SPATIAL DEPENDENCE AND REGIONAL CONVERGENCE IN BRAZIL

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Abstract: The majority of the studies on regional convergence ignore the spatial characteristics of the problem. In a recent paper Rey and Montouri (1999) considered the issue of income regional convergence on US under the spatial econometric perspective. The present paper follows the Rey and Montouri's (1999) approach and introduces some spatial econometric techniques for convergence among Brazilian states. State data over the 1970-95 period is considered. As in the US case, strong patters of spatial correlation are found during the period. The spatial econometric analysis reveals that spatial error dependence seems to be present, and by ignoring it one would cause a model misspecification.

1 Introduction

Economic analysis is increasingly focusing on issues related to the spatial dimension of problems. The importance of taking the spatial effects into account was reviewed extensively by Anselin (1988)[1] and since then, a growing literature attest to the importance of the problem and the errors and misspecifications that can occur if spatial issues are ignored in cross-sectional data analysis involving geographic units. Among such economic problems is the question of regional per capita income convergence; the current proscribed methodology would suggest that the econometric analysis of regional convergence should consider the possibility of spatial dependence among the regions. However, it was not until recently that the possibility of spatial dependence was considered in dealing with regional convergence. Rey and Montouri (1999) were the first to explicitly consider the spatial dependence in the convergence of per capita income among the U.S. states, and Fingleton (1999) was the first to apply spatial econometric techniques for the European Union.

The present paper follows Rey and Montouri (1999) and incorporates the tools of spatial econometrics in the study of convergence of per capita income among of Brazilian states. Previous studies for Brazil, for instance Azzoni (1997, 1999, 2000) and Ferreira (1996), estimate the rate of convergence among the states. These studies, however, fail to test for the presence of spatial dependence among the states.

The results of this paper indicate that the spatial effects are, in fact, relevant. The Moran's *I* statistic are significant for all years, and the tests for spatial dependence on the residuals of the estimated equations were also significant for the entire period. As expected the general model indicates the slow rate of convergence; however, the observation of the Moran's scatterplots suggests some convergence within the regions.

[1] By neglecting the possible spatial dependence one can bring misspecification problems such as biased estimated of the standard deviation under ordinary least square (OLS) is applied.

The next section provides a short review of convergence theory and approaches to spatial correlation. Section 3 reviews recent approaches to measurement of income convergence in Brazil and concludes with a description of the data to be used in the current analysis. Measures of spatial dependence for the data set are calculated in section 4, while section 5 presents the empirical results. The final section offers some concluding comments.

2 Convergence

Since the work of Baumol (1986) there has been an increasing number of papers that focus on per capita income convergence. Some of these studies focus on the cross-sectional dispersion (σ and β-convergence) while others undertake a time-series view (stochastic convergence). Barro (1991), Barro and Sala-i-Martin (1992) are examples of the first type of convergence. This paper will focus on the cross-sectional dispersion, as such, the σ and β-convergence concepts will be briefly discussed below.

2.1 σ-convergence

The idea of sigma-convergence is to use the standard deviation or the coefficient of variation (CV) to measure the cross-sectional dispersion of the log of per capita income over time. A decrease over time in the CV would indicate convergence, and an increase would indicate otherwise.

2.2 β-convergence

The other cross-sectional convergence concept is based on the idea that if poor countries grow faster than richer ones, the per capita income of the former would catch up with the latter. The simple unconditional model is given in (1):

$$\ln\left(\frac{y_{i,t+T}}{y_{i,t}}\right) = \alpha + \beta \ln(y_{i,t}) + \varepsilon_{i,t} \tag{1}$$

$y_{i,t}$ is the per capita income of state i at year t, α is a constant and β is the coefficient to be estimated. The error terms are by assumption identically independent normally distributed. The dependent variable is then the growth rate between period t and period $t+T$, while the independent variable is the log the per capita income in the initial period. Convergence requires that β is negative in (1). Chatterji (1992) has pointed out that in order to guarantee that variance of the per capita income has decreased from the initial period to the final one, i.e., beta-convergence implies sigma-convergence, and for the states to reach a steady state it is necessary that $-2 < \beta < 0$.[2]

2.3 Spatial Econometrics Approaches

The econometric modeling of spatial relations among geographic or economic units is one of most interesting, yet most difficult, tasks. In implementing econometric models for macro regions of a country, or states in one of those regions, one should not ignore the effects of spatial dependence, namely spatial autocorrelation and spatial heterogeneity, in the estimation and inferences phases, since the possibility exists that problems will arise.[3] Given the special nature of these effects, the problems involving spatial relations can be addressed using the methodology developed in field of spatial econometrics.[4] In econometrics, serial correlation has been extensively treated in the temporal dimension, and even though the problem has been much more central in other disciplines (like geography, sociology, and geology), almost no attention has been given to the spatial case in the econometric “mainstream”. However, in contrast to the time series problem, where the notion of a lagged variable can be dealt with in a straightforward way, in the spatial context, there are many possible directions of interaction, complicating the analysis in a significant way, as pointed out by Anselin (1988, chapter 3). To better understand these problems, it is necessary to introduce the concept of spatial correlation and heterogeneity.

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[2] Chatterji (1992) calls weak convergence the case in which $\beta < 0$ of and strong convergence when $-2 < \beta < 0$.

[3] As has been shown, ordinary least square (OLS) estimates that ignore the spatial dependence will be inefficient and/or biased (see Anselin, 1988).

[4] Jean Paelinck first introduced the term spatial econometrics in the 1970’s to name the field of applied econometrics dealing with these problems. However, the publication of Anselin’s (1988) monograph heightened the interest in this subfield of econometric analysis.

2.4 Spatial effects

2.4.1 Spatial autocorrelation

The notion of spatial autocorrelation was introduced by Cliff and Ord (1973). It is possible to find some different definitions of spatial autocorrelation in the literature. Vasiliev

(1996), for instance, defines spatial autocorrelation as a "sophisticated summary measure of the influences that neighbors have on each other in geographic space". Anselin and Bera (1998) defined it as being "the coincidence of value similarity with locational similarity". In any case, it is agreed that a positive autocorrelation occurs when similar values for the random variable are clustered together in space, and negative autocorrelation appears when dissimilar values are clustered in space.[5] The problem caused by the presence of spatial autocorrelation is, basically, its implication that the sample contains less information than the parts that are uncorrelated (Anselin and Bera, 1998).

In a general sense, and the one that will be used in this paper, spatial autocorrelation implies the absence of independence among observations in cross-sectional data. In other words, it can be taken to mean "the existence of a functional relationship between what happens at one point in space and what happens elsewhere" (Anselin, 1988 p. 11). The relationship can originate as a measurement error problem that stems from the fact that the data for the variables of interest are divided in "artificial" units such as states, counties or cities, that most often do not coincide with real spatial dimension of the phenomena under consideration. Spillover effects are likely to occur and the error terms in different units are likely to be related to each other.

On the other hand, spatial autocorrelation can originate as a result of a true spatial interaction among the variables.[6] This relation can be expressed by the following function, so that every observation $i \in S$ is related to a typical, y_i, variable in the other spatial units.

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[5] Vasiliev (1996) provides an intuitive idea of the problem, with a detailed example that includes maps,.

[6] Anselin (1998) called this form of autocorrelation a "more fundamental one".

$$y_i = f(y_1, y_2, ... y_N), \quad i \in S \tag{2}$$

where S is the set containing all spatial units.

2.1.2 Spatial heterogeneity

There are also problems, besides the one mentioned above, that stem from the lack of homogeneity of the spatial units themselves. Different units (states, cities, etc.) have, for instance, different sizes, shapes, densities, and these differences can generate measurement errors that can cause heteroskedasticity.

One way the spatial heterogeneity problem can be handled is to express it in a similar way to spatial autocorrelation, i.e.,

$$y_{it} = f_{it}(x_{it}, \beta_{it}, \varepsilon_{it}) \tag{3}$$

where i is the spatial unit, and t is time

The expression above combines cross-section and time series data. The dependent variable y is a time-spatial function of the vector of independent variables, x_i, the vector of parameters β, and the vector of errors, ε_i. In this case, there are more parameters than observations and the model cannot be estimated without imposing some restrictions on its structural form (Anselin, 1988).

It is worth noticing that it is not easy to differentiate spatial autocorrelation from spatial heterogeneity, as pointed out by Anselin and Bera (1998). They argued that in a cross-section setting, the two effects might be equivalent from the point for view of the observation, generating difficulties in establishing whether the problem was due to clustering of outliers (heteroskedasticity) or due to a spatial stochastic process yielding clustered outliers (spatial autocorrelation).

2.4.2 Weight matrix

A very useful device for bringing the notion of space to the econometric model is given by the weight matrix. This matrix, usually denoted **W**, can be used in order to capture adjacency patterns of areal units. In the simplest case, a symmetric matrix is defined by having the element (i, j) set equal to 1 if i and j are neighbors and 0 otherwise. By convention, the diagonal elements are set to zero, w_{ii}=0.[7] The weight matrix can be row standardized, denoted by the superscript *s*, with each of the non-zero elements being defined as $w_{ij}^{s} = w_{ij} \big/ \sum_{j} w_{ij}$. In this matrix, the elements of the rows sum to one. Besides facilitating the interpretation of the weights (that lie between 0 and 1) as an averaging of neighboring values, this manipulation ensures the comparability between models of the spatial parameters in many spatial stochastic processes (Anselin and Bera, 1998).[8]

Cliff and Ord (1973, 1981) proposed a matrix where the elements are given by a combination of the relative length of common borders and a distance measure, i.e.,

$$w_{ij} = \left(d_{ij}\right)^{-a} \left(\beta_{ij}\right) \tag{4}$$

where *a* is a parameter, d_{ij} stands for the distance between *i* and *j*, and β_{ij} is the proportion of common boundary between *i* and *j*, from *i*'s point of view. The resulting matrix is usually asymmetric, unless $\beta_{ij} = \beta_{ji}$.

There are still other more complex specifications of weight matrices based, for instance, on economic variables (see Case *et al*., 1993). In any case, the weight matrix adopted must satisfy some necessary regularity conditions that can be translated into the fact that the weights must be non-negative and finite (see Anselin, 1988 and Anselin and Bera, 1998).

The lack of a unique procedure to select a weight matrix has generated alternative approaches to address the problems caused by misspecification of such a matrix (see for instance Stetzer, 1982, Florax and Rey, 1995 and Griffith, 1996). Griffith, in particular, presents a guide on the specification of a weight matrix. Following the questions proposed by Stetzer (1982) related to the practical effects of different specifications, misspecification implications and possible applicable rules, Griffith concludes that the specification of the weight matrix does make a practical difference in spatial analysis. The fact is that the statistical qualities of the maximum likelihood estimators (MLE) are affected by misspecification problems creating problems for

[7] Some authors define *W* as a row standardized matrix and define the binary matrix as a contiguity matrix *C* (see for instance Griffith, 1996).

spatial statistical analysis.[9] He also concludes that there are in fact some rules that can be applied when specifying a weight matrix. The first rule states that is "better to posit some reasonable geographic weight matrix specification then to assume all entries are zero". In other words, ignoring the spatial dependence is not the best alternative. In total, these rules provide some guidance about the number of observations of the sample, form of the matrix etc. In general terms, the rules state that number of areal units should be at least 60, and that low order spatial statistical model are preferable than high order ones (See Griffith, 1996, p. 80).[10]

2.4.3 Spatial lag operators

The main argument in favor of using a spatial weight matrix is to associate a variable, at one point in space, to the observation of the variable in other spatial locations. In contrast to time series, where the relation in time can be expressed by the simple notion of lag operator L, where $L^s y = y_{t-s}$ shifts y_t s periods back on time, in space the problem becomes more complicated. The additional complication stems from the fact that there are many

possible directions over which the spatial shift operator can be applied. There are three basic types of shift applicable on a regular lattice. The criteria are named after pieces in the chess game, and the simplest one is the rook criterion, where the neighbors are the units to the east, west, south and north. Following the same idea, the others are the bishop and the queen criteria.

In empirical applications it is hardly the case where one can encounter a regular grid structure. In this situation, on an irregular grid, it becomes difficult to a make a choice of the directions that are relevant for the dependence in the analysis to be undertaken. The absence of regular lattices is more serious in the case of space-time models.[11] One solution that has been offered to this

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[8] It should be noted that the row-standardized matrix is no longer symmetric, which can create additional difficulties in some econometric procedures.

[9] More specifically, he suggests that misspecification of the weight matrix does not bias a mean estimator, but it affects the statistical efficiency and biases the variance estimator S^2. The paper presents other theorems that relate to alternative specifications such as rook's and queen's criterion (see Griffith, 1996).

[10] It is important to note that these rules are applied specifically to pure cross-section models. They do not apply to the space-time process when the asymptotic properties are based on the time dimension.

[11] Hooper and Hewings (1981) showed that, unless a regular lattice is used, it is possible for a $y_{i,t}$ stationary process to have an autocorrelation function AC(s,k) that varies (for fixed s, k) as one moves across space.

problem is the use of the concept of a spatial lag operator L^s. The idea is to use a weighted sum of the values of neighboring units. Hence:

$$L^s y_i = \sum_j w_{ij}^s y_j \quad \forall j \in S_i \tag{5}$$

where y_i is an element of a vector of random variable $\boldsymbol{y}$, $w_{ij} \in \mathbf{W}$ (the weight matrix) and S_i is the neighboring set. In matrix notation this would be:

$$L^s \mathbf{y} = \mathbf{W}_s \mathbf{y} \tag{6}$$

It is also possible to define higher order spatial lag operators. By multiplying **W** by **Wy** is equivalent to generating $\mathbf{W}^2\mathbf{y}$, a second order spatial lag. However, this kind of operation brings some problem of circularity that must be taken care of before continuing with the estimation procedures (see Blommestein, 1985 and Anselin and Smirnov, 1996).

3 σ-convergence and Moran's I statistic

This section presents the relationship between σ-convergence and the measure of spatial dependence referred to as Moran's *I* statistic. Figure 1 shows these two indices for the Brazilian's states from 1970 to 1995. There are no data for many of the states of the North of Brazil for the period prior to 1986, and for this reason the sample is reduced.[12] Moreover, for the period before 1985, the data are distributed in five years intervals. Thus, from 1970 to 1985 the series are discontinuous.[13] As can be seen from the dotted line, when the entire period is considered, there is some indication of long-term convergence. The level of the dispersion for the last year (0.61) is smaller than the initial dispersion at the first year (0.79). It is interesting to note that during the first half of the 1970's, still a period of high rates of growth for the Brazilian economy, the data indicate the existence of divergence. The convergence begins after 1975 and goes on during the 1980's. Thus, the increase of the dispersion seems to be associated with

[12] In fact some states were created during the 1980's, for instance Tocantins.

[13] The points correspond to the years of 1970, 1975, 1980 and 1985.

periods of economic growth, while the convergence occurs when the rate of growth decreases,[14] as noted by Azzoni (1997). He suggests that in periods of faster economic growth, the sectors that are more positively affected are concentrated in the richest states (in the Southeast of Brazil) and, therefore, the income concentration increases. The opposite would happen in periods of recession.

<<insert figure 1 here>>

The other series presented in Figure 1 is the Moran's *I* statistic. This statistic tests for the presence of spatial dependence among the geographic units, and can be expressed as:[15]

$$I_t = \left(\frac{n}{s_0}\right) \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij} x_{it} x_{it}}{\sum_{i=1}^{n}\sum_{j=1}^{n} x_{it} x_{it}} \tag{7}$$

where w_{ij} is an elements of the weight matrix $\boldsymbol{W}$ so that it is equals to 1 if i and j are neighbors and 0 otherwise. n is the number of spatial units (in this case, states); x_{it} is the log of per capita income of state i at year t, and s_0 is equals to the sum of all elements of $\boldsymbol{W}$.

The Moran's coefficients were highly significant for all years[16] providing support for the hypothesis of spatial dependence. This is important since it implies the possibility that the convergence models that ignore such spatial dependence would be misspecified. In contrast to measure of σ-convergence, the Moran's *I* statistics increases over the entire period, implying increasing spatial dependence for the per capita income in Brazil. That may an indication that the economic interconnections among the states have increased over time or that they are responding more similarly to economic signals. This finding seems to be consistent with the idea that the degree of regional integration should increase with the level of economic development (see

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[14] When other periods before 1970 are considered, it can be observed that from 1964 to 1975 (not shown in the figure), years of the economic miracle in Brazil, there exists a tendency towards divergence. However, such tendency is offset by the behavior of the series in the remaining years, specially the 1975's.

[15] The structure of the Moran's I is similar to the Durbin-Watson test for autocorrelation.

[16] The coefficients were significant at 1% for almost all years, with exception of 1962 (at 5%) , and 1963 and 1994 (at 2%).

Magalhães, *et al*., 1999). The 1980's seem to be to only period that presents a small decrease in the spatial dependence. However, this downward tendency is broken in the 1990's, with the index of spatial dependence returning back to its high levels of the 1970s by 1994.

According to the observations of Figure 1, it appears to be the case that, the spatial autocorrelation among the Brazilian states follows the tendency of the per capita income dispersion. As pointed out by Rey and Montouri (1999), this suggests that states with relative high income tend to be located close to other high-income states, and vice-versa. Thus, the usual hypothesis that the states can be treated as independent observations would not apply for the case in hand.

3.1 Moran Scatterplot

A way to take a closer look at the pattern of spatial concentration in Brazil is to observe the so-called Moran's scatterplots. The idea of the Moran scatterplot is to display the standardized values for each unit against their spatial lag value. Figure 2 plots the log of per capita income for each state, against the log of the per capita income of their neighbors. The figure is divided into four quadrants. The first quadrant, **I**, presents the states that have high per capita income (above the average) and that are surrounded by rich neighbors; the second quadrant (**II**) includes the poor states with rich neighbors. The states with per capita income below the average and poor neighbors are in the third quadrant and, finally, the rich states with poor neighbors can be found in the fourth quadrant.

It can be noted from figure 2 that São Paulo (SP), Rio de Janeiro (RJ) and Distrito Federal (DF) are the richest states in 1970. The two first are surrounded by above average income neighbors, while the Distrito Federal is surround by average income neighbors. It also can be noted that the Northeast states are the poorest, and are all surrounded by poor neighbors.[17] All the nine Northeast states are in the third quadrant of figure 2, showing a strong regional concentration with respect to per capita income at that time.

<<insert figure 2 here>>

Figure 3 shows the Moran scatterplots for 1995. São Paulo and Distrito Federal still are the richest states, but it seems that their neighbors' income increased over this period of time. More than 20 years later the Northeast states still appear in the third quadrant, suggesting a still present strong regional per capita income concentration in Brazil. In fact, if anything, figure 3 seems to indicate that the South and Southeast states became relatively richer during the period, increasing the regional concentration.

<<insert figure 3 here>>

4 β-convergence and spatial econometrics

This section introduces the issue of spatial dependence into the β-convergence model. It begins by considering the effects of spatial dependence on the error terms, and then the case of "true" spatial interaction among the states is examined.

A common assumption in the unconditional model given by (1) is that the error terms are *i.i.d.*. That is, it is usually assumed that:

$$E(\varepsilon_t \varepsilon_t^{'}) = \sigma_t^2 I \tag{8}$$

Hence, the existence of possible spillover effects across states it is not acknowledged. Rey and Montouri (1999) recognized that a model of convergence, by dealing with spatial units, should take into consideration possible spatial effects that would result from spillover effects. They then extended equation (1) to include some possible forms of spatial dependence. They identified three different possible models that are displayed below.[18]

4.1 Spatial error model

The first modification would be the case where the error term follows a spatial autoregressive process as showed in (9)

$$\varepsilon_t = \lambda W \varepsilon_t + u_t \tag{9}$$

[17] Recall that some of the states of the North where excluded from the calculations due to lack of data.
[18] These effects are the representation of the spatial dependence presented in section 2.4 of this paper.

λ is a scalar spatial error coefficient, and u_t is normally distributed with mean zero and constant variance. Substituting (9) into (1) results in spatial error regression given by (10):

$$\ln(\frac{y_{t+T}}{y_t}) = \alpha + \beta \ln(y_t) + (I - \lambda W) u_t \tag{10}$$

This type of spatial dependence would be the result of some missing variables. For example, the absence of a variable to control for the spatial relationship among the states would lead to spatially correlated error terms, and the estimation of equation (1) would to lead to unbiased, but inefficient estimates.

4.2 Spatial lag model

The second possibility is the spatial lag model. In this model the spatial dependence is considered as being created by actual interaction among the states. In this case a spatial lag dependent variable is added to the right hand side of (1). ρ is a scalar spatial lag coefficient and ε follows a normal zero one distribution:

$$\ln(\frac{y_{t+T}}{y_t}) = \alpha + \beta \ln(y_t) + \rho W \ln(\frac{y_{t+T}}{y_t}) + \varepsilon_t \tag{11}$$

4.3 Spatial cross regressive model

The third case considered is one where the spatial variable is the independent variable. Rey and Montouri refer to this model as being a spatial cross-regressive one, and it is represented by equation (8).

$$\ln(\frac{y_{t+T}}{y_t}) = \alpha + \beta \ln(y_t) + \phi W \ln(y_t) + \varepsilon_t \tag{12}$$

These models will be estimated for the Brazilian case in the next section. For the β-convergence models the period 1970 to 1995 and two sub-periods (1970-80 and 1980-95) are considered.

5 Econometric results

This section presents the main econometric results. First, equation (1) is estimated by least square and the residuals are tested for the presence of spatial dependence. Then, the models with spatial dependence are estimated and analyzed. The estimations are performed using the program Spacestat.

5.1 Unconditional models

Table 1 displays the results for the unconditional ordinary least square (OLS) model. The β's are negative and significant for two out the three periods. The coefficient was not significant for the sub-period 1970-80. The respective convergence rates are also displayed in the Table 1.

The rate of convergence for the entire period was of 0.008. The overall rate was driven by the convergence in the sub-period of 1980-1995, 0.013, since that from 1970 to 1980 the data show no significant convergence among the states. It is worth noticing that the fact that convergence was not found in the first sub-period is in accord with the σ-convergence results in figure 1, and with the, already mention, behavior noted by Azzoni (1997). It is interesting to point out that the regional convergence in the Brazilian economy during the 1980's can be though as the richest states growing slower and not the poorest states growing faster.[19]

<< insert tables 1 here>>

Once the models were estimated, the next step is to test for the presence of spatial dependence. If the spatial dependence is found, then equations (10), (11) and (12) can be estimated.[20] Table 2 displays the tests for presence of spatial dependence in the residuals of the three regressions. As can be observed in the table, the hypothesis of spatial dependence cannot be rejected for the entire period. Although the Moran's *I* coefficient is not significant, the robust LM tests (for error

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[19] It is also interesting to point the Ferreira and Ellery Jr. (1996) found a significant rate of convergence for the Brazilian states for the period 1970-80. This rate was less than the half of the convergence rate for 1980-1990. Possible explanations for the different in our results are the use of a different data source and sample. In any case, the results indicate the lack of or weaker convergence rate for the 1970's than for the 1980's.

[20] The standardized zero one matrix is used for the estimation presented in paper. The results with the inverse distance matrix were similar to the ones presented here, and for this reason are not included in the paper.

and lag) are both significant. The same is not true for the sub-periods. For the first one, 1970-80, only the robust LM lag test is significant, and only at 10% level. For the second one, however, spatial dependence does seem to be present. Hence, given the tests results, the models are estimated with the inclusion of the spatial dependence variables for the cases where the tests were significant.

<< insert table 2 here>>

5.2 Spatial dependence models

Table 3 presents the results of the spatial dependence models for β-convergence. The Table includes all three possible spatial processes. The best model is selected by the Akaike Information Criteria (AIC) and the Shwarz Criteria (SC). In all cases the spatial error model out performs the spatial lag model, as it was expected given the suggestion of Anselin and Rey (1991).[21]

The β ‘s are negative, and significant, with the exception of the coefficients for the period 1970-80. Since the spatial dependence was not found in the sub-period the inclusion of the spatial terms should not change the estimates of the β. Moreover, the fact that the error spatial model is the best one for the entire period should imply that the estimated that do not considered the spatial dependence among the stated would be unbiased but would be inefficient. However, the estimate rate of convergence for 1970-95 is large the one presented without spatial convergence. The result need more attention as it suggests that something else is going on with the data.

<<insert table 3 here>>

6 Conclusions

This paper undertook an empirical analysis of regional convergence in Brazil with special consideration to the problem of spatial dependence among the states. The results indicated the presence of spatial dependence as it was observed by the Moran’s *I* coefficient and the Moran’s scatterplots. In particular, plots seem to indicate a regional disparity, with the Northeast states concentrating in the third quadrant – poor states surrounded by poor states.

The spatial dependence was also verified in the regression analysis, which implies that the unconditional model was misspecified. The changes in the rate of convergence were not very large. However, it is possible to infer from the results in hand that, although some convergence among states is taking place, it seems to be more of regional phenomena or perhaps some type of club convergence than a global convergence process. States like Distrito Federal and São Paulo would be leading the way while the Northeast states forming a second group or club.

The hypothesis of club convergence has yet to be empirically verified for Brazil, however, the present paper has shown that the spatial dimension must be considered when dealing with problems involving the Brazilian states.

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[21] Anselin and Rey (1991) argue that the model would be selected according the level of significance of the LM test. In the case in hand, the LM of the error was significant at higher level than the LM of the spatial lag.

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Appendix

Figure 1: σ convergence and spatial autocorrelation for Brazil, 1970-95

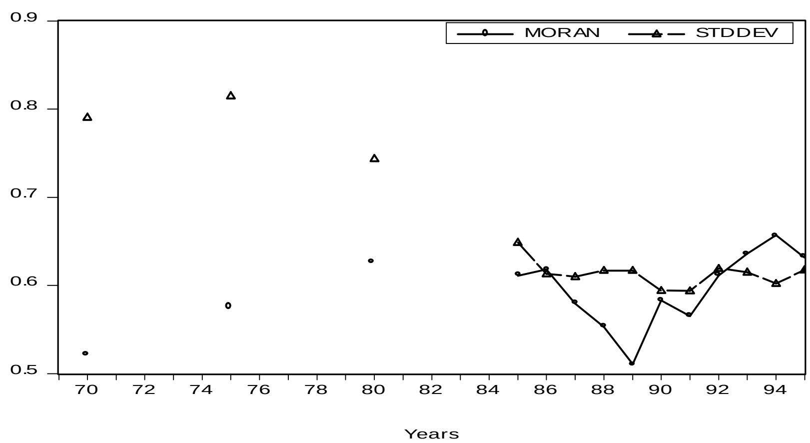

Figure 2: Moran scatterplot real state per capita income, 1970

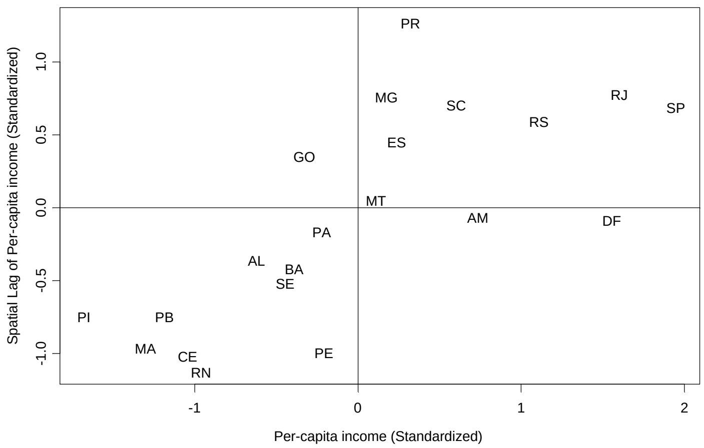

Figure 3: Moran scatterplot real state per capita income, 1995

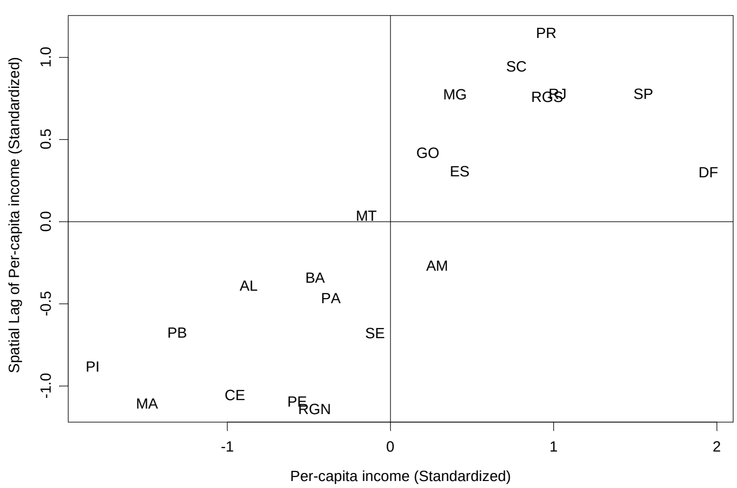

Table 1: Unconditional model OLS estimation

	R^2	AIC	SC	F-Test	β (t-value)	Convergence rate
1970-1995	0.282	-8533	-6.444	8.850	-0.199	0.008
				0.007	(-2.975)	
1970-1980	0.027	-3.0439	-0.954	0.522	-0.055	0.006
				0.470	(-0.722)	
1980-1995	0.263	-10.815	-8.725	8.118	-0.174	0.013
				0.010	(-3.483)	

Notes: AIC stands for Akaike Information Criterion and SC stands for the Schwarz Information Criteria. The convergence rate is obtained As ln(β+1)/-k, where k is number of years in the period.

Table 2: Tests for spatial dependence

	TEST	Moran's I (error)	Robust LM (error)	Robust LM (lag)
1970-95	Value	1.459	3.470	2.758
	p-value	0.144	0.062	0.096
1970-80	Value	1.420	2.175	2.705
	p-value	0.155	0.140	0.100
1980-95	Value	0.537	0.122	0.139
	p-value	0.590	0.726	0.708

Table 3: Spatial dependence models

	AIC	SC	β	z-value	λ,ρ , ϕ	z-value for spatial coeff.	Convergence rate (θ)
1970-95							
Spatial error (ML)	-10.135	-8.046	-0.278	-3.772	0.437	2.173	0.012
Spatial lag (ML)	-6.585	-3.452	-0.198	-2.883	0.064	0.276	0.008
Cross regressive (OLS)	-6.654	-3.521	-0.197	-2.846	0.150	0.323	0.008
1970-80							
Spatial error (ML)	-8.221	-6.132	-0.0002	-0.005	-0.657	-3.192	0.000
Spatial lag (ML)	-6.429	-3.295	-0.026	-0.463	-0.388	-3.041	0.002
Cross regressive (OLS)	-12.635	-9.501	0.011	0.186	-1.235	-3.641	-0.001
1980-95							
Spatial error (ML)	-10.815	-8.726	-0.173	-2.983	0.006	0.025	0.011
Spatial lag (ML)	-8.840	-5.707	-0.169	-2.645	0.047	0.198	0.011
Cross regressive (OLS)	-6.654	-3.521	-0.197	-2.846	0.150	0.323	0.014

Notes: See table 1 for comments.