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Urban and rural population growth in a spatial panel of municipalities

Diego Firmino Costa da Silva[a], J. Paul Elhorst[b] and Raul da Mota Silveira Neto[c]

ABSTRACT

Urban and rural population growth in a spatial panel of municipalities. *Regional Studies*. Using Bayesian posterior model probabilities and data pertaining to 3659 Brazilian minimum comparable areas (MCAs) 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 neighbourhood 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.

KEYWORDS

population growth; regions; spatial interaction; dynamic spatial panel models; spillover effects

摘要

行政区空间面板中的城市与乡村人口成长。区域研究。运用贝式后验模型概率，以及巴西于 1970 年至 2010 年间，三千六百五十九个最小可比区域（MCAs）的数据，对于导致两种空间计量经济规范，并结合广泛的潜在邻里矩阵母体的人口成长动态的两种理论设定进行相互检定。最佳的效果结合，包括了生产显着的长期空间外溢效应的五项决定因素。如同诸多过往的人口成长研究一般忽略这些外溢，已被证实会低估它们的影响，以及根据这些决定因素的政策方法之效力。

关键词

人口成长; 区域; 空间互动; 动态空间面板模型; 外溢效应

RÉSUMÉ

La croissance démographique urbano-rurale d'un panel spatial de municipalités. *Regional Studies*. Employant des probabilités et des données postérieures bayesiennes concernant 3 659 zones comparables minimales au Brésil entre 1970 et 2010, on met à l'épreuve, l'un contre l'autre, deux contextes théoriques de la dynamique de la croissance démographique qui ont pour résultat deux spécifications économétriques spatiales combinées avec une large gamme de matrices de voisinage éventuelles. La meilleure combinaison compte cinq déterminants qui créent d'importantes retombées spatiales à long terme. On montre ici que ne pas faire attention à de telles retombées, ce que font beaucoup des études antérieures de la croissance démographique, sous-estime leur impact et, par la suite, l'efficacité des mesures politiques qui répondent à ces déterminants-là.

MOTS-CLÉS

croissance démographique; régions; interaction spatiale; modèles dynamiques spatiaux en panel; retombées

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ZUSAMMENFASSUNG

Städtisches und ländliches Bevölkerungswachstum in einem räumlichen Panel von Gemeinden. *Regional Studies*. Mithilfe von Bayesschen posterioren Modellwahrscheinlichkeiten und den Daten von 3659 brasilianischen vergleichbaren Mindestgebieten im Zeitraum von 1970 bis 2010 erfolgt eine vergleichende Überprüfung von zwei theoretischen Konstellationen der Bevölkerungswachstumsdynamik, die zu zwei räumlichen ökonometrischen Spezifikationen in Kombination mit einem breiten Spektrum von potenziellen Nachbarschaftsmatrizen führen. Die leistungsfähigste Kombination besteht aus fünf Determinanten, die signifikante langfristige räumliche Übertragungseffekte hervorbringen. Ein Ignorieren dieser Übertragungseffekte, wie es in zahlreichen früheren Bevölkerungswachstumsstudien erfolgte, führt nach unseren Ergebnissen zu einer Unterschätzung ihrer Auswirkung und somit der Wirksamkeit der politischen Maßnahmen zur Beeinflussung dieser Determinanten.

SCHLÜSSELWÖRTER

Bevölkerungswachstum; Regionen; Räumliche Wechselwirkungen; Dynamische räumliche Panelmodelle; Übertragungseffekte

RESUMEN

Crecimiento demográfico urbano y rural en un panel espacial de municipios. *Regional Studies*. Mediante las probabilidades de un modelo bayesiano posterior y datos de 3659 áreas mínimas comparables de Brasil durante el periodo entre 1970 y 2010, comparamos dos entornos teóricos de dinámicas de crecimiento demográfico que dan como resultado dos especificaciones econométricas espaciales en combinación con un amplio espectro de posibles matrices vecinas. La mejor combinación consta de cinco determinantes que producen a largo plazo efectos indirectos espaciales significativos. Demostramos que al ignorar estos efectos indirectos, tal como se ha hecho en muchos estudios previos de crecimiento demográfico, se subestiman sus repercusiones y, por tanto, la eficacia de las medidas políticas que actúan en estos determinantes.

PALABRAS CLAVES

crecimiento de población; regiones; interacción espacial; modelos dinámicos de paneles espaciales; efectos indirectos

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INTRODUCTION

Brazilian urbanization represents a highly significant, robust social phenomenon; the percentage of people living in urban centres in Brazil increased from 55.9% in 1970 to 84.4% in 2010 (Instituto Brasileiro de Geografia e Estatística (IBGE – Brazilian Bureau of Geography and Statistics), 2011). This process resulted largely from improved economic and social prospects in cities (Da Mata, Deichmann, Henderson, Lall, & Wang, 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 favourable supply and demand conditions, including market potential variables, better schooling, and limited opportunities in the agricultural sector, favoured the growth of Brazilian cities. However, these studies are limited in two aspects. First, by considering only a subset of Brazilian cities, they provide an incomplete 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 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 grow 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, they do not consider urban dynamics after the year 2000, a period of price stability, as well as income convergence, among the Brazilian states (Silveira Neto & Azzoni, 2012). Substantial increases in the production of commodities and agricultural goods during this period had positive impacts on the opportunities available in towns further distant from large urban centres.

Spatial dependence is known to be particularly severe for small spatial units, such as municipalities (Boarnet, Chalermpong, & Geho, 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 neighbouring 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 neighbouring 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 & Koch, 2007) may be more prevalent among small, neighbouring urban centres 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 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 of which any support for these effects is not simply an artefact 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, Scheinkman, and Shleifer (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 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 a 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 labour 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 labour 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 modelled explicitly. Suppose the total output of an economy is given by:

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

where P_{it} represents the population size in economy i at time t in their role of workers; K_{it} denotes traded capital; and $\bar{Z}_i$ 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 socioeconomic 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 labour related to social, technological and political sources in the own economy (i) a_{it}, as well as those in neighbouring economies ($j \neq i$) a_{jt}; and 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 $N \times N$ neighbourhood matrix $\mathbf{W}$ in which $0 \leq w_{ij} \leq 1$ and $w_{ij} = 0$ if $i = j$. Substituting equation (2) into equation (1) represents the total output of an economy, whose first-order conditions for capital and labour, that is, capital income (normalized price = 1) and the wage rate (denoted S_{it}), are equal to their marginal products, and yields the following labour demand equation, after the optimal solution for capital is substituted in the condition for labour:

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

As this labour demand equation shows, higher wages reflect higher productivity and less 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 people (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 neighbouring 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:

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

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 labour is mobile; higher wages in urban areas are 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 $\bar{V}_t$, application of the spatial equilibrium condition produces the following results when substituting the demand equation for housing derived in equation (8) into equation (7), such that it yields the indirect utility function in equation (9), equal to $\bar{V}_t$:

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

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:

$$h = (p_H / \delta c_0)^{1/\delta - 1}$$

which implies that total housing supply is given by:

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

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

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

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

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

where D_N and ψ are detailed in Appendix A in the supplemental data online. According to Glaeser and Gottlieb (2009), the spatial equilibrium condition means that in a dynamic model, only lifetime utility levels are 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, $\bar{V}_{t+1}/\bar{V}_t$, and equation (13) can be rewritten as:

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

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:

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

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

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

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

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) (LeSage & Pace, 2009). Since the right-hand side of this model also contains the dependent variable, lagged one period, it also could be labelled a dynamic SDEM model.

The utility function specified in equation (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 neighbouring economies. If residents of quickly growing cities suffer in terms of quality of life, they might move to neighbouring areas. Therefore, assuming individual utility correlates negatively with the level of population (population size) and the population growth rate of neighbours, the utility function may take the more complicated form:

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

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:

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

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 neighbours. Three productivity and two amenity-related variables that will be introduced below 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 in equations (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:

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

where $\mathbf{Y}_t$ denotes an $N\times 1$ vector that consists of one observation of the dependent variable for every economy ($i = 1, \ldots, N$) in the sample at time t ($t = 1, \ldots, T$), 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 of 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 equation (19) denotes its time-lagged value, whereas a vector or matrix pre-multiplied by $\mathbf{W}$ denotes the spatially lagged value. The $N \times N$ matrix $\mathbf{W}$ 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 $\boldsymbol{\varepsilon}_t = (\varepsilon_{1t}, \dots, \varepsilon_{Nt})^{\mathrm{T}}$ that consists of i.i.d. disturbance terms, which have zero mean and finite variance σ^2; the $N \times 1$ vector $\boldsymbol{\mu} = (\mu_1, \dots, \mu_N)^{\mathrm{T}}$ 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 ($t = 1, \dots, T$), 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. Relationship between econometric and theoretical model equations

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

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 neighbourhood matrix could not be defined, and the impact of spatial interaction effects could not be estimated consistently. Only when neighbouring units are part of the sample is it possible to measure the impact of neighbouring 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 & Pace, 2009). Elhorst (2012) shows that the matrix of (true) partial derivatives of the expected value of the dependent variable with respect to the kth independent variable for $i = 1, \dots, N$ in year t for the long-term is given by the $N \times N$ matrix:

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

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 kth 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, Le Gallo, and Jayet (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 equation (7), while the spatial multiplier matrix:

$$[(1-\tau)\mathbf{I} - (\delta+\eta)\mathbf{W}]^{-1}$$

in equation (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 equation (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 equation (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 a local spillover model and the utility functions specified in equations (7) or (17), as well as to choose between different potential specifications of the neighbourhood 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 neighbourhood matrix, as well as the Bayesian posterior model probabilities of different neighbourhood 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 (LR), Wald and/or Lagrange multiplier (LM) 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 $\omega_{\max}$ and $\omega_{\min}$ represent respectively the largest and the smallest (negative) eigenvalue of the neighbourhood 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 5–6). 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 1970, 1980, 1991, 2000 and 2010, as conducted by the Instituto Brasileiro de Geografia e Estatística (IBGE; Brazilian Bureau of Geography and Statistics), complemented by data collected by the Instituto de Pesquisa Econômica Aplicada (IPEA – Brazilian Institute for Applied Economic Research).

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 3952 to 5565. 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, Pimentel, & Alvarenga, 2010), a spatial panel is obtained of 3659 MCAs during 1970–2010 (see also Da Mata et al., 2007). For a geographical delineation of these MCAs, see Appendix B in the supplemental data online.

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 3659, t spans from 1980 to 2010, in correspondence with equation (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 SDM is used, it also depends on the population growth rate in neighbouring 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.

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

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 years) that is literate	Census/IBGE
ln GDP per capita	Natural log of gross domestic product (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 years)	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/population)	Census/IBGE
Mean age	Mean age	Census/IBGE
Amenity-related variables (θ) (see equations (6) and (15b))		
ln density	Natural log of people per square kilometre	IPEADATA
Homicide rate	(Number of homicides)*(100 000/population)	IPEADATA
Water company	Share of households supplied by the water company	Census/IBGE
Sewer company	Share of households supplied by the sewer company	Census/IBGE

Note: IBGE, Instituto Brasileiro de Geografia e Estatística (Brazilian Bureau of Geography and Statistics); IPEA, Instituto de Pesquisa Econômica Aplicada (Brazilian Institute for Applied Economic Research).

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 in the supplemental data online.

EMPIRICAL ANALYSIS

The estimation results of the parameters of equation (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.

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 (d.f.), $p < 0.01$) reject this hypothesis. Similarly, the hypothesis that the time-period fixed effects are jointly insignificant can be rejected (789.06, 3 d.f., $p < 0.01$). These results justify the extension of the model with spatial and time period fixed effects. Appendix E in the supplemental data online 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 (spatial auto-regressive (SAR) specification) or for the error terms (spatial error model (SEM) specification), LM tests are used, applied to a first-order, binary, contiguity neighbourhood matrix that is row-normalized to ensure row sums equal to 1. These LM tests follow a chi-squared distribution with 1 d.f. 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

Table 3. Population growth: non-spatial and dynamic spatial models

	OLS plus time- and spatial-specific fixed effects		Dynamic SDM plus fixed effects (bias correction)			
Explanatory variables	**Coefficient**	***t***	**Coefficient**	***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						
Number of observations	10977		10977			
R^2	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	**				

Notes: OLS, ordinary least squares; SDM, spatial Durbin model.
**Significant at 1%; *significant at 5%.

suggest extending the non-spatial model with a spatially lagged dependent variable. However, if the robust LM tests reject a non-spatial model in favour of the spatial lag model or SEM, one of these models must be carefully endorsed. LeSage and Pace (2009) and Elhorst (2014b) also recommend considering the SDM and testing whether it can be simplified to the spatial lag or SEM. 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 neighbourhood matrix, to find the specification of **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 neighbours 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 neighbourhood 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 (see Appendix D in the supplemental data online). If the neighbourhood matrix is specified as a first-order binary contiguity matrix or as a five-nearest neighbours matrix, the Bayesian posterior model probabilities point to the SDM specification. The average number of neighbours in the sample amounts to 4.98, so these two neighbourhood matrices are not substantially different. Conversely, if higher-order binary contiguity matrices or nearest-neighbours matrices with more neighbours are adopted, the Bayesian posterior model probabilities provide further evidence in favour of the SDEM specification. However, by also considering the log-marginal values of the different specifications of the neighbourhood 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 SEM. 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:

$$H_0\text{: } \boldsymbol{\theta} = 0 \text{ and } \eta = 0$$
$$H_0\text{: } \boldsymbol{\theta} + \delta\boldsymbol{\beta} = 0 \text{ and } \eta + \delta\tau = 0$$

That is, it is tested whether the dynamic spatial Durbin might be simplified to a dynamic spatial lag model or dynamic SEM. Both tests follow a chi-squared distribution with $K+1$ d.f. (the 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 equation (17), which posits that the utility of individuals correlates negatively with the level of population (population size) and the population growth rate of their neighbours, and to the global spillover model, which posits that $\delta \neq 0$.

DETERMINANTS OF BRAZILIAN POPULATION DYNAMICS

The results reported in the second column of Table 3 show that six of the 13 spatially lagged explanatory variables in the dynamic SDM specification appear statistically significant at the 5% level. The coefficients of the spatially lagged

Table 4. Comparison of model specifications and neighbourhood 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 neighbours	Log marginal	3539.69	3601.04	3521.72	3597.88
	Model probabilities	0.0000	0.9594	0.0000	0.0406
6 nearest neighbours	Log marginal	3551.02	3613.06	3539.41	3613.60
	Model probabilities	0.0000	0.3676	0.0000	0.6324
7 nearest neighbours	Log marginal	3548.94	3606.39	3537.52	3606.54
	Model probabilities	0.0000	0.4622	0.0000	0.5378
8 nearest neighbours	Log marginal	3551.30	3607.94	3541.97	3610.07
	Model probabilities	0.0000	0.1054	0.0000	0.8946
9 nearest neighbours	Log marginal	3561.30	3610.94	3553.84	3613.93
	Model probabilities	0.0000	0.0474	0.0000	0.9526
10 nearest neighbours	Log marginal	3560.11	3607.68	3556.60	3609.52
	Model probabilities	0.0000	0.1373	0.0000	0.8627
20 nearest neighbours	Log marginal	3526.87	3552.07	3534.30	3552.99
	Model probabilities	0.0000	0.2853	0.0000	0.7147

Source: Authors' own calculations, based on LeSage (2014).

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 equation (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).

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 neighbouring MCAs has been greater in the previous decade. This movement or deconcentration of people to neighbouring areas, perhaps to escape the bustle of the city, represents a convergence effect. However, as a feedback effect of this behaviour, 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 1 percentage point, the population growth rate in the area increases by 0.083 percentage points, and in neighbouring 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 neighbouring units, aligns with the theoretical proposition introduced in equation (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 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 gross domestic product (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 a stronger presence of manufacturing activities. Rural GDP per capita also has a positive and significant direct effect on population growth, such

Table 5. Long-term direct and spillover effects of homogenous dynamic spatial model

	Long-term effects			Underestimation of the long-term effect in the non-spatial model (%)
Explanatory variable	**Direct (I)**	**Spillover (II)**	**Total (III)**	**(IV)**
Lagged population growth rate	−0.918 (−113.15)	0.137 (7.03)	−0.781 (40.17)	–
Literacy rate	0.083 (2.38)	0.143 (1.73)	0.226 (2.48)	41.4
ln of GDP per capita	0.057 (12.65)	−0.001 (−0.11)	0.055 (3.96)	9.2
ln of rural GDP per capita	0.014 (5.61)	−0.008 (−1.14)	0.006 (0.89)	−42.8
ln rural population	−0.043 (−13.99)	−0.021 (−1.97)	−0.064 (−5.55)	34.1
Agriculture	−0.247 (−8.09)	0.004 (0.06)	−0.242 (−2.97)	−5.1
Manufacturing/services	0.003 (2.24)	0.004 (1.06)	0.007 (1.63)	37.4
Workforce occupied	0.394 (10.35)	0.167 (1.51)	0.561 (4.47)	14.8
Birth rate	0.018 (9.52)	0.027 (3.37)	0.044 (5.48)	61.9
Mean age	0.010 (7.14)	0.004 (1.16)	0.013 (4.53)	−1.1
ln density	−0.145 (−22.47)	−0.141 (−6.72)	−0.286 (−12.91)	57.5
Homicide rate	0.000 (0.36)	−0.007 (−1.80)	−0.007 (−1.57)	58.3
Water company	0.028 (1.93)	−0.028 (−0.72)	0.001 (0.02)	0.0
Sewer company	−0.040 (−2.71)	−0.043 (−1.40)	−0.082 (−2.56)	85.4

Note: t-values are given in parentheses.

that municipalities that offer income opportunities remain attractive. However, neither of these three variables has positive spillover effects on its 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 1 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 one child for every 1000 inhabitants in a given area, the population growth rate in that area itself increases by 0.018 percentage points in the long-term, and by 0.027 percentage points in its surroundings. This latter figure represents the cumulative effect over all neighbours; considering the finding that the average number of neighbours is 4.98, the average spillover effect per neighbour 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 neighbouring 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 in population growth of Brazilian municipalities.

As for the variables associated with 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 to a kind of convergence in population size across cities. Interestingly, this adverse effect also spills over to neighbouring 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 1 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 equation (7) that disamenities in one economy harm individuals and deter prospective migrants in neighbouring economies.

The proportion of people with access to public water has a positive 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 sewerage 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 the Fundação Getúlio Vargas (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 $\hat{a}/(1-\hat{o})$, where $\hat{a}$ is the coefficient estimate of a particular explanatory variable; and $\hat{o}$ 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 modelling 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, and a higher urban or rural GDP per capita are traditional factors having a positive effect on population growth in Brazilian cities, since they improve labour 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 neighbouring 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 also due to spillover effects 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 centres) 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 equation (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 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 in the supplemental data online.

CONCLUSIONS

This article proposes an economic–theoretical model for city population growth, derives an explicit econometric spatial model from it, and estimates 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 with productivity and amenities of their neighbours. 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 with local productivity, the results obtained indicate that the population growth of the Brazilian MCAs is positively affected by the level of human capital (literacy rate), the level of GDP per capita, and the manufacturing/services employment shares ratio. Furthermore, in the case of human capital, there are spillovers arising from neighbouring 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 neighbouring 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, five produce significant spillover effects in the long-term: rural population size, population density, birth rate, literacy rate and 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 neighbours 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, which 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 favouring 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 childcare facilities, reduce crime and coordinate housing construction with neighbouring 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 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 neighbouring municipalities. 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.

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DISCLOSURE STATEMENT

No potential conflict of interest was reported by the authors.

SUPPLEMENTAL DATA

Supplemental data for this article can be accessed at http://10.1080/00343404.2016.1144922

NOTES

1. An 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 behaviour 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 equation (19) are correlated with the spatial fixed effects μ, which is the spatial counterpart of the Nickell bias, as shown by Yu, de Jong, and Lee (2008) and Lee and Yu (2010) for a dynamic spatial panel data model with and without 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 instead are available from the authors 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 a universe of 3659 MCAs, these MCAs were big cities or municipalities influenced by big cities.

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