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Sección ARTÍCULOS

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Spatial Dependence and Regional Convergence in Brazil[1]

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ABSTRACT: The present paper introduces some spatial econometric techniques to the convergence issue among Brazilian states. State data over the 1970-95 period are considered to explore previous results that suggested convergence. As in the US case, strong patterns of spatial correlation are found during the period. The spatial econometric analysis reveals that spatial error dependence seems to be present resulting in the potential for model misspecification. The results indicate 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 São Paulo dominate the first group while the Northeast states form a second group or club.

JEL classification: N63 R12, F14.

Key words: Industrial Location, Wage Gradient, Spanish Economic History.

1. Introducción

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) and since then, a growing literature attests to the importance of the problem of 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 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

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among the U.S. states, and Fingleton (1999) was the first to apply spatial econometric techniques for the European Union[3].

Previous studies for Brazil, such as Ferreira and Ellery (1996), Azzoni (1997, 1999, 2000), Ferreira and Diniz (1995) and Ferreira (2000), that estimate the rate of convergence among the states do not test for the presence of spatial dependence among the states[4]. It is possible, however, that if the Brazilian states are spatially correlated, the rates of convergence found in these papers could be biased. In several other Latin American countries, the issue of convergence has been explored (see Aroca *et al*., 2006 and Bonet, 2003); the findings reveal considerable variability in outcomes, with periods of convergence and divergence but little evidence of long-run tendencies. In Colombia, as in Brazil, significant concentration of economic activity in one or more states presents a challenge in modeling convergence; the case of Brazil is further complicated by differences in the geographical size of regions.

The present paper employs spatial econometric tools for analysis of the convergence problem in Brazil. In order to do so, a sample of 21 Brazilian states is considered for the 1970-95 period. Both σ-convergence and β-convergence are verified and the data are tested for the presence of spatial dependence.

The results indicate that the spatial effects are, in fact, relevant. 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. The model for β-convergence with the spatial terms indicates a slow rate of convergence; however, the observation of the Moran's scatterplots suggests convergence within the macro regions.

The next section will briefly discuss the idea of convergence and spatial dependence. Section 3 will present an exploratory analysis of the convergence properties among states for Brazil using some spatial econometrics tools. First, a global measure of spatial dependence, the Moran's *I*, is calculated and its trend is compared to the behavior of the σ-convergence. Then, a local measure of spatial dependence is presented, with which it will be possible to observe the relations among the states and its neighbors in terms of per capita income. Section 4 presents the empirical results. The final section offers some concluding remarks.

2. Convergence and spatial autocorrelation

In the last fifteen years, the area of economic growth has been extensively treated in the economic empirical literature. The central ideas focus on the identification of the

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3 Bernat Jr. (1996) used the spatial econometric tools to test the Kaldor's Law in the United States at the state level. However, Rey and Montouri (1999) seems to be to first to apply this technique to a convergence model for this country.

4 Ferreira and Ellery (1996) consider the regional dimension of the convergence problem through regional dummies. The tools of spatial econometrics go beyond the inclusion of a dummy variable, as will be seen in what follows.

factors that generate growth in the long run. A natural question that arises in that discussion is the degree to which poorer economies reach the levels of income of the richer economies, that is to say, the possibility that the difference between countries or regions, in terms of per capita income, decreases over time.

The existence of convergence is found theoretically in models built from a growth model where the technological progress is exogenous and the production function presents diminishing marginal returns separately in each of the inputs (such as in Solow-type models). Those hypotheses allow for situations where the economic growth of the richest economies would tend to decrease due to the decreasing returns of the additional investments. In this way, if the rate of technological progress is constant and identical among all the economies, and if the saving rates, the population growth rates and the depreciation rates are the same, the poorest economies would tend to present a larger rate of economic growth and they would end up reaching the same level of income of the richest ones. This type of convergence is known as absolute convergence, in the sense that all economies would converge to the same level of per capita income in the long run (see Barro and Sala-i-Martin, 1992).

According to Barro and Sala-i-Martin (1992), besides the absolute convergence, it is possible to consider the β-convergence that can be considered as conditional convergence. The difference between the two types of convergence can be traced to the fact that while the first, the absolute, would consider all countries converging to one unique steady-state, in the case of the second one (conditional), the possibility exists for different steady-states for each country (See also Obstefeld and Rogoff, 1996).

In this paper, the convergence hypothesis will be tested in two different, but complementary, approaches. The first one will be based on idea of β-convergence[5]. A simple unconditional model for absolute convergence is given in (1):

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

$y_{i,t}$ 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 identical, independent, and 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 should be negative in (1).

The second one is the σ-convergence, where the standard deviation, or the coefficient of variation (CV), is used to measure the cross-sectional dispersion of the logarithm of the per capita income across time. A decrease in the standard deviation

[5] Following the work of Rey and Montouri (1999), the present analysis deals only with absolute convergence. The models of convergence of time series or stochastic convergence will not be dealt with either (for an illustration in such models see, for instance, Carlino and Mills, 1996 or Bernard and Durlauf, 1995).

would indicate convergence while an increase would indicate divergence (see Barro and Sala-i-Martin, 1991)[6].

As pointed out in the introduction, economic analysis is increasingly focusing on issues related to the spatial dimension of problems. The spatial dimension is certainly an important characteristic when attention is directed to regional per capita income convergence. Although the current methodology would suggest that the econometric analysis of regional convergence should consider the possibility of spatial dependence among regions, it was not until recently that the possibility of spatial dependence was considered in dealing with regional convergence (see, for instance, Rey and Montouri, 1999, and Fingleton, 1999).

Previous studies for Brazil, such as Ferreira and Diniz (1995), Ferreira and Ellery (1996), Azzoni (1997, 1999, 2000) and Ferreira (2000), that estimate the rate of convergence among the states do not test for the presence of spatial dependence among the states[7]. It is possible, however, that if the per capita income of the Brazilian states are spatially correlated, the rates of convergence found in these papers could be biased.

The main problem stems from the possibility of the existence of spatial autocorrelation in the data. There are several 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»[8]. Anselin and Bera (1998) defined it as being «the coincidence of value similarity with locational similarity.» However it is defined, most analysts agree 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[9]. 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 (Mankiw, 1995; 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). The relationship can originate as a measurement error problem that stems from the fact that the data for the variables of interest are divided into «artificial» units such as states, counties or cities, that most often do not coincide with the real

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[6] Chatterji (1992) has pointed out that in order to guarantee that the 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 $-2 < \beta < 0$. Chatterji (1992) calls weak convergence the case in which $\beta < 0$ of and strong convergence when $-2 < \beta < 0$.

[7] Ferreira and Ellery (1996) consider the regional dimension of the convergence problem through regional dummies. The tools of spatial econometrics go beyond the inclusion of a dummy variable, as will be seen in what follows.

[8] As pointed by an anonymous referee, the idea of space can also be thought in terms of an «economic space». As he argued, the weight matrix, shown below, captures both economic and geographic spatial interactions.

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

(and often unknown) 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[10]. In any case, the presence of spatial autocorrelation can lead to biased or inefficient results. The following sections explore to what extent the spatial autocorrelation affects the analysis in the case of Brazil.

3. Regional disparities in Brazil

Brazil is a country with high regional inequality. As table 1 shows, the per capita income of the Northeast, the poorest region, represented less than half of the country's per capita income in 1970, while the per capita income in the Southeast, richest region, was 150% of the national income. In 1995, these differences had not significantly changed.

Table 1. Regional per capita income as a percentage of national per capita income in Brazil, select years

Regions	*1970*	*1980*	*1990*	*1995*
North	57.37	66.88	76.95	68.93
Northeast	39.51	41.64	45.29	44.83
Southeast	152.39	143.29	136.31	139.68
South	96.19	108.07	110.90	106.67
Center-West	66.29	78.61	101.46	97.96
Brazil	100.00	100.00	100.00	100.00

Source: IBGE.

These disparities become even larger when the states are considered. According to the IBGE data, in 1970 the per capita income of the richest state, São Paulo, was almost nine times the per capita income of the poorest state, Piauí. In 1995, this difference was still significant, but had decreased to six times[11].

The regional inequality also becomes evident through analysis of the coefficient of variation. Figure 1 shows the relationship between σ-convergence and the Moran's I statistic 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

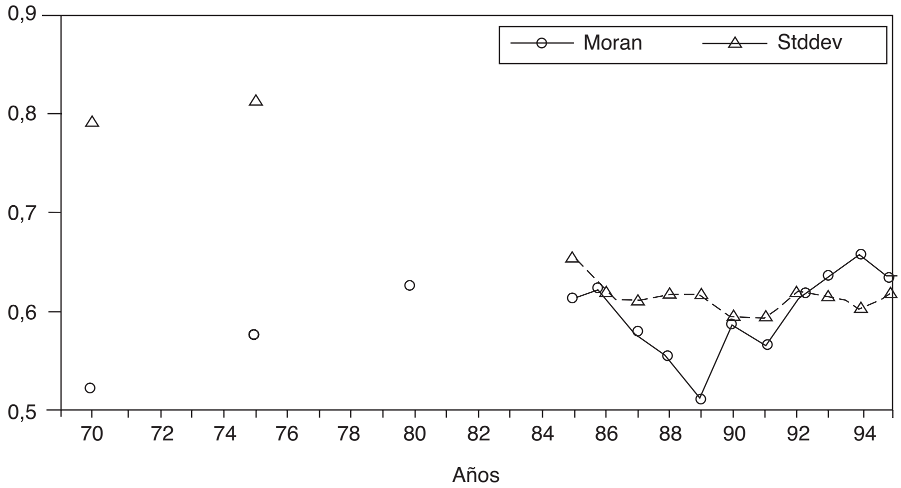
[10] There are also problems, besides the one mentioned above, that stem from the lack of homogeneity of the spatial units themselves. Different units (states, cities, etc.) have, for instance, different sizes, shapes, densities, and these differences can generate heteroskedasticity measurement errors. It is worth noticing that it is not easy to differentiate spatial autocorrelation from spatial heterogeneity, as pointed out by Anselin and Bera (1998).

[11] Map 1 in the appendix presents the Brazilian states by region.

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

five year 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 continues during the 1980's. Thus, the increase of the dispersion seems to be associated with periods of economic growth[14], as noted by Azzoni (1997). He also 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.

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



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:

$$It = \frac{n}{s_0} \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij} x_{it} x_{ft}}{\sum_{i=1}^{n} \sum_{j=1}^{n} x_{it} x_{ft}} \qquad [2]$$

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

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.

where w_{ij} is an elements of the weight matrix **W** so that it is equal 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 **W**. The weight matrix can be row standardized, denoted by the superscript *s*, with each of the non-zero elements being defined as $w^s_{ij} = w_{if} / \sum_j w_{ij}$. 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)[15]. The results presented below are based on a row standardized matrix.

The Moran coefficients were highly significant for all years[16], providing support for the hypothesis of positive spatial dependence. This is important since it implies that any convergence models that ignore such spatial dependence would be misspecified. In contrast to the measure of σ-convergence, the Moran's *I* statistic increases from 1970 to 1995, implying increasing spatial dependence for per capita income in Brazil. This finding may be an indication that the economic interconnections among the states have increased over time or that they are responding in a more similar fashion to economic signals. This interpretation would seem to be consistent with the idea that the degree of regional integration should increase with the level of economic development (see Magalhães, *et al.*, 1999). It is worth note that the increase in the spatial dependence is not uniform over time. While it increases rapidly during the 1970s, it decreases in the 1980s. However, this downward tendency is broken in the 1990's, with the index of spatial dependence returning back by 1994 to the high levels observed in the 1970s.

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. The positive trend presented by the data 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

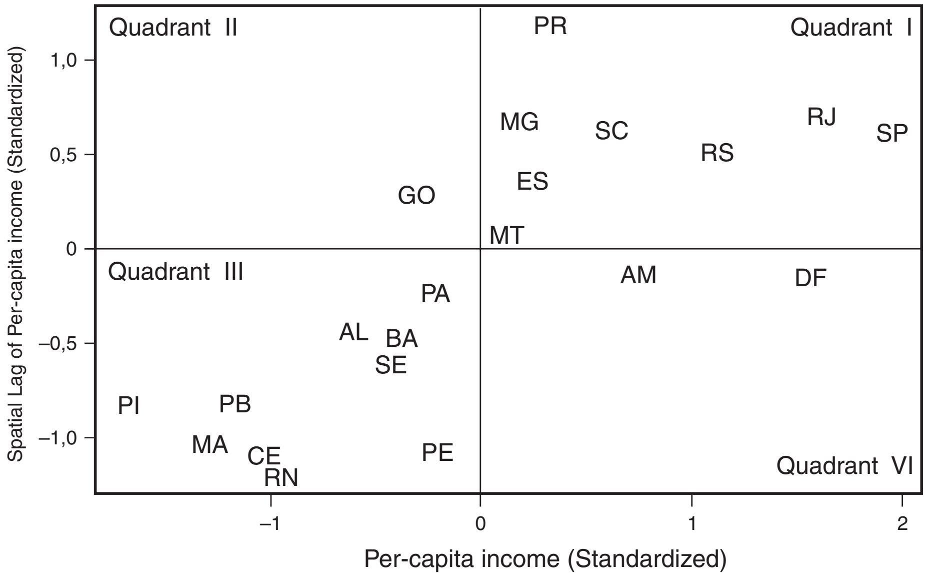
A way to take a closer look at the pattern of spatial concentration in Brazil is through construction of Moran's scatterplots. The idea of the Moran scatterplot is to display the standardized values for each unit against their spatial lag value. Figure 2 plots the log of per capita income for each state, 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**) contains the poor states with

[15] 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. There are still other more complex specifications of weight matrices based, for instance, on economic variables (see Case *et al*., 1993).

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

rich neighbors. The states with per capita income below the average and poor neighbors are in the third quadrant (**III**) and, finally, the rich states with poor neighbors can be found in the fourth quadrant (**IV**).

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



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[17]. The first two are surrounded by above average income neighbors, while the Distrito Federal is surrounded by average income neighbors. Note also that the Northeast states are the poorest, and they are all surrounded by poor neighbors[18]. 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.

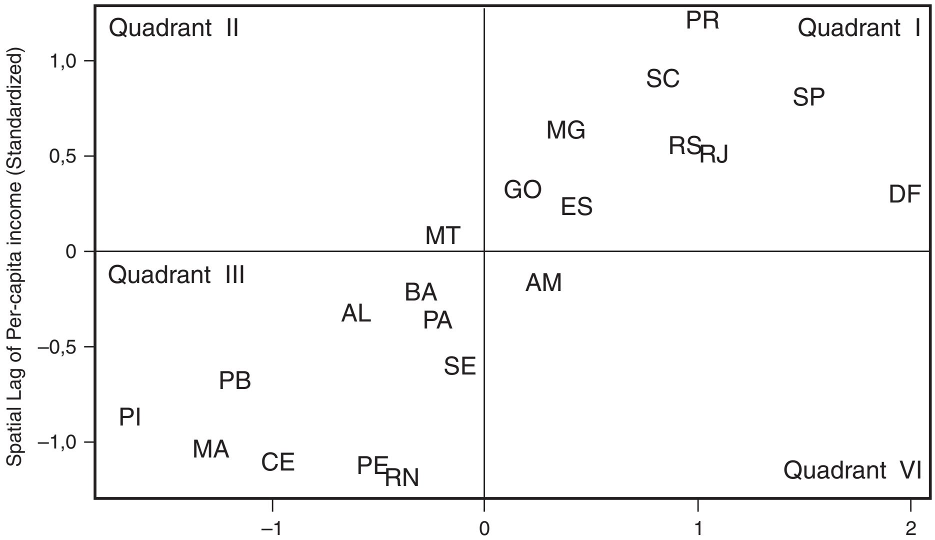
Figure 3 shows the Moran scatterplots for 1995. São Paulo and Distrito Federal still are the richest states, but it seems that their neighbors' income increased over this period of time. More than 20 years later, the Northeast states still appear in the third quadrant. The results continue to reinforce the presence of 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, further increasing the regional concentration.

These results suggest that, first, there exists an indication of spatial autocorrelation in Brazil and that the differences in the terms of per capita income have remai-

[17] Table A1 in the appendix presents the 20 Brazilian states and the Distrito Federal with their abbreviations.

[18] Recall that some of the states of the North where excluded from the calculations due to lack of data.

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



ned strong over time, indicating weak, or at least the absence of, convergence among the states. The next logical step is to test for the presence of spatial dependence on the β-convergence model. This is done is the following sections, first by introducing the spatial effect in the model and by estimating the models for the Brazilian case.

3.2. 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:

$$E(\varepsilon_t \varepsilon_t') = \sigma_t^2 \mathbf{I} \qquad [3]$$

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, identifying three different possible models that are displayed below[19].

[19] These effects are the representation of the spatial dependence discussed in section 2.

Spatial error model

The first modification would be the case where the error term follows a spatial autoregressive process shown in [4]

$$\varepsilon_t = \lambda \mathbf{W} \boldsymbol{\varepsilon}_t + u_t \qquad [4]$$

where λ is a scalar spatial error coefficient, and u_t is normally distributed with mean zero and constant variance. Substituting (4) into (1) results in a spatial error regression given by (5):

$$\ln\left(\frac{y_{i,t+T}}{y_{i,t}}\right) = \alpha + \beta \ln (y_{i,t}) + (\mathbf{I} - \lambda \mathbf{W})^{-1} u_t \qquad [5]$$

This type of spatial dependence could 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 [5] by ordinary least square (OLS) would to lead to unbiased, but inefficient estimates.

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. Accordingly, 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:

$$\ln\left(\frac{y_{i,t+T}}{y_{i,t}}\right) = \alpha + \beta \, \mathrm{In} \, (y_{i,t}) + \rho \mathbf{W} \ln\left(\frac{y_{i,t+T}}{y_{i,t}}\right) + \varepsilon_t \qquad [6]$$

Spatial cross regressive model

The third case considered is one where the spatial variable is the spatially lagged dependent variable. Rey and Montouri (1999) refer to this model as being a spatial cross-regressive one, and it is represented by equation [7].

$$\ln\left(\frac{y_{i,t+T}}{y_{i,t}}\right) = \alpha + \beta \, \mathrm{In} \, (y_{i,t}) + \text{ø} \mathbf{W} \ln (y_t) + \varepsilon_t \qquad [7]$$

Equation [7] differs from equation [6] in the sense that in the former the presence of spatial dependence implies that the growth rate of an individual state is affected by the initial per capita income level of its neighbors, while in the latter its growth is affected by the growth rate of its neighbors.

These models will be estimated for the Brazilian states 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. The use of these sub-periods will help to observe if the convergence patterns in Brazil differs between a period of high national economic growth rates (the 1970's) and a period of low national growth rates (1980's). Moreover, by considering these periods, it will be possible to compare the results to other studies for Brazil.

4. 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. The results presented in the spatial dependence tests and model estimations were obtained by using a row standardized contiguity matrix. Similar results were found with a distance matrix, but they are not reported[20].

Table 2 displays the results for the unconditional ordinary least square (OLS) model. The β's are negative and significant for two out of the three periods; the coefficient was not significant for the sub-period 1970-80. The respective convergence rates are also displayed in the table 2.

Table 2. Unconditional model OLS estimation

	R^2	*AIC*	*SC*	*F-Test (p-value)*	β *(t-value)*	*Convergence rate*
1970-1995	0.282	–8.533	–6.444	8.850 0.007	–0.199 (–2.975)	0.008
1970-1980	0.027	–3.0439	–0.954	0.522 0.470	–0.055 (–0.722)	0.006
1980-1995	0.263	–10.815	–8.725	8.118 0.010	–0.174 (–3.483)	0.013

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

The annual rate of convergence for the entire period was of 0.008 (0.8%). The overall rate was driven by the convergence in the sub-period of 1980-1995, 0.013 (1.3%), since, from 1970 to 1980, the data show no significant convergence among the states. It is worth noting that the fact that convergence was not found in the first sub-period is in accord with the *s*-convergence results in figure 1, and this finding is consistent with Azzoni's (1997) interpretation that was noted earlier. Regional convergence in the Brazilian economy during the 1980's can be considered as generated by a process whereby the richest states were growing more slowly rather than the poorest states growing faster[21].

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20 The estimations are performed using the program Spacestat.

21 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.

Once the models were estimated, the next step is to test for the presence of spatial dependence. If spatial dependence is found, then equations [5], [6] and [7] can be estimated. Table 3 displays the tests for the 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 Moran's *I* coefficient is not significant, the robust LM tests (for error 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.

Table 3. 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

Notes: LM stands for Langrage Multiplier.

Table 4 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 Schwarz Criteria (SC). In all cases, the spatial error model out-performs the spatial lag model, as was expected given the suggestion of Anselin and Rey (1991)[22]. However, for the sub-period 1970-80 the cross regressive model is the best model, as indicated by the AIC and SC criteria.

The estimated βs are all negative, and significant, with the exception of the coefficients for the period 1970-80 in the cross regressive model. The result is similar to the one found by the OLS. In fact, since the spatial dependence was not found in this sub-period, the inclusion of the spatial terms should not change the estimates of the β.

The most interesting result is found for the entire sample. The coefficient for the spatial dependence (λ) is positive (0.437) and highly significant. The estimated β is –0.278 and is larger, in absolute value, than the one estimated by OLS. As a consequence, the estimated rate of convergence for 1970-95 (0.012) is also larger than the one presented without spatial convergence (0.008). This new coefficient also implies a shorter half-life than the one presented by OLS estimates. While in the OLS scena-

[22] 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.

rio the half-life would be 78 years, with the spatial correction this time would reduced to 53 years[23]. These results are similar to the ones found to the Europe (see Gallo *et al*., 2003). Clearly, 53 years is still a long period, but this result represents the importance of incorporating some measure of the spatial dependence.

In sum, the results indicate that by ignoring the spatial dependence present in the data, one would conclude that the convergence rate among the Brazilian states were smaller than they were during the analyzed period.

Table 4. 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 2 for comments.

5. Conclusions

This paper undertook an empirical analysis of regional convergence in Brazil with special consideration directed to the problem of spatial dependence among the states. The results indicated the presence of spatial dependence, based on the Moran's *I* coefficient and the Moran's scatterplots. In particular, the plots 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 a regional phenomenon or perhaps some type of club convergence than a global convergence process. States like São Paulo would be a dominant force in one club while the Northeast states would form a second group or club.

[23] The half-life is calculated as $-\ln(0.5)/\theta$.

The hypothesis of club convergence (see, for instance, Quah, 1996, Chatterji, 1992 or Chatterji and Dewhurst, 1996) in a spatial econometric formulation 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. Given the importance of spatial effects and the presence of several models to incorporate them, the analyst would be hard pressed to provide a justification for not taking them into account. The idea of club or group convergence suggests that different spatial regimes need to be explored to test for the robustness of the results; at the same time, some consideration needs to be given to the presence of hierarchical effects – convergence between nations and the influence on convergence between regions and its influence on convergence between sub-regions. Convergence analysis in terms of per capita income needs to be complemented by consideration of other indicators, such as wage differences among similar types of workers in different regions. This kind of analysis, although commonly used for comparisons among countries, has not been used for regional analyses[24].

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[24] See Williamson (1996) and Wood (1995) for applications the kind of analysis for country level.

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Appendix

Table A1. Brazilian regions and states used in the analysis

Regions/States	*Abbreviation*	*Regions/States*	*Abbreviation*
North		**Southeast**	
Amazonas	AM	São Paulo	SP
Pará	PA	Minas Gerais	MG
Northeast		Rio de Janeiro	RJ
Maranhão	MA	Espírito Santo	ES
Piauí	PI	**South**	
Ceará	CE	Paraná	PR
Rio Grande do Norte	RN	Santa Catarina	SC
Paraíba	PB	Rio Grande do Sul	RS
Pernambuco	PE	**Center-West**	
Alagoas	AL	Mato Grosso	MT
Sergipe	SE	Goiás	GO
Bahia	BA	Distrito Federal	DF

Map 1. Brazilian states by regions