Research Article

Spatial Dimensions of Economic Growth in Brazil

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The contribution of this paper is to explore time and spatial scale dimensions of economic growth in Brazil using alternative panel data techniques to provide a measure of the extent of spatial autocorrelation (in kilometres) over three decades (1970–2000) as well as discussing the determinants of economic growth at a variety of geographic scales (minimum comparable areas, micro-regions, meso-regions, and states). The magnitude and statistical significance of growth determinants such as schooling, population density, population growth, and transportation costs are dependent on the scale of analysis. Moreover, the extent of residual spatial autocorrelation showed that it seems to vary across spatial scales. Indeed, spatial autocorrelation seems to be bounded at the state level and it shows positive and statistically significant values across distances of more than 1,500 kilometres at the other three spatial scales. Among other results, the study suggests that the nonspatial panel data techniques are not able to deal with spatially correlated omitted variables across different spatial scales, except for the state level where nonspatial panel data models seem to be appropriate to investigate growth determinants and convergence process in the Brazilian states case.

1. Introduction

This paper explores time and spatial scale dimensions of economic growth in Brazil using alternative panel-data techniques to provide a measure of the extent of spatial autocorrelation (in kilometres) over three decades (1970–2000) and it discusses the determinants of economic growth at a variety of geographic scales (minimum comparable areas, micro-regions, meso-regions, and states). The focus is on a descriptive analysis of the extent of the spatial autocorrelation effects in the context of regional growth literature, by testing whether the residuals of traditional growth model estimates are spatially autocorrelated at different spatial scales using standard panel data models between 1970 and 2000 in Brazil. This approach allows us to investigate whether alternative nonspatial panel data models (that control for time invariant fixed effects) eliminate or, at least, mitigate the spatial autocorrelation. One of the advantages of using panel data framework is that it allows, as noted by Islam [1], for differences in aggregate production functions for all the regions in the form of unobservable individual fixed effects, for instance correcting for omitted variable bias.

Some studies so far, such as Elhorst et al. [2], advances the growth literature by using spatial econometric techniques to focus on time-space models, but they only examine the process of economic growth at one single spatial scale. However, as suggested by Resende [3] (Resende [3] focuses on the examination of the determinants of Brazilian regional economic growth at a variety of geographic scales using a cross-sectional data set only over the 1990s period.) the need for spatial models (and therefore, the use of W matrices) depends on the level of spatial aggregation used in the data. In other words, the empirical exercise conducted by Resende [3] shows that spatial autocorrelation appears only at finer scales. With the exception this latter work, the studies thus far have only examined the existence of spatial autocorrelation in the process of economic growth at a single spatial scale to infer the consistency of spatial growth models with reality (e.g., [4–8]). Herein, this study of regional economic growth explores both time and spatial scale dimensions.

Throughout this paper the term “spatial autocorrelation” is used because it takes a more conservative and descriptive view of the process of spatial interactions found in the empirical literature. Words such as spatial externalities,

spatial effects, spatial spillovers, spatial dependence, and interaction effects often suggest a relationship of causality between variables. However, given the problems to determine causality in the literature of economic growth [9, 10] and of spatial econometrics in general [11, 12], the term spatial autocorrelation is preferred in the current analysis. It is also discussed throughout the paper how spatial autocorrelation in the residuals can be interpreted in light of the alternative available theories. Among other results, this paper shows that, at the state level in the Brazilian case, there is not spatial autocorrelation in the residuals of nonspatial panel data models demonstrating that these models are appropriate to investigate growth determinants and convergence process. However, for the other spatial scales under analysis, the results show that nonspatial panel data techniques are not able to deal completely with spatially autocorrelated residuals across those spatial scales.

The remainder of this paper is organised as follows. Section 2 briefly reviews the literature on economic growth, focusing on the problems found in this literature. Section 3 discusses the empirical methods of the study. Section 4 describes the dataset and the W matrices used in the analysis. In Section 5, the results are reported and discussed. Section 6 presents the main conclusions.

2. Review of the Literature

This literature review section aims to situate the discussion of the role of spatial scales in the growth of literature as well as the issue of spatial interactions across regions, which can ultimately affect economic growth. First, theoretical and empirical literature is discussed. Then, some econometric issues in the growth literature are listed, and the modifiable areal unit problem (MAUP) and ecological fallacy (EF) are discussed.

In mainstream economic theory, the debate about factors that affect long-run economic growth began with Solow's [13] growth model. This model, also called the exogenous growth model, has been augmented by the inclusion of variables for educational capital [14], health capital [15, 16], migration [17], and knowledge spillovers [6–8]. These theoretical models predict conditional β -convergence, which means that if countries (or regions) differ in the parameters that determine their steady-state (structural characteristics such as saving rates, human capital, and infrastructure), each country (or region) should be converging towards its own steady state level of per capita income and not towards a common level. After the Solow model, an alternative set of growth theories was developed, the so-called endogenous growth models. For instance, Romer [18] stresses the externalities of knowledge investment, and Lucas [19] shows the positive externalities of human capital accumulation. Other examples of the endogenous growth model are Romer [20], Barro [21], and Alesina and Rodrik [22]. These models are based on the presence of constant or increasing returns to capital, which breaks down the neoclassical model's prediction of convergence, leading to the conclusion that economies can diverge over time.

The interest of the empirical investigation of the convergence hypothesis is derived from the seminal paper of Baumol [23], which tests the prediction of convergence based on a simple linear regression model where the per capita income growth rate of 72 countries is regressed on their initial per capita incomes by means of the Ordinary Least Squares (OLS) method. Barro [24] has followed the same empirical approach, but his study is original because it links cross-country growth regressions to alternative growth theories and determinants. (Durlauf et al. [10] make this point and also note that the standard regressions used in empirical growth research “are sometimes known as Barro regressions, given Barro's extensive use of such regressions to study alternative growth determinants.”) Durlauf et al. [10] point out that while Baumol [23], Abramovitz [25], and many others view convergence as the process of follower countries “catching up” to leader countries by adopting their technologies; Barro [24], Mankiw et al. [14], and others adopt the neoclassical model view that convergence is driven by diminishing returns to factors of production. Robinson [26], Grier and Tullock [27], and Kormendi and Meguire [28] employed such regressions earlier, but these studies seem to have received less attention due to their appearance before endogenous growth theory emerged as a primary area of macroeconomic research, which, since then, have attracted interest in the empirical evaluation of growth theories [10].

After a first wave of cross-country regressions, there was a widespread interest in testing the convergence hypothesis and other growth determinants among regions within countries or groups of countries (e.g., US states and European Union regions). For example, Barro and Sala-I-Martin [29] study convergence among US states and regions as well as European regions, Armstrong [30] examines convergence and growth determinants using European Union regions, and Sala-I-Martin [31, 32] present results for US states, Japanese prefectures, European regions, and Canadian provinces. As noted by Islam [1] most of these studies have been conducted in the framework of single cross-country regression in which it is econometrically difficult to allow for differences in the production function. Then, Islam [1] proposed panel data framework that allows for differences of the aggregate production functions in the form of unobservable individual fixed effects. Moreover, in recent years, the spatially augmented Solow model has been examined using the appropriate spatial statistics and econometric methods due to the recognition that the traditional growth equation may suffer from a misspecification due to omitted spatial dependence [2, 4–6]. This debate focuses on identifying and testing for factors involved in growth processes and respective spatial interaction effects across regions. Finding an appropriate spatial econometric specification to identify the correct argument(s) of spatially autocorrelated residuals is beyond the scope of this paper. It is worth noting that the issue of the correct spatial specification is not consensual [33], although it is an important point because each spatial specification (substantive or nuisance) gives alternative interpretations and policy implications for the process of economic growth [34]. (There are alternative explanations for the existence of spatial autocorrelation in the residuals of the growth

equations. For instance, nuisance spatial dependence (spatial error) 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” [35]. Another explanation is related to unobserved determinants that are correlated across regions [34]. Possible unobserved determinants of economic growth not included in these models include cultural, institutional and technological factors, which might be correlated across spatial units. One possible advantage of panel data framework is that if these unobserved determinants are supposed to be constant over time, the fixed-effect (FE), first-difference-over-time (FD) and system GMM (SYS-GMM) methods might eradicate them, at least partially. Moreover, Fingleton and López-Bazo [34] 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. [6] discuss in some detail the substantive arguments for spatial dependence across regions). Furthermore, it is possible that nuisance and substantive arguments may be operating at the same time in the process of economic growth.

Regarding the literature about Brazil, most papers on economic growth use state-level data to run growth regressions [36–40]. Recently, growth regressions have been used to examine economic growth among Brazilian municipalities [41–44]. Cravo [45] and Cravo and Resende [46] are the few studies on Brazilian economic growth using micro-regional data.

Despite much corroboration of conditional β -convergence in the empirical literature, the conditional β -convergence result remains controversial, suffering from substantial drawbacks as shown by, for instance, Friedman [47] and Quah [48] who stress that a negative coefficient for initial per capita income can be due to the more general phenomenon of mean reversion, and by reading convergence into this scenario, growth researchers are falling into Galton's fallacy [49]. To sum up, the main problems with this growth literature include, (i) identification of β -convergence and economic divergence, (ii) endogeneity, (iii) outliers, (iv) missing data, (v) parameter heterogeneity, (vi) measurement error, (vii) robustness with respect to choice of control variables, (viii) spatial correlation in errors, and (ix) the MAUP. For a comprehensive discussion of topics (i) to (vii), see Durlauf et al. [10]. The problem of spatial correlation in errors (viii) is discussed in the next section. For this reason, herein, the focus is on MAUP and EF only.

According to Rey and Janikas [50], while a number of studies have examined the robustness of growth regression with respect to choice of control variables [51–53], changes in geographic scale have yet to be incorporated into this important line of research. Magrini [35] points out that other authors call for greater attention to the issue of what spatial scale is most appropriate for regional analysis [54–56]. Recently, Resende [3] analyses Brazilian economic growth on four spatial scales (municipalities, micro-regions, spatial clusters, and states) between the years of 1991 and 2000. Growth equations were systematically estimated—using the same time period and explanatory variables—across those spatial scales to demonstrate that the estimated coefficients

change with the geographic scale. Moreover, robustness tests identified variables that are simultaneously significant on different spatial scales—higher educational and health capital and better local infrastructure were related to higher rates of economic growth—although their impacts on growth may differ across spatial scales [3].

This strategy returns to the exploration of the statistical literature, which proposes two approaches to analysing this measurement issue: the MAUP and the EF. MAUP refers to the variability in statistical results endemic to the selection of different area units [57]. EF appears when parameters estimated from macrolevel data are used to make inferences about behavioural and socioeconomic relations at a more disaggregate level (individual/microlevel). Basically, MAUP and EF can be related to the measurement issue because both indicate an aggregation bias or effect. Peeters and Chasco [58] note that the term EF—typically used in social sciences (e.g., [59])—is similar to the MAUP in geography (e.g., [57, 60, 61]). Anselin [62] observes that even in very simple situations, the ecological approach creates problems of interpretation. Glaeser et al. [63] associated this problem with the social multiplier argument, showing that aggregation may strongly influence coefficient sizes. Basically, the social multiplier is the ratio of aggregate coefficients (estimated at some macrolevel) to individual coefficients. In one of the examples given by the authors, they found that the social multiplier of human capital is 2.172, by regressing wages on years of schooling at the state level and at the individual level and then taking the ratio of these two coefficients. This result supports the existence of a social multiplier that rises with the level of aggregation, and it corroborates the idea that there are human capital spillovers [63].

Finally, it is worth noting that recent empirical literature has been focused on the analysis of MAUP in several areas of urban and regional economics. For instance, Briant et al. [64] evaluate, in the context of economic geography estimations, the magnitude of the distortions possibly induced by the choice of various French geographic stratifications. Fingleton [65] also examines agglomeration processes operating at multiple levels of spatial aggregation using the UK and the EU regional data sets. Yamamoto [66] investigates regional per capita income disparities in the USA on multiple spatial scales between 1955 and 2003, focusing on methods such as inequality indices, kernel density estimation, and spatial autocorrelation statistics.

The next section describes the empirical methods to evaluate how the results of growth equations change with various scale levels in Brazil. Specifically, it focuses on estimating nonspatial dynamic panel data growth models at different geographic scales and then evaluates the variability in the estimated coefficients and the extent of spatial correlation in errors that may be associated with the strength of the spatial interactions across regions.

3. Empirical Methods

Panel data models have been widely used in empirical growth literature [1, 67–69]. (Spatial panel econometrics estimators

suggested by Elhorst [70–72] and Lee and Yu [73–76] are not the focus of this paper). Indeed, Islam [49] points out that “the convergence research gradually moved from the cross-section to the panel approach.” Islam [1], Temple [9], Islam [49], and Durlauf et al. [10] present a detailed literature review of this line of inquiry. The main usefulness of using the panel data approach lies in its ability to address the omitted variable bias (OVB) problem often detected in the cross-sectional regressions by controlling for the omitted variables that are constant over time in the form of individual effects. (However, panel data models are not without problems, which include a small sample bias and a short frequency at which data are considered. See Islam [49] for details.)

The specifications used in this paper to study economic growth are the traditional panel data growth regressions, as presented in Durlauf et al. [10], wherein income per capita growth rates are regressed on conditioning variables and income per capita levels. As discussed in the dataset section, the dependent variable comprises averaged income per capita growth rates over ten-year periods between 1970 and 2000; this implies that the panel data set contains three time periods only ($T = 3$). Moreover, the explanatory variables are given in terms of initial values in each decade. As noted by Temple [9], to mitigate endogeneity problems, researchers often make use of initial values. Four alternative methods to estimate panel data are used at four spatial scales. First, the pooled Ordinary Least Squares (OLS) model is an estimate that assumes that there is not any omitted variable correlated with the included variables. The following dynamic panel data growth model (1) is estimated via the pooled OLS specification:

$$g_{i,t} = \beta y_{i,t} + \psi X_{i,t} + \pi Z_{i,t} + \eta_t + \varepsilon_{i,t}, \quad (1)$$

where $g_{i,t}$ is equivalent to $(\ln y_{i,t+1} - \ln y_{i,t})/10$ and represents a vector with observations for averaged per capita income growth rates for each spatial unit i at each decade t ($i = 1, \dots, N$; $t = 1, \dots, T$). (More precisely, the denominator of $(\ln y_{i,t+1} - \ln y_{i,t})/10$ is 10 only for the 1970–1980 period. Because per capita income is only available in 1991 (and not in 1990), the denominator for the 1980–1991 period is 11 and for the 1991–2000 period is 9.) Moreover, $y_{i,t}$, the initial income per capita, and $X_{i,t}$ represent those growth determinants that are suggested by the Solow growth model. $X_{i,t}$ contains a constant, human capital variable (proxied by averaged years of schooling), and the population growth $(n_{i,t} + d + g)$ adjusted for depreciation (d) and technological growth (g), under the usual assumption that $d + g$ equals 0.05. $Z_{i,t}$ represents other growth determinants not included in Solow’s theory. η_t is a time-specific effect and $\varepsilon_{i,t}$ is the vector of error terms. As explained by Durlauf et al. [10] “the inclusion of time-specific effects is important in the growth context, not least because the means of the log output series will typically increase over time, given productivity growth at the world level.”

However, as previously stated, a major motivation for using the panel data approach has been the ability to allow for differences in the aggregate production function across countries or regions [1]. With this aim, panel data with individual fixed effects (also known as Least Squares with

Dummy Variables, LSDV) is estimated by means of the following regression (2):

$$g_{i,t} = \beta y_{i,t} + \psi X_{i,t} + \pi Z_{i,t} + \eta_t + \mu_i + \varepsilon_{i,t}. \quad (2)$$

In this fixed-effect (FE) formulation, μ_i is included and represents individual-specific effects. This framework allows for unobservable differences in the production function, which is an improvement in relation to the single cross-section regressions. Indeed, Islam [1] advocates that this panel data framework makes it possible to reconcile neoclassical empirics of growth and development economics because much of the discussion of development economics is thought to have been directed at ways to improve the country (or region) specific aspect of the aggregate production function, which focus attention on all the tangible and intangible factors (e.g., institutional characteristics) that may enter into its respective individual effect.

Another way to deal with unobserved fixed effects that are constant over time is to use the first-differencing (FD) method. Equation (3) takes first differences over time to get rid of unobserved fixed effects. The first-differenced equation has the following formulation:

$$\Delta g_{i,t} = \beta \Delta y_{i,t} + \Delta X_{i,t} \psi + \Delta Z_{i,t} \pi + \eta_t + \varepsilon_{i,t} - \varepsilon_{i,t-1}, \quad (3)$$

where Δ is the first-difference operator. It is worth noting that in (3) the $y_{i,t-1}$ component of $\beta \Delta y_{i,t}$ is correlated with the $\varepsilon_{i,t-1}$ component of the new composite error term, which means at least one of the explanatory variables in the first-differenced equation will be correlated with the residuals [10]. In this case, instrumental variable procedures would be required to address the endogeneity problem that emerges in growth regressions with this formulation. This point also applies to dynamic panel data models with fixed effects (2) when the number of time periods (T) is small, as demonstrated by Nickell [77]. The strategy developed by Arellano and Bond [78] uses the first differences to eliminate the cross-sectional fixed effects, and then it applies GMM using lagged levels of the series as instruments for lagged first differences (DIFF-GMM). However, Bond et al. [79] point out that lagged levels can be weak instruments for first differences because a variable such as educational attainment may influence income per capita growth with a considerable delay (i.e., the presence of highly persistent series) and the first-differenced GMM estimator is expected to be poorly behaved. To overcome the problems of the standard DIFF-GMM estimator, Blundell and Bond [80] proposed the system GMM estimator (SYS-GMM), which can substantially reduce biases, and thus, more precise parameter estimates can be obtained. The SYS-GMM estimator uses not only lagged levels as instruments for first-differences, but also lagged first-differences are used as instruments for levels. As noted by Durlauf et al. [10] “[t]his builds in some insurance against weak identification, because if the series are persistent and lagged levels are weak instruments for first differences, it may still be the case that lagged first differences have some explanatory power for levels.” However, the SYS-GMM approach is not without problems, as discussed in Roodman [81]. (For instance, SYS-GMM easily generates instruments that are numerous. Roodman

[81] points out that “[s]imply by being numerous, instruments can overfit instrumented variables, failing to expunge their endogenous components and biasing coefficient estimates towards those from noninstrumenting estimators.”) The results using the pooled OLS, FE, FD (without instruments), and SYS-GMM are presented in Section 5. The motivation to use four panel data methods to evaluate the extent of spatial autocorrelation across different spatial scales is derived from the fact that alternative methods may differently deal with spatial autocorrelation, and this fact might be of interest to place a set of results into a meaningful spatial perspective.

The final step of the empirical strategy is to measure the extent of spatial autocorrelation by means of the analysis of the variability of estimated coefficients and spatial correlation in errors across multiple spatial scales. As explained earlier, the estimated coefficients may carry information on the strength of the spatial interactions across individuals and regions, a phenomenon that was called by Glaeser et al. [63] the “social multiplier” effect. The drawback in the application of this approach to the empirical growth literature is the reliance of such literature on aggregate data to conduct the estimations. However, it is still possible to give some evidence of this social multiplier effect, or simply, aggregation effect, if the minimum comparable area (MCA) level—which should be assumed to be the microlevel of analysis (instead of the individual)—is compared with the estimations using another aggregate level (e.g., micro-regional, meso-regional, or state level). These results will be examined in Section 5.

Moreover, the primary focus of this paper is to investigate the spatial autocorrelation in the residuals. It is expected that part of the spatial autocorrelation remains as a residual of the regressions in at least one or more spatial scales. The failure to account for spatial autocorrelation in the error term in economic growth regressions yields unbiased estimates for the estimated parameters but a biased estimate of the parameters’ variance. Furthermore, ignoring substantive spatial dependence (e.g., a spatial lag model) will produce biased estimates of the coefficients. Indeed, this is the motivation of all spatial econometric literature, including the estimation of spatially augmented Solow models by means of spatial econometric techniques. To analyse the spatial autocorrelation in the residuals of the traditional panel data regressions, the global Moran’s I statistic is calculated for the regression’s residuals using different spatial weight (W) matrices (distance-based matrices), which can capture the degree to which spatial interdependencies become less important with geographical distance.

Global spatial autocorrelation is calculated based on Moran’s I statistic [82]. To evaluate the spatial autocorrelation in each time span of the panel (1970s, 1980s, and 1990s), Moran’s I is calculated for cross-sectional errors generated by the panel data estimations. This approach provides information on the spatial autocorrelation effects across three decades. Furthermore, the residuals of the panel data estimations were time averaged, and then, Moran’s I statistics were also calculated. Moran’s I statistic is written in the following form (in the matrix form, Moran’s I using

a row-standardised W matrix is $I = e'We/e'e$, where e are cross-sectional residuals [83]):

$$I = \frac{\sum_i \sum_j w_{ij} (\varepsilon_i - \bar{\varepsilon})(\varepsilon_j - \bar{\varepsilon})}{\sum_i (\varepsilon_i - \bar{\varepsilon})^2}, \quad (4)$$

where w_{ij} are elements of a spatial weighting matrix that is row standardised such that the elements w_{ij} in each row sum to 1. ε_i and ε_j are the values of the cross-sectional errors, $\bar{\varepsilon}$ is the mean of the errors, and $\sum_i (\varepsilon_i - \bar{\varepsilon})^2$ is the variance normalisation factor. The spatial weighting matrices employed in this analysis are discussed in the next section. If $I \approx 0$, then there is no evidence of spatial autocorrelation in the residuals, that is, residuals tend to move independently. If Moran’s I statistic is greater than zero, there is a positive spatial autocorrelation, that is, areas with high residual values tend to be close to areas with high residual values (and vice versa). Finally, if Moran’s I statistic is smaller than zero, there is a negative autocorrelation; that is, places with high residual values are close to neighbouring places with low residual values, and vice versa. The statistical significance of Moran’s I is calculated using the permutation approach [84]. The next section describes the data set including the spatial scales and the spatial weight matrices used in the analysis.

4. Dataset and Spatial Weight Matrices

To investigate the extent of spatial autocorrelation on different scale levels in the context of growth regression estimates, the paper makes use of four Brazilian geographic stratifications: 27 states, 134 meso-regions, 522 micro-regions, and 3,657 minimum comparable areas (MCAs). (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.) As explained earlier in this thesis, it was necessary to make some adjustments in the data because the number of municipalities increased from 3,920 municipalities in 1970 to 5,507 municipalities in 2000. To address this problem, municipalities were merged into 3,657 MCAs—defined by Reis et al. [85] as sets of municipalities whose borders were constant from 1970 to 2000. All data had then been aggregated to match these MCAs, which are the most disaggregated spatial units in this study. The data was drawn from the MCA level and then grouped to form other spatial scales.

The first part of Table 1 shows the four spatial scales and some statistics concerning their sizes (in square kilometres). Brazil is divided into 27 states (more precisely, there are 26 states and one federal district) 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 being a group of contiguous municipalities within the same

TABLE 1: Spatial scales in Brazil (areas and distances to ensure connectivity).

Spatial Scales	States ($n = 27$)	Meso-regions ($n = 134$)	Micro-regions ($n = 522$)	MCAs* ($n = 3,657$)

Area (in kilometres ²)				
Mean	312,994.0	63,065.9	16,189.3	2,310.9
Minimum	5,771.0	2,937.0	190.0	8.0
Maximum	1,558,987.0	650,338.0	439,498.0	367,284.0
Std. dev.	372,070.2	103,804.4	42,082.8	14,157.4
Minimum distance between centroids** to ensure connectivity for all regions (in kilometres)				
	786.5	571.5	520.9	401.5
Cut-off	Average number of neighbouring regions using alternative W matrices			
Queen	3.8	5.1	5.6	5.9
400 km	—	—	—	520.4
500 km	—	—	84.3	707.4
600 km	—	21.7	101.8	894.5
700 km	—	26.8	123.6	1,080.9
800 km	4.4	31.9	145.6	1,267.3
900 km	5.0	37.3	167.1	1,444.2
1,000 km	6.2	42.6	188.5	1,611.6
1,500 km	10.4	67.1	283.7	2,274.7
2,000 km	15.7	90.9	377.6	2,916.5

Note: own elaboration from data of IBGE. *Minimum comparable areas (MCAs). **The centroids were calculated using the GeoDa software. In the menu option of GeoDa, centroids are central points. Central points are the average of the x and y coordinates of a polygon's vertices.

state. The micro-regions were grouped according to natural and production characteristics. Meso-regions are larger areas than the micro-regions and were also proposed by IBGE. This spatial scale is based on the following dimensions: the social aspects, the natural setting, and the communication and place network as an element of space articulation.

The information in the panel data was collected from IPEADATA (Institute of Applied Economic Research—Instituto de Pesquisa Econômica Aplicada), which has organized the population census information (from IBGE) of 1970, 1980, 1991, and 2000. From these data points, the dependent variable is the averaged annual income per capita growth rates for each time span; that is, the panel data set contains three time periods: 1970–1980, 1980–1991, and 1991–2000. Per capita income information is deflated to Real (R\$, the Brazilian currency) in 2000. The income per capita growth rates are averaged over ten years because MCA data is 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 [67]. 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. However, the chosen periods may be influencing the results, and specific problems might emerge when business cycles are not symmetric across space. 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. (Population growth is adjusted for depreciation (δ) and technological growth (g), under the usual assumption that $\delta + g$ equals 0.05 (e.g., [14]). The natural log of this variable is not taken because it has some negative values.) Logged transportation costs between MCAs and São Paulo city are from IPEADATA. These transportation cost data are for the years 1968, 1980, and 1995. This variable for 1970 and 1991 is estimated via interpolation. The cost of transportation to São Paulo is calculated through a linear program procedure as the minimum cost (given road and vehicle conditions) of traveling between a MCA's major headquarters and São Paulo. 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). Table 3 presents the correlation matrix of the explanatory variables. Table 4 shows the summary statistics of the variables in the panel.

A spatial weight (W) matrix is used to model spatial relationships between regions to calculate the Moran's I statistic discussed in the previous section. Pure geographical weights are considered, which are exogenous, to mitigate endogeneity problems. The W matrices used herein are based on geographical distance (distance between centroids) with the same fixed-distance critical cut-off for all regions. The $n \times n$ standardised W matrix provides the "structure" of spatial relationships by defining neighbouring areas that should be connected. In this paper, given the uneven size of the spatial units, distance-based W matrices are employed. Furthermore, the results using distance-based W matrices are comparable across spatial scales, and these W matrices allow for measuring the extent of the spatial autocorrelation (in kilometres) across those spatial scales. Specifically, the element w_{ij} in the matrix is 1 if areas i and j are within " d " kilometres, and 0 otherwise. Moreover, by convention, the diagonal elements $w_{ii} = 0$. Table 1 shows the minimum distance " d " between centroids to ensure connectivity for all spatial units in each spatial scale. For instance, at the MCA level, the minimum distance between centroids to ensure connectivity for all MCAs is 400 kilometres. On the other hand, a cut-off distance of 786.5 kilometres is needed to ensure connectivity for all states. Given these minimum cut-off distances, I have chosen the following cut-offs (in kilometres) to conduct the analysis of the extent of spatial autocorrelation: 400 (only MCAs), 500 (only MCAs and micro-regions (actually, for the micro-regional level, the initial cut-off is 520 kilometres, which is the minimum distance between centroids to ensure connectivity for all micro-regions.)), 600 (MCAs, micro- and meso-regions), 700 (MCAs, micro- and meso-regions), 800 (all scales), 900 (all), 1,000 (all), 1,500 (all), and 2,000 (all). This criterion avoids a situation in which rows and columns in W have only zero values. (Le Gallo and Ertur [86] note that if unconnected observations are found, they are implicitly eliminated from the computed global Moran's I statistic, but this leads to a change in the sample size and thus must be explicitly accounted for in statistical inference.) The bottom part of Table 1 shows the average number of neighbouring regions using alternative distance-based matrices. The results using these spatial weight matrices based on different cut-off distances are shown in the next section. In addition, the standardised first-order contiguity matrix (also called the queen contiguity matrix) is used for comparative purposes, in which the element w_{ij} in the matrix is 1 if areas i and j share borders or vertices, and 0 otherwise.

5. Results

This section aims to report and to discuss the results of growth regressions at four spatial scales (MCAs, micro-regions, meso-regions, and states), applying four alternative panel data methods (pooled OLS, fixed-effects (FE), first

difference (FD), and SYS-GMM). The empirical strategy was to include all available data in the models to try to control for factors that drive economic growth and also may explain spatially autocorrelated economic growth. Therefore, the diagnostics for spatial autocorrelation in the residuals of these growth equations represents such spatial correlations that are left unexplained after controlling for some observable determinants of economic growth in Brazil. It is important to note that when conditioning variables were dropped from the models and only per capita income growth was regressed on initial per capita income (the absolute β -convergence case), the values for spatial autocorrelation in the residuals for all spatial scales and methods increased as expected. (For the absolute β -convergence case, estimations at all spatial scales suffer from higher spatial autocorrelation than the conditional β -convergence ones, because the Moran's I statistics in the residuals of former estimations present the highest values.) For instance, Silveira-Neto and Azzoni [40] found that after conditioning their models on variables with strong geographic patterns across states in Brazil, spatial dependence disappeared. These authors suggest that statistically significant explanatory variables reveal the potential channels through which spatial dependence in the process of income convergence may occur.

The baseline specification (1) is estimated via pooled OLS for the four spatial scales under analysis. Spatial dependence was assessed by applying the Moran's I statistics in the error terms. Table 2 shows the results for these estimations in columns (1), (5), (9), and (13). This specification includes all the available explanatory variables and time dummies for the decades of 1980 and 1990 that control for time-specific effects. Of note, high R -squared values can be observed in all estimations. For instance, the R -squared in column 1 (pooled OLS at the AMC level) is 0.805. However, if the time dummies are dropped from the regression the R -squared goes to 0.4520 (not shown in Table 2). It means that time dynamics has a relevant explanatory power in the Brazilian case. This fact is observed for all estimation techniques and spatial scales. Moreover, unobserved heterogeneity between areas might be an important issue in the current analysis. To take into account this aspect, three panel data methods are used to control for unobserved heterogeneity between areas that may be helpful in dealing—at least partially—with unobservable factors that can be correlated across neighbouring areas. The growth regression specifications represented by (2) and (3) are estimated, which represent, respectively, the fixed-effect (FE) and first-difference (FD) methods. Table 2 presents the results for the FE estimations in columns (2), (6), (10), and (14) and for the FD estimations in columns (3), (7), (11), and (15). In addition, the SYS-GMM estimations aim to alleviate biases due to endogenous explanatory variables, and their results are in columns (4), (8), (12), and (16). However, the SYS-GMM results should be viewed with caution because the Sargan/Hansen tests are rejected under the null hypothesis that instruments are valid—for regressions at the four spatial scales—suggesting that the instruments of the GMM-SYS are not valid. This indicates that the use of the GMM-SYS might be adding more endogeneity to the system. Unfortunately, due to data unavailability, this empirical exercise uses only

TABLE 2: Panel data model results and diagnostics for spatial autocorrelation.

Spatial scale Method	Minimum comparable area (MCA)				Micro-region				Meso-region				State			
	OLS (1)	FE (2)	FD (3)	SYS-GMM (4)	OLS (5)	FE (6)	FD (7)	SYS-GMM (8)	OLS (9)	FE (10)	FD (11)	SYS-GMM (12)	OLS (13)	FE (14)	FD (15)	SYS-GMM (16)
Explanatory variables																
In (income per capita)	-0.0290*** (0.0007)	-0.1051*** (0.0010)	-0.1250*** (0.0010)	-0.0681*** (0.0101)	-0.0305*** (0.0016)	-0.0851*** (0.0028)	-0.1084*** (0.0027)	-0.0348*** (0.0078)	-0.0346*** (0.0032)	-0.0779*** (0.0057)	-0.1072*** (0.0057)	-0.0327*** (0.0126)	-0.0487*** (0.0084)	-0.0931*** (0.0120)	-0.1135*** (0.0127)	-0.0480 (0.0300)
Population growth ($n + g + d$)	-0.0164 (0.0112)	0.0244 (0.0180)	0.0282 (0.0180)	0.4190*** (0.1099)	-0.0095 (0.0211)	-0.0516 (0.0394)	0.0104 (0.0366)	0.2770*** (0.0990)	0.0203 (0.0432)	-0.1475 (0.0918)	-0.0203 (0.0897)	0.2643 (0.1635)	-0.0100 (0.0893)	-0.1947 (0.1471)	0.00746 (0.1548)	0.4272 (0.2833)
In (years of schooling)	0.0091*** (0.0004)	0.0009** (0.0004)	0.0015*** (0.0005)	0.0122*** (0.0040)	0.0263*** (0.0015)	0.0039 (0.0028)	0.0050 (0.0031)	-0.0020 (0.0070)	0.0303*** (0.0032)	0.0124** (0.0056)	0.0166*** (0.0064)	0.0233** (0.0119)	0.0457*** (0.0095)	0.0242* (0.0134)	0.0314** (0.0159)	0.0686** (0.0322)
In (population density)	-0.0006*** (0.0002)	-0.0089*** (0.0013)	-0.0098*** (0.0015)	-0.0066*** (0.0015)	-0.0013*** (0.0003)	-0.0132 (0.0024)	-0.0121*** (0.0027)	-0.0054 (0.0040)	-0.0011*** (0.0005)	-0.0183*** (0.0047)	-0.0155*** (0.0053)	0.0094 (0.0063)	-0.0021* (0.0011)	-0.0141* (0.0084)	-0.0094 (0.0098)	0.0106 (0.0089)
In (transportation cost to SP)	-0.0129*** (0.0004)	0.0056* (0.0028)	0.0031 (0.0028)	-0.0307*** (0.0059)	-0.0067*** (0.0006)	0.0106** (0.0050)	0.0151*** (0.0046)	-0.0281*** (0.0068)	-0.0071*** (0.0011)	0.0120 (0.0084)	0.0173** (0.0077)	0.0015 (0.0109)	-0.0101*** (0.0028)	0.0468*** (0.0161)	0.0476*** (0.0152)	0.0096 (0.0167)
Constant	0.3026*** (0.0052)	0.4060*** (0.0226)	0.0076*** (0.0014)	0.5623*** (0.0750)	0.2552*** (0.0091)	0.3722*** (0.0418)	-0.0022 (0.0030)	0.4332*** (0.0778)	0.2708*** (0.0167)	0.3596*** (0.0729)	-0.0043 (0.0058)	0.1526 (0.1304)	0.3463*** (0.0443)	0.1260 (0.1375)	0.0097 (0.0122)	0.1064 (0.2439)
Time dummies	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Observations	10,971	10,971	7,314	10,971	1,566	1,566	1,044	1,566	402	402	268	402	81	81	54	81
R-squared	0.805	0.923	0.954	—	0.910	0.960	0.978	—	0.935	0.969	0.983	—	0.940	0.977	0.987	—
Adjusted R-squared	0.805	0.884	0.954	—	0.909	0.940	0.978	—	0.934	0.953	0.983	—	0.934	0.961	0.985	—
Diagnostics for spatial autocorrelation:																
Moran's I in the residuals (70s)	0.2737***	0.3411***	—	0.4541***	0.3640***	0.3558***	—	0.4807***	0.2630***	0.1201**	—	0.4354***	0.1439	-0.1471	—	-0.0366
Moran's I in the residuals (80s)	0.2704***	0.1555***	0.2816***	0.4001***	0.3665***	0.3388***	0.3330***	0.3668***	0.1436***	0.2358***	0.0847*	0.5517***	0.0018	0.0570	-0.1174	0.1483
Moran's I in the residuals (90s)	0.2426***	0.3189***	0.2656***	0.3992***	0.3978***	0.4231***	0.4358***	0.4385***	0.4778***	0.4166***	0.4964***	0.5328***	0.3306**	0.2397**	0.2016*	0.3197**
Moran's I in the averaged residuals	0.4529***	++	0.4029***	0.5357***	0.4490***	++	0.4459***	0.4610***	0.3380***	++	0.2911***	0.5996***	0.0586	++	0.1000	0.1210

Note: standard errors in parentheses; *** significant at 1%; ** significant at 5%; * significant at 10%. Moran's I significance test based on the permutation approach with ten thousand permutations and the spatial weight matrix is the queen contiguity matrix. ++ For fixed-effects (FE) estimations, the time-averaged residuals are zero by construction; therefore Moran's I statistics are not calculated. All SYS-GMM results are from the one-step estimates and include 11 instruments. In all SYS-GMM estimations, all growth determinants are treated as potentially endogenous.

TABLE 3: (a) Correlation matrix of the explanatory variables (minimum comparable areas, MCAs). (b) Correlation matrix of the explanatory variables (micro-regions). (c) Correlation matrix of the explanatory variables (meso-regions). (d) Correlation matrix of the explanatory variables (states).

(a)

Explanatory variables	1	2	3	4	5
1 $\ln(\text{income per capita})$	1	0.18	0.68	0.22	-0.69
2 $(n + g + d)$	0.18	1	0.08	0.07	-0.05
3 $\ln(\text{average years of schooling})$	0.68	0.08	1	0.21	-0.54
4 $\ln(\text{population density})$	0.22	0.07	0.21	1	-0.30
5 $\ln(\text{transportation cost to SP})$	-0.69	-0.05	-0.54	-0.30	1

Note: own elaboration. Number of observations = 10,971.

(b)

Explanatory variables	1	2	3	4	5
1 $\ln(\text{income per capita})$	1	0.16	0.85	0.26	-0.67
2 $(n + g + d)$	0.16	1	0.06	-0.21	0.07
3 $\ln(\text{average years of schooling})$	0.85	0.06	1	0.34	-0.63
4 $\ln(\text{population density})$	0.26	-0.21	0.34	1	-0.47
5 $\ln(\text{transportation cost to SP})$	-0.67	0.07	-0.63	-0.47	1

Note: own elaboration. Number of observations = 1,566.

(c)

Explanatory variables	1	2	3	4	5
1 $\ln(\text{income per capita})$	1	0.13	0.87	0.29	-0.62
2 $(n + g + d)$	0.13	1	0.02	-0.37	0.24
3 $\ln(\text{average years of schooling})$	0.87	0.02	1	0.38	-0.59
4 $\ln(\text{population density})$	0.29	-0.37	0.38	1	-0.54
5 $\ln(\text{transportation cost to SP})$	-0.62	0.24	-0.59	-0.54	1

Note: own elaboration. Number of observations = 402.

(d)

Explanatory variables	1	2	3	4	5
1 $\ln(\text{income per capita})$	1	0.03	0.88	0.21	-0.55
2 $(n + g + d)$	0.03	1	-0.10	-0.60	0.44
3 $\ln(\text{average years of schooling})$	0.88	-0.10	1	0.27	-0.52
4 $\ln(\text{population density})$	0.21	-0.60	0.27	1	-0.69
5 $\ln(\text{transportation cost to SP})$	-0.55	0.44	-0.52	-0.69	1

Note: own elaboration. Number of observations = 81.

TABLE 4: Summary statistics of the variables in the panel (1970–2000).

Variables		States	Meso-regions	Micro-regions	MCAs*
Average annual income per capita growth rates between 1970 and 1980, 1980 and 1991, and 1991 and 2000	Mean	0.0473	0.0475	0.0473	0.0483
	Minimum	−0.0266	−0.0756	−0.0786	−0.1934
	Maximum	0.1088	0.1329	0.1558	0.3709
	Std. dev.	0.0422	0.0467	0.0485	0.0541
ln (income per capita), 1970, 1980 and 1991	Mean	4.6197	4.4842	4.3288	4.1966
	Minimum	3.2472	2.9627	2.5869	0.2718
	Maximum	5.8605	5.9564	6.0514	6.2442
	Std. dev.	0.5981	0.6674	0.6955	0.7041
$(n + g + d)$, 1970, 1980, and 1991	Mean	0.0778	0.0701	0.0656	0.0594
	Minimum	0.0581	0.0238	−0.0221	−0.1197
	Maximum	0.1986	0.1986	0.3220	0.3220
	Std. dev.	0.0210	0.0180	0.0197	0.0212
ln (years of schooling), 1970, 1980, and 1991	Mean	0.9977	0.8516	0.7102	0.5803
	Minimum	−0.1039	−0.7391	−1.3856	−46.0517
	Maximum	2.0015	2.0015	2.0015	2.1748
	Std. dev.	0.4890	0.6064	0.6533	0.8238
ln (population density), 1970, 1980, and 1991	Mean	2.5834	2.9085	3.0423	3.2179
	Minimum	−1.7278	−2.2713	−3.9118	−3.9118
	Maximum	5.6895	7.4888	8.5627	9.4510
	Std. dev.	1.7605	1.6641	1.4901	1.2664
ln (transportation cost to SP), 1970, 1980, and 1991	Mean	7.7425	7.4226	7.3370	7.2085
	Minimum	5.3315	4.6706	3.7987	2.3026
	Maximum	9.2782	9.5446	9.6053	9.6175
	Std. dev.	0.8386	0.9197	0.9345	0.8734
Observations		81	402	1,566	10,971

Note: own elaboration. * Minimum comparable areas (MCAs).

three time periods ($T = 3$), a fact that does not allow for using lags of earlier periods as instruments that might be more exogenous. In this sense, Roodman [81] points out that “[w]here system GMM offers the most hope, it may offer the least help.” Nevertheless, the SYS-GMM results are shown for comparative purposes.

First, it is important to examine the magnitude of the estimated coefficients at a variety of geographic scales. The coefficients of initial income per capita are negative and statistically significant in all estimations except for the SYS-GMM estimation at the state level (column 16 in Table 2), where the coefficient is not statistically significant. This negative correlation between the growth rate and the initial per capita income suggests mean reversion, conditional β -convergence, or both. Of note, given the estimation method, the coefficients of the initial income per capita are relatively similar at different spatial scales. For instance, using the pooled OLS method, the coefficient is -0.0290 (s.d. = 0.0007) at the MCA level and -0.0305 (s.d. = 0.0016) at the micro-regional level. On the other hand, the coefficient of the initial income per capita, using the FE method, is -0.1051 (s.d. = 0.0010) at the MCA level and -0.0851 (s.d. = 0.0028) at the micro-regional level. Therefore, it seems that distortions of conditional β -convergence coefficients due to panel data method choices are

much larger than variations due to the spatial scale of analysis. Indeed, Islam [1] provides a statistical explanation for the faster convergence rate in the FE framework compared to the pooled OLS approach (see also the seminal paper of Nickell [77]). He shows that in the framework of single cross-section regression (or even, pooled OLS regressions), 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, $(\dots)$, is also positive. Thus, the estimated coefficient of $y_{i,t-1}$ is biased upward. $(\dots)$ This explains why we get lower convergence rates from single cross-section regressions and pooled regressions that ignore correlated individual country effects” Islam [1].

Here, the same intuition provided by Islam [1] can be used to present the results, which indicate 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 at all spatial scales. Then, he points out “[c]ontrary to what may appear at first sight, the finding of a higher rate of conditional convergence actually calls for more policy activism” [1]. Improvements in these unobserved factors (e.g., technology levels and institutions) may have direct positive effects on the region’s long-run income level, including a higher transitional growth rate. Abreu et al. [87] also argue that as regional-fixed effects control unobserved heterogeneity, the results that include fixed effects lead to higher estimates of the rate of convergence. Of note, when the spatial distribution of these fixed-effect terms is analysed, it is possible to observe a clustering of high values in the south, southeast, and central-west of Brazil at the MCA spatial scale, for instance (see Figure 7). This fact suggests that fixed effects are really capturing a higher level of, for example, technology and institutions in the south, southeast, and central-west which are the most developed areas in Brazil. However, this spatial distribution of the fixed effects is not able to mitigate the spatial autocorrelation that is presented in the errors of the regression as discussed below.

Furthermore, it is worth noting that the club convergence hypothesis cannot be ruled out given the growing evidence that this hypothesis is the correct one for the Brazilian case [3, 42, 44, 88]. Interestingly, as noted by Islam [1] “*instead of adopting the panel data approach, the other way to control for differences in technology and institutions is to classify the countries into similar groups*.” The panel data approach with fixed effects allows for differences in the aggregate production function across individual regions (MCA, micro-region, meso-region, or state), and the club convergence analysis allows for differences in the aggregate production function across groups of regions. Both approaches obtain higher rates of convergence when the results are compared to the estimations that do not control for such differences.

If the variability of other estimated coefficients is analysed at different geographic scales, it suggests that the choice of the spatial scale is more important than the panel data method choice. For instance, the average-year-of-schooling coefficient may carry information about the strength of the spatial interactions across individuals and regions, a phenomenon that coined the “social multiplier” effect by Glaeser et al. [63]. The strategy followed by Glaeser et al. [63] returns to the exploration of the ecological fallacy literature, which demonstrates that the estimated coefficients in aggregate models represent a blend of individual and contextual effects [62, 89]. Herein, there are not estimations at the individual level, yet it is possible to give some evidence of this social multiplier effect if the MCA level—which should be assumed to be the microlevel of analysis (instead of the individual)—is compared with the estimations using another aggregate level (e.g., micro-regional, meso-regional or state level). For instance, the years-of-schooling coefficient at the MCA level is 0.0091 (s.d. = 0.0004) and at the state

level is 0.0457 (s.d. = 0.0095) using the pooled OLS method. (Results based on standardised coefficients provide similar qualitative findings. To move from the metric to the standardised coefficients, the following formula should be applied: $\theta_k \text{ standardized} = \theta_k \text{ unstandardized} \times (Sx_k/Sg)$, where θ_k represents the coefficients of the explanatory variable k , Sx_k is the standard deviation of the explanatory variable K and Sg is the standard deviation of the dependent variable. Table 4 provides the standard deviations of all variables) This result is in line with the social multiplier argument, suggesting that there are human capital spillovers.

The coefficients of population growth are statistically not significant for all estimations, excepting the SYS-GMM estimations at the MCA and micro-regional levels. As noted by Barro and Sala-I-Martin [17], “*the growth of population reflects the behavior of fertility, mortality, and migration*.” Population growth effects on economic growth may present different results across different spatial scales, because migration pattern—which is one component of population growth—may vary across different scale levels (e.g., intra- versus interregional migration). For instance, the contrast in area sizes means that daytime commuting across municipalities can be more significant if compared to states. Of note, unlike newly born persons, migrants come with accumulated human capital, and for this reason, the results depend on whether immigrants have more or less human capital (i.e., are typically skilled or unskilled) than the residents of the receiving region (see Chapter 9 in [17]). It is probably because of a balance between countervailing effects, the population growth coefficient may become statistically insignificant. Other variables under analysis are population density and transportation cost to São Paulo. Population density coefficients might present different results for the different spatial scales being analysed because the strength of agglomeration effects might vary with the size of the spatial unit (e.g., agglomeration-related centripetal forces may be much more relevant at the municipal than at the state level); in addition, analysing the influence of reductions in transportation costs on economic growth at multiple scale levels allows us to distinguish, for instance, this influence within the borders of a state from that occurring between states. Population density coefficients are negative and statistically significant at the 1% level on the MCA, micro- and meso-regional spatial scales; however, the coefficients are no longer significant at the 5% level on the state-level stratification. These results are contrary to the argument that agglomeration effects foster 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 be operating for the analysed period (1970–2000). For the pooled OLS results, the transportation cost coefficients are statistically significant (and negative) at all spatial scales. This finding indicates that reductions in transportation costs over the period of 1970 to 2000 have a positive impact on economic growth at all Brazilian scales. The analysis of FE and FD results reveal that reductions in transportation costs may have a negative impact on economic growth. However, these latter results might be imprecise because these estimates control for fixed effects

when transportation costs already have a clear component that is fixed, the distance between each spatial unit and the spatial unit represented by São Paulo. Therefore, the FE and FD estimates for the transportation cost coefficients might only be picking up the variable part of transportation costs (for instance, roads conditions or quality). Furthermore, the SYS-GMM results show the significance of the coefficients for the transportation costs at the MCA and micro-regional levels, suggesting that reductions in transportation costs had a positive impact on growth only within the borders of the meso-regions and states between 1970 and 2000; a fact that has already been documented by Resende [3] for the 1990s in Brazil.

Finally, the bottom part of Table 2 shows the spatial autocorrelation diagnostics using a first-order contiguity matrix (the queen contiguity matrix) for all spatial scales and methods. The test is based on Moran's I statistic applied to cross-sectional residuals generated by the panel data estimations. This approach allows for measuring the strength of spatial autocorrelation in the residuals across three decades (1970s, 1980s, and 1990s). Moreover, Moran's I statistics in the time-averaged residuals are calculated to provide an idea of the average pattern of spatial autocorrelation over the whole period of analysis. For fixed-effects (FE) estimations, the time-averaged residuals are zero by construction and, therefore, Moran's I statistics are not calculated. A preliminary spatial analysis of the residuals using the most common contiguity matrix (i.e., the queen matrix) shows that spatial phenomena might be relevant for the study of Brazilian regional growth determinants, depending on the spatial scale of analysis. Indeed, growth estimations at the state level using four econometric methods show weak evidence of spatial autocorrelation across the error terms. In sum, Moran's I statistics are not statistically significant in cross-sectional and time-averaged residuals at the state level. Only in the residuals from the period of the 1990s is Moran's I statistically significant at the 5% level (in the pooled OLS, FE, and SYS-GMM specifications). On the other hand, spatial autocorrelation in the residuals has been detected at three other spatial scales (MCAs, micro-regions, and meso-regions) using alternative econometric methods. These results suggest that standard panel data methods (pooled OLS, FE, FD, and SYS-GMM) do not have the ability to deal completely with spatial phenomena in the Brazilian regional growth case. However, this preliminary conclusion can be subjected to the choice of the queen W matrix. For this reason, subsequently, a sensitivity analysis is conducted using alternative distance-based W matrices. Among other advantages, this kind of W matrix can indicate the degree to which spatial autocorrelation behaves with geographical distance.

Of note, Baltagi and Pirotte [90] pointed out that tests of hypothesis based on the standard panel data estimators that ignore spatial dependence can lead to misleading inference. Specifically, these authors investigate the standard panel data estimators under spatial dependence using Monte Carlo experiments. This fact highlights that the coefficients analysed above should be interpreted with caution. The analyses of the residuals of the regressions conducted in

this paper investigate the presence and extent of the spatial autocorrelation in errors of the standard panel data models across multiple spatial scales. This descriptive analysis is a first step in implementing a framework to measure and interpret the presence of spatial spillovers using spatial data models across multiple spatial scales. For instance, for some spatial scales there may be some spatial process that needs the use of spatial econometrics; for other scales the use of spatial econometrics might not be necessary because the spatial autocorrelation does not appear in the residuals.

Table 5 reports the evolution of the spatial autocorrelation in the cross-sectional residuals derived from the panel data estimations at multiple levels of spatial aggregation over the period 1970–2000 using the Moran's I statistic. Three decades are analysed separately: the 1970s, 1980s, and 1990s. Furthermore, Table 6 documents the assessment of spatial autocorrelation in the time-averaged residuals. As explained earlier, Moran's I is a global measure of spatial correlation, which evaluates the degree of similarity or dissimilarity among values in spatially close areas. Along with the test statistics presented in columns (1) to (16), Tables 5 and 6 provide the associated significance level (***) significant at 1%, ** significant at 5%, * significant at 10%) based on the permutation approach with 10,000 permutations. The results for alternative weight matrices based on different cut-off distances of 400, 500, 600, 700, 800, 900, 1,000, 1,500, and 2,000 kilometres are listed.

For a better illustration of the results in Table 5, Figures 1, 2, and 3 present Moran's I statistics in the residuals of pooled OLS estimations on the y -axis and the cut-off distances in the x -axis, respectively, for the 1970s, 1980s, and 1990s. These figures have the following interesting features. First, irrespective of the spatial weight matrix used, there is evidence that the residuals of growth estimations have become more clustered over time, except at the MCA level. Indeed, spatial autocorrelation in the 1990s is at the highest level at the micro-regional, meso-regional, and state levels. The positive signs of Moran's I indicate that the error terms are becoming more and more similar among neighbouring spatial units. In other words, a positive spatial autocorrelation demonstrates that areas with relatively high (low) residual values—which may be explained by unobservable variables—are located close to other areas with relatively high (low) residual values more often than it would be observed if their locations were purely random. This similar pattern can be observed when FE and FD methods are used (see Table 5).

Secondly, focusing on the analysis of the spatial autocorrelation in each decade, the results show evidence that the magnitude of interactions varies at different spatial scales and declines with distance. Indeed, at the MCA and the micro-regional levels, the spatial autocorrelation in residuals shows a decay trend, and it is statistically significant across distances of more than 1,500 kilometres, but the spatial autocorrelation is largely reduced when the distance is more than 900 kilometres, in particular for the 1970s and 1980s. At the meso-regional level, the values of the Moran's I statistics suggest that the spatial linkages decrease steadily over distances up to 900–1,000 kilometres, beyond which the null hypothesis of no spatial correlation cannot be rejected (at least for the

TABLE 5: Diagnostics for spatial autocorrelation by means of Moran's I in the cross-sectional residuals of the estimations of Table 2.

Spatial scale Method	Minimum comparable area (MCA)				Micro-region				Meso-region				State			
	OLS (1)	FE (2)	FD (3)	SYS- GMM (4)	OLS (5)	FE (6)	FD (7)	SYS- GMM (8)	OLS (9)	FE (10)	FD (11)	SYS- GMM (12)	OLS (13)	FE (14)	FD (15)	SYS- GMM (16)
Spatial weight matrix: 400 km																
Moran's I in the residuals (70's)	0.1204***	0.1306***	—	0.2238***	—	—	—	—	—	—	—	—	—	—	—	—
Moran's I in the residuals (80's)	0.1106***	0.0677***	0.1122***	0.1729***	—	—	—	—	—	—	—	—	—	—	—	—
Moran's I in the residuals (90's)	0.1033***	0.1286***	0.1104***	0.1963***	—	—	—	—	—	—	—	—	—	—	—	—
Spatial weight matrix: 500 km																
Moran's I in the residuals (70's)	0.1046***	0.1069***	—	0.1897***	0.1546***	0.1951***	—	0.2065***	—	—	—	—	—	—	—	—
Moran's I in the residuals (80's)	0.0855***	0.0471***	0.0863***	0.1431***	0.1296***	0.1458***	0.1399***	0.1757***	—	—	—	—	—	—	—	—
Moran's I in the residuals (90's)	0.0741***	0.1039***	0.0867***	0.1608***	0.2291***	0.2572***	0.2463***	0.1861***	—	—	—	—	—	—	—	—
Spatial weight matrix: 600 km																
Moran's I in the residuals (70's)	0.0890***	0.0857***	—	0.1605***	0.1252***	0.1511***	—	0.1623***	0.1407***	0.1388***	—	0.3561***	—	—	—	—
Moran's I in the residuals (80's)	0.0661***	0.0300***	0.0668***	0.1195***	0.0938***	0.1116***	0.1075***	0.1498***	0.1634***	0.2643***	0.1394***	0.4788***	—	—	—	—
Moran's I in the residuals (90's)	0.0482***	0.0800***	0.0641***	0.1295***	0.1955***	0.2117***	0.2033***	0.1409***	0.4009***	0.3118***	0.3740***	0.4324***	—	—	—	—
Spatial weight matrix: 700 km																
Moran's I in the residuals (70's)	0.0771***	0.0687***	—	0.1418***	0.0915***	0.1212***	—	0.1180***	0.1374***	0.1006***	—	0.3416***	—	—	—	—
Moran's I in the residuals (80's)	0.0513***	0.0174***	0.0516***	0.1022***	0.0690***	0.0847***	0.0816***	0.1243***	0.1319***	0.2297***	0.1049***	0.4151***	—	—	—	—
Moran's I in the residuals (90's)	0.0283***	0.0617***	0.0472***	0.1053***	0.1641***	0.1813***	0.1722***	0.0942***	0.3633***	0.2768***	0.3314***	0.4125***	—	—	—	—
Spatial weight matrix: 800 km																
Moran's I in the residuals (70's)	0.0676***	0.0518***	—	0.1270***	0.0668***	0.0891***	—	0.0807***	0.0739***	0.0990***	—	0.3077***	0.2449***	—0.2716*	—	—0.0141
Moran's I in the residuals (80's)	0.0388***	0.0100***	0.0379***	0.0869***	0.0533***	0.0631***	0.0558***	0.0990***	0.0857***	0.1460***	0.0665***	0.3691***	0.1096	0.1805*	—0.1362	0.1021
Moran's I in the residuals (90's)	0.0159***	0.0478***	0.0362***	0.0873***	0.1381***	0.1539***	0.1468***	0.0574***	0.3456***	0.2976***	0.3196***	0.3718***	0.4721***	0.3318**	0.2930**	0.4296***
Spatial weight matrix: 900 km																
Moran's I in the residuals (70's)	0.0611***	0.0364***	—	0.1157***	0.0463***	0.0630***	—	0.0534***	0.0247	0.0084	—	0.2823***	0.1646	—0.2583*	—	—0.0463
Moran's I in the residuals (80's)	0.0282***	0.0077***	0.0258***	0.0727***	0.0342***	0.0505***	0.0318***	0.0775***	0.0385**	0.1088***	0.0091	0.3263***	0.0588	0.1788*	—0.1779	0.1086
Moran's I in the residuals (90's)	0.0124***	0.0389***	0.0311***	0.0758***	0.1314***	0.1418***	0.1381***	0.0373***	0.2867***	0.2192***	0.2595***	0.3350***	0.5725***	0.3763***	0.3631**	0.4639***
Spatial weight matrix: 1000 km																
Moran's I in the residuals (70's)	0.0573***	0.0249***	—	0.1082***	0.0322***	0.0410***	—	0.0381***	—0.0059	—0.0280	—	0.2380***	0.0452	—0.0971	—	—0.1078
Moran's I in the residuals (80's)	0.0215***	0.0080***	0.0168***	0.0625***	0.0273***	0.0461***	0.0152***	0.0626***	0.0254*	0.0946	—0.0163	0.3020***	0.2046**	0.2634**	0.0596	0.0953
Moran's I in the residuals (90's)	0.0131***	0.0336***	0.0293***	0.0699***	0.1258***	0.1277***	0.1291***	0.0210***	0.2774***	0.2018***	0.2529***	0.3090***	0.3320***	0.0920	0.1167*	0.3531***
Spatial weight matrix: 1500 km																
Moran's I in the residuals (70's)	0.0417***	0.0111***	—	0.0778***	0.0125***	0.0092**	—	0.0176***	—0.0009	—0.0367**	—	0.1562***	—0.0569	—0.1001	—	—0.1803***
Moran's I in the residuals (80's)	0.0055***	0.0018***	0.0030***	0.0276***	0.0190***	0.0375***	—0.0040	0.0296***	—0.0054	0.0518***	—0.0354***	0.1892***	0.0718*	0.1255**	0.0067	—0.0171
Moran's I in the residuals (90's)	0.0154***	0.0253***	0.0233***	0.0537***	0.1034***	0.0827***	0.0920***	0.0114***	0.2035***	0.1319***	0.1689***	0.1993***	0.2859***	0.0770	0.0765*	0.2449***
Spatial weight matrix: 2000 km																
Moran's I in the residuals (70's)	0.0189***	0.0042***	—	0.0399***	0.0030**	0.0049**	—	0.0155***	—0.0119	—0.0171	—	0.0749***	—0.0839	—0.0643	—	—0.0618
Moran's I in the residuals (80's)	—0.0026***	0.0005***	—0.0018***	0.0099***	0.0047**	0.0267***	—0.0078***	0.0168***	0.0014	0.0521***	—0.0273***	0.1238***	0.0780**	—0.0146	—0.0801	0.0635***
Moran's I in the residuals (90's)	0.0120***	0.0189***	0.0184***	0.0317***	0.0710***	0.0597***	0.0666***	0.0116***	0.1370	0.0922***	0.1209***	0.1180***	0.1145**	0.0247	—0.0096	0.1253***

Note: *** significant at 1%, ** significant at 5%, * significant at 10% based on the permutation approach with 10,000 permutations.

TABLE 6: Diagnostics for spatial autocorrelation by means of Moran's I in the time-averaged residuals of the estimations of Table 2.

Spatial scale	Minimum comparable area (MCA)				Micro-region			Meso-region			State					
Method	OLS (1)	FE (2)	FD (3)	SYS- GMM (4)	OLS (5)	FE (6)	FD (7)	SYS- GMM (8)	OLS (9)	FE (10)	FD (11)	SYS- GMM (12)	OLS (13)	FE (14)	FD (15)	SYS- GMM (16)
Diagnostics for spatial autocorrelation—Spatial weight matrix:																
400 km cut-off	0.1983***	++	0.1621***	0.2589***	—	++	—	—	—	++	—	—	—	++	—	—
500 km cut-off	0.1586***	++	0.1331***	0.2184***	0.1401***	++	0.2577***	0.1653***	—	++	—	—	—	++	—	—
600 km cut-off	0.1262***	++	0.1076***	0.1852***	0.1156***	++	0.2134***	0.1274***	0.1742***	++	0.2561***	0.4874***	—	++	—	—
700 km cut-off	0.1010***	++	0.0874***	0.1614***	0.0842***	++	0.1812***	0.0835***	0.1373***	++	0.2070***	0.4484***	—	++	—	—
800 km cut-off	0.0810***	++	0.0685***	0.1416***	0.0601***	++	0.1488***	0.0487***	0.0950***	++	0.2224***	0.4130***	0.1718*	++	0.0158	0.1334
900 km cut-off	0.0675***	++	0.0524***	0.1253***	0.0448***	++	0.1292***	0.0239***	0.0785***	++	0.1493***	0.3990***	0.0947	++	0.0765	0.1026
1,000 km cut-off	0.0600***	++	0.0409***	0.1148***	0.0387***	++	0.1104***	0.0080***	0.0707***	++	0.1258***	0.3623***	0.0561	++	0.0160	0.0481
1,500 km cut-off	0.0459***	++	0.0274***	0.0784***	0.0318***	++	0.0687***	−0.0053	0.0304***	++	0.0789***	0.2300***	−0.0573	++	0.0358	−0.0594
2,000 km cut-off	0.0236***	++	0.0169***	0.0417***	0.0106***	++	0.0441***	0.0053*	−0.0029	++	0.0480***	0.1267***	−0.0783	++	0.0098	0.0286

Note: *** significant at 1%, ** significant at 5%, * significant at 10% based on the permutation approach with ten thousand permutations. The residuals of the panel data estimations were time averaged and then Moran's I statistics were calculated. ++ For fixed-effects (FE) estimations, the time-averaged residuals are zero by construction; therefore, Moran's I is not calculated.

FIGURE 1: Moran's I in the residuals of the OLS regression (1970s Period). Note: all Moran's I statistics at the state level are not statistically significant at the 1% level. Moran's I statistics using distance cut-offs of 900, 1,000, 1,500, and 2,000 kilometres at the meso-regional level are not statistically significant at the 1% level.

FIGURE 2: Moran's I in the residuals of the OLS regression (1980s Period). Note: all Moran's I statistics at the state level are not statistically significant at the 1% level. Moran's I statistics using distance cut-offs of 900, 1,000, 1,500, and 2,000 kilometres at the meso-regional level are not statistically significant at the 1% level.

1970s and 1980s). Interestingly, at the state level, where the minimum distance between centroids to ensure connectivity for all states is 800 kilometres, there is evidence of no statistical significance of Moran's I for any choice of the spatial weight matrix. The diagnostics for spatial autocorrelation by means of Moran's I in the time-averaged residuals presented in Table 6 confirms this observation. Therefore, the analysis of the residuals at multiple scale levels suggests that spatial autocorrelation may be bounded within each state.

Finally, it appears from Tables 5 and 6 that the Moran's I statistic provides similar values of residual spatial correlation for each panel data method. In other words, irrespective of the panel data strategy choice (i.e., using pooled OLS, FD, FE or SYS-GMM), the results of the Moran's I statistic are very similar. Note that for FE estimations, the time-averaged residuals are zero by construction and, therefore, Moran's I is not calculated. Figures 4, 5, and 6 illustrate this empirical evidence for the time-averaged residuals of pooled OLS, FD and SYS-GMM regressions. These results indicate that traditional dynamic panel data models were not able to address spatially autocorrelated residuals in this empirical exercise. It was expected that FE, FD and SYS-GMM methods could, at least partially, address the problem of spatially

FIGURE 3: Moran's I in the residuals of the OLS regression (1990s Period). Note: All Moran's I statistics using a distance cut-off of 2,000 kilometres at the meso-regional and state levels are not statistically significant at the 1% level.

FIGURE 4: Moran's I in the time-averaged residuals of pooled OLS regressions. Note: Moran's I statistics at the state level are not statistically significant at the 1% level. Moran's I statistic using distance cut-off of 2,000 kilometers at the meso-regional level is not statistically significant at the 1% level.

correlated omitted variables. However, the results show that the Moran's I statistics for FD and SYS-GMM estimations are very similar (or even higher) to those of pooled OLS estimations. Of note, the FE estimations were able to partially deal with spatially autocorrelated residuals because, as can be observed in Table 5, the Moran's I statistics for the FE estimations—at least for the MCA scale—are lower than those of pooled OLS estimations. For the case of SYS-GMM, this technique introduced more spatial autocorrelation in the models. Moreover, it is important to note that the state-level spatial scale was able to address the spatial autocorrelation irrespective of the panel data method choice. Therefore, this empirical exercise indicates that traditional panel data models (and the included explanatory variables) do not incorporate all of the channels of interdependence between spatial units within states.

6. Conclusions

This study provides empirical evidence that the Brazilian economic growth process between 1970 and 2000 varied according to the spatial scale under analysis. Four Brazilian geographic scales are used in the current analysis: MCAs, micro-regions, meso-regions, and states. Alternative panel

FIGURE 5: Moran's I in the time-averaged residuals of FD regressions. Note: Moran's I statistics at the state level are not statistically significant at the 1% level.

FIGURE 6: Moran's I in the time-averaged residuals of SYS-GMM regressions. Note: Moran's I statistics at the state level are not statistically significant at the 1% level. Moran's I statistics using distance cut-offs of 1,000, 1,500, and 2,000 kilometres at the micro-regional level are not statistically significant at the 1% level.

data models were systematically estimated across those spatial scales to evaluate the extent of spatial autocorrelation in the residuals of growth equations and to demonstrate that the estimated coefficients change with the geographic scale. First, it was shown that data aggregation may strongly influence coefficient sizes because they may carry information on the strength of the spatial interactions across individuals and regions, as suggested by Glaeser et al. [63]. For instance, the current analysis corroborates the notion that there are human capital spillovers by showing evidence that the magnitude of the average-years-of-schooling coefficient is much larger at the state level than the one estimated at the MCA level, which might be assumed to be the microlevel of analysis (instead of the individual level). Moreover, it has been observed that differences of conditional β -convergence coefficients due to panel data method choices are much larger than variations due to the spatial scale of analysis. For instance, faster convergence rate in the FE framework compared to the pooled OLS approach is verified. This fact indicates that persistent differences in technology levels and institutions (represented by fixed effects) are important factors in understanding economic growth across regions [1].

Regarding the analysis of the extent of residual spatial autocorrelation often detected in traditional regional growth

FIGURE 7: Spatial distribution of estimated fixed-effects at MCA level. Note: in the map, the ranges were defined using equal intervals. Estimated individual effects come from the FE estimation at minimum comparable area (MCA) in Table 2 (panel data model results and diagnostics for spatial autocorrelation), column (2).

regressions, it was shown that such spatial autocorrelation seems to vary across spatial scales. Indeed, spatial autocorrelation seems to be bounded at the state level because it appears that Moran's I statistic is not statistically significant for any choice of the spatial weight matrix, beginning from an 800-kilometre cut-off. On the other hand, although the spatial autocorrelation in residuals of the other three spatial scales shows positive and statistically significant values across distances of more than 1,500 kilometres, their levels are largely reduced when the distance is more than 900 kilometres, in particular for the 1970s and 1980s. Interestingly, an increasing clustering of the regressions' residuals over time was demonstrated, in particular over the 1990s period.

Of note, the causes of spatial correlation in the residuals are related to nuisance and substantive factors. For instance, augmented 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 [6]. Among other arguments, a plausible one is related to pecuniary externalities, such as those created by a specialised labour market or forward and backward linkages that might be the cause of externalities across regions. The traditional panel data models used herein were not able to distinguish between alternative explanations of spatial interactions across regions. Furthermore, in this

empirical exercise, the FE, FD, and SYS-GMM approaches do not completely eliminate the problem of spatially correlated omitted variables. However, it is important to note that at the state level, there is not spatial autocorrelation in the residuals of nonspatial panel data models (including the pooled OLS model) demonstrating that these models are appropriate to investigate growth determinants and convergence process in the Brazilian states case. However, for the MCAs, micro-regions, meso-regions, the results show that nonspatial panel data techniques are not able to deal completely with spatially autocorrelated residuals across those spatial units. Indeed, addressing this identification problem is still a challenging issue for the (spatial) econometric literature. One contribution of this empirical exercise is to highlight all of these features using alternative panel data strategies, demonstrating that a multiple spatial dimensional analysis may be useful to investigate regional economic growth determinants and convergence process.

Appendices

A.

See Tables 3 and 4, and Figure 7.

B.

See Tables 5 and 6.

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