dependent variable and no spatially autocorrelated error term must be rejected. With robust tests, the hypothesis of no spatially lagged dependent variable can be rejected. Conversely, the hypothesis of no spatially autocorrelated error term cannot be rejected, at 10% significance. These test results suggest extending the non-spatial model with a spatially lagged dependent variable. However, if the robust LM tests reject a non-spatial model, in favor of the spatial lag or spatial error models, one must carefully endorse one of these models. LESAGE and PACE (2009) and ELHORST (2014b) also recommend considering the spatial Durbin model and testing whether it can be simplified to the spatial lag or spatial error model. This study takes a broader view and applies the Bayesian approach. First, the Bayesian posterior model probabilities of the SDM and SDEM specifications are calculated, as well as the simpler SAR and SEM specifications, to identify which model specification best describes the data. Second, this analysis is repeated for several specifications of the neighborhood matrix, to find the specification of $\boldsymbol{W}$ that best describes the data. In total, 11 matrices are considered: p-order binary contiguity matrices for p = 1–3, an inverse distance matrix, and q-nearest neighbors matrices for q = 5–10 and 20.

The results in Table 4 show that the SAR and SEM models are always outperformed by either the SDM or SDEM specifications. Therefore, spatially lagged explanatory variables (*WX)* are important and should be included in the model. The worst performing spatial neighborhood matrix in terms of the log marginal likelihood value is the inverse distance matrix, which corroborates the point that decomposing market potential variables into their underlying components and considering the spatially lagged values of these components creates a much greater degree of empirical flexibility (Appendix D). If the neighborhood matrix is specified as a first-order binary contiguity matrix or as a 5-nearest neighbors matrix, the Bayesian posterior model probabilities point to the SDM specification. The average number of neighbors in the sample amounts to 4.98, so these two neighborhood matrices are not substantially different. Conversely, if higher-order binary contiguity matrices or nearest neighbors matrices with more neighbors are adopted, the Bayesian posterior model probabilities provide further evidence in favor of the SDEM specification. However, by also considering the log-marginal values of the different specifications of the neighborhood matrix, it is to be noted that the first-order binary contiguity matrix and the SDM specification achieve the best performance of all 44 combinations, in line with the initial robust LM test statistics for the non-spatial panel data model, which pointed to a spatial lag rather than a spatial error model. In turn, it has been decided to estimate the dynamic SDM specification using the bias-corrected ML estimator developed by LEE and YU (2010).[4] The estimation results are in the second column of Table 3. The results then serve to test H_0: $\boldsymbol{\theta} = \boldsymbol{0}$ and $\eta = 0$ and H_0: $\boldsymbol{\theta} + \delta\boldsymbol{\beta} = \boldsymbol{0}$ and $\eta + \delta\tau = 0$. That is, it is tested whether the dynamic spatial Durbin might be simplified to a dynamic spatial lag model or dynamic spatial error model. Both tests follow a chi-squared distribution with $K + 1$ degrees of freedom (number of spatially lagged explanatory variables and the spatially lagged dependent variable) and take the form of a Wald test, because the simplified models have not been estimated. The results reject both hypotheses, but again, a spatial econometric model extended to include a spatially lagged dependent variable is more likely than its counterpart with a spatially autocorrelated error term. Overall, the empirical results point to the utility function specified in (17), which posits that the utility of individuals correlates negatively with the level of population (population size) and the population growth rate of their neighbors, and to the global spillover model, which posits that $\delta \neq 0$.

<< Table 4 around here >>

DETERMINANTS OF BRAZILIAN POPULATION DYNAMICS

The results reported in second column of Table 3 show that six of the thirteen spatially lagged explanatory variables in the dynamic SDM specification appear statistically significant at the 5% level. The coefficients of the spatially lagged dependent variable at time t and t–1, $\mathbf{WY}_t$ and $\mathbf{WY}_{t-1}$, are also significant. A necessary and sufficient condition for stationarity, $\tau + \delta + \eta$

= 0.0755 + 0.3439 + 0.0681 = 0.4875 < 1, is satisfied.

Table 5, columns (I)-(III), reports long-term estimates of the direct, spillover and total effects, derived from the parameter estimates using (20).[5] To draw inferences regarding the statistical significance of these effects, the variation of 100 simulated parameter combinations is used, drawn from the variance-covariance matrix implied by the ML estimates. The number of explanatory variables with significant (5%) spillover effects is three and with weakly significant (10%) spillover effects is two; this count is less than the number of significant spatial interaction effects because they depend on more than just one parameter—that is, five parameters in the long term (Equation 20).

<< Table 5 around here >>

First of all, the long-term, direct, spillover, and total effect estimates of the growth rate represent significant convergence and deconcentration effects. The direct effect amounts to -0.918, and the total effect is -0.781; they are both significant. That is, the greater the population growth in the MCA in the previous decade, the smaller it will be in the next decade, and vice versa. This finding points to convergence. The spillover effect of 0.137 is also significant, which indicates that population growth can be stimulated if population growth in neighboring MCAs has been greater in the previous decade. This movement or deconcentration of people to neighboring areas, perhaps to escape the bustle of the city, represents a convergence effect. However, as a feedback effect of this behavior, the city starts growing again, such that the total convergence effect diminishes. This rationale helps explain the reduction of the convergence effect from -0.918 to -0.781.

Regarding the influence of factors associated to local productivity, first note that if the literacy rate increases by one percentage point, the population growth rate in the area increases by 0.083 percentage points, and in neighboring areas by 0.143 percentage points. The last effect points to spatial spillover effects and is weakly significant (10%). The first finding, the positive relationship between educational attainment and population growth, matches GLAESER and SAIZ's (2004) and DA MATA *et al*.'s (2007) arguments that economies with better educated people are productivity-enhancing and more adaptable to technological change. The second finding, the positive relationship between educational attainment and population growth in neighboring units, aligns with the theoretical proposition introduced in (2), namely, that knowledge accumulated in one economy depends on knowledge accumulated in others.

Just as the literacy rate, most variables associated with local productivity have the expected signs, although not all of them do produce significant spillover effects. As expected and in contrast to CHI and VOSS (2011), the share of employment in agriculture has a negative effect of 0.247 percentage points on population growth in the long term, due to the reduction in economic opportunities, especially for women. A greater share of employment in manufacturing relative to services and GDP per capita instead have positive, significant effects. These two results are consistent with the idea that the growth of productivity is higher in municipalities with bigger markets and with stronger presence of manufacturing activities. Rural GDP per capita also has a positive and significant direct effect on population growth, such that municipalities that offer income opportunities remain attractive. However, neither of these three variables have positive spillover effects on their environment. DA MATA *et al*. (2007) note that their rural variables perform poorly, due to limited variation and multicollinearity, but by decomposing the market potential variables, this article avoids such problems.

In contrast to rural GDP per capita, the direct effect of the rural population is negative and significant. A one percentage point increase of the rural population has an adverse effect on population growth, equal to 0.043 percentage points. The spillover effect amounts to -0.021 and is statistically significant; this implies that rural municipalities surrounded by other rural municipalities tend to grow one and a half times slower than rural municipalities close to urban areas. These negative effects are probably explained by the strong correlation between this variable and the absence or insufficiency of local provision of basic household infrastructure in Brazilian municipalities with high rural population, making these localities less attractive.

The birth rate not only produces a significant direct effect, but also a significant spillover effect that, in terms of magnitude, is greater than the direct effect. If the birth rate increases by 1 child for every 1,000 inhabitants in a given area, the population growth rate in that area itself increases by 0.018 percentage points in the long term, and 0.027 percentage points in its surroundings. This latter figure represents the cumulative effect over all neighbors; considering the finding that the average number of neighbors is 4.98, the average spillover effect per neighbor is likely around 0.005. The significant direct and spillover effects of the birth rate confirm the hypotheses that the population grows faster if it is relatively immobile and that due to deconcentration this growth partly spreads out to neighboring areas. The impact of the mean age of the population is positive and significant. If this mean age increases by one year, the population growth rate increases by 0.01 percentage points. During the observation period, the mean age increased, from 23 in 1970 to 32 in 2010, and this finding corroborates the view that economic opportunities grow when the number of working-age adults increases, relative to the dependent population. Finally, consistent with GLAESER *et al.*'s (1995) idea that potential migrants do not move to areas with high unemployment rates, a positive direct effect is obtained of the percentage of economically active population that is occupied on population growth of Brazilian municipalities.

As for the variables associated to local amenities, note that all variables, when statically significant, have the expected signs, and some of them with important spillover effects. Specifically, the direct effect of population density is negative and significant, corroborating the hypothesis that densely populated cities deter prospective migrants with their poor living conditions. To some extent this negative effect may also be related with a kind of convergence in population size across cities. Interestingly, this adverse effect also spills over to neighboring MCAs. The spillover effect is negative and significant and, in terms of magnitude, almost as substantial as the direct effect. If population density in a city increases by one percentage point, the population growth rate falls by 0.145 percentage points in the long term in the city, and by 0.141 in its surroundings. Even stronger results are uncovered related to homicide rates. The direct effect is insignificant, but the spillover effect is negative and weakly significant (10%), such that city surroundings pay the price for this disamenity. The negative relationships of both population density and the homicide rate with population growth in surroundings corroborates the theoretical proposition from (7) that disamenities in one economy harm individuals and deter prospective migrants in neighboring economies.

The proportion of people with access to public water has a positive effect and significant effect on population growth, but the proportion of people with access to public sewer does not. This variable partly reflects the price of urban space: If the supply of housing with access to public sewer is relatively inelastic, the prices of this type of housing might increase so much that prospective migrants would be discouraged, and the population growth rate would decrease again. Research by FGV (2010) suggests that sanitation enables construction with higher added value and appreciation in the value of existing buildings.

The significant spillover effects obtained for some variables make it interesting to compare the long-term total effects reported in Table 5, derived from the dynamic SDM specification, against those from the non-spatial model reported in the first column of Table 3.

The long-term total effect of the latter model can be obtained by calculating $\beta/(1 - \tau)$, where β is the coefficient estimate of a particular explanatory variable and τ is the coefficient estimate of the dependent variable (population growth rate), lagged one decade. The results of these comparisons are presented in Table 5, column (IV). The long-term total effect of the rural population amounts to, according to the spatial model, -0.064 and, according to the non-spatial model, -0.0433/(1 – (-0.0271) = -0.0422. Therefore, the effect in the non-spatial model is underestimated by 34.1%. For the other variables that produce significant spatial spillover effects, 57.5% is found for population density, 61.9% for the birth rate, 41.4% for the literacy rate, and 58.3% for the homicide rate. The degree of underestimation averages 27% across all explanatory variables, thus a non-spatial modeling approach, as the previous ones applied to Brazilian cities' population dynamics, evidently does not reflect the full impact of policy measures that act on these variables.

The above findings about the population dynamics of Brazilian cities are consistent with stylized facts about the historical pattern of occupation across Brazilian's physical space. The observed convergence effect of city growth during 1970-2010 is consistent with the initial growth of cities located in the eastern part of the country, mainly the South and Southeast, where the biggest cities are located, and the more recent population increase in cities located in the Midwest and North. The initial expansion of cities, mainly in the Southeast, is related to the pattern of Brazilian economic growth that started with a high concentration of economic activities in mainly manufacturing. During the most recent decades, the economic opportunities for exporting agricultural products and commodities extracted from the economic exploration of the Cerrado area increased the attractiveness of the Midwest and North, composed of small and medium sized cities. At the same time, urban problems associated with congestion and the lack of infrastructure services reduced the attractiveness of big cities of the Southeast. The analysis in this article also disclosed the main determinants explaining these movements. A better educated workforce, a higher share of employment in manufacturing relative to services, a higher urban or rural GDP per capita are traditional factors having a positive effect on population growth in Brazilian cities, since they improve labor productivity. In fact, these factors are also associated with the historical regional disparities of income during the sample period (AZZONI, 2001) and are all consistent with the general patterns of the population exodus from the Northeastern cities, the poorest region of the country, and the immigration to the cities located in the Southeast during most of 1970-2010. This process was strengthened by the spillover effects caused by a better educated workforce, the fact that knowledge accumulated in one city may also benefit neighboring cities, a result that up to now has not been documented in the literature. Similarly, the negative effects on the growth of cities' populations due to growing population density and homicide rates, not only in the cities themselves but due to spillover effects also in their surroundings, are entirely consistent with the negative impacts on well-being arising from the congestion of public spaces, deficient urban infrastructures (which, for example, explain the very high commuting time of Brazilian urban centers) and the increased urban violence experienced by Brazilian cities during the last decades (MOURA and SILVEIRA NETO, 2015).

Finally, although the theoretical model does not explicitly consider any kind of urban hierarchy conditioning the influence of the variables on urban dynamic, a heterogeneous version of (19) is estimated, so as to consider potentially different influences of the variables for metropolitan versus non-metropolitan cities. The idea is to explore structural differences in population growth dynamics across cities that belong to and do not belong to a metropolitan region. The biggest municipalities in Brazil generally present a broader set of services (including federal government activities), specific kinds of manufacturing activities (with different degree of returns to scale), and higher levels of human capital and are located in metropolitan regions. The approach, thus, explores the possibility of different direct and spillover effects associated with the proximity to these big Brazilian cities.[6] The results are reported and discussed in Appendix F.

CONCLUSION

This article proposes an economic-theoretical model for city population growth, derive an explicit econometric spatial model from it, and estimate the effects of variables associated with the population growth of Brazilian cities during the period 1970-2010. This application represents an important extension of previous studies, since it includes both urban and rural economies to cover the whole country and accounts for spatial interaction effects among these economies.

Consistent with the proposed model, the parameter estimates of the variables associated with local productivity and city amenities generate a plausible model structure, i.e., they take the theoretically expected signs, with only one exception. In addition, population dynamics of Brazilian MCAs are substantively affected by their location, i.e., they are evidently associated to productivity and amenities of their neighbors. Furthermore, these results are consistent with both the historical pattern of occupation across Brazilian's physical space, where the spatial dynamic of population is strongly linked to economic opportunities, and the more recent movements of lower growth of Brazilian's big cities due to congestion of public services and lack of infrastructure.

More specifically, among the set of factors associated to local productivity, the results obtained indicate that the population growth of the Brazilian MCAs are positively affected by the level of human capital (literacy rate), the level of GDP per capita, and by the manufacturing/services employment shares ratio. Furthermore, in the case of human capital, there are spillovers arising from neighboring MCAs that also positively affect the population growth of the Brazilian MCAs. Regarding the set of variables associated with local amenities, the evidence indicates that population growth of Brazilian cities is positively affected by the level of public water provision and negatively by the share of employment in agriculture. There are also spillover effects related to some amenities: demographic density and homicide rates of neighboring MCAs negatively affect the population growth of Brazilian MCAs.

To investigate the extent to which the spatial extension of the population growth model makes a difference, the number of explanatory variables is counted causing significant spatial interaction effects. Of the 13 determinants of population growth, 5 produce significant spillover effects in the long term: rural population size, population density, the birth rate, the literacy rate, and the homicide rate. A change of one unit in one of these variables significantly affects population growth in other units, a phenomenon that has been ignored in most previous studies of population growth. By comparing the results with the evidence obtained from a non-spatial panel, it is demonstrated that a non-spatial approach for Brazil substantively underestimates the long-term total effects of the explanatory variables: underestimation averages 27% across all explanatory variables. Regarding the last four determinants, it is found that the magnitude of the cumulative effect across all neighbors is as great as the magnitude of the impact on the city itself.

In order to explore heterogeneities of the results associated with belonging to metropolitan areas, that includes the biggest cities of the country, additional results are generated for non-metropolitan and metropolitan MCAs. While for non-metropolitan MCAs these results are similar to the ones previously obtained, for the set of metropolitan MCAs positive and significant spillover effects are found associated with the variable GDP per capita, but not for the human capital variable (literacy rate). These results are consistent, respectively, with both the better road infrastructure and stronger returns to scale in the economic activities in these MCAs and with the higher and more homogenous levels of schooling in these localities.

From the perspective of government policies directed to stimulate cities' population growth, the results not only suggest important determinants to focus on, but also the ones that tend to be more effective. Specifically, in addition to implement policies favoring highly productive economic activities, such as manufacturing, and policies to improve well-being through better housing infrastructure, the government must mainly act on determinants that generate both direct and spatial spillover effects. Thus, localities that would hope to stimulate growth should better educate their population, offer good child-care facilities, reduce crime, and coordinate housing construction with neighboring localities, to spread the population over a larger area. Due to resources limitations, most Brazilian cities acting on these determinants, for example, to improve education and to reduce crime, need the co-participation of federal or state governments. Another reason why this is essential is because the benefits of stimulating population growth partly accrue to neighboring muncipalities. Ignoring this implies the risk of not only directing resources to less effective policy measures, but also of promoting unnecessary competition among municipalities with potential unwanted consequences for the finance of cities.

Acknowledgements – The authors thank two referees and the participants of several conferences all over the world for their helpful comments on previous versions of this paper.

REFERENCES

ANSELIN L., LE GALLO J. and JAYET H. (2008) Spatial panel econometrics, in MATYAS L. and SEVESTRE P. (Eds) *The Econometrics of Panel Data, Fundamentals and Recent Developments in Theory and Practice*, pp. 901-969, 3rd edition. Kluwer, Dordrecht.

AZZONI C. (2001) Economic growth and regional economic inequality in Brazil, *The Annals* *of Regional Science* **35**, 133–152.

BOARNET M.G., CHALERMPONG S. and GEHO E. (2005) Specification issues in models of population and employment growth, *Papers in Regional Science* **84**, 21-46.

BRUECKNER J.K. (2003) Strategic interaction among governments: an overview of empirical studies, *International Regional Science Review* **26**, 175-188.

CHI G. and VOSS P.R. (2011) Small-area population forecasting: borrowing strength across space and time, *Population, Space and Place* **17**, 505-520.

DA MATA D., DEICHMANN U., HENDERSON J.V., LALL S.V. and WANG H.G. (2007) Determinants of city growth in Brazil, *Journal of Urban Economics* **62**, 252-272.

DURANTON G. and PUGA D. (2013) *The Growth of Cities*. CEPR Discussion Papers 9590.

ELHORST J.P. (2012) Dynamic spatial panels: models, methods and inferences, *Journal of Geographical Systems* **14**, 5-28.

ELHORST J.P. (2014a) *Spatial Econometrics: From Cross-Sectional Data to Spatial Panels*. Springer, Heidelberg.

ELHORST J.P. (2014b) Matlab software for spatial panels, *International Regional Science Review* **37**, 385-401.

ERTUR C. and KOCH W. (2007) Growth, technological interdependence and spatial externalities: theory and evidence, *Journal of Applied Econometrics* **22**, 1033-1062.

FGV (2011) *Benefícios Econômicos da Expansão do Saneamento Básico*. Instituto Trata Brasil - Fundação Getúlio Vargas.

GLAESER E.L. (2008) *Cities, Agglomeration and Spatial Equilibrium*. Oxford University Press, Oxford.

GLAESER E.L. and GOTTLIEB J.D. (2009) *The Wealth of Cities: Agglomeration Economies and Spatial Equilibrium in the United States*. NBER working paper No. 14806.

GLAESER E.L. and SAIZ A. (2004) The rise of the skilled city, *Brookings Wharton Papers on*

Urban Affairs **5**, 45-94.

GLAESER E.L., SCHEINKMAN J.A. and SHLEIFER A. (1995) Economic growth in a cross-section of cities, *Journal of Monetary Economics* **36**, 252-272.

HENDERSON J.V. (1988) *Urban Development, Theory, Fact, and Illusion*. Oxford University Press, Oxford.

IBGE (2011) *Sinópse do Censo Demográfico 2010 – Brasil*. Available at: http://www.censo2010.ibge.gov.br/sinopse/.

LEE L.F. and YU J. (2010) A spatial dynamic panel data model with both time and individual fixed effects, *Econometric Theory* **26**, 564-597.

LESAGE J.P. (2014) Spatial econometric panel data model specification: a Bayesian approach, *Spatial Statistics* **9**, 122-145.

LESAGE J.P. and PACE R.K. (2009) *Introduction to Spatial Econometrics*. CRC Press and Taylor & Francis Group, Boca Raton, FL.

LIMA R.C. and SILVEIRA NETO R.M. (2015) Physical and human capital and Brazilian regional growth: a spatial econometric approach for the period 1970-2010, *Regional Studies*. doi:10.1080/00343404.2015.1053447

MILLS E.S. (1967) An aggregative model of resource allocation in a metropolitan area, *American Economic Review* **57**, 197-210.

MOURA K. and SILVEIRA NETO R. (2015) Individual and contextual determinants of victimization in Brazilian urban centers: a multilevel approach, *Urban Studies*. doi: 10.1177/0042098015580899

RESENDE G.M. (2013) Spatial dimensions of economic growth in Brazil, *Hindawi Publishing Corporation, ISRN Economics,* 1-19. doi.org/10.1155/2013/398021

REIS E., PIMENTEL M. and ALVARENGA A.I. (2010) *Áreas Mínimas Comparáveis Para os Períodos Intercensitários de 1872 a 2000*. IPEA.

ROBACK J. (1982) Wages, rents, and the quality of life, *Journal of Political Economy* **90**, 1257-1278.

ROSEN S. (1979) Wage-based indexes of urban quality of life, in MIEZKOWSKI P.N. and STRASZHEIM M.R. (Eds) *Current Issues in Urban Economics*, pp. 74-104. John Hopkins University Press, Baltimore.

SILVEIRA NETO R.M. and AZZONI C.R. (2012) Social policy as regional policy: market and non-market factors determining regional inequality, *Journal of Regional Science* **51**, 1-18.

SCORZAFAVE L.G. and SOARES M.K. (2009) Income inequality and pecuniary crimes, *Economic Letters* **104**, 40–42.

YAP L.Y.L. (1976) Rural-urban migration and urban underemployment in Brazil, *Journal of Development Economics* **3**, 227-243.

YU J., JONG R. de and LEE L. (2008) Quasi-maximum likelihood estimators for spatial dynamic panel data with fixed effects when both n and T are large, *Journal of Econometrics* **146**, 118-134.

Table 1. Relationship between econometric and theoretical model equations

Econometric model	Theoretical model
$\tau\mathbf{Y}_{t-1}$	$\psi\tau\log\left(\frac{P_{it}}{P_{it-1}}\right)$
$\delta\mathbf{WY}_t$	$\psi(-(\nu+\sigma))\left(\sum_{j\neq i}^{N} w_{ij}\log\frac{P_{jt+1}}{P_{jt}}\right)$
$\eta\mathbf{WY}_{t-1}$	$\psi\sigma\left(\sum_{j\neq i}^{N} w_{ij}\log\frac{P_{jt}}{P_{jt-1}}\right)$
$\mathbf{X}_t\boldsymbol{\beta}$	$\left(1+\frac{(\delta-\alpha\delta+\alpha)}{\delta}\right)X'_{it}(\lambda_a+\lambda_\theta)$
$\mathbf{WX}_t\boldsymbol{\theta}$	$\left(\eta+\rho\frac{(\delta-\alpha\delta+\alpha)}{\delta}\right)\sum_{j\neq i}^{N} w_{ij}X'_{jt}(\lambda_a+\lambda_\theta)$
$\boldsymbol{\varepsilon}_t$	$\psi\left(\log\left(\frac{\overline{V}_{t+1}}{\overline{V}_t}\right)+\varepsilon_{it+1}+\xi_{it+1}\right)$
$\lambda\mathbf{Wv}_t$	$\psi\left(\eta\sum_{j\neq i}^{N} w_{ij}\varepsilon_{jt+1}+\rho\frac{(\delta-\alpha\delta+\alpha)}{\delta}\sum_{j\neq i}^{N} w_{ij}\xi_{jt+1}\right)$

Table 2. Description, type and data source of explanatory variables

Explanatory variables	Description	Data source
Dependent variable		
population growth rate	Population growth rate	IPEADATA
Productivity-related variables (a), see equations (2) and (15a)		
literacy rate	Percentage of population (age>25) that is literate	Census/IBGE
ln GDP per capita	Natural log of GDP per capita (prices of 2010)	IPEADATA
ln rural GDP per capita	Natural log of rural GDP per capita (prices of 2010)	IPEADATA
ln rural population	Natural log of share of population living in rural areas	IPEADATA
Agriculture	Percentage of people working in agriculture, livestock, hunting and related services (age>10)	Census/IBGE
manufacture/service	Relationship between the number of employees in manufacturing and the service sector	Census/IBGE
workforce occupied	Workforce occupied (employment rate)	IPEADATA
birth rate	(Mean of number of children born alive and still living)*(1000/Pop)	Census/IBGE
mean age	Mean age	Census/IBGE
Amenity-related variables (θ), see equations (6) and (15b)		
ln density	Natural log of people per squared kilometres	IPEADATA
homicide rate	(Number of homicides)*(100000/Pop)	IPEADATA
water company	Share of households supplied by water company	Census/IBGE
sewer company	Share of households supplied by sewer company	Census/IBGE

Table 3. Population Growth: Non-Spatial and Dynamic Spatial Models

	OLS + Time- and Spatial-Specific Fixed Effects		Dynamic SDM + Fixed Effects (bias correction)			
Explanatory Variables	Coeff	T	Coeff	t	Spatial	t
Dependent variable lagged in space and/or time						
WY_t (δ)					0.3439	**
Y_{t-1} (τ, τ and η)	-0.0271	**	0.0755	**	0.0681	**
Productivity-related variables (a), see equations (2) and (15a)						
literacy rate	0.1361	**	0.0681	**	0.0395	
ln GDP per capita	0.0513	**	0.0527	**	-0.0248	**
ln rural GDP per capita	0.0088	**	0.0135	**	-0.0095	**
ln rural population	-0.0433	**	-0.0391	**	0.0068	
Agriculture	-0.2612	**	-0.2315	**	0.1063	**
manufacturing/service	0.0045	**	0.0021	**	0.0016	
workforce occupied	0.4911	**	0.3535	**	-0.0681	
birth rate	0.0172	**	0.0150	**	0.0072	**
mean age	0.0135	**	0.0089	**	-0.0020	
Amenity-related variables (θ), see equations (6) and (15b)						
ln density	-0.1248	**	-0.1256	**	-0.0221	**
homicide rate	-0.0030	**	0.0006		-0.0042	*
water company	0.0081		0.0274		-0.0255	
sewer company	-0.0123		-0.0365	**	-0.0058	
Regression diagnostics						
No. Obs.	10977		10977			
R-squared	0.711		0.743			
Log Likelihood	4144.11		5580.37			
Spatial lag, OLS model:						
LM	909.32	**	Spatial lag, SDM model:			
LM(robust)	114.89	**	*Wald*		54.39	**
Spatial error, OLS model:						
LM	796.34	**	Spatial error, SDM model:			
LM(robust)	1.91		*Wald*		134.23	**
Joint significance						
LR(spatial fe=0)	8674.60	**				
LR(time fe=0)	789.06	**				

** Significant at 1%. *Significant at 5%.

Table 4. Comparison of Model Specifications and Neighborhood Matrices

W Matrix	Statistics	SAR	SDM	SEM	SDEM
Binary Contiguity	log marginal	3566.85	3616.03	3548.42	3611.80
	model probabilities	0.0000	0.9855	0.0000	0.0145
First and Second Order	log marginal	3562.21	3574.79	3558.60	3579.41
	model probabilities	0.0000	0.0097	0.0000	0.9903
First, Second and Third Order	log marginal	3527.98	3528.75	3535.86	3536.28
	model probabilities	0.0001	0.0003	0.3974	0.6022
Inverse distance	log marginal	3368.78	3444.87	3363.32	3455.44
	model probabilities	0.0000	0.0000	0.0000	1.0000
5 nearest neighbors	log marginal	3539.69	3601.04	3521.72	3597.88
	model probabilities	0.0000	0.9594	0.0000	0.0406
6 nearest neighbors	log marginal	3551.02	3613.06	3539.41	3613.60
	model probabilities	0.0000	0.3676	0.0000	0.6324
7 nearest neighbors	log marginal	3548.94	3606.39	3537.52	3606.54
	model probabilities	0.0000	0.4622	0.0000	0.5378
8 nearest neighbors	log marginal	3551.30	3607.94	3541.97	3610.07
	model probabilities	0.0000	0.1054	0.0000	0.8946
9 nearest neighbors	log marginal	3561.30	3610.94	3553.84	3613.93
	model probabilities	0.0000	0.0474	0.0000	0.9526
10 nearest neighbors	log marginal	3560.11	3607.68	3556.60	3609.52
	model probabilities	0.0000	0.1373	0.0000	0.8627
20 nearest neighbors	log marginal	3526.87	3552.07	3534.30	3552.99
	model probabilities	0.0000	0.2853	0.0000	0.7147

Source: Own calculations, based on LESAGE (2014)

Table 5. Long-term Direct and Spillover Effects of Homogenous Dynamic Spatial Model

Explanatory Variables	Long-Term Effects			Underestimation of Long-Term Effect in Non-Spatial Model (%)
	Direct (I)	Spillover (II)	Total (III)	(IV)
lagged population growth rate	-0.918	0.137	-0.781	-
	(-113.15)	(7.03)	(40.17)	
literacy rate	0.083	0.143	0.226	41.4
	(2.38)	(1.73)	(2.48)	
ln of GDP per capita	0.057	-0.001	0.055	9.2
	(12.65)	(-0.11)	(3.96)	
ln of rural GDP per capita	0.014	-0.008	0.006	-42.8
	(5.61)	(-1.14)	(0.89)	
ln rural population	-0.043	-0.021	-0.064	34.1
	(-13.99)	(-1.97)	(-5.55)	
Agriculture	-0.247	0.004	-0.242	-5.1
	(-8.09)	(0.06)	(-2.97)	
manufacturing/services	0.003	0.004	0.007	37.4
	(2.24)	(1.06)	(1.63)	
workforce occupied	0.394	0.167	0.561	14.8
	(10.35)	(1.51)	(4.47)	
birth rate	0.018	0.027	0.044	61.9
	(9.52)	(3.37)	(5.48)	
mean age	0.010	0.004	0.013	-1.1
	(7.14)	(1.16)	(4.53)	
ln density	-0.145	-0.141	-0.286	57.5
	(-22.47)	(-6.72)	(-12.91)	
homicide rate	0.000	-0.007	-0.007	58.3
	(0.36)	(-1.80)	(-1.57)	
water company	0.028	-0.028	0.001	0.0
	(1.93)	(-0.72)	(0.02)	
sewer company	-0.040	-0.043	-0.082	85.4
	(-2.71)	(-1.40)	(-2.56)	

Note: t-values in parentheses.

APPENDIX

Appendix A: Detailed expressions of ψ and D_N in (13)

$$\psi = \frac{\delta(1-\gamma)}{(1-\gamma)\left(\alpha(\delta-1)+\delta\varphi+\delta\tau\right)-(\delta-\alpha\delta+\alpha)(\beta+\gamma-1)}$$

$$D_N = \psi\left(\alpha\log\alpha+(1-\alpha)\log(1-\alpha)+\left(\frac{\delta-\alpha\delta-\alpha}{\delta}\right)\left(\log\beta+\left(\frac{\gamma}{1-\gamma}\right)\log\gamma+\left(\frac{1-\beta-\gamma}{1-\gamma}\right)\log\bar{Z}\right)\right.$$
$$\left.-\frac{\alpha(\delta-1)}{\delta}-\frac{\alpha}{\delta}\log(\delta c_0)+\left(\frac{\alpha(\delta-1)}{\delta}\right)\log\bar{L}\right).$$

Appendix B: A map of Minimum Comparable Areas (1970–2010) in Brazil

Source: Geographical delineation by the authors.

Appendix C: Motivation separate explanatory variables

For the set of variables associated with local productivity, the following variables are considered: a measurement of local human capital, measures of market potential and agglomeration gains, and characteristics of local productive structure. The positive influence of human capital on urban dynamics for U.S. cities is well documented (GLAESER *et al*. 1995; GLAESER and SAIZ, 2004; SHAPIRO, 2006; GLAESER, 2008); as for Brazilian cities, DA MATA *et al*. (2007) also found a positive association between human capital and population growth. This kind of association is commonly interpreted as the effect of local skills on productivity growth through knowledge or information spillovers (LUCAS, 1988; BLACK and HENDERSON, 1999). As stated in the main text, this study focuses specifically on the share of people aged 25 years and over who are literate.

According to DURANTON and PUGA (2013), the availability of road infrastructure is another important component, and agglomeration effects drive city growth. DA MATA *et al*. (2007) argue that city growth depends on demand and supply factors, which they summarize as the incomes a city can pay out and the incomes people demand to live in a city, respectively. To measure these factors, they use market potential variables, which depend partly on road transport networks. The demand market potential of a spatial unit in turn is defined as the product of per capita income and population size, divided by transport costs, summed over all spatial units in the sample. To describe the supply side, they consider two gravity measures for each spatial unit: the sum of per capita rural income divided by transport costs over all other spatial units in the sample, and the sum of the rural population divided by transport costs over all other spatial units in the sample. Both constitute market potential measures, in that they measure the potential population supply to a city from nearby rural areas.

From a spatial econometric view, market potential variables can be interpreted as spatially lagged explanatory variables or exogenous interaction effects, because they measure the impact of X variables in one spatial unit on the dependent variable in another spatial unit. However, disadvantages of using market potential variables are that a certain neighborhood matrix structure is imposed on these X variables, without testing the structure first, and that their direct and spillover effects suffer from inflexibility. A detailed explanation is provided in appendix D, showing that more empirical flexibility is introduced when decomposing market potential variables into their underlying components. Only then the direct and spillover effects can vary with different explanatory variables that determine the market potential, while the specification of $\mathbf{W}$ can be tested for and thus to what extent MCAs likely interact. Just as in DA MATA *et al*. (2007), it is assumed that the population growth rate depends on GDP per capita, rural GDP per capita, rural population size, and their spatially lagged values, but as separate variables, so that agglomeration effects can be tested for.

This article also includes other demand and supply factors that can affect productivity and city growth: the industry mix and the size of the workforce. GLAESER *et al*. (1995) control for the share of employment in manufacturing and find that it has an adverse effect on population growth. DA MATA *et al*. (2007) control for the ratio between the share of employment in manufacturing to that of services, to account for local adjustments relative to changes in national output composition, and find a positive effect. CHI and VOSS (2011) include the share of employment in agriculture, though they removed this variable from the model when it emerged as insignificant. Yet this study still considers the share of employment in agriculture, because of its focus on population growth in Brazil, with its vast agricultural areas; especially at the beginning of the observation period, the number of women in the labor force was relatively high, mostly as unpaid and low productivity workers on family farms who combined their agricultural work with childcare. When income levels started to rise, such as through the expansion of the manufacturing sector and the introduction of new technologies, women's labor force participation rates tended to fall (GOLDIN 1995; MAMMEN and PAXSON, 2000). Men moved into new blue-collar jobs that increased family-level income, such that unearned income effects reduced women's participation. In addition, a high share of employment in agriculture means relatively less employment in urban occupations, which may affect local agglomeration gains from diversification (GLAESER *et al*., 1995). In summary, it is expected that the share of employment in agriculture has a negative effect on population growth, due to the implied low productivity and the reduction in economic opportunities, especially for women, and to its potentially reduced gains from diversification. Similar to DA MATA *et al*. (2007), this study also considers the ratio between the share of employment in manufacturing and that of services as a potential factor affecting local productivity dynamics.

GLAESER *et al*. (1995) also control for unemployment, because potential migrants do not move to areas with high unemployment rates. They find an adverse effect on U.S. population growth after 1970; this study thus uses the percentage of the economically active population that is occupied as an additional supply side factor. This variable offers an opposite of the unemployment rate.

Although GDP per capita measures often appear in empirical growth studies, they ignore a critical dimension of population dynamics, namely, populations' evolving age structure. Each age group in a population behaves differently, and the distribution across age groups changes over time, so economic opportunities can be boosted or slow down temporarily. Whereas prime-age adults supply labor and savings, the young require education, and the aged need health care and retirement income. Economic opportunities then should increase when the number of working-age adults is large, relative to the dependent population, but decrease when a population rapidly ages. By translating an economic model formulated as GDP per capita growth into a comparable model of GDP per worker, which largely determines demand and supply conditions in a city and its surroundings, different studies have shown that demographic variables might be important (BLOOM and WILLIAMSON, 1998; CHOUDHRY and ELHORST, 2010; KELLEY and SCHMIDT, 2005). Such variables include the mean age of the population and the birth rate. If the population of a particular region is relatively immobile, differences in population growth across areas within that region likely are due mainly to differences in fertility (GLAESER *et al*., 1995), which is an important reason to consider the birth rate.

From the theoretical model, the other influence on city growth arises from factors associated with local amenities that affect individuals' welfare. Here local characteristics are considerd that are directly associated to local quality of life and city infrastructure. In fact, two of the key drivers of city growth that DURANTON and PUGA (2013) identify are infrastructure and housing supply. The first follows from the monocentric city model; the second determines how cities react to positive or negative shocks. If the supply of houses is limited by geographical constraints or land-use regulations, a positive shock leads to higher housing prices. If the supply of houses is elastic, housing prices might increase to some extent, but the local inhabitants and incoming migrants react by choosing to live in smaller dwellings. Important infrastructural components of the housing supply in Brazil are the proportions of people with access to public water or public sewers; insufficient supply may cause higher prices and deter potential migrants. These two variables also appear in CHI and VOSS's (2011) study, whereas GLAESER *et al*. (1995) consider expenditures on sanitation. These variables increased from, respectively, 14% and 5% in 1970 to 71% and 37% in 2010. In addition, population density can control for the second factor. Many cities could take in more people, though at the expense of the quality of the living conditions, which might deter prospective migrants. Because it takes time to build public goods, infrastructure, or housing, the residents of quickly growing cities may suffer more in terms of their quality of life.

Brazilian cities are also characterized by very high levels of urban violence, a factor that directly affects urban life quality (SCORZAFAVE and SOARES, 2009; MENEZES *et al*., 2013). DA MATA *et al*. (2007) explicitly mention local crime and violence, measured by the homicide rate or number of homicides per one million inhabitants and this variable exerts a negative and significant effect on population growth in their study. DURANTON and PUGA (2013) also highlight the importance of (dis)amenities for urban growth. So, the homicide rate is included in the present study as well.

Appendix D: Non-Flexibility of market potential variables

To demonstrate the non-flexibility of market potential variables, consider the non-dynamic spatial panel data model with $\tau = \eta = 0$ in (19), in which the population growth rate $Y = \log(P_{t+1}/P_t)$ is explained by rural GDP per capita (rGDPc) in the own spatial unit and those observed in neighboring units:

$$\ln \mathbf{Y}_{t+1} = \delta \mathbf{W} \ln \mathbf{Y}_t + \beta \ln(\mathbf{rGDPc}_t) + \theta \ln(\mathbf{W} * \mathbf{rGDPc}_t) + \mathbf{R}, \tag{D.1}$$

where **R** is a rest term containing the other explanatory variables, the fixed effects, and the error term. Logs of all variables are taken, similar to DA MATA *et al*. (2007). Because (D.1) is in vector form, **W*****rGDPc** offers another expression for market potential, provided that **W** is specified as an inverse distance matrix. Both variables take log forms, so the matrix of partial derivatives of the expected value of the dependent variable with respect to $rGDPc_{it}$ for $i = 1, \ldots, N$ in year t is given by

$$\left[\frac{\partial E(\ln \mathbf{Y})}{\partial \ln(rGDPc_1)} \quad \cdots \quad \frac{\partial E(\ln \mathbf{Y})}{\partial \ln(rGDPc_N)} \right]_t = (\mathbf{I} - \delta \mathbf{W})^{-1} [\beta \mathbf{I}_N + \theta \mathbf{S}], \tag{D.2}$$

where **S** is an $N \times N$ matrix whose elements are defined by $s_{ij} = w_{ij} GDP_j / (w_{i1} GDP_1 + \cdots + w_{iN} GDP_N)$. Because s_{ij} measures the rural GDP per capita of one MCA relative to all other MCAs, the rows of ***S*** always sum to unity, independent of the relative location of a particular MCA—that is, whether it is located on the periphery or in the core of Brazil. In other words, irrespective of how **W** is specified, the structure of the partial derivatives in (D.2) is exactly the same as in (20), provided that $\tau = \eta = 0$, because the rows of both **S** and **W** sum to unity. In contrast, by replacing ln(**W*****rGDPc**) with **W***ln(**rGDPc**) and decomposing the composite variables, such as market potential, into their underlying components (which leads to partial derivatives similar to those in (20)), more empirical flexibility is introduced, including the opportunity to test how **W** should be specified and thus to what extent MCAs likely interact. Furthermore, the magnitudes of the direct and spillover effect estimates can vary with different explanatory variables that determine the market potential.

Appendix E: Correlation Coefficients Among the Explanatory Variables

ln rural population	1.00												
ln density	-0.25	1.00											
mean age	-0.32	0.13	1.00										
birth rate	-0.29	-0.16	-0.05	1.00									
literacy rate	-0.30	0.14	0.60	-0.15	1.00								
Agriculture	0.23	-0.32	-0.31	0.21	-0.48	1.00							
manufacturing/service	-0.09	0.11	0.14	-0.07	0.20	-0.19	1.00						
workforce occupied	0.09	-0.04	-0.29	0.14	-0.20	0.48	-0.08	1.00					
ln GDP per capita	-0.26	0.19	0.40	-0.13	0.76	-0.42	0.19	-0.07	1.00				
ln rural GDP per capita	0.10	-0.44	0.02	0.19	0.05	0.46	-0.07	0.38	0.20	1.00			
homicide rate	-0.05	0.17	0.02	-0.13	0.14	-0.25	-0.03	-0.19	0.18	-0.19	1.00		
water company	-0.36	0.26	0.56	-0.18	0.65	-0.64	0.11	-0.40	0.55	-0.20	0.18	1.00	
sewer company	-0.30	0.26	0.51	-0.13	0.53	-0.45	0.11	-0.22	0.49	-0.10	0.07	0.64	1.00

Appendix F: Metropolitan and non-metropolitan heterogeneities

Following Table 5, Table F1 also reports direct and spillover effects of the variables on population growth for non-metropolitan (columns V and VI) and metropolitan (columns VII and VIII) municipalities, to explore possible structural difference between them and to account for potential non-linearities. In the empirical model, the differentiated effects by metropolitan and non-metropolitan conditions are obtained by interacting each variable with a dummy for the condition of belonging to a metropolitan area. The results appear to indicate important heterogeneities associated with belonging to a metropolitan region. Those that are statistically different from their counterparts in the homogenous model are marked grey.

Firstly, regarding the influence of variables associated with local productivity, note that while the direct and spillover effects for non-metropolitan municipalities are basically similar to the ones in the homogenous model, those obtained for metropolitan localities present important particularities. Specifically, no statistically significant direct or spillover effects are found arising from the human capital variable (literacy rate), a result explained by the higher and more homogenous levels of schooling in these localities. Similarly, the direct effects arising from the variables rural GDP per capita and the manufacturing/services ratio are not statistically significant for MCAs belonging to metropolitan areas. These two results are consistent with a minor importance of rural markets and a more productive services sector in these areas. Related to this, the spillover effect of rural population is also no longer significant, both in metropolitan and non-metropolitan MCAs. This indicates that the significant spillover effect previously obtained for the entire set of MCAs is solely explained by the difference between non-metropolitan and metropolitan MCAs. Another spillover effect no longer significant for metropolitan MCAs is the birth rate. By contrast, only for metropolitan MCAs a positive and significant spillover effect is found associated with the variable GDP per capita. Apparently, the belonging to a metropolitan area is important for a municipality to take advantage from markets in its surroundings. Note that this spillover effect is consistent with both the better road infrastructure and stronger returns to scale in the economic activities generally present in these MCAs.

The results for the influence of the amenity-related variables on population growth of Brazilian cities in the heterogeneous model are quite different from those in the homogeneous model. Differently from previous results, neither the direct nor the spillover effect of the homicide rate on population growth is significant, a result valid for both non-metropolitan and metropolitan MCAs. Just as for the rural population, this indicates that the weakly significant spillover effect previously obtained for the entire sample is solely explained by the difference between non-metropolitan and metropolitan MCAs. As for metropolitan MCAs, this study also obtains different direct effects for the variables associated with the public availability of water and sewer: different from the previous results, the availability of public water now presents a negative direct effect on population growth and the availability of public sewer a positive one. The latter result is in line with the better conditions present in metropolitan regions, where the supply of housing with this service tends to be more elastic to market conditions. On the other hand, the negative direct effect of availability of water appears to reflect the difficulty in water provision or the exhaustion in the availability of this resource in metropolitan areas. This situation tends to be associated with higher prices of housing in these MCAs, making them less attractive.

Finally note that the direct and spillover effects of population density, both for non-metropolitan and metropolitan MCAs, are negative and significant; this once more corroborates the hypothesis that densely populated cities deter prospective migrants with their more expensive living conditions not only to their own MCAs but also to their surroundings.

Overall, the conclusion must be that the results obtained for metropolitan municipalities in the heterogeneous model point to some important non-linearities that were left undisclosed in the homogenous model. Further research is need to investigate whether this also holds when considering more groupings, as well as whether this is related to any kind of urban hierarchy.

Table F1. Long-term Direct and Spillover Effects of Heterogeneous Dynamic Spatial Model

Explanatory Variables	Long-Term Effects Non-Metropolitan Areas in Heterogeneous Regression		Long-Term Effects Metropolitan Areas in Heterogeneous Regression	
	Direct (V)	Spillover (VI)	Direct (VII)	Spillover (VIII)
lagged population growth rate	-0.922	0.123	-0.922	0.123
	(-109.13)	(6.28)	(-109.13)	(6.28)
literacy rate	0.076	0.127	-0.015	0.024
	(2.68)	(1.65)	(-0.12)	(0.07)
ln of GDP per capita	0.050	-0.008	0.079	0.072
	(11.57)	(-0.60)	(6.52)	(1.65)
ln of rural GDP per capita	0.019	-0.011	0.001	0.002
	(6.48)	(-1.36)	(0.29)	(0.17)
ln rural population	-0.061	-0.011	-0.023	-0.015
	(-15.04)	(-0.80)	(-5.53)	(-1.06)
Agriculture	-0.217	0.070	-0.414	-0.323
	(-8.76)	(0.96)	(-3.78)	(-0.97)
manufacturing/services	0.003	0.004	0.002	-0.005
	(2.19)	(0.96)	(0.37)	(-0.42)
workforce occupied	0.340	0.085	0.361	0.100
	(8.56)	(0.75)	(3.29)	(0.42)
birth rate	0.017	0.026	0.094	0.160
	(9.29)	(4.30)	(2.17)	(1.18)
mean age	0.009	0.003	0.007	-0.000
	(6.29)	(0.81)	(1.66)	(-0.02)
ln density	-0.135	-0.138	-0.175	-0.100
	(-20.28)	(-6.46)	(-14.04)	(-2.96)
homicide rate	0.000	-0.000	-0.000	0.001
	(0.91)	(-0.90)	(-0.72)	(0.73)
water company	0.041	-0.006	-0.226	0.170
	(2.53)	(-0.14)	(-4.92)	(1.25)
sewer company	-0.043	-0.017	0.022	-0.114
	(-3.31)	(-0.52)	(0.64)	(-1.13)

Note: t-values in parentheses. Significance levels of numbers marked grey in the heterogeneous model are different from their counterparts in the homogenous model.

REFERENCES (additional in appendix)

BLACK D. and HENDERSON V. (1999) A theory of urban growth, *Journal of Political Economy* **107**, 252-283.

BLOOM D.E. and WILLIAMSON J.G (1998) Demographic transition and economic miracles in emerging Asia, *World Bank Economic Review* **12**, 419-455.

CHOUDHRY M.T. and ELHORST J.P. (2010) Demographic transition and economic growth in China, India and Pakistan, *Economic Systems* **34**, 218-236.

GOLDIN C. (1995) The U-shaped female labor force function in economic development and economic history, in SCHULTZ T.P. (Ed) *Investment in women's human capital*, pp. 61-90. Chicago University Press, Chicago.

KELLEY A.C. and SCHMIDT R.M. (2005) Evolution of recent economic-demographic modeling: a synthesis, *Journal of Population Economics* **18**, 275-300.

LUCAS R. (1988) On the mechanism of economic development, *Journal of Monetary Economics* **22**, 3-42.

MAMMEN K. and PAXSON C. (2000) Women's work and economic development, *Journal of Economic Perspectives* **14,** 141-164.

MENEZES T., SILVEIRA NETO R., MOTEIRO C. and RATTON J. L. (2013) Spatial correlation between homicide rates and inequality: evidence from urban neighborhoods, *Economic Letters* **120**, 97–99.

SHAPIRO J.M. (2006) Smart cities, quality of life, productivity, and the growth effects of human capital, *Review of Economic and Statistics* **88**, 324-335.

[1] A MCA is a municipality or aggregation of municipalities necessary to enable consistent spatial analyses over time; more details are provided when discussing the data.

[2] A more sophisticated approach that also includes the housing market is available in GLAESER (2008).

[3] DURANTON and PUGA (2013) cite cyclical behavior and sluggish adjustment as reasons to measure population growth over periods of five or ten years.

[4] This bias correction is needed because the dependent variables lagged in time and in both space and time on the right-hand side of (19) are correlated with the spatial fixed effects μ, which is the spatial counterpart of the Nickell bias, as shown by YU *et al*. (2008) and LEE and YU (2010) for a dynamic spatial panel data model without and with time-period fixed effects, respectively.

[5] Since the analysis is based on data observed over 10-year time intervals, the short-term effects do not differ greatly from the long-term effects. For this reason they are not reported, but available upon request.

[6] The numbers of MCAs that belonged to a metropolitan region in Brazil were 115 in 1980, 120 in 1991 and 285 in 2000. From an universe of 3,659 MCAs, these MCAs were big cities or municipalities influenced by big cities.