ANPEC 2012 - Área 9 - Economia Regional e Urbana

Evaluating Multiple Spatial Dimensions of Economic Growth in Brazil using Spatial Panel Data Models, 1970-2000

Guilherme Mendes Resende*
Alexandre Xavier Ywata de Carvalho*
Patrícia Alessandra Morita Sakowski*
*Institute for Applied Economic Research (IPEA)/Government of Brazil

Abstract

The goal of this paper is to evaluate the results of regional economic growth estimates at multiple spatial scales using spatial panel data models. The spatial scales examined are minimum comparable areas, micro-regions, meso-regions and states over the period between 1970 and 2000. Alternative spatial panel data models with fixed effects were systematically estimated across those spatial scales to demonstrate that the estimated coefficients change with the scale level. The results show that the conclusions obtained from growth regressions are dependent on the choice of spatial scale. First, club convergence hypothesis cannot be rejected suggesting there are differences in the convergence processes between the north and south in Brazil. Moreover, the positive average-years-of-schooling coefficient gets larger as more aggregate spatial scales are used. Transportation costs effect is positive and statistically significant to economic growth only at the state level. Population density coefficients show that higher populated areas are harmful to economic growth demonstrating somehow that congestion effects are operating at the MCA, micro-regional and meso-regional spatial scales, but their magnitudes vary across the geographic scales. Finally, the values of spatial spillovers coefficients also vary according to the spatial scale under analysis. In general, such coefficients are statistically significant at the MCA, micro-regional and meso-regional levels; but, at state level those coefficients are no longer statistically significant suggesting that spatial spillovers are bounded in space.

Keywords: Spatial externalities; Economic growth; Spatial scales; Spatial panel; Brazil.

Resumo

O objetivo deste estudo consiste em avaliar os resultados de estimações de crescimento econômico regional em múltiplas escalas espaciais utilizando modelos de painel espacial. As escalas espaciais examinadas são áreas mínimas comparáveis, micro-regiões, meso-regiões e estados no período entre 1970 e 2000. Modelos alternativos de painel espacial com efeitos fixos foram estimados sistematicamente nessas escalas espaciais para demonstrar que os coeficientes estimados variam de acordo com a escala utilizada. Os resultados mostram que as conclusões obtidas a partir de regressões de crescimento dependem da escolha da escala espacial. Primeiramente, a hipótese de convergência de clube não pode ser rejeitada, sugerindo haver diferenças nos processos de convergência entre o Norte e Sul do Brasil. Além disso, o coeficiente positivo da média de anos de escolaridade aumenta quanto mais agregada a escala espacial utilizada. O efeito de custos de transporte é positivo e estatisticamente significante para o crescimento econômico apenas no nível do estado. Os coeficientes da densidade populacional mostram que áreas mais densamente povoadas são prejudiciais para o crescimento econômico, sugerindo efeitos de congestionamento no nível de AMC, micro-regiões e meso-regiões, mas a magnitude desses coeficientes varia de acordo com a escala geográfica. Finalmente os coeficientes de transbordamento espacial também variam conforme a escala espacial sob análise. Em geral, esses coeficientes são estatisticamente significativos nos níveis de AMC, micro-região e meso-região; mas, no nível estadual, deixam de ser estatisticamente significativos, sugerindo que transbordamentos espaciais são limitados no espaço.

Palavras-chave: Externalidades espaciais; Crescimento Econômico; Escalas Espaciais; Painel espacial; Brasil.

JEL Classification: C23, O18, R11.

1. Motivation

During the last two decades, an increasing dissemination of spatial econometrics techniques has been observed among regional scientists, economists and researchers in several fields (Anselin, 1988; LeSage, 1999; Conley, 1999). The vast research of applied spatial econometrics on the interdependencies among spatial units and their effects on, among others, regional economic growth, trade flows, knowledge spillovers, migration, housing prices, tax interactions, city's growth controls (e.g., López-Bazo et al., 2004; Gamboa, 2010; Fischer et al., 2009; LeSage and Pace, 2008, Jeanty et al., 2010; Gérard et al., 2010; Brueckner, 1998) is well known. However, this literature still lacks a better understanding of the potential reasons why models estimated at different geographic scales yield different results in the context of regional economic growth empirics.

Of note, Resende (2011a) investigates the determinants of Brazilian regional economic growth at a variety of geographic scales using a cross-sectional data set over the 1990s period. Moreover, Resende (2011b) advances the growth literature by using panel data models across several spatial scales; but the process of economic growth in Brazil is only examined using non-spatial panel data models. This investigation refers back to the Modifiable Areal Unit Problem (MAUP)[1], but it sheds new light on a core problem in the literature related to regional economic growth. The choice of the spatial scale of analysis is a problematic issue in applied research (Behrens and Thisse, 2007). In this sense, the paper seeks to investigate to what extent ambiguities about spatial scale undermine, or inform, our understanding of regional growth determinants and convergence[2].

Except from Resende (2011a) and Resende (2011b)[3] the studies thus far have only investigated the determinants of economic growth at a single spatial scale to infer the consistency of spatial growth models with reality (e.g., Rey and Montouri, 1999; Fingleton, 1999; López-Bazo et al., 2004; Ertur and Koch, 2007; Elhorst et al., 2010, Fischer, 2011). For instance, Elhorst et al. (2010) employ spatial econometric techniques to focus on time-space models; but they only examine the process of economic growth at one single spatial scale. Thus, the goal of this paper is to evaluate the results of regional economic growth estimates at multiple spatial scales using alternative spatio-temporal models recently proposed in the spatial econometrics literature.

The spatial scales examined are minimum comparable areas (referred to as municipalities), micro-regions, meso-regions and states, which are often employed in the empirical literature about Brazil and cover the period between 1970 and 2000. To our knowledge, this is the first study of regional economic growth exploring both time and different spatial scale dimensions in the context of spatial panel data models. Previous studies only investigate both time and space at a single spatial scale. The idea of this paper is to systematically repeat a spatial panel data model originally developed to examine this phenomenon at a single geographic scale across multiple scales. Initially, this approach lead us to the investigation of the measurement issue that might cause variability in regional economic growth estimates due to the use of different spatial scales, likely due to the MAUP. However, it is important to bear in mind that it might be the case that structural (theory based) issues may be underlying economic growth at different scales and, thus, we provide some theoretical arguments for such variability in empirical results found across different geographic scales[4].

The paper is organized as follows. Section 2 provides a discussion on the potential theoretical reasons for different results found across economic growth models estimated at different spatial scales. Section 3 describes the spatial panel data models employed in the empirical analysis. In section 4, the data set and

[1] MAUP is associated to the uncertainties on the choice of alternative number of zones (or zoning systems) and the implications that this holds for spatial analysis (Openshaw and Taylor, 1981).

[2] It is worth noting that there has been a growing empirical literature on the analysis of MAUP in several areas of urban and regional economics such as Yamamoto (2008), Briant et al. (2010), Fingleton (2011) and Menon (2012).

[3] Of note, Ávila and Monastério (2008) analyse MAUP on per capita income convergence process in the Rio Grande do Sul state in Brazil using two geographic scales (municipalities and "Conselhos Regionais de Desenvolvimento"/COREDEs).

[4] In Resende (2011a), there is an initial discussion on this issue. Herein, we provide more theoretical arguments for such differences across scales (see Section 2).

the spatial scales are shown. Section 5 presents the results and the respective discussion follows in Section 6. Section 7 concludes the paper.

2. **The Spatial Scope of Economic Growth Determinants: Potential Theoretical Reasons for Different Results across Models Estimated at Different Spatial Scales**

In the mainstream of economics, economic growth theories provide several factors that may have been responsible for driving regional performance. The debate on long run economic growth determinants came with Solow's (1956) growth model and has been augmented by many others by the inclusion of education capital (Mankiw et al., 1992), migration (Barro & Sala-i-Martin, 2003), and growth externalities (López-Bazo et al., 2004; Ertur & Koch, 2007) to cite some. Moreover, the so-called endogenous growth models, pioneered by Romer (1986) and Lucas (1988), seek to explain why differences in per capita income arise and persist over time. Herein, we provide some theoretical reasons to explain how the explanatory variables used in the econometric specifications discussed in the next section may impact economic growth at different spatial scales.

- Physical capital (and the convergence hypotheses). Information on physical capital is often unavailable at subnational levels, and thus this variable is excluded from the set of explanatory variables of regional growth regressions. The lack of availability of physical capital measures at finer regional level is not restricted to Brazil, as noted in Lesage and Fisher (2008) in a study for Europe. This fact is problematic because it causes the omitted variable problem which may bias the regressions estimates. Some panel data approaches partially deal with this problem by including fixed effects which might control for this kind of omitted variable (Islam, 1995). Despite such omission, the neoclassical growth framework (see Solow, 1956) provides a simple rationale for the convergence hypothesis. The convergence property comes from the law of decreasing returns to capital accumulation [i.e., capital tends to accumulate slower (faster) in regions where it is relatively abundant (scarce)]. We introduce the initial level of income to control for decreasing returns to capital accumulation (Ottaviano and Pinelli, 2006). It is important to explain why it is expected to verify differences in the magnitudes of the convergence coefficient at different spatial scales. In the regressions estimates, the sizes of the initial income per capita coefficients are expected to be larger at finer spatial scales because, for instance, municipalities resemble the notion of an open economy with perfect capital mobility. Barro et al.'s (1995) neoclassical model of open economy with perfect capital mobility predicts (the possibility) that economies will jump instantaneously to a steady state of income per capita; this can be understood by a higher rate of convergence. The assumption of a more open economy is not difficult to justify in the municipal level context in Brazil, considering that the intensity of flows of capital, trade and people across municipal borders is higher than across state borders. States can thus be viewed as more closed economies than municipalities.

- Human capital. Glaeser et al. (2003) show that the presence of positive spillovers or strategic complementarities creates a "social multiplier" where aggregate coefficients of human capital (proxied, for instance, by years of schooling) will be greater than individual coefficients. In the context of this current study, we can think of municipalities as being the micro (individual) level of analysis. For this reason, it is possible to argue that at the aggregate level (e.g., at micro-regional or state level), the coefficient of human capital may be inflated by externalities. Glaeser et al. (2003) point out that the coefficients may rise with the level of aggregation due to the existence of a social multiplier, which also supports the idea that there are human capital spillovers, as suggested by a wide body of literature (e.g. Lucas 1988 and Rauch 1993).

- Population density. New economic geography models (Baldwin and Forslid, 2000) show the positive impact of agglomeration externalities on economic growth rates. Population density is expected to be the proxy for agglomeration effects within a region. The magnitude of these agglomeration effects may depend on the spatial scale of analysis, because, for instance, population density probably appears to be higher at a finer scale (e.g., municipalities) than population density at a spatial scale within larger regions (such as a state). Thus, centripetal effect of agglomerations might be operating at finer scales or, in other words, agglomeration-related centripetal forces may be much more relevant at the local than at the state level.

- Transportation costs. Theoretical models (Ottaviano and Puga, 1998; Lafourcade and Thisse, 2008) have shown that with decreasing transportation costs, regional inequalities will increase and then decrease. Other models integrate an endogenous growth model with the core-periphery model showing that a decrease in transportation costs may have non-linear effects on growth (Baldwin et al., 2003). For the Brazilian case, Da Mata et al. (2007a) have found that transportation costs are inversely related to the rate of economic growth. The impact of transportation infrastructure on economic growth may vary as the geographic scale of analysis changes. For instance, if this impact is analysed at the state level, the focus will be on the connectivity between these aggregate regions. On the other hand, at the municipal level, such an analysis might examine the impact of transportation cost reductions within the borders of states.

- Population growth. Barro and Sala-i-Martin (2003) point out that population growth represents the behavior of fertility, mortality and migration. The impacts of population growth on economic growth may display different results across different geographic scales, because migration pattern – which is one component of population growth – may vary across different scale levels (e.g., intra- versus inter-regional migration). For instance, the contrast in area sizes means that daytime commuting across municipalities can be more significant if compared to states. Moreover, if we are able to analyze only the migration effects, we need to bear in mind that, unlike newly born persons, migrants come with accumulated human capital; and for this reason, the results depends on whether immigrants have more or less human capital (i.e., if they are typically skilled or unskilled) than the residents of the receiving region (Barro and Sala-i-Martin, 2003).

- Spatial externalities. The spatial growth model specifications discussed in the next section seek to capture the effects of spatial externalities. It is important to note that the extent and strength of these externalities may depend on the level of aggregation of the spatial units. For instance, spatial autocorrelation might be higher at the municipal level than at the state level, because, for instance, states are more self-contained than municipalities or, in other words, states are much more closed economic entities than municipalities. As noted by Oates (1999) it is possible to increase the size of the jurisdiction to deal with such spillovers, thereby internalizing the benefits and costs. Corrado and Fingleton (2012) note that hierarchical models (also known as multilevel models) can be used in regional science and spatial economics to study a hierarchy of effects from cities, regions containing cities, and countries containing regions; thus, not recognizing these effects emanating from different hierarchical levels can lead to incorrect inference. Herein, the adopted approach is to systematically replicate the regression specification chosen to examine the extent of spatial externalities at a single scale across multiple spatial scales. Lall and Shalizi (2003) enumerate some theoretical reasons why location effects and spatial externalities matter in examining determinants of growth that include: (i) agglomeration economies[5]; (ii) Marshallian externalities of knowledge diffusion and labor market pooling[6]; (iii) common informal norms and institutions[7]; (iv) policy adoption[8]. Although much of these

---

[5] "*Drawing on the central argument of the 'new economic geography' literature, growth in any region is influenced by its ability to access large markets (Krugman, 1995; Venables, 1998). These economies are not a function of the size of a specific industry but of the overall size of the agglomeration. Thus, competitive enterprises accessing larger markets can enhance productivity. In addition to market size, agglomeration benefits potentially include access to specialized services (banking and finance), interindustry linkages, physical and economic infrastructure, and a larger medium for information exchange. Limiting the scope of the analysis to administrative units without considering the economic agglomeration (to which the region may belong) and the effects of market access are likely to limit the scope of the analysis*" (Lall and Shalizi, 2003: 664).

[6] "*For technological externalities, innovations in one region are adopted in neighboring regions through diffusion, thereby creating convergence in production processes and linkages in development outcomes. In Marshall's (1920) terminology, diffusion is spatially localized and does not extend to all locations. The second source of Marshallian agglomeration is labor market pooling, where production units in one region can gain access to a shared pool of labor in the larger regional economy*" (Lall and Shalizi, 2003: 664).

theoretical arguments on spatial externalities are about their positive effects, it is possible to point out some reasons why negative spatial externalities effects can be observed. For instance, with regard to the policy adoption argument discussed above, there could also "*be negative policy imitation where governments may not necessarily maximize growth but maximize rent-seeking and this behavior may be imitated by governments in neighboring regions*" (Lall and Shalizi, 2003: 665). Moreover, Lall and Shalizi (2003: 679) suggest that improvements in the structural variables (e.g., economic structure, workforce quality, and infrastructure quality) are likely to increase growth performance in the region; however, "*if growth in a particular region is higher than that of its neighbors, the region is likely to attract mobile capital and skilled labor from neighboring regions, thereby having a detrimental effect on growth performance in neighboring regions*". The spatial models discussed next are a way to model these spatial externalities via spatial lags of the dependent and/or explanatory variables and/or spatial disturbances specifications.

3. Spatial Panel Data Models

To study the impact of the explanatory variables upon economic growth at a variety of geographic scales, we employed spatial panel data models. These models try to account for spatial correlations, allowing at the same time for the existence of idiosyncratic effects (fixed or random) for the regional observational units. Indeed, the presence of spatially autocorrelated residuals in the non-spatial growth regressions motivates the estimation of the spatially augmented Solow models – as presented in Rey and Montouri (1999), López-Bazo et al. (2004) and Ertur and Koch (2007), for instance – to deal with such spatial autocorrelation.

However, it is worth noting that there are alternative explanations for the existence of spatial autocorrelation in the residuals of the growth equations. Nuisance spatial dependence (spatial error) is one potential justification. As explained by Magrini (2004: 2763), it "may result from measurement problems such as a mismatch between the spatial pattern of the process under study and the boundaries of the observational units." It is also likely that regions that are geographically close together may experience random shocks that affect both simultaneously. Another explanation is related to unobserved determinants that are correlated across regions (Finglenton and López-Bazo, 2006). Possible unobserved determinants of economic growth not considered in these models include cultural, institutional and technological factors, which might be correlated across spatial units.

Moreover, Fingleton and López-Bazo (2006) note that substantive dependence (spatial lag and/or spatial cross-regressive) assumes that across-region externalities are due to knowledge diffusion and pecuniary externalities. López-Bazo et al. (2004) discuss in some detail the substantive arguments for spatial dependence across regions. These authors built a spatially augmented growth model based on Mankiw et al. (1992) demonstrating that economic growth and initial productivity in the other regions boost growth in a given region, which is explained by regional spillovers of the diffusion of technology from other regions, caused by investments in physical and human capital. However, López-Bazo et al. (2004) recognize that it is also plausible that these externalities across economies might be caused by pecuniary externalities other than knowledge spillovers – such as those created by a specialized market for labor or output, or forward and backward linkages drawn from trade in intermediate goods – which are related with increasing returns at the firm level, as noted by contributors from the so-called new economic geography (Fujita et al., 1999).

Accounting for these spatial autocorrelations in growth regressions is essential to have reliable inferences. Of note, Baltagi and Pirotte (2010) examine the standard panel data estimators under spatial dependence using Monte Carlo experiments and show that when the spatial coefficients are large, hypothesis test(s)

---

[7] "*Neighboring regions are quite likely to share common informal norms and institutional structures making them react similarly to exogenous shocks (North, 1990)*" (Lall and Shalizi, 2003: 665).

[8] "*Growth rates could be correlated across space due to 'copy cat policy adoption' (Easterly and Levine, 1998). They suggest that policies leading to high growth may provide a model of the efficacy of public intervention to governments in neighboring regions*" (Lall and Shalizi, 2003: 665).

based on standard panel data estimators that ignore spatial dependence can lead to misleading inference. Moreover, Arbia and Petrarca (2011) present a general framework to investigate the effects of MAUP on spatial econometric models showing how the presence of spatial effects affects the classical results. Arbia and Petrarca (2011) concentrate on the loss in efficiency of the parameters' estimators due to aggregation.

Recently, new developments on spatial panel data models have emerged in the spatial econometrics literature, proposing alternative spatio-temporal models to investigate convergence and growth of regions (Elhorst et al., 2010), regional markets (Keller and Shiue, 2007), and labor economics (Foote, 2007), among other fields. Anselin et al. (2008) provide a list of alternative spatial panel data models. In the same way, Elhorst (2012: 5) examines a collection of spatial dynamic panel data (SDPD) models that include one or more of the following variables and/or error terms: "*a dependent variable lagged in time, a dependent variable lagged in space, a dependent variable lagged in both space and time, independent variables lagged in time, independent variables lagged in space, serial error autocorrelation, spatial error autocorrelation, spatial-specific and time-period-specific effects*".

Lee and Yu (2010) examine some recent developments in spatial panel data models for both static and dynamic cases which consider the fixed effects, spatial lags and spatial disturbances specifications [for other surveys, see also Elhorst (2010a, 2012)]. Specifically, these spatial dynamic panel data models can be applied to investigate economic growth and convergence processes of regions which employ income per capita growth rates versus lagged levels of the explanatory variables. To study the robustness of the results, we considered several model specifications for the spatial dependence structure. Both fixed and random effect models were estimated, considering spatial lags for the dependent and explanatory variables, and considering different error spatial dependences.

The general model specification is given by

$$y = \lambda(I_T \otimes W)y + X\beta + u, \qquad (1)$$

where y is the vector with the dependent variable, X is the matrix with explanatory variables (which includes the log of the initial period level of the dependent variable), β is the vector of unknown coefficients, and W is the weight matrix built according to the neighborhood relations among observational units. Coefficient λ corresponds to the autoregressive parameter, and it gives a measure of the spatial dependence between the response variable in different geographic units. We assume that λ is smaller than one in absolute value.

As normally used in spatial econometric models, the W matrix used in this paper is standardized, such that all rows sum to one (see Anselin, 1988). The term I_T corresponds to the identity matrix, with dimension T (the number of time periods), and symbol $\otimes$ corresponds to the Kronecker product. The matrix representation above assumes the data are sorted such that the first block of observations corresponds to the first time period, the second block corresponds to the second time period, and so on.

The error term u can have several representations, varying according to the presence of idiosyncratic variability among regional units, and varying according to the spatial dependence structure. The discussion here considers only models with fixed or random effects, for models with none of these effects can be easily derived from the ones presented below. Besides, the several specification tests performed on our empirical data rejected the hypothesis of no idiosyncratic terms.

Assuming that there are idiosyncratic effects, represented by the terms in the N dimensional vector μ (where N is the number of observational units), the first specification considered for the term u is given by:

$$u = (i_T \otimes I_N)\mu + \epsilon, \qquad (2)$$

where i_T is a $T \times 1$ vector of ones, I_N is an identity matrix with dimension N, and ϵ is a vector with dimension $TN \times 1$, with the error terms. Spatial dependence can also be assumed for ϵ according to

$$\epsilon = \rho(I_T \otimes W)\epsilon + \nu, \qquad (3)$$

where ρ is an autoregressive coefficient for the error terms (we assume that ρ is smaller than one in absolute value) and ν is a random vector, with all terms independent and normally distributed with zero mean and variance σ_ν^2. We will refer to the representation in (2) as Baltagi's representation (see Baltagi, 2008, and Baltagi et al., 2003).

Another way to include spatial dependence along with idiosyncratic terms in the term u in equation (1) is by specifying the spatial lags directly for the term u, according to

$$u = \rho(I_T \otimes W)u + \epsilon, \qquad (4)$$

with $\epsilon = (i_T \otimes I_N)\mu + \nu$. This representation was considered in Kapoor et al. (2007). Because of the structure in (4), spatial correlation applies to both the individual effects in μ and the remainder error terms in ϵ. We will refer to this second model as Kapoor's representation. Estimation of models including both the spatial lag term $(I_T \otimes W)y$ and spatial dependence for the error components with Kapoor's representation is possible only when using random effects estimation. For fixed effects, one can only use Baltagi's representation.

Finally, it is important to note that Gibbons and Overman (2012) criticize these spatial models by arguing that distinguishing which of these spatial models generates the data that the researcher has at hand is very difficult in applied research. For instance, it is hard to discriminate the model implied in Equation (1) from the model represented in Equation (5):

$$y = X\beta + \delta_x(I_T \otimes W)X + u \qquad (5)$$

Equation (5) describes the spatial model known as spatially lagged X regression model (SLX, or spatial cross-regressive model) that assumes interactions between exogenous characteristics of nearby observations (WX) directly affect Y. Gibbons and Overman (2012) point out that researchers interested in spatial spillovers should incorporate a reduced form specification such as in Equation (5), which may better identify causality in most cases (see Partridge et al., 2012, for a comprehensive discussion)[9]. Equation (5) may incorporate a spatial lag of the dependent variable (known as spatial Durbin model/SDM) or spatial dependence for the error components (known as spatial Durbin error model/SDEM). The empirical exercise conducted herein compares alternative spatial panel data growth models across a variety of geographic scale. The purpose of this approach is to better understand the determinants of Brazilian economic growth and their respective spatial spillovers (because policy conclusions greatly differ across alternative models) as well as to show that the geographic scale of analysis is an unavoidable feature (because growth determinants would differ across different spatial scales). All estimations presented in this paper were performed using the splm package in R (see Millo and Piras, 2012).

4. Data

In order to evaluate the results of regional economic growth estimates at a variety of geographic scales, this paper applied alternative spatio-temporal models to the same dataset used in Resende (2011b). Table 3.1 presents the four Brazilian geographic stratifications in the dataset – 27 states, 134 meso-regions, 522 micro-regions and 3,657[10] minimum comparable areas (MCAs) – and shows some statistics concerning their sizes (in square kilometers). The data are drawn from the MCA level, which is the most disaggregated spatial units in this study, and then grouped to form the other spatial scales.

[9] Partridge et al. (2012: 170) further explain that "*Gibbons and Overman argue that their preferred starting point is natural experiments that use geographical, institutional, or historic factors to identify causality. While natural experimental approaches raise their own problems of only assessing "cute" experiments or searching for valid instruments, Gibbons and Overman argue that identification is more transparent and less prone to the errors we described above*".

[10] The total number of MCAs is 3,659, but this paper uses 3,657. Fernando de Noronha (in the state of Pernambuco) and Ilhabela (in the state of São Paulo) were excluded because they are islands and do not adjust to the spatial weight matrices used in the analyses. These exclusions do not alter the results of the paper.

Table 3.1 – Spatial scales in Brazil to analyze the period between 1970 and 2000

States (n = 27)	**Meso-regions** (n = 134)	**Micro-regions** (n = 522)	**MCAs*** (n = 3,657)
			
Area Mean = 312,994 Km^2 Area Min = 5,771 Km^2 Area Max 1,558,987 Km^2 Area Standard Deviation = 372,070 Km^2	Area Mean = 63,066 Km^2 Area Min = 2,937 Km^2 Area Max 650,338 Km^2 Area Standard Deviation = 103,804 Km^2	Area Mean = 16,189 Km^2 Area Min = 190 Km^2 Area Max 439,498 Km^2 Area Standard Deviation = 42,083 Km^2	Area Mean = 2,311 Km^2 Area Min = 8 Km^2 Area Max 367,284 Km^2 Area Standard Deviation = 14,157 Km^2

Note: Own elaboration from data of IBGE. * Minimum Comparable Areas (MCAs).

MCAs were defined by Reis et al. (2005) as sets of municipalities whose borders were constant from 1970 to 2000, to address the comparability problem generated by the increase in the number of municipalities from 3,920 in 1970 to 5,507 in 2000. Brazil is divided into 27 states[11] that are the main political-administrative units in the country. Municipalities (MCAs in the case of this paper) represent the smallest administrative level, dealing with local policy implementation and management. Micro- and meso-regions are homogeneous regions defined by IBGE (Brazilian Institute of Geography and Statistics – Instituto Brasileiro de Geografia e Estatística) as a group of contiguous municipalities within the same state. Micro-regions were grouped according to natural and production characteristics. Meso-regions are larger areas than micro-regions and were put together according to the following dimensions: social aspects, natural setting, and communication network as an element of space articulation. According to IBGE (2011) the division of Brazil into micro- and meso-regions is "*relevant to formulate public policies; to subsidize the system of decisions relative to the localization of economic, social and tributary activities; to subsidize the planning, surveys and identification of space structures of metropolitan areas and other forms of urban and rural agglomerations.*"

Data were collected from IPEADATA (Institute of Applied Economic Research – Instituto de Pesquisa Econômica Aplicada/IPEA), which has organized the population census information (from IBGE) of 1970, 1980, 1991 and 2000. Based on these four data points, the dependent variable was calculated as the averaged annual income per capita growth rate[12] for each time span: 1970-1980, 1980-1991 and 1991-2000. Per capita income information is deflated to Real (R$, the Brazilian currency) in 2000.

Table 3.2 presents summary statistics for the dependent variable for each of the three time periods at the different spatial scales. For each decade, the simple mean of the averaged annual income per capita growth rates increases in absolute value with the level of disaggregation. In the first period (1970-1980), while the average of income per capita growth rates was 8.81% at the state level, it was 9.36% at the MCA level. Similarly, in the period between 1980 and 1991, the fall in income per capita was more intense at the MCA level (-1.71%) than at the state level (-0.72%). The same pattern occurs between 1991

[11] More precisely, there are 26 states and one federal district.

[12] The income per capita growth rates are averaged over ten years because MCA data are only available from the Brazilian population censuses conducted every ten years. Furthermore, given the presence of business cycle effects, the choice of ten-year growth averages seems to be a reasonable approach to avoid those influences (Caselli et al.,1996). For instance, the 1973 and 1979 "oil price shocks" affected the Brazilian economy. In 1994, Brazil launched the "Plano Real" (Real Plan), the stabilization program that ended a long period of high inflation rates that had started in the 1970s.

and 2000, when the average growth of income per capita reached 6.83% at the MCA level against 6.10% at the municipal level. Data dispersion is also higher in the more disaggregated geographic scales.

Table 3.2 - Summary statistics of income per capita growth rates variable

Spatial Scales	States (n = 27)	Meso-regions (n = 134)	Micro-regions (n = 522)	MCAs* (n = 2,657)
Averaged annual per capita growth rates				
1970-1980				
Mean	0,0881	0,0918	0,0915	0,0936
Min	0,0474	0,0474	0,0140	-0,0938
Max	0,1088	0,1329	0,1437	0,3709
Std. Dev.	0,0152	0,0157	0,0191	0,0296
1980-1991				
Mean	-0,0072	-0,0134	-0,0154	-0,0171
Min	-0,0266	-0,0756	-0,0786	-0,1297
Max	0,0143	0,0163	0,0329	0,2190
Std. Dev.	0,0100	0,0125	0,0139	0,0232
1991-2000				
Mean	0,0610	0,0641	0,0658	0,0683
Min	0,0118	0,0118	-0,0007	-0,1934
Max	0,0766	0,0994	0,1558	0,1991
Std. Dev.	0,0148	0,0135	0,0160	0,0252
Average number of regions using the queen contiguity matrix				
Queen (W matrix)	3,8	5,1	5,6	5,9

Note: Own elaboration from data of IBGE. * Minimum Comparable Areas (MCAs).

Explanatory variables are given in terms of initial values, that is, values in 1970, 1980 and 1991. The socioeconomic data are logged per capita income, logged average years of schooling, logged population density and population growth[13]. Logged transportation costs between MCAs and São Paulo city are also from IPEADATA. The cost of transportation to São Paulo is calculated through a linear program procedure as the minimum cost (given road and vehicle conditions) of travelling between a MCA‘s major headquarters and São Paulo. These transportation cost data are available for the years 1968, 1980 and 1995. Values for the years 1970 and 1991 were estimated via interpolation. Finally, the econometric specifications include time dummies for the decades of 1980 and 1990 (the time dummy for the 1970 decade was excluded from the regressions to avoid perfect multicollinearity).

The spatial weight (W) matrix used herein is the standardized first-order contiguity matrix (also called the queen contiguity matrix), in which the element w_{ij} in the matrix is 1 if areas *i* and *j* share borders or vertices, and 0 otherwise. The average number of regions using the queen contiguity matrix is presented in the bottom part of Table 3.2. Moreover, *k*-nearest neighbors weight matrices (in which each region has the same number of neighbors) were used (k=5 and k=10) for robustness checks and the main qualitative results remain the same.

5. Empirical Results

In this section, we present the estimation results for models estimated at different Brazilian geographic scales. Initially, we present the results for the model estimated at the less aggregated level, which corresponds to the Minimum Comparable Areas (MCAs). The following subsections present the results for estimation at increasingly aggregated levels: microregions, mesoregions and states. Discussions and comparisons of the results across the geographic scales are conducted in Section 6.

---

[13] Population growth is adjusted for depreciation (δ) and technological growth (g), under the usual assumption that δ+g equals 0.05 (e.g., Mankiw et al., 1992). The natural log of this variable is not taken due to the presence of negative values.

5.1. Results at MCA Level

Initially, we employed several Lagrange multiplier tests for panel data models, to test for the presence of spatial correlation in the observations and to test for the presence of idiosyncratic effects (individual regional effects). These tests are discussed in Baltagi et al. (2003) and Millo and Piras (2012). A summary of the tests results are presented in Table 5.1 below. Tests for the presence of individual regional effects are based on random effects models, such that the null hypothesis contains an assumption that $\sigma_\mu^2 = 0$. Nonetheless, if the null hypothesis is rejected, there is evidence against using a pooled regression estimator or some variation of it that accounts for spatial dependence.

Table 5.1 - Lagrange multiplier tests for the presence of regional individual effects and the presence of spatial correlation at the MCA level

Test #	Hypothesis tested	P-value
1	Null hypothesis of λ = 0 and σ_μ^2 = 0, under the alternative that at least one of these two components is not zero	< 0.0000
2	Null hypothesis of σ_μ^2 = 0, assuming λ = 0, under the one-sided alternative that σ_μ^2 > 0	------
3	Standardized version of test (2) above	------
4	Null hypothesis of λ = 0, assuming that σ_μ^2 = 0, under the two-sided alternative that λ ≠ 0	< 0.0000
5	Standardized version of test (4) above	0.9992
6	Null hypothesis of σ_μ^2 = 0, assuming possible existence of spatial dependence (λ may be different than 0), under the one-sided alternative that σ_μ^2 > 0	<0.0000
7	Null hypothesis of λ = 0, assuming possible existence of random effects (σ_μ^2 may be different that 0), under the two-sided alternative that λ ≠ 0	<0.0000

Note: Own elaboration.

The results in table 5.1 above indicate the presence of both regional individual effects and spatial correlation in the panel regression model. For tests (2) and (3), the resulting tests statistics had negative values, which may be due to the fact that these tests assume the absence of spatial correlation. In the same way, test (5) had a resulting p-value very close to one, although the unstandardized version resulted in a p-value close to zero. In any case, tests (2), (3), (4) and (5) suffer of lack of robustness, because they assume either absence of spatial correlation or absence of regional individual effects. Tests (6) and (7) are more robust, and they both indicated the presence of both effects (spatial correlation and idiosyncratic effects).

Based on the test results, we can proceed to parameter estimation. We estimated both fixed effects and random effects models, so as to have an idea of the robustness of our conclusions. Tables 5.2 and 5.3 below show the estimation results for models estimated at the MCAs level. Table 5.2 has results for fixed effects models, whereas Table 5.3 presents the results for random effect models. For random effects, we also estimated models with Kapoor's representation (not shown), but the results were similar to the results from Baltagi's representation.

Table 5.2 - Estimation results for spatial panel data fixed effects models at the MCA level

Variable	Spatial dependence specifications			
	Non-spatial dependence (1)	Spatial lag (2)	Baltagi's representation (3)	Spatial lag and spatial error dependence (4)
Log per capita income	-0.105100***	-0.104850***	-0.106238***	-0.106348***
Log population growth (n+g+d)	0.024271	0.027144	0.030318*	0.029922
Log education	0.000949*	0.000908*	0.001230***	0.001387**
Log transportation cost to São Paulo	0.005549	0.004522	0.006898**	0.008469**
Log population density	-0.008891***	-0.008674***	-0.007647***	-0.007279***
Dummy variable for decade 1980	-0.009935***	-0.005518***	-0.008591***	-0.014813***
Dummy variable for decade 1991	0.056904***	0.057344***	0.057767***	0.056787***
Spatial lag for the dep. variable (λ)	----	0.045498***	----	-0.061589**
Spatial lag for error components (ρ)	----	----	0.183343***	0.270577^{++}
R-squared	0.926923	0.927062	0.926889	$^{+++}$

Note: For the significance level in the estimations in the table, (***) means statistically significant at level 0.1%, (**) means statistically significant at level 1% and (*) means statistically significant at level 5%. ($^{++}$) means that there was no standard error or p-value reported, and ($^{+++}$) means that the residuals do not sum to zero and the R-squared was not calculated. Model (1), with no spatial dependence, was estimated using the within estimator. Models for spatial lag (2) and for Baltagi's representation (3) were estimated by maximum likelihood. Model (4), including both spatial lag and error spatial dependence, was estimated using GMM.

According to the results in Table 5.2, we note that the coefficients for spatial dependence (λ and ρ) are statistically significant for all fixed effects specifications. The estimates for ρ seem to be higher than the estimates for λ. When both spatial parameters are included (model 4), the autocorrelation parameter λ has a negative sign. When spatial dependence for the error terms (models 3 and 4) is included, transportation cost to São Paulo becomes statistically significant. Moreover, from the analysis of models 2, 3 and 4, higher economic growth rates at the MCA level are positively related to education and negatively associated with income per capita (conditional convergence) and population density. It is important to note the statistical significance of the time dummies for the 80's and 90's. Of note, high R-squared values can be observed in all estimations. For instance, the R-squared in column 1 (non-spatial model at the AMC level) is 0.9269. However, if the time dummies are dropped from the regression the R-squared goes to 0.5720 (not shown in Table 5.2). This means that time dynamics have a relevant explanatory power in the Brazilian case. This fact is observed for all estimation techniques and geographic scales.

Table 5.3 - Estimation results for spatial panel data random effects models at the MCA level

Variable	Spatial dependence specifications			
	Non-spatial dependence (5)	**Spatial lag (6)**	**Baltagi's representation (7)**	**Spatial lag and Baltagi's representation (8)**
Intercept	0.722365***	0.281552***	0.296934***	0.327859***
Log per capita income	-0.095229***	-0.028705***	-0.029159***	-0.027410***
Log population growth (n+g+d)	0.067672***	-0.010857	-0.008534	0.001988
Log education	0.003236***	0.008781***	0.008672***	0.007427***
Log transportation cost to São Paulo	-0.037963***	-0.012662***	-0.012807***	-0.011622***
Log population density	-0.000784	-0.000583**	-0.000562**	-0.000441*
Dummy variable for year 1980	-0.037403***	-0.077489***	-0.092234***	-0.148397***
Dummy variable for year 1991	0.024934***	-0.014743***	-0.017862***	-0.030344***
Spatial lag for the dep. variable (λ)	----	0.137026***	----	-0.502051***
Spatial lag for error components (ρ)	----	----	0.153120***	0.555498***
R-squared	0.912423	0.774965	0.804480	0.411778

Note: For the significance level in the estimations in the table, (***) means statistically significant at level 0.1%, (**) means statistically significant at level 1% and (*) means statistically significant at level 5%. Models (5), (6), (7) and (8) were estimated by maximum likelihood. For models (7) and (8), using a Baltagi's representation for error components spatial dependence, we estimated equivalent models, with Kapoor's representation, and the results were very similar.

From Table 5.3, we notice that the results for the fixed effects and for the random effects models are quite similar. The random effects models assume that the regional individual effects are uncorrelated with the error terms, whereas for the fixed effect models, this correlation needs not be null. To test whether the zero correlation assumption is valid, so that we can rely on the random effects estimation results, we can resort to the spatial Hausman test, discussed in Mutl and Pfaffermayr (2011). The results for the spatial Hausman test, considering an underlying model with both spatial lag ($\lambda \neq 0$) and error spatial dependence ($\rho \neq 0$), rejected the null hypothesis that both fixed effects and random effects models are equivalent, with a p-value smaller than 1.0e-10. Therefore, we have evidence in favor of considering the results from the fixed effects model. Indeed, Durlauf et al. (2005) note that most of panel data growth studies employ a fixed effects (within-group) estimator rather than a random effects estimator[14]. In the discussion section, we analyze and compare the fixed effects terms across the four geographic scales under investigation.

To better understand the variables affecting municipality growth, we present in Table 5.4 the estimation results for a fixed effects model, where we add spatial lags for the explanatory variables (WX) to the list of right-hand-side variables. We estimate the model with and without a spatial lag. Note that the model with a spatial lag (10) is known as the Spatial Durbin Model (SDM). LeSage and Fischer (2008) prefer the SDM specification arguing that the conjunction of plausible circumstances likely to arise in applied spatial growth regression modeling makes this model specification a natural choice over competing

[14] Durlauf et al. (2005) explain that standard random effects estimators require that the individual effects are distributed independently of the explanatory variables, and this requirement is clearly violated for a dynamic panel by construction, given the dependence of log initial period level of the dependent variable on individual effects.

alternatives. However, Gibbons and Overman (2012) favor model (9). For identification reasons, the model with both spatial lag and spatial error dependence could not be estimated by maximum likelihood[15]. Numerical instability also occurred when using generalized method of moments for the model with both spatial components, because the instruments contain spatial lags of independent variables, and these lags are already included into the right-hand-side variables. Therefore, the specifications in Table 5.4 either contain a spatial component in the error terms or include a spatial lag for the dependent variable.

Note that the three models estimated in Table 5.4 present similar results. Higher economic growth within one MCA is negatively related to income per capita (conditional convergence) and positively associated with population growth and education. Furthermore, as argued by Sardadvar (2012) the results show how education levels are beneficial to economic growth if found within one MCA, but disadvantageous if found in neighboring regions (W*log education). Moreover, the results show that economic growth within one MCA is positively influenced by its neighbors' income per capita levels (W*log per capita income)[16]. Moreover, other coefficients for spatial dependence (λ and ρ) present positive signs and are statistically significant.

Table 5.4 - Estimation results for spatial panel data fixed effects models with spatial lags of the explanatory variables at the MCA level

Variable	Spatial dependence specifications		
	Spatial cross-regressive model (SLX) (9)	**SDM (10)**	**Baltagi's representation (SDEM) (11)**
Log per capita income	-0.11501***	-0.11496***	-0.11510***
Log population growth (n+g+d)	0.04718*	0.04873**	0.04855**
Log education	0.00133**	0.00130***	0.00147***
Log transportation cost to São Paulo	0.00489	0.00451	0.00427
Log population density	-0.00181	-0.00166	-0.00161
W*log per capita income	0.03485***	0.03608***	0.03392***
W*population growth (n+g+d)	-0.06679	-0.05918*	-0.05469
W*log education	-0.00205*	-0.00231**	-0.00186*
W*log transportation cost to São Paulo	0.01466*	0.01354**	0.01563**
W*log population density	-0.01222***	-0.01167***	-0.01072***
Dummy variable for year 1980	-0.02666***	-0.02011***	-0.02587***
Dummy variable for year 1991	0.04759***	0.04789***	0.04779***
Spatial lag for the dep. variable (λ)	----	0.07444***	----
Spatial lag for error components (ρ)	----	----	0.15792***

Note: For the significance level in the estimations in the table, (***) means statistically significant at level 0.1%, (**) means statistically significant at level 1% and (*) means statistically significant at level 5%.

5.2. Results at Micro-Regional Level

In total, the country is divided into 522 microregions. The results for fixed effects estimation are shown, without and with spatial lags for explanatory variables in Tables 5.5 and 5.6, respectively. In Table 5.5, only the per capita income coefficient is statistically significant for all specifications, indicating the process of conditional convergence at the micro-regional level. Moreover, in all spatial dependence specifications the coefficients for spatial dependence (λ and ρ) are positive and statistically significant.

In Table 5.6, we find that per capita income is negatively related to growth, while its spatial lag is positively associated with growth as suggested by the theoretical spatial growth models (e.g., López-Bazo et al., 2004; Ertur and Koch, 2007; Sardadvar, 2012). The positive spatial lag of income per capita means that one microregion located in a relatively rich neighbourhood will tend to have a higher per capita income growth (with other things being equal). In the spatial lag model (10) population growth fosters economic growth within one microregion; but economic growth within one microregion is negatively influenced by its neighbors' population growth (W*population growth). Similarly to MCAs' results,

[15] The over parameterization, in terms of spatial components, caused numerical instability in the optimization process.
[16] Sardadvar (2012) develops a spatial neoclassical growth model explaining these results.

spatial dependence specifications present positive and statistically significant coefficients for spatial dependence (λ and ρ); although higher values can be observed for the micro-regional level.

Table 5.5 - Estimation results for spatial panel data fixed effect models at the microregion level

Variable	Spatial dependence specifications			
	Non-spatial dependence (1)	Spatial lag (2)	Baltagi's representation (3)	Spatial lag and spatial error dependence (4)
Log per capita income	-0.08506***	-0.075369***	-0.096067***	-0.095525***
Log population growth (n+g+d)	-0.05162	-0.027045	0.061710*	0.060210
Log education	0.00389	0.002299	0.002028	0.002161
Log transportation cost to São Paulo	0.01059*	0.000243	0.000279	0.001400
Log population density	-0.01324***	-0.010268***	-0.000796	-0.000936
Dummy variable for year 1980	-0.02467***	0.005377	-0.019650***	-0.025571**
Dummy variable for year 1991	0.04379***	0.042499***	0.045226***	0.043831***
Spatial lag for the dep. variable (λ)	----	0.395592***		-0.054056
Spatial lag for error components (ρ)	----	----	0.664554***	0.657960^{++}
R-squared	0.96162	0.96773	0.95976	$^{+++}$

Note: For the significance level in the estimations in the table, (***) means statistically significant at level 0.1%, (**) means statistically significant at level 1% and (*) means statistically significant at level 5%. ($^{++}$) means that there was no standard error or p-value reported, and ($^{+++}$) means that the residuals do not sum to zero and the R-squared was not calculated. Model (1), with no spatial dependence, was estimated using the within estimator. Models for spatial lag (2) and for Baltagi's representation (3) were estimated by maximum likelihood. Model (4), including both spatial lag and error spatial dependence, was estimated using GMM.

Table 5.6 - Estimation results for spatial panel data fixed effect models with spatial lags of the explanatory variables at the microregion level

Variable	Spatial dependence specifications		
	Spatial cross-regressive model (SLX) (9)	SDM (10)	Baltagi's representation (SDEM) (11)
Log per capita income	-0.09654***	-0.09822***	-0.09565***
Log population growth (n+g+d)	0.06554	0.08678**	0.06248*
Log education	0.00229	0.00141	0.00181
Log transportation cost to São Paulo	-0.00410	-0.00563	-0.00389
Log population density	0.00133	0.00269	-0.00024
W*log per capita income	0.02468***	0.07053***	0.01525**
W*population growth (n+g+d)	-0.33368***	-0.17670**	-0.14330
W*log education	-0.00003	-0.00045	0.00495
W*log transportation cost to São Paulo	0.02379	0.01459	0.02098*
W*log population density	-0.03024***	-0.01412***	-0.01478**
Dummy variable for year 1980	-0.03042***	-0.01076***	-0.02777***
Dummy variable for year 1991	0.04410***	0.01798***	0.04157***
Spatial lag for the dep. variable (λ)	----	0.61882***	----
Spatial lag for error components (ρ)	----	----	0.62415***

Note: For the significance level in the estimations in the table, (***) means statistically significant at level 0.1%, (**) means statistically significant at level 1% and (*) means statistically significant at level 5%.

5.3. Results at Meso-Regional Level

We now present the results using 134 Brazilian mesoregions. Tables 5.7 and 5.8 show the results for fixed effects estimations, without and with spatial lags for explanatory variables, respectively. In Table 5.7, the per capita income coefficient is statistically significant for all specifications and indicates conditional convergence process at meso-regional level. Moreover, higher economic growth is positively related to education level for all specification in Table 5.7. In models (2) and (3), the coefficients for spatial dependence (λ and ρ) are positive and statistically significant. However, when both spatial components are included in specification (4), the statistical significance disappears.

In Table 5.8, the spatial models (10) and (11) show that there is conditional convergence and that higher educational level is beneficial to growth within mesoregions. The coefficients of the spatial lags of population density are statistically significant in all specification and show that economic growth within one mesoregion is negatively influenced by its neighbors' population density (W*log population density). Moreover, spatial dependence specifications present positive and statistically significant coefficients for spatial dependence (λ and ρ); although their magnitudes are lower than those estimated at the micro-regional level.

Table 5.7 - Estimation results for spatial panel data fixed effect models at the mesoregion level

Variable	Spatial dependence specifications			
	Non-spatial dependence (1)	Spatial lag (2)	Baltagi's representation (3)	Spatial lag and spatial error dependence (4)
Log per capita income	-0.07795***	-0.07343***	-0.08412***	-0.08137***
Log population growth (n+g+d)	-0.14754	-0.13980*	-0.03165	-0.07946
Log education	0.01237*	0.01010*	0.01561**	0.01362*
Log transportation cost to São Paulo	0.01202	0.00554	0.00936	0.00713
Log population density	-0.01829***	-0.01522***	-0.00599	-0.01009*
Dummy variable for year 1980	-0.03101***	-0.00045	-0.02966***	-0.01001
Dummy variable for year 1991	0.03469***	0.03824***	0.03072***	0.03631***
Spatial lag for the dep. variable (λ)	----	0.34579***	----	0.20342
Spatial lag for error components (ρ)	----	----	0.50436***	0.30934
R-squared	0.97035	0.97368	0.96929	+++

Note: For the significance level in the estimations in the table, (***) means statistically significant at level 0.1%, (**) means statistically significant at level 1% and (*) means statistically significant at level 5%. (++) means that there was no standard error or p-value reported, and (+++) means that the residuals do not sum to zero and the R-squared was not calculated. Model (1), with no spatial dependence, was estimated using the within estimator. Models for spatial lag (2) and for Baltagi's representation (3) were estimated by maximum likelihood. Model (4), including both spatial lag and error spatial dependence, was estimated using GMM.

Table 5.8 - Estimation results for spatial panel data fixed effect models with spatial lags of the explanatory variables at the mesoregion level

Variable	Spatial dependence specifications		
	Spatial cross-regressive model (SLX) (9)	SDM (10)	Baltagi's representation (SDEM) (11)
Log per capita income	-0.08803***	-0.08841***	-0.08685***
Log population growth (n+g+d)	-0.01846	0.01085	-0.03268
Log education	0.01214	0.01341*	0.01237*
Log transportation cost to São Paulo	-0.00010	0.00261	0.00326
Log population density	-0.00203	0.00062	-0.00364
W*log per capita income	0.01515	0.04256***	0.00507
W*population growth (n+g+d)	-0.44103*	-0.28020	-0.34559*
W*log education	-0.00477	-0.00829	-0.00187
W*log transportation cost to São Paulo	0.01893	0.00910	0.01534
W*log population density	-0.04230***	-0.02823***	-0.03636***
Dummy variable for year 1980	-0.02632**	-0.01022	-0.01992*
Dummy variable for year 1991	0.04734***	0.03099***	0.05006***
Spatial lag for the dep. variable (λ)	----	0.43106***	----
Spatial lag for error components (ρ)	----	----	0.42779***

Note: For the significance level in the estimations in the table, (***) means statistically significant at level 0.1%, (**) means statistically significant at level 1% and (*) means statistically significant at level 5%.

5.4. Results at State Level

Tables 5.9 and 5.10 bring the estimation results from models without and with spatial lags for explanatory variables. From Table 5.9 we note that growth estimations at the state level using spatial dependence specifications show weak evidence of spatial spillovers. Indeed, Resende (2011b) demonstrates that the diagnostics for spatial autocorrelation in the error terms using Moran's I statistics in non-spatial panel models (similar to that in column 1 in Table 5.9) are not statistically significant at the state level in Brazil. For this reason the coefficient for spatial dependence (λ) is not statistically significant in column (2) and (4); and the estimate for ρ seems to be statistically significant only at 5% level in column (3). This finding indicates that, at the state level, the use of spatial econometrics might not be necessary because the spatial autocorrelation does not appear in the residuals. In this sense, model (1) is the most appropriate to investigate economic growth determinants at the stale level.

In model (1), only income per capita and transportation cost coefficients are statistically significant. The former suggests conditional convergence at the state level and the latter indicates that reductions in transportation costs may have a negative impact on economic growth. Of note, as argued by Resende (2011b) these results should be interpreted with caution because these estimates control for fixed effects when transportation costs already have a clear component that is fixed (namely, the distance between each spatial unit and the spatial unit represented by São Paulo). Therefore, the transportation cost coefficients might only be picking up the variable part of transportation costs (for instance, road conditions or quality) showing that improvements in road conditions are positively related to economic growth at state level. Table 5.10 also shows negligible effects of spatial dependence components (λ and ρ) in columns (10) and (11). The next section presents a discussion of the results described herein comparing the results found across the four geographic scales.

Table 5.9 - Estimation results for spatial panel data fixed effect models at the state level

Variable	Spatial dependence specifications			
	Non-spatial dependence (1)	Spatial lag (2)	Baltagi's representation (3)	Spatial lag and spatial error dependence (4)
Log per capita income	-0.09311***	-0.09205***	-0.09505***	-0.09280***
Log population growth (n+g+d)	-0.19468	-0.19199	-0.11385	-0.15366
Log education	0.02419	0.023889*	0.03543**	0.02848*
Log transportation cost to São Paulo	0.04676**	0.043943***	0.04254**	0.04101*
Log population density	-0.01412	-0.01334*	-0.00530	-0.00911
Dummy variable for year 1980	-0.00511	0.00054	-0.01167	0.00140
Dummy variable for year 1991	0.05578**	0.05557***	0.04163**	0.05005**
Spatial lag for the dep. variable (λ)	----	0.07659	----	0.11809
Spatial lag for error components (ρ)	----	----	0.27317*	0.12471
R-squared	0.97806	0.97818	0.97723	+++

Note: For the significance level in the estimations in the table, (***) means statistically significant at level 0.1%, (**) means statistically significant at level 1% and (*) means statistically significant at level 5%. (++) means that there was no standard error or p-value reported, and (+++) means that the residuals do not sum to zero and the R-squared was not calculated. Model (1), with no spatial dependence, was estimated using the within estimator. Models for spatial lag (2) and for Baltagi's representation (3) were estimated by maximum likelihood. Model (4), including both spatial lag and error spatial dependence, was estimated using GMM.

Table 5.10 - Estimation results for spatial panel data fixed effect models with spatial lags of the explanatory variables at the state level

Variable	Spatial dependence specifications		
	Spatial cross-regressive model (SLX) (9)	SDM (10)	Baltagi's representation (SDEM) (11)
Log per capita income	-0.10120***	-0.10147***	-0.10008***
Log population growth (n+g+d)	-0.22026	-0.17916	-0.21387
Log education	0.05089**	0.05269***	0.04753***
Log transportation cost to São Paulo	0.03582	0.03592	0.03699
Log population density	-0.00655	-0.00272	-0.00553
W*log per capita income	0.03042	0.03870	0.02213
W*population growth (n+g+d)	-0.57569	-0.55927	-0.68470
W*log education	-0.07804*	-0.07703**	-0.06810**
W*log transportation cost to São Paulo	0.04382	0.03231	0.04093
W*log population density	-0.04415	-0.04387*	-0.05021**
Dummy variable for year 1980	0.01660	0.01967	0.02060
Dummy variable for year 1991	0.11129**	0.09985***	0.11220***
Spatial lag for the dep. variable (λ)	----	0.16543	----
Spatial lag for error components (ρ)	----	----	0.17986

Note: For the significance level in the estimations in the table, (***) means statistically significant at level 0.1%, (**) means statistically significant at level 1% and (*) means statistically significant at level 5%.

6. Discussion

This section aims to discuss the results of economic growth regressions estimated at four geographic scales (MCAs, microregions, mesoregions and states) using alternative spatial panel data methods controlling for fixed effects. Non-spatial panel data models with fixed effects were also estimated for comparative purposes.

In the previous section we note that the coefficients of (log) initial income per capita are negative and statistically significant in all estimations and geographic scales. This negative correlation between the per capita income growth rate and the initial per capita income may suggest conditional β-convergence; but we need to take into account the interpretation of fixed effects in this result. Resende (2011b) shows faster convergence rate in the fixed effects framework compared with the pooled OLS approach.

Of note, when the panel data with fixed effects is adopted in economic growth analyses, it creates a bridge between development economics and the neoclassical empirics of growth because this framework allows for unobservable differences in the production function which focuses attention on all the tangible and intangible factors (e.g., institutional characteristics) that may enter into its respective individual effect (Islam, 1995). Islam (1995) argues that persistent differences in technology level and, for instance, institutions are an important factor in understanding economic growth across regions; because when these variables are included in the regressions in the form of fixed effects, the convergence process occurs at a faster rate[17]. Then, improvements in these unobserved factors (e.g, technology levels and institutions) might produce positive effects on the region's long-run income level, including a higher transitional growth rate.

Herein, when the spatial distribution of these fixed effect terms is analyzed across the four geographic scales (see Figure A.1 in appendix A)[18] we observe a clustering of high values in the south, southeast and central-west of Brazil at the MCA spatial scale, for instance. This fact suggests that fixed effects are really capturing a higher level of, for example, technology and institutions in these regions, which are the most developed areas in Brazil, generating higher growth rates in the analyzed period. However, this spatial distribution of the fixed effects shows some variation across spatial scales. If we observe the fixed effect at the MCAs within each state, we clearly find such variability. For instance, we may conclude that the state of São Paulo presents a higher fixed effect - which may be interpreted as good institutions - that generates higher growth rates. However, we need to bear in mind that, within this state we have MCAs (municipalities) that present values for fixed effects as low as in MCAs in the North region (where we observe the clustering of low fixed effects values). In this sense, the analysis of this phenomenon at a variety of geographic scales presents us a better understanding of these fixed effects.

Furthermore, it is important to note that the evidence of conditional convergence using the fixed effects approach may lead us to conclude that the club convergence hypothesis[19] cannot be ruled out. Indeed,

[17] Islam (1995) explains the faster convergence rate in the FE framework compared with the pooled OLS approach arguing that in the latter approach (or in the framework of single cross-section regression) the technology variable, A(0), being unobservable or unmeasurable, is left out of the equation (or, incorporated in the error term): *"[t]his actually creates an omitted variable problem. Since this omitted variable is correlated with the included explanatory variables, it causes the estimates of the coefficients of these variables to be biased. The direction of bias can be assessed from the standard formula for omitted variable bias. The partial correlation between A(0) and the initial value of y (income per capita) is likely to be positive, and the expected sign of the A(0) term in the full regression, (...), is also positive. Thus, the estimated coefficient of yi,t-1, is biased upward. (...) This explains why we get lower convergence rates from single cross-section regressions and pooled regressions that ignore correlated individual country effects*" Islam (1995: 1147).

[18] These fixed effects come from the spatial Durbin model (SDM). The spatial distribution of fixed effects using other spatial models is very similar; and for this reason they are not shown here.

[19] Ertur et al. (2006: 8) highlight that "*the concept of club convergence is based on endogenous growth models that are characterized by the possibility of multiple, locally stable, steady state equilibria as in Azariadis and Drazen (1990). Which of these different equilibria an economy will be reaching depends on the range to which its initial conditions belong. In other words, economies converge to one another if their initial conditions are in the 'basin of attraction' of the same steady state equilibrium. When convergence clubs exist, one convergence equation should be estimated per club, corresponding to different regimes*".

there is growing evidence that the club convergence hypothesis is the correct one for the Brazilian case (Andrade et al., 2004; Laurini et al. 2005; Coelho and Figueirêdo, 2007, Resende, 2011a). Of note, Islam (1995) points out that instead of using the panel data method, the other way to control for differences in technology and institutions is to classify regions (or countries) into similar clubs. The club convergence analysis allows for differences in the aggregate production function across groups of regions. Classifying regions into similar groups (or clubs) has been the approach adopted in some recent studies (Coelho and Figueirêdo, 2007; Cravo, 2010; Resende, 2011a; Cravo and Resende, 2012). In this sense, the fixed effects findings described above are consistent with the club convergence hypothesis for the Brazilian case. Moreover, the variability of conditional β-convergence coefficients due to the geographic scale of analysis seems to be small using fixed effects models. Coefficients sizes range from -0.07343 (in Table 5.7, column 2) at meso-regional level to -0.11510 (in Table 5.4, column 11) at MCA level. It is worth noting that higher rates of convergence at the MCA level suggest that municipalities are more open economies (Barro et al., 1995) than more aggregated regions such as mesoregions. For this reason, MCAs present faster convergence rates to their own state-steady levels of income per capita.

Now we turn to the analysis of the variability of other estimated coefficients at different geographic scales. In most cases, the coefficients of population growth are statistically insignificant at 5% level. It is probably because of a balance between countervailing behavior effects of fertility, mortality, and migration that the population growth coefficient becomes statistically insignificant. The average-year-of-schooling coefficient inflates as more aggregate data is used. For instance, using the spatial lag model, the years-of-schooling coefficient is 0.000908 at the MCA level, 0.002299 at the micro-regional level, 0.01010 at the meso-regional level, and 0.023889 at the state level. This might suggest the strength of the spatial interactions across individuals and regions, a phenomenon coined as the "social multiplier" effect by Glaeser et al. (2003).

The analysis of spatial models results reveals that transportation costs effects are statistically significant to economic growth only at the state level. As explained earlier, in the fixed effects approach, the transportation cost coefficients might only be picking up the variable part of transportation costs (for instance, road conditions or quality). In this sense, we may conclude that improvements in road conditions are positively related to economic growth at the state level.

In some spatial panel data specifications, population density coefficients are negative and statistically significant at the MCA (Table 5.2), micro-regional (Table 5.5) and meso-regional (Table 5.7) spatial scales. These results are contrary to the argument that agglomeration effects are beneficial to economic growth because the negative signs of the population density coefficients mean that higher populated areas are harmful to economic growth, demonstrating somehow that congestion effects might explain this negative effect for the analyzed period (1970-2000). Moreover, it is important to highlight that the magnitudes and statistical significance levels also vary across the geographic scales. For instance, at the state level, population density does not seem to be an important factor to growth.

Finally, the evidence collected from spatial spillovers coefficients shows that their magnitudes vary according to the spatial scale under analysis. In the spatial lag specification, the spatial lag for the dependent variable (λ) presents positive and statistically significant coefficients at the MCA (0.045498), micro-regional (0.395592) and meso-regional (0.34579) levels. On the other hand, at state level such coefficient is no longer statistically significant suggesting that spatial spillovers are bounded in space as already found in Resende (2011a). Moreover, as discussed earlier, the mechanisms that might explain the spatial interactions among regions may be related to nuisance or substantive arguments. The results suggest that both mechanisms may be the origin of spatial linkages observed in this empirical exercise. Some authors such as LeSage and Fischer (2008) prefer the spatial Durbin Model (SDM) specification over competing alternatives. This model can be supported by theoretical spatial growth model such as those developed by López-Bazo et al. (2004), Ertur and Koch (2007) and Sardadvar (2012). For instance, spatial Solow growth models demonstrate that regional spillovers of the diffusion of technology across regions are caused by the spatial dimension of investments in physical and human capital (López-Bazo et al., 2004). However, it is important to note that the correct identification of the most appropriate empirical spatial model is still a challenging issue to be addressed by the spatial econometric literature [see, for instance, Partridge et al. (2012) and Gibbons and Overman (2012)].

7. Conclusions

The goal of this paper was to evaluate the results of regional economic growth estimates at multiple spatial scales using spatial panel data models. The spatial scales examined were minimum comparable areas, micro-regions, meso-regions and states over the period between 1970 and 2000. Alternative spatial panel data models with fixed effects were systematically estimated across those spatial scales to demonstrate that the estimated coefficients change with the scale level.

The results show that the conclusions obtained from growth regressions are dependent on the choice of spatial scale. First, the fixed effects used in the spatial models allowed differences in the aggregate production function focusing attention on all the tangible and intangible fixed effects that underlie much of the discussion of development economics (Islam, 1995). We may conclude that improvements in unobserved fixed factors (e.g, technology levels and institutions) produced positive effects on growth rates at the four spatial levels. The spatial distribution of these fixed effect terms are clustered across space. One result of this finding is that club convergence hypothesis cannot be rejected suggesting there are differences in the convergence processes between the north and south in Brazil. However, spatial distribution of the fixed effects shows some variation across spatial scales. It is worth noting that higher rates of convergence at the MCA level were found, suggesting that municipalities are more open economies than more aggregated regions.

This paper also showed that determinants of economic growth estimated on different geographic scales change with the scale. In most cases, the coefficients of population growth are statistically insignificant at 5% level, except at the meso-regional level using the spatial lag specification. The positive average-years-of-schooling coefficient gets larger as more aggregate spatial scales are used. Moreover, transportation costs effect is positive and statistically significant to economic growth at the state level showing that improvements in road conditions are positively related to economic growth only at the state level. Population density coefficients show that higher populated areas are harmful to economic growth demonstrating somehow that congestion effects are operating at the MCA, micro-regional and meso-regional spatial scales, but their magnitudes vary across the geographic scales.

Finally, the values of spatial spillovers coefficients also vary according to the spatial scale under analysis. In general, such coefficients are statistically significant at the MCA, micro-regional and meso-regional levels; but, at state level those coefficients are no longer statistically significant suggesting that spatial spillovers are bounded in space.

References

ALESINA, A., RODRIK, D. (1994) Distributive politics and economic growth. *Quarterly Journal of Economics*, 109: 465-490.

ANDRADE, E., LAURINI, M., MADALOZZO, R., PEREIRA, P. (2004). Convergence clubs among Brazilian municipalities. *Economics Letters*, 83: 179–184.

ANSELIN, L. (1988). *Spatial Econometrics: Methods and Models*. Kluwer Academic Publisher, Dordrecht.

ANSELIN L, LE GALLO J, JAYET H (2008) Spatial panel econometrics. In: Mátyás L., Sevestre, P. (eds.) *The econometrics of panel data, fundamentals and recent developments in theory and practice*, Kluwer, Dordrecht: 627–662

ÁVILA, R. P., MONASTÉRIO, L. M. (2008) MAUP e a análise espacial: Um estudo de caso para o Rio Grande do Sul. *Análise Econômica* (UFRGS), 26: 239-265.

BALTAGI, B. H. (2008). *Econometric Analysis of Panel Data*. 4th edition. John Wiley & Sons, New York.

BALTAGI, B. H., PIROTTE, A. (2010) Panel data inference under spatial dependence. *Economic Modelling*, 27(6): 1368-1381.

BALTAGI B.H., SONG S.H., KOH W. (2003). Testing Panel Data Regression Models with Spatial Error Correlation. *Journal of Econometrics*, 117, 123-150.

BARRO, R., SALA-I MARTIN, X. (2003) *Economic growth*. Cambridge, Mass.: MIT, 2ed.

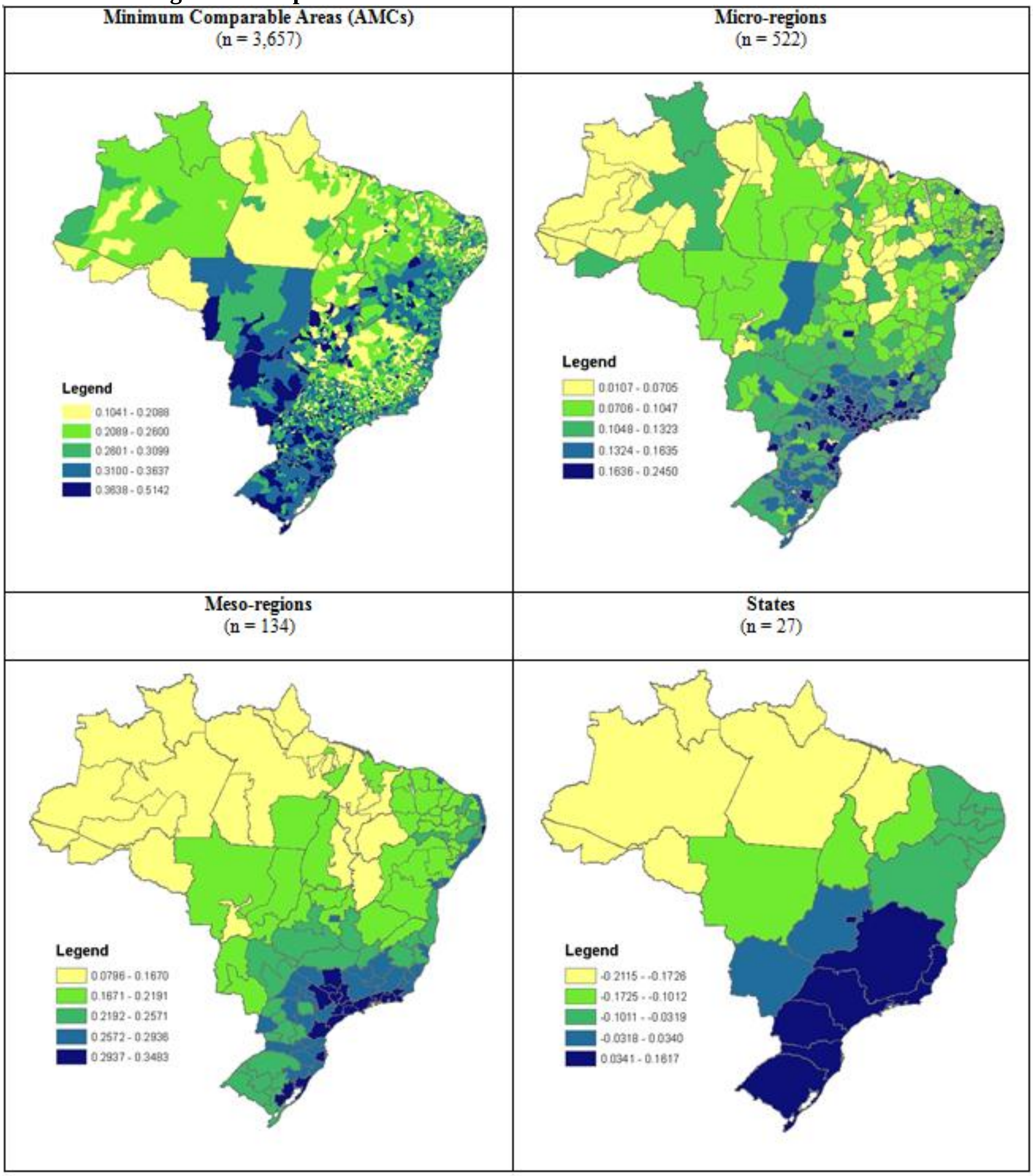
BEHRENS, K., THISSE, J. F. (2007) Regional economics: A new economic geography perspective. *Regional Science and Urban Economics*, 37: 457–465.
BLOOM, D., CANNING, D., SEVILLA, J. (2004) The effect of health on economic growth: A production function approach. *World Development*, 32 (1): 1–13.
BRIANT, A., COMBES, P. P., LAFOURCADE, M. (2010) Dots to boxes: Do the size and shape of spatial units jeopardize economic geography estimations? *Journal of Urban Economics*, 67: 287-302.
BRUECKNER, J. K. (1998) Testing for strategic interaction among local governments: The case of growth controls. *Journal of Urban Economics*, 44: 438–467.
CASELLI, F., ESQUIVEL, G., LEFORT, F. (1996). Reopening the convergence debate: A new look at cross country growth empirics. *Journal of Economic Growth*, 1 (3): 363–389.
COELHO, R. L. P., FIGUEIREDO, L. (2007) Uma análise da hipótese da convergência para os municípios Brasileiros. *Revista Brasileira de Economia*, 61: 331–352.
CRAVO, T. A. (2010) SMEs and economic growth in the Brazilian micro-regions. *Papers in Regional Science*, 89: 711–734.
CRAVO, T., RESENDE, G. M. (2012) Economic growth in Brazil: A spatial filtering approach. *The Annals of Regional Science*, DOI: 10.1007/s00168-012-0504-6.
DURLAUF, S. N., JOHNSON, P. A., TEMPLE, J. R. W. (2005) Growth econometrics. In: Aghion, P., Durlauf, S. (Eds) *Handbook of Economic Growth*, Elservier.
ELHORST, J. P. (2010a) Spatial panel data models. In: Fischer, M., Getis, A. (eds) *Handbook of applied spatial analysis*. Springer, Berlin, Heidelberg and New York: 377–407.
ELHORST, J. P. (2010b) Dynamic panels with endogenous interaction effects when T is small. *Regional Science and Urban Economics*, 40: 272–282.
ELHORST, J. P. (2012) Dynamic spatial panels: models, methods, and inferences. *Journal of Geographical System*, 14: 5–28.
ELHORST J. P., PIRAS G., ARBIA G. (2010) Growth and convergence in a multi-regional model with space-time dynamics. *Geographical Analysis*, 42(3): 338–355.
ERTUR C., KOCH, W. (2007) Growth, Technological interdependence and spatial externalities: theory and evidence. *Journal of Applied Econometrics*, 22: 1033–1062.
FERREIRA, A., (2000). Convergence in Brazil: Recent trends and long-run prospects. *Applied Economics*, 32: 479-489.
FINGLETON, B. (1999) Estimates of time to economic convergence: An analysis of regions of the European Union. *International Regional Science Review*, 22: 3-34.
FINGLETON, B. (2011) The empirical performance of the NEG with reference to small areas. *Journal of Economic Geography*, 11: 267–279.
FINGLETON, B., LÓPEZ-BAZO, E. (2006) Empirical growth models with spatial effects. *Papers in Regional Science*, 85: 177-198.
FISCHER, M. (2011) A spatial Mankiw–Romer–Weil model: theory and evidence. *Annals of Regional Science*, 47(2): 419-436.
GAMBOA, O. R. E. (2010) The (un)lucky neighbour: Differences in export performance across Mexico's states. *Papers in Regional Science*, 89 (4):777-799.
GÉRARD, M., JAYET, H., PATY, S. (2010) Tax interactions among Belgian municipalities: Do interregional differences matter? *Regional Science and Urban Economics*, 40: 336–342.
GIBBONS, S., OVERMAN, H. (2012) Mostly pointless spatial econometrics? *Journal of Regional Science*, 52: 172–191.
GLAESER, E. L., SACERDOTE, B. I., SCHEINKMAN, J. A. (2003) The social multiplier. *Journal of the European Economic Association*, 1 (2-3): 345-353.
IBGE (2011) *Division into regions*. Instituto Brasileiro de Geografia e Estatística. (available at: http://www.ibge.gov.br/english/geociencias/geografia/default_div_int. shtm, accessed on 10/01/2011).
IPEADATA. *Dados macroeconômicos e regionais* (available at: http://www. ipeadata.gov.br).
ISLAM, N. (1995) Growth empirics: A Panel data approach. *Quarterly Journal of Economics*, 110 (4): 1127-1170.
ISLAM, N. (2003) What have we learnt from the convergence debate? *Journal of Economic Surveys*, 17: 309–362.

JEANTY, P., PARTRIDGE, M., IRWIN, E. (2010) Estimation of a spatial simultaneous equation model of population migration and housing price dynamics. *Regional Science and Urban Economics*, 40: 343–352.
KAPOOR, M., KELEJIAN, H.H., PRUCHA, I.R. (2007). Panel Data Model with Spatially Correlated Error Components. *Journal of Econometrics*, 140(1), 97-130.
LALL, S.V., SHALIZI, Z. (2003) Location and growth in the Brazilian Northeast. *Journal of Regional Science*, 43: 663-681.
LAURINI, M., ANDRADE, E., VALLS, P., (2005). Income convergence clubs for Brazilian Municipalities: a non-parametric analysis. *Applied Economics*, 37 (18): 2099-2118.
LEE, L., YU, J. (2010) Some recent developments in spatial panel data models. *Regional Science and Urban Economics*, 40: 255–271.
LESAGE, J. P. (1999) *Spatial econometrics*. The Web Book of Regional Science, Regional Research Institute, West Virginia University, Morgantown, WV (available at: http://www.rri.wvu.edu/ WebBook/LeSage/spatial/spatial.html)
LESAGE, J. P., FISCHER, M. M. (2008) Spatial growth regressions: Model specification, estimation and interpretation. *Spatial Economic Analysis*, 3(3):275.
LESAGE, J. P., PACE, R. K. (2008) Spatial econometric modeling of origin-destination flows. *Journal of Regional Science*, 48: 941-967.
LÓPEZ-BAZO, E., ARTÍS, M., VAYÁ, E. (2004) Regional externalities and growth: evidence from European regions. *Journal of Regional Science*, 44: 43–73.
LUCAS, R. (1988) On the mechanics of economic development. *Journal of Monetary Economics*, 22 (1): 3-42.
MAGRINI, S. (2004) Regional (di)convergence. In: Henderson, J. V., Thisse, J. F. (eds) *Handbook of Regional and Urban Economics*, ed. 1, vol. 4, chapter 62: 2741-2796.
MANKIW, N. G., ROMER, D., WEIL, D. N. (1992) A Contribution to the empirics of economic growth, *Quarterly Journal of Economics*, 107: 407-37.
MCDONALD, S., ROBERTS, J. (2002) Growth and multiple forms of human capital in an augmented Solow model: A panel data investigation. *Economics Letters*, 74: 271-276.
MCMILLEN, D.P. (2010) Issues in spatial data analysis. *Journal of Regional Science*, 50(1): 119-141.
MENON, C. (2012) The bright side of MAUP: Defining new measures of industrial agglomeration. *Papers in Regional Science*, 91 (1): 3-28.
MILLO, G., PIRAS, G. (2012) splm: Spatial Panel Data Models in R. *Journal of Statistical Software*, 47(1), 1–38.
MUTL, J., PFAERMAYR, M. (2011). The Hausman Test in a Cliff and Ord Panel Model. *Econometrics Journal*, 14, 48-76.
OPENSHAW, S., TAYLOR, P.J. (1981) The Modifiable Areal Unit Problem. In: Wrigley, N., Bennett, R. (ed) *Quantitative Geography, a British View*. London: Routledge and Kegan.
PARTRIDGE, M. D., BOARNET, M., BRAKMAN, S., OTTAVIANO, G. (2012) Introduction: Whither spatial econometrics? *Journal of Regional Science*, 52 (2): 167-171.
REIS E. J., TAFNER P., PIMENTEL M., MEDINA M., MAGALHAES K., REIFF L. O., SERRA R.V. (2005) *O PIB dos municípios brasileiros: metodologia e estimativas, 1970-96*. IPEA Discussion Paper, n. 1064, Brasília.
RESENDE, G. M. (2011a) Multiple dimensions of regional economic growth: The Brazilian case, 1991-2000. *Papers in Regional Science*, 90 (3): 629-662.
RESENDE, G. M. (2011b) Multidimensional economic growth in Brazil, 1970-2000: What is the extent of spatial autocorrelation? In: IX Encontro Nacional da Associação Brasileira de Estudos Regionais, Natal.
REY, S. J., MONTOURY, B. D. (1999) U.S. regional income convergence: A spatial econometric perspective. *Regional Studies*, 33: 143-156.
ROMER, P. M. (1986) Increasing returns and long-run growth. *Journal of Political Economy*, 94 (5): 1002-1037.
SARDADVAR, S. (2012) Growth and disparities in Europe: Insights from a spatial growth model. *Papers in Regional Science*, 91(2): 257–274.
SOLOW, R. M. (1956) A contribution to the theory of economic growth. *Quarterly Journal of Economics*, 70: 65-94.

YAMAMOTO, D. (2008) Scales of regional income disparities in the USA, 1955–2003. *Journal of Economic Geography*, 8: 79-103.

Appendix A

Figure A.1 - Spatial distribution of estimated fixed-effects at MCA level



Note: In the map, the ranges were defined using natural breaks (Jenks) intervals. Estimated individual fixed effects come from the spatial Durbin models (SDM).