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Spatial externalities between Brazilian municipios and their neighbours*

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Abstract

Clustering of economic performance and growth in space has generated considerable research on the spillovers and linkages among geographical neighbours. In this paper, we study the growth process of a large sample of Brazilian municipalities for the period 1970-1996 and attempt to evaluate the spatial externalities at work among them. We estimate the convergence speed of per capita income among municipios and test whether spatial externalities are linked to local income growth. Conditionally on structural characteristics, we find evidence of convergence between municipios and of positive spatial dependence in growth. These two facts could help explain the persistent inequalities between municipios and the increasing clustering of poor localities in the Northeast region.

Keywords: Local growth, convergence, spatial externalities, spatial econometrics, Brazil.
JEL codes: O40, R11, R12.

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1 Introduction

Economic growth is not a uniform process over space. Within countries, some regions grow more rapidly than others and these differences may result in poorer regions catching up with wealthier regions, or, on the contrary, increasing income gaps. Brazil offers a good example of a country with regions of very different levels of development. The Northeast in particular is much less developed than the southern part of the country. Home of 28% of the population in 2000, the Northeast produced only 13.1% of GDP in 2001, whereas the Southeast produced 57% of GDP, with 43% of the population. As a result, per capita income was only 47% of the national average while that of the Southeast was 34% above. The poorest state, Maranhão, in the Northeast region, had a per capita income level about 6 times lower than the richest state, São Paulo. And the Northeast is not catching up with the south: in 1937 the per capita income in São Paulo was five times that of Piauì also in the Northeast (Azzoni and Servo, 2002).

Poorer, the Northeast is also more unequally developed than other regions of Brazil. The wealthiest state in Northeast has a GDP per capita more than 2.5 times larger than the poorest, whereas this ratio is only 1.7 in the Southeast. Over time, this tendency to higher inequality in the Northeast has increased. Based on a measure of per capita GDP of the Brazilian municipalities, our own calculations show that, in 1970, the Northeast was the region with the less equal distribution, with a Theil index of 0.36. By 1996, the Theil index in the Northeast had increased to 0.39, whereas it had decreased in the regions Center-West, South and Southeast.

High inequality and low development is not only the problem of the northern part of Brazil. Goldsmith and Wilson (1991) see in Northeastern underdevelopment major restraints on true development and modernization of Brazil. Their argument runs as follows: high inequality between the Northeast and the Center-South regions translates into high disparities in the level of wages and "*as long as the alternative of cheap wages exists and capitalists can use the Northeast's army of potential workers to restrain industrial wages in the growing Center-South, then changes in the core will be limited and its economy distorted, too.*" Thus, the low level of wages in the North relative to the South and the high levels of fertility restrain the modernization of the Brazilian economy and reduce the size of its domestic market. This in turns does not allow the economy to reach the ultimate stage of development, that Rostow termed "the age of mass consumption".

In this paper we document and analyse the evolution of GDP per capita in the Northeast and in other regions of Brazil. We use measures of GDP per capita at the municipality level computed in 1970 and 1996. These data are used in two different and complementary types of analysis. First, we document the evolution of per capita GDP inequality in Brazil as a whole, and in the North and Northeast on one hand and in the Center-South on the other hand. We use Theil index decomposition to analyse the changes in GDP per capita inequality over the period 1970-1996. We find that inequality increased in the North and in the Northeast regions and decreased in other regions of the country. Next, we use Moran's I indexes and Moran scatter plots to analyse the extent and the changes of spatial inequalities among Brazilian municipios. We find evidence of polarized development and poverty traps. Relatively low productive municipios tend to be grouped together in the North and Northeast, and this tendency increases overtime, whereas municipios with a GDP per capita higher than average tend to be grouped in the South of the country.

This observation leads us, in the second part of our empirical analysis, to analyse the process of growth in per capita GDP. The emergence of poverty traps and polarized development could result from the existence of externalities across neighbouring municipios. For instance, if being surrounded by relatively highly productive municipios is good for development because of technological or pecuniary externalities, one could expect to observe the kind of pattern we find in Brazil. We estimate several versions of a growth model at the municipality level, allowing for different kinds of spatial dependence among neighbouring municipios. We find evidence of positive externalities across the Brazilian municipios, that could explain the emergence of poverty traps.

The next section presents a short literature survey of recent growth studies in Brazil. Section 3 presents the data. Section 4 gives the results of the Theil index decompositions and of the spatial statistical analysis. In section 5, we briefly present a theoretical model of growth with spatial externalities and expose the results of our econometric estimations. Finally, section 6 concludes.

2 Literature survey

Among the determinants of local growth, the role of externalities has been much discussed in the recent literature (Glaeser et al., 1992). These externalities not only matter for growth within a given city or region but also for growth between neighbouring regions (Lopez-Baso et al., 2004).

Growth at a given location may affect growth of neighbours through several channels. First, due to technological externalities, a locality may benefit from improved economic conditions in another. For instance, if some firms in a locality have developed innovative processes, knowledge spillovers may favor the diffusion of new technologies to firms at neighbouring locations. Linkages between input suppliers and final producers may also be critical: if a final consumption good produced at a particular location benefits from a booming demand, upstream firms in the same region will thrive. Finally, proximity of an important economic centre may improve matching on the labor market, thus reducing costs and increasing labour productivity.

Pecuniary externalities may also matter in spatial growth differentials. On the one hand, growth at a given location may create new market opportunities for firms in neighbouring localities, through the increased demand resulting from higher incomes. On the other hand, the same process may attract new firms and workers, thus increasing land rents. Transmission of this land market tension to nearby localities can reduce incentives for firms to locate there, and therefore attenuate growth prospects.

Finally, local economic growth may foster migration from less dynamic places. The impact of this migration on both the departure and arrival locations depends on various factors, notably the migrants' education level, the substitutability between skilled and unskilled workers in production and the state of local labour markets.

Understanding how local growth may spread to neighbours or may hinder their economic performance is critical for policy design. Local policies aiming at fostering growth may have positive or adverse effects on nearby localities. Sorting between the "good" and the "bad" channels may help designing more efficient policies. Land and transportation policies are also a closely related issue: some spatial externalities are driven by the functioning of the land market. When rising rents in a growing locality are transmitted to adjacent locations, for instance, public policies may be needed to reduce market tensions, through the development of new land plots or the improvement of transportation networks. In this case again, evaluating the strength and spatial scope of pecuniary externalities can help improving these policies.

In the recent years, several papers have analysed the dynamics of regional growth in Brazil. Azzoni (2001) investigates the evolution of regional inequality over the period 1939-1995, using standard statistical and regression methods for analysing σ and β-convergence between the Brazilian states. He finds signs of regional income convergence, but with important oscillations in the evolution of inequality over time as well as across regions within the country.[1] The methods used in this paper are "standard" in the sense that, as most surveys studying regional convergence at that time, it did not consider the issue in a spatial econometric perspective. In other words, regional economies are considered in isolation, independently of their spatial location and/or the spatial links with other economic units. However, as shown by Anselin and Bera (1998) the failure to hold account of spatial dependence in linear regression models may lead to biased and/or inefficient estimators. This obviously applies to growth regressions for which there are plenty of good theoretical arguments suggesting that spatial dependence is likely to occur, and has been confirmed, among others, by the works of Rey and Montouri (1999) for the United States, Lopez-Bazo et al. (2004) for Europe, and Magalhães et al. (2000) for Brazil. Recent papers on this topic are therefore using spatial econometric methods. Abreu et al. (2004) provide an extensive survey of the empirical literature on growth and convergence that has taken the role of space into account.

Another trend in the convergence literature, following Quah (1997), focuses on the dynamics of income distribution. Few works combine this approach with the possible role of space in the growth process (see Magrini, 2004). Bosch Mossi et al. (2003) use local indicators of spatial association (LISA, see Anselin 1995) together with Markov transition matrices and stochastic kernels to study the convergence of per capita income among Brazilian states over the 1939-1998 period and to what extent spatial spillovers are apparent. They find strong evidence of spatial clustering, with poor (rich) states tending to be close in proximity to other poor (rich) states. Their results also indicate that regions are becoming more homogeneous internally but that differences between regions are increasing. Moreover they find evidence of spatial spillovers among states. First, states with wealthier neighbours have a greater chance of moving upward on the income ladder. Second, the clustering between the rich, southeastern, states and the poor, northeastern, states tends to become stronger over time, to the extent that states that originally did not belong to a cluster, ultimately ended up being part of one of the two distinct

[1] See also Ferreira (2000) for a closely related paper using the same methods but on a shorter period. As Azzoni (2001), Ferreira finds evidence of σ and β-convergence across regions.

clusters. Intradistribution dynamics is investigated at a finer geographical level by Andrade et al. (2004), though without the spatial dimension: they test the convergence hypothesis among the Brazilian municipalities over the 1970-1996 period. They find no evidence of convergence. On the opposite, results suggest that municipalities form convergence clubs and that these clubs are persistent over time, so that poor and rich municipalities maintain their relative income status. However there is also some mobility within clubs, with some poor and rich municipalities becoming respectively relatively richer and poorer.

Using finely disaggregated spatial data in the analysis of the growth process clearly is a progress: first, it permits to take intraregional disparities into account and second, it makes it easier to relate findings of spatial dependence to the potential role of local externalities. Focusing on the Brazilian Northeast, Lall and Shalizi (2003) test for β-convergence across municipalities using spatial econometrics methods. Using the growth in labour productivity, measured as earnings per worker, as the dependent variable in the econometric analysis, they find that conditionally on structural characteristics, earnings per workers exhibit signs of convergence. Surprisingly they also find that growth in municipalities is negatively influenced by growth in their neighbourhood. Lall and Shalizi offer two alternative explanations for this result. One is that productivity growth in one locality is likely to attract capital and labour from the neighbouring localities, thereby having a negative effect on growth in these areas. As the authors point out, this assumes that productive factors are mobile across regions and can be efficiently used in their new locations. These assumptions might be unrealistic in a low income country context where mobility is low. The second is that, due to the low level of opportunities for local producers of the Northeast to increase the scale of production, productivity enhancements in any location are likely to result in productivity or profitability reductions in neighbouring locations. Whatever the explanation, it would be interesting to determine whether this result is specific to the Northeast, in which case the second explanation would become the most likely, to the extent that producers in other regions are less limited in their opportunities to extend the markets for their goods.

3 Data

Our variable of interest is the growth of the per capita gross domestic product at the municipality (municipio) level over the 1970-1996 period. Per capita GDP of the municipios have been computed by the Instituto de Pesquisa Econômica Aplicada (IPEA). First, IPEA calculates a proxy for the value added of the three main sectors in the economy (agriculture, industry and services) in each municipality, using data from production units census on each sector's total production and total expenditures. Then, subtracting expenditures from the value of production, one obtains a proxy for the value added by sector in each municipality. The value added for every sector and for each of the 27 states in Brazil is then obtained by adding up the proxies for the municipal value added. In a third step, IPEA calculates the share of each municipality in its own state's sectoral value added. Fourth, IPEA multiplies this share by the state's sectoral GDP. Sectoral GDP for each state is calculated by IBGE, the Brazilian institute of statistics. This step produces an estimate of sectoral GDP for each municipality. Finally, the proxy for total GDP of each municipality is obtained by adding up the proxies for GDP of all sectors (agriculture, industry and services). The methodology is presented in details by Reis et al. (2004).

There are two difficulties with the use of these data. First, Brazil is today made up of 5561 municipios. In 1970, there were only 3951 municipios. The permanent creation of new municipalities through the redistricting of existing units has been particularly intense in the North region (the number of municipios in this region has more than doubled between 1980 and 2001), while it has been slower in the Southeast, already endowed with a greater number of municipios. When trying to study the growth process of local units, such a variation in their number over time is clearly a nuisance, since it makes it impossible to compare municipio-level variables over time. It is therefore necessary to work as if no new municipios were created after 1970. The same approach is followed by Andrade et al. (2004). This leads us to work with units defined by IPEA as "Áreas Mínimais Comparáveis" (minimum comparable areas, hereafter AMC, see IPEA's web site[2] for details). AMC-level data were generally directly available from IPEA. When this was not the case, for education variables for instance, we reconstituted AMC data from available municipio-level data. In what follows, we use indifferently the terms municipio and AMC. Second, a national level price index is used to express AMC per capita GDP in year 2000 reais. But over the 1970-1996 period, Brazil has been marked by years of very high inflation and it is likely that, in those years, not all regions experienced the same increase in prices. Thus, though we have access to IPEA data for intermediate years between 1970 and 1996 (namely 1975, 1980 and 1985), we chose not to use them in the econometric analysis, as we cannot control for regional price variations. Our assumption is that large regional variations in prices are less likely to occur in years of low inflation and, following years of high inflation, should not persist once inflation rates are back to reasonable levels. Thus, since both 1970 and 1996 are years of relatively low inflation, we expect heterogeneity in regional inflation rates to be low over the 1970-1996 period.

Since we want to examine the role of spatial externalities in the growth process of local units, heterogeneity in their geographical sizes may be a problem. Indeed, it seems difficult to assume that externalities between very large municipios may be similar in nature as those arising between smaller units. Size differences between AMC being huge, we chose to exclude the states made up of very large units and to restrict the analysis to the Eastern part of the country, where AMC are smaller and more homogeneous in size. We also excluded the island of Fernado de Noronha – belonging to the state of Pernambuco – far away in the Atlantic Ocean. We therefore work with a sample of 3487 AMC over a total of 3659 (our sample represents more than 95% of the Brazilian AMC). As a result, the mean size of AMC in the sample is 1052 square kilometres, while it is 2310 square kilometres if all AMC are included (the mean size of out-of-sample AMC is 28398 square kilometres). Our sample of AMC comprises all of Northeast, Southeast and South regions, plus the states of Tocantins (region North) and Goias and the Federal District of Brasilia (region Centre West). Though it accounts for only 43% of the Brazilian territory, it

[2] http://www.ipeadata.gov.br

represented more than 90% of the population and GDP over the period. The description of the variables used in the analysis, their sources and summary statistics are presented in Table 1.

Table 1: Description of the variables used and summary statistics

Variable	Description (sources)	Brazil		Sample	
		Mean	St. Dev.	Mean	St. Dev.
Number of observations		3659		3487	
Initial income (y_0)	Per capita GDP, 1970, R$ of 2000 (IPEA, IBGE)	1471	1906	1483	1943
Income 1996	Per capita GDP, 1996, R$ of 2000 (IPEA, IBGE)	3095	3229	3111	3266
Growth 1970-1996 (g)	Growth of per capita GDP	0.755	0.565	0.759	0.559
Education	Mean number of years of education, people aged 25 +, 1970 (IPEA, IBGE)	1.37	0.81	1.37	0.82
Illiteracy	Illiteracy rate, people aged 15 +, 1970 (IPEA, IBGE)	0.44	0.18	0.44	0.18
Urbanization	Share of urban population, 1970 (IBGE)	0.33	0.21	0.33	0.21
Electricity	Share of households with electricity, 1970 (IBGE)	0.24	0.23	0.25	0.23
Agriculture		0.46	0.22	0.45	0.22
Industry	Share of sector in GDP, 1970 (IPEA)	0.16	0.17	0.16	0.17
Services		0.38	0.15	0.38	0.15
Labour force	Share of people aged 25 +, 1970 (IBGE)	0.36	0.04	0.36	0.04
Household size	Mean size of households, 1970 (IBGE)	5.48	0.46	5.45	0.44
Area	Area, square kilometers (IBGE)	2310	14155	1052	2295
Region dummies					
Center-West		0.061		0.046	
North		0.039		0.01	
Northeast		0.355		0.372	
South		0.162		0.17	
Southeast		0.383		0.402	

4 Inequalities between municipios

4.1 Theil index decomposition

Over the last thirty years, global inequalities between Brazilian municipalities have decreased: the Theil ($GE(1)$) index of income inequalities between municipalities has decreased from 0.41 in 1970 to 0.3 in 1996.[3] However, Brazil is a vast country with huge differences between regions and it seems necessary to provide a more detailed account of this evolution. We compute the share of different components of global spatial inequalities using a two-stage nested decomposition of the Theil index. As is well known, general entropy indexes are additively decomposable, so that any index of this family can be written as the sum of exclusive and exhaustive sub-indexes (Shorrocks, 1984). If we use the AMC as the basic unit of observation, and since each AMC belongs to one of the 27 Brazilian states and each state belongs to one of the 5 regions (North, Northeast, Center-West, Southeast and South), the familiar Theil index ($GE(1)$) can be written

[3]In this section, we do not restrict the analysis to the sample described above and provide results for the whole country.

as:

$$T = \sum_i \sum_j \sum_k \left(\frac{Y_{ijk}}{Y}\right) \ln\left(\frac{Y_{ijk}/N_{ijk}}{Y/N}\right)$$

where Y_{ijk} and N_{ijk} are respectively the income and the population of the AMC k in state j and region i, and Y and N are the total income and population of the country (i.e. $Y = \sum_i \sum_j \sum_k Y_{ijk}$ and $N = \sum_i \sum_j \sum_k N_{ijk}$). This can be rewritten as:

$$\begin{aligned} T &= \sum_i \sum_j \sum_k \left(\frac{Y_{ijk}}{Y}\right) \left\{ \ln\left(\frac{Y_{ijk}/N_{ijk}}{Y_{ij}/N_{ij}}\right) + \ln\left(\frac{Y_{ij}/N_{ij}}{Y_i/N_i}\right) + \ln\left(\frac{Y_i/N_i}{Y/N}\right) \right\} \\ &= \frac{1}{Y} \left\{ \sum_i \sum_j \sum_k Y_{ijk} \ln\left(\frac{Y_{ijk}/N_{ijk}}{Y_{ij}/N_{ij}}\right) + \sum_i \sum_j Y_{ij} \ln\left(\frac{Y_{ij}/N_{ij}}{Y_i/N_i}\right) + \sum_i Y_i \ln\left(\frac{Y_i/N_i}{Y/N}\right) \right\} \\ &= \sum_i \left(\frac{Y_i}{Y}\right) \sum_j \left(\frac{Y_{ij}}{Y_i}\right) T_{ij} + \sum_i \left(\frac{Y_i}{Y}\right) T_i + T_{BR} \end{aligned}$$

where T_{BR} is the Theil index of inequality between regions, T_i is the inequality index between states in region i and T_{ij} is the inequality index between AMC in state j in region i. The weighted sum of within-state indexes form the within-state component of the global index, and the weighted sum of between-state indexes form the intermediate between-state component.

In the top panel of Table 2, we present the evolution of the global index and of the share of each component: the between-regions and between-states components have decreased over the period, while the within-state component has increased, which is consistent with the formation of two convergence clubs, observed by Andrade et al. (2004). The bottom panel of Table 2 presents the evolution of the Theil index for each region: inequalities between municipios have increased in the Northeast and the North, while they have decreased in the South and the Southeast. This evolution is compatible with the existence of persistent poverty traps in the North and Northeast. Those findings clearly require a more detailed investigation of the spatial pattern of income distribution and growth.

4.2 Exploratory spatial data analysis

In this section we use statistical measures of global and local spatial association to investigate the dependence across the level of the municipios average per capita incomes. The extent of spatial dependence of a given variable among a set of spatially distributed units can be assessed by computing a measure of global statistical dependence such as the Moran's I statistic:

$$I = \frac{n}{S_0} \sum_i \sum_j w_{ij} z_i z_j / \sum_i z_i^2 = \frac{n}{S_0} \frac{z'Wz}{z'z} \tag{1}$$

where n is the number of municipios, $(W)_{ij} = w_{ij}$ is a weight indicating how region i is spatially connected to region j, $S_0 = \sum_i \sum_j w_{ij}$ is a scaling factor and z_i and z_j are values of the log-average income per capita in municipios i and j (i.e. $z_i = \ln(y_i/\bar{y})$ where y_i is the income per

Table 2: Evolution of income inequalities between municipios – 1970-1996

	1970	1996
Global Theil	0.415	0.31
Between regions	33 %	29 %
Between states	18 %	11 %
Within states	49 %	60 %
Intraregional between-municipios Theil indexes		
North	0.19	0.24
Northeast	0.36	0.39
Center-West	0.26	0.21
South	0.2	0.19
Southeast	0.29	0.19

capita in municipio i). We have computed the Moran's I statistic using several definitions for the weight matrix W: first and higher orders binary contiguity matrices (up to the fourth order) and distance-based neighbourhood matrices with different distance bounds (100, 150, 200 and 300 kilometres). For the first order contiguity matrix, $w_{ij} = 1$ if i and j share a common border and 0 otherwise. For the n^{th} order contiguity matrix, $w_{ij} = 1$ if i and j share a common border or if j shares a border with a $(n-1)^{\text{th}}$ order neighbour of i and 0 otherwise. For distance-based matrices, $w_{ij} = 1$ if the distance between i and j's centroids is less than a certain threshold and 0 otherwise. For all matrices, $w_{ii} = 0$ for all i. In order to normalize the outside influence upon each region, the weights are normalized, so that $\sum_j w_{ij} = 1$ for each i. In this case expression (1) simplifies since $S_0 = n$. Positive values of the Moran's I indicate positive spatial dependence, that is the clustering of similar attribute values, whereas negative values are associated with the clustering of dissimilar values.[4]

The Moran's I statistic can be decomposed into a set of local indicators of spatial association (LISA), as developed by Anselin (1995). For municipio i the value of the LISA is given by:

$$I_i = \frac{n z_i \sum_j w_{ij} z_j}{\sum_i z_i^2} \tag{2}$$

and we have $I = \frac{1}{S_0} \sum_i I_i$. Using a method suggested by Anselin (1995), it is possible to generate an empirical distribution of the LISA index. This distribution can then be used to assess the statistical significance of the local statistics.[5] The LISA for each municipio therefore gives a indication of significant spatial clustering of similar values around that observation. A

[4]The Moran's I statistic gives an indication of the degree of linear association between the vector z of observed values and the vector Wz of spatially weighted averages of neighbouring values. Values of I larger (resp. smaller) than the expected value under the hypothesis of no spatial autocorrelation, $E(I) = -1/(n-1)$, indicate positive (resp. negative) spatial autocorrelation, that is the clustering of similar (resp. dissimilar) attribute values.

[5]Due to global spatial autocorrelation, we use Bonferroni pseudo-significance levels of inference (Anselin, 1995), that is if, in the absence of spatial autocorrelation, the significance level is set to α, in the present case, the significance level is set to α/k , where k is the number of municipios in the contiguity set. Another possible choice is the Sidàk pseudo-significance level that is equal to $1-(1-a)^{1/k}$. However, this requires the local statistics to

positive value indicates spatial clustering of similar values (high or low) whereas a negative value indicates spatial clustering of dissimilar values between a region and its neighbours.

The Moran scatterplot is another tool for studying the local clustering of similar or dissimilar values. For each locality, it plots the spatial lag, $\sum_j w_{ij}z_j$, against the original value z_i. The four different quadrants of the scatterplot correspond to the four possible types of local spatial association between a region and its neighbours. Regions with a high value (relative to the mean) surrounded by regions with high values are in the top right quadrant (HH). On the opposite, regions with low values, surrounded by regions with low values are found in the bottom left quadrant (LL). At the top left, one finds regions with low values, surrounded by regions with high values (LH) and at the bottom right, regions with high values, surrounded by regions with low values (HL). Quadrants HH and LL (respectively LH and HL) refer to positive (resp. negative) spatial autocorrelation indicating the spatial clustering of similar (resp. dissimilar) values.

We have computed the values of the global Moran's I statistic for the log-average GDP per capita in years 1970 and 1996, as well as for the growth rate of the per capita GDP over the 1970-1996 period. Results are shown in Figures 1 and 2, which present the values of the Moran's I for the different variables and for the different neighbourhood concepts used.

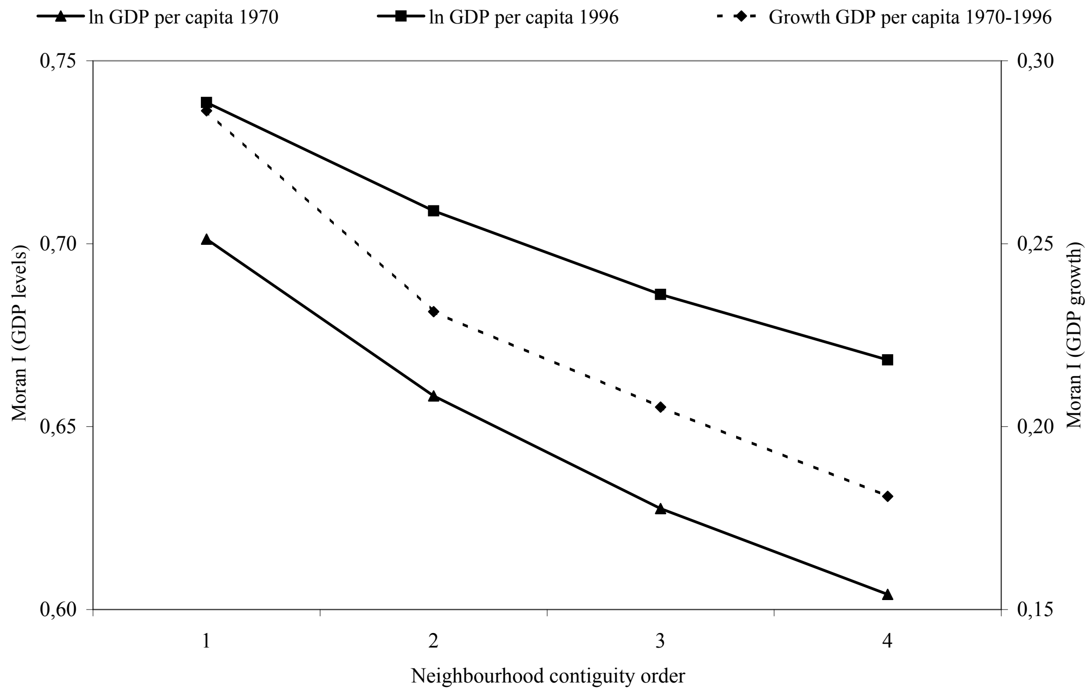
In all cases, we find highly (1%) significant and positive values of the Moran's global statistic, indicating clustering of similar values of the GDP per capita level in 1970 and 1996 and of the growth rate. In other words, municipios with relatively high (resp. low) values of per capita GDP are localized close to other municipios with relatively high (resp. low) per capita GDP more often than if their localization were purely random. This tendency appears to reinforce over time, since the Moran statistic is found higher in 1996 than in 1970 for all the neighbourhood concepts. The same kind of evidence is found for the per capita GDP growth rate. One can notice that, logically, the value of the Moran's statistic decreases with the order of the contiguity matrix or with the threshold distance. This is not surprising if one expects the degree of spatial association to decrease with the distance between municipios.

The Moran scatterplots in Figures 3, 4 and 5 give a visual representation of this association. Figures 3 and 4 show the scatterplots obtained for GDP per capita in 1970 and 1996 respectively. We can see that most municipios are found in either quadrant HH or LL. Only a small proportion of municipios are found in quadrants LH or HL and nearly all municipios with significant LISA statistics are found in quadrant HH or LL. The table 3 summarizes the results of Figures 3 and 4 and shows, by state and for both years 1970 and 1996, the percentage of municipios located in quadrants HH or LL, with a LISA statistic significant at the 5% level.

The first striking feature is that the municipios in the HH quadrant mostly belong to the Southeast and South regions, whereas those in the LL quadrant mostly belong to the Northeast. This shows evidence of a spatial clustering between the Northeast on one side, and the Southeast and South on the other side, a result also found by Bosch Mossi et al. (2003) at the state level. Second, the comparison between 1970 and 1996 shows the changes in this clustering pattern over

be multivariate normal, which is unlikely to be the case with LISA. The chosen pseudo-significance level does not require this assumption.

Figure 1: Moran's I, contiguity neighbourhoods

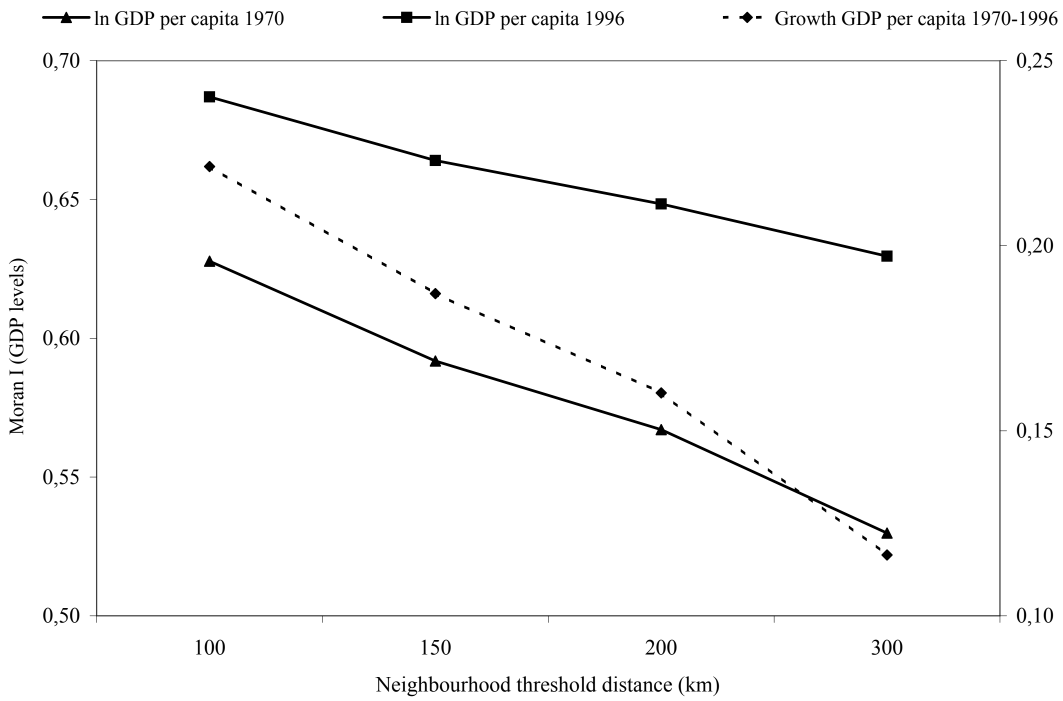


the period. We find that the proportion of municipios in the LL quadrant tends to increase for almost all of the states in the North and Northeast, whereas the proportion of municipios in the HH quadrant is rather stable. Thus over the period 1970-1996 the extent of spatial clustering seems to increase in Brazil as a whole, but this dynamics appears to be mainly due to the specific growth pattern of the Northeast.

The Moran scatterplot for growth is presented in 5 together with the States percentage of significant LISA statistics in Table 4. The pattern is not as clear as with the GDP per capita levels. The percentage of municipios with a significant LISA statistic in much lower. However, the same opposition between the Northeast and the southern states appears. The states with a significant proportion of municipios in the LL quadrant (namely Alagoas (AL), Bahia (BA) and Maranhão (MA)) all belong to the Northeast region. In the HH quadrant, the only state with a sizeable proportion of municipios presenting a significant level of spatial association with neighbouring municipios is Paraná (PR), located in the South region.

Altogether, these results accord with the emergence of convergence clubs found by Bosch Mossi et al. (2003) at the state level, and by Andrade et al. (2003) at the municipios level, but with a different method of investigation. This pattern of spatial statistical association between GDP per capita levels and growth rates remains to be explained. In particular it does not tell

Figure 2: Moran's I, distance-based neighbourhoods



us anything about causal relationships. In order to go beyond these results one needs to develop a theoretical model and to employ econometric methods of analysis, to which we now turn.

5 Spatial dependence and convergence between municipios

5.1 Spatial dependence in growth and level of income: some theoretical developments

In a recent paper Lopez-Bazo et al. (2004) presented a simple model of growth that allows for externalities across economies. This model provides the basis of our empirical investigations. Output, Y, is produced using labour, L, physical, K, and human, H, capital. The technology is assumed to be of the Cobb-Douglas type with constant returns to scale, so that output per capita in municipio i in period t, y_{it}, is a function of the levels of per capita physical and human capital, k_{it} and h_{it} and of the state of technology, A_{it}:

$$y_{it} = A_{it} k_{it}^{\tau_k} h_{it}^{\tau_h}$$

where τ_k and τ_h are internal returns to physical and human capital respectively. The assumption of constant returns to scale in labour and both types of capital implies that $\tau_k + \tau_h < 1$.

Technology in municipio i, A_{it}, is assumed to depend on the technological level of the neighbouring municipios, which is in turn related to their stocks of both types of capital:

$$A_{it} = A_t(k_{\rho it}^{\tau_k} h_{\rho it}^{\tau_h})^{\gamma}$$

where A_t is an exogenous component, common to all municipios and $k_{\rho it}$ (resp. $h_{\rho it}$) denotes the average physical (resp. human) capital ratio in the neighbouring municipios. The γ coefficient measures the externality across municipios. If γ is positive, a one percent increase in the level of the per capita average physical stock of neighbouring municipios increases technology in municipio i by $\gamma\tau_k$ percent. Thus, under this assumption, a municipio benefits from investments made by its neighbours.

Given the assumptions of internal constant returns to scale and of technological externalities, the growth rates of physical and human capital in each municipio are assumed to be decreasing functions of their stocks, but are increasing functions of the stocks of these factors in the neighbouring municipios. As pointed out by Lopez-Bazo et al., this means that investments in physical and human capital are going to be more profitable, and therefore larger, in municipios surrounded by other municipios with high stocks of these factors. In contrast, incentives to invest will be lower in municipios surrounded by others with low capital intensity. This could explain the emergence of convergence clubs.

5.2 Estimating β-convergence between municipios

Our assumptions on technological spillovers across municipios lead to the following empirical growth equation (see Lopez-Bazo et al. (2004) for details):

$$g = c - (1 - e^{-\beta T}) \ln y_0 + \frac{(1 - e^{-\beta T})\gamma}{1 - \tau_k - \tau_h} \ln y_{\rho 0} + \gamma g_\rho + \varepsilon \tag{3}$$

where g is the per capita GDP growth rate, y_0 is the per capita GDP at the beginning of the observation period, g_ρ and $y_{\rho 0}$ are the average values of g and y_0 over neighbouring municipios and ε is a random term that is assumed centered, normally distributed with variance σ^2. If the rate of convergence, β, is significantly positive, poorer areas tend to grow faster than wealthier ones. When γ is equal to zero, this model reduces to the standard neo-classical growth model of unconditional convergence. In the presence of positive technological externalities, γ is positive and both the average level of per capita GDP in neighbouring municipios at the beginning of the observation period and the average growth rate in the neighbourhood have a positive effect on the steady state growth rate. Growth will be higher in municipios surrounded by neighbours with high initial per capita GDP and high rates of growth.

We complete equation (3) by adding on the right-hand side a set, X, of control variables that could cause differences in the rate of technological progress and the steady state across municipios:

$$g = c - (1 - e^{-\beta T}) \ln y_0 + \frac{(1 - e^{-\beta T})\gamma}{1 - \tau_k - \tau_h} \ln y_{\rho 0} + \gamma g_\rho + X\delta + \varepsilon. \tag{4}$$

This inclusion is also necessary in order to control for similarities between neighbouring municipios, which, in the absence of these variables, could cause the coefficients of $\ln y_{\rho 0}$ and g_ρ to be found spuriously significant. In the set of control variables we include the shares of the primary and secondary sectors in GDP, to account for the heterogeneity in the industrial mix across municipios, the illiteracy rate among individuals aged 15 or over, which proxies for the level of human capital, the share of people aged 25 or over, proxying for the relative size of the local labour force, the mean size of households, which helps controlling for socio-cultural differences, the share of urban population, and the share of households with electricity, which proxies for local public infrastructures. All variables are measured in 1970.

The spatial lags of GDP per capita in 1970 and growth rates are computed using the row-standardized spatial weight matrix, W. The econometric model is thus written:

$$g = c + \alpha \ln y_0 + \theta \ln(W y_0) + \gamma W g + X\delta + \varepsilon. \tag{5}$$

We estimate several versions of the model presented in equation (4), starting with the standard OLS specification ($\gamma = 0$) and then including spatial lag variables. Note that according to our structural model, $\gamma = 0$ implies $\theta = 0$ in the above equation. In what follows we shall not impose this restriction. We also contrast the results of the spatial lag model with those of the spatial error model, in which the model residuals follow a spatially auto-regressive process:

$$\begin{aligned} g &= c + \alpha \ln y_0 + \theta \ln(W y_0) + X\delta + \varepsilon \\ \varepsilon &= \lambda W \varepsilon + u \end{aligned}$$

where u is an uncorrelated and homoskedastic error term.

The results are presented in Tables 5 to 8. Table 5 shows the results obtained when spillovers across municipios are neglected ($\gamma = \theta = 0$). First, we consider the absolute convergence model, where the only regressor is the log of initial per capita income. This model assumes that all municipios have the same steady-state. The fit we obtain being very poor, this assumption does not seem correct. As expected, conditional convergence estimations lead to higher rates of convergence across municipios. The variable proxying for human capital initial endowment has the expected sign and is strongly significant: municipios less richly endowed with human capital tend to grow at a slower pace. Infrastructures also play a key role in growth prospects: municipios where households had better access to electricity in 1970 have grown faster. The level of urbanization in 1970 has a negative impact on growth. The best fit is obtained when regional fixed effects are included (column 3) and we will use this model in the subsequent analysis. For this model, the point estimate of the yearly rate of convergence between municipios is 3.8%.[6]

Results obtained in section 4.2 clearly indicate that levels and growth of per capita GDP

[6]The yearly rate of convergence is given by $\beta = -\ln(1 + \alpha)/T$.

are spatially clustered. For this reason, we compute various tests of residual spatial autocorrelation using the weight matrices defined above. The Moran's I test is simply the application of the Moran's I to OLS residuals. A significant value indicates that the residuals are spatially correlated, which is the case for all the OLS models we have estimated. Note that tests results reported in Table 5 are obtained using the second order contiguity matrix; the first order matrix leads to similarly significant results. LM (Lagrange multiplier) tests are used to obtain a more precise idea of the kind of spatial dependence involved (Anselin and Bera, 1998). We first conducted the test while imposing $\theta = 0$. The Lagrange multiplier test for the spatial lag model (LM lag) tests the null hypothesis $\gamma = 0$. This test is significant for all the convergence models proposed, indicating that the null hypothesis $\gamma = 0$ must be rejected. Since the spatial lag model of equation (5) reduces to the simple convergence model (equation 4) when $\gamma = \theta = 0$, this latter model must be rejected. The LM test for the presence of spatial error autocorrelation (LM error) tests the null hypothesis $\lambda = 0$, where λ is the spatial autoregressive coefficient for the error lag $W\varepsilon$ in the following model:

$$\begin{aligned} g &= c + \alpha \ln y_0 + X\delta + \varepsilon \\ \varepsilon &= \lambda W \varepsilon + u. \end{aligned} \tag{6}$$

The LM error test is significant in all cases, indicating that the hypothesis $\lambda = 0$ must be rejected. Both the spatial lag and the spatial error models are therefore preferable to our initial model. Since the robust LM lag test (test of $\gamma = 0$ in the presence of local misspecification involving spatial-dependent error process) has a lower value than the robust LM error test (test of $\lambda = 0$ in the local presence of γ), this would lead to prefer the spatial error model (Anselin et al., 1996).

We estimated both models using different spatial weight matrix definitions (the first and second order contiguity matrices, as well as a spatial weight matrix based on various distance cut-offs). In the spatial lag model, since the spatially lagged dependent variable Wg is correlated with the error term, OLS estimation will yield biased inconsistent estimates. In the spatial error model, OLS estimates are not biased but inefficient, due to the error covariance matrix being non spherical. As shown by Anselin and Bera (1998), both models can be consistently and efficiently estimated by maximum likelihood and this is the choice we made. Results reported in Table 6 are those obtained with the second order contiguity matrix since the log-likelihood was systematically higher for models estimated with this weight matrix. Interestingly, the application of this criterion would lead to prefer the spatial error model over the spatial lag model, which confirms the results given by the robust LM tests. For the spatial lag model, we find a positive spatial dependence between the growth rates of municipios belonging to the same neighbourhood and, for the spatial error model, we find a positive spatial autocorrelation in measurement errors or in possibly omitted variables. The estimated yearly rates of convergence are quite different: 3.3% for the spatial lag model and 4.4% for the spatial error model, a figure quite higher than what was estimated in the initial model.

We now relax the assumption that the initial level of income in neighbouring municipios does not affect the growth rate of GDP per capita (θ is no longer imposed to equal 0). The spatial cross-regressive model is obtained when $\theta \neq 0$ and $\gamma = 0$ (Anselin, 2003):

$$g = c + \alpha \ln y_0 + \theta \ln(W y_0) + X\delta + \varepsilon. \tag{7}$$

This model can be safely estimated by means of OLS. The model was estimated using first and second order contiguity matrices, but the latter one provided the best fit. Results are presented in Table 7. Compared to the initial model (Table 5), the inclusion of the spatially lagged initial income improves the estimation. We find a significant positive impact of the initial income of the neighbourhood on growth and an estimated rate of convergence of 4.3% per year. The tests of residual spatial autocorrelation indicate that this model does not capture the full extent of spatial effects. Interestingly, while the robust LM error test is significant, this is no longer the case for the robust LM lag test, which indicates that the null hypothesis of $\gamma = 0$ (in the presence of a spatial-dependent error process) cannot be rejected. This result points to the spatial cross-regressive spatial error model as the correct specification:

$$\begin{aligned} g &= c + \alpha \ln y_0 + \theta \ln(W y_0) + X\delta + \varepsilon \\ \varepsilon &= \lambda W \varepsilon + u. \end{aligned} \tag{8}$$

For the sake of completeness, we also the estimate the spatial cross-regressive spatial lag model which corresponds to our structural model (equation (5)):

$$g = c + \alpha \ln y_0 + \theta \ln(W y_0) + \gamma W g + X\delta + \varepsilon. \tag{9}$$

Estimation results of these models using the second order contiguity matrix are presented in Table 8. Both models clearly outperform the spatial cross-regressive model of equation (7). We obtain a point estimate of 4.4% for the yearly rate of convergence between municipios in the spatial cross-regressive spatial error model and of 4.1% in the spatial cross-regressive spatial lag model. Both the coefficient of the spatially lagged initial income and the spatial autoregressive coefficient for the error lag or for the growth lag are positive and highly significant. Consistent with the robust LM tests in the spatial cross-regressive model, the log-likelihood is higher for the spatial error version of the model, which is therefore our preferred specification.

One can give a structural interpretation to the results of the spatial cross-regressive spatial error model. Computing the reduced form of ε in terms of u and replacing in equation (8), one gets:

$$g = (I - \lambda W)c + \alpha \ln y_0 + \theta \ln(W y_0) + \lambda W g + X\delta - \lambda \alpha W \ln y_0 - \lambda \theta W \ln(W y_0) - \lambda W X \delta + u \tag{10}$$

This equation is directly comparable to equation (9). Several comments are in order. First, the values of γ and λ are found quite close to each other in Table 8, which indicates that both models predict a quite similar impact of the neighbours' growth on the growth of a given municipio. Second, provided that $\ln(Wy_0)$ and $W \ln y_0$ are close enough[7], the overall impact of the initial income of neighbours on growth in the spatial cross-regressive spatial error model can be approximated by $\theta - \lambda\alpha$, while it is directly measured by θ in the spatial cross-regressive spatial lag model. This impact is thus higher in the former ($\theta - \lambda\alpha = 0.643$) than in the latter ($\theta = 0.371$). Third, the spatial cross-regressive spatial error model implies that the initial income of more distant neighbours, through the variable $W \ln(Wy_0)$, has a modest negative impact on growth.

How do these results relate to our previous findings of persistent spatial clustering of low income municipios in the North and Northeast during the period 1970-1996 ? While convergence estimations indicate that poor municipios tend to catch up with richer ones over time (a usual result of β-convergence regressions), the average income level of neighbours has a positive impact on growth. Other things being equal, a municipio located in a relatively poor neighbourhood will therefore tend to have a lower income growth. Moreover, the growth of the neighbours matters as well: the growth of a given municipio will be higher if it is surrounded by fast growing municipios. Given the extent of spatial clustering in incomes in 1970, these characteristics of the local growth process have logically led to a reinforcement of this clustering over time.

6 Conclusion

This paper shows that the presence of spatial externalities in the growth process of the Brazilian municipalities can help explain the diverging pattern of inequalities at the local level during the period 1970-1996: while the municipios in the southern part of the country have experienced some convergence, this is not the case in the northern regions. Inequalities between municipios have tended to increase in the Northeast and North regions and low income localities have become more spatially clustered, indicating that the polarization of economic activities in these regions has increased.

In order to try and explain this phenomenon, we estimate the $\beta-$convergence between municipios, taking into account the role of spatial dependence. We find that, while the estimated global convergence speed is quite high, both the initial income and growth of neighbouring municipios impact the local growth process. Since low income localities were spatially clustered in the North and Northeast in 1970, their own growth process has been negatively influenced by their relative location in the country.

These results raise some important policy issues. First, policies designed to promote economic growth and reduce regional poverty in the North and Northeast should take account of the potential spillovers of geographically targeted investments in physical and human capital stocks. Second, it seems likely that only vigorous public efforts aimed at these regions may succeed in reverting the current trend. In particular, the presence of positive externalities imply that the public promotion of growth poles in the Northeast may help improve the economic condition of larger areas.

Finally, further research is needed in order to provide a clearer assessment of the nature

[7]Which is the case, with a correlation of 0.99.

of the externalities at work among Brazilian municipios. Indeed, while the theoretical model we used explicitly focus on technological externalities, pecuniary externalities may well imply a similar growth process, but with different implications. Moreover, taking into account the potential heterogeneity of the growth process between regions, which has not been explored in this paper, could certainly improve our understanding of local growth in Brazil.

References

[1] **Abreu, M., H.L.F. de Groot and R.J.G.M. Florax (2004):** "Space and Growth", *Tinbergen Institute Discussion Paper* TI 2004-129/3.

[2] **Andrade, E., M. Laurini, R. Madalozzo and P.L. Valls Pereira (2004):** "Convergence clubs among Brazilian municipalities", *Economics Letters*, **83**: 179-184.

[3] **Anselin, L. (1995):** "Local indicators of spatial association-LISA", *Geographical Analysis*, **27**: 93-115.

[4] **Anselin, L. (2003):** "Spatial externalities, spatial multipliers and spatial econometrics", *International Regional Science Review*, **26**: 153-166.

[5] **Anselin, L. and A.K. Bera (1998):** "Spatial Dependance in Linear Regression Models with an Introduction to Spatial Econometrics", in *Handbook of Applied Economic Statistics*, A. Ullah and D. E.A. Gilles eds., Marcel Dekker, Inc., New-York - Basel - Hong Kong.

[6] **Anselin, L., A.K. Bera, R. Florax and M.J. Yoon (1996):** "Simple diagnostic tests for spatial dependence", *Regional Science and Urban Economics*, **26**: 77-104.

[7] **Azzoni, C.R. (2001):** "Economic growth and regional income inequality in Brazil", *The Annals of Regional Science*, **35**: 133-152.

[8] **Azzoni, C.R. and L. Servo (2002):** "Education, cost of living and regional wage inequality in Brazil", *Papers in Regional Science*, **81**: 157-175.

[9] **Bosch Mossi, M., P. Aroca, I.J. Fernandez and C.R. Azzoni (2003):** "Growth Dynamics and Space in Brazil", *International Regional Science Review*, **26**, 3: 393-418.

[10] **Ferreira, A. (2000):** "Convergence in Brazil: recent trends and long-run prospects", *Applied Economics*, **32**: 479-489.

[11] **Glaeser, E., H. Kallal, J. Scheinkman and A. Shleifer (1992):** "Growth in cities", *Journal of Political Economy*, **100**: 1126-1152.

[12] **Goldsmith, W. and R. Wilson (1991):** "Poverty and distorted industrialization in the Brazilian Northeast", *World Development*, **19**: 435-455.

[13] **Lall, S.V. and Z. Shalizi (2003):** "Location and growth in the Brazilian Northeast", *Journal of Regional Science*, **43**, 4: 663-681.

[14] **Lopez-Bazo, E., E. Vaya and M. Artis (2004):** "Regional externalities and growth: Evidence from European regions", *Journal of Regional Science*, **44**: 43-73.

[15] **Magalhães A., G.J.D. Hewings and C.R. Azzoni (2000):** "Spatial Dependance and Regional Convergence in Brazil", *REAL Discussion Paper* 00-T-11.

[16] **Magrini, S. (2004):** "Regional (di)convergence", in *Handbook of Regional and Urban Economics, 4*, V. Henderson and J.-F. Thisse eds., North Holland, Amsterdam.

[17] **Quah, D. (1997):** "Empirics for growth and distribution: stratification, polarization and convergence clubs", *Journal of Economic Growth*, **2**: 27-59.

[18] **Reis, E., P. Tafner, M. Pimentel, R.V. Serra, L.O. Reiff, K. Magalhães and M. Medina (2004):** "Èstimativas do PIB dos municípios brasileiros, 1970-96: Metodologia e resultados", August, available at http://www.ipeadata.gov.br.

[19] **Rey, S.J. and B.D. Montouri (1999):** "US regional income convergence: A spatial econometric perspective", *Regional Studies*, **33**, 2: 143-156.

[20] **Shorrocks, A.F. (1984):** "Inequality decomposition by population subgroups", *Econometrica*, **52**: 1369-1386.

Figure 3: Moran scatterplot – log GDP per capita 1970

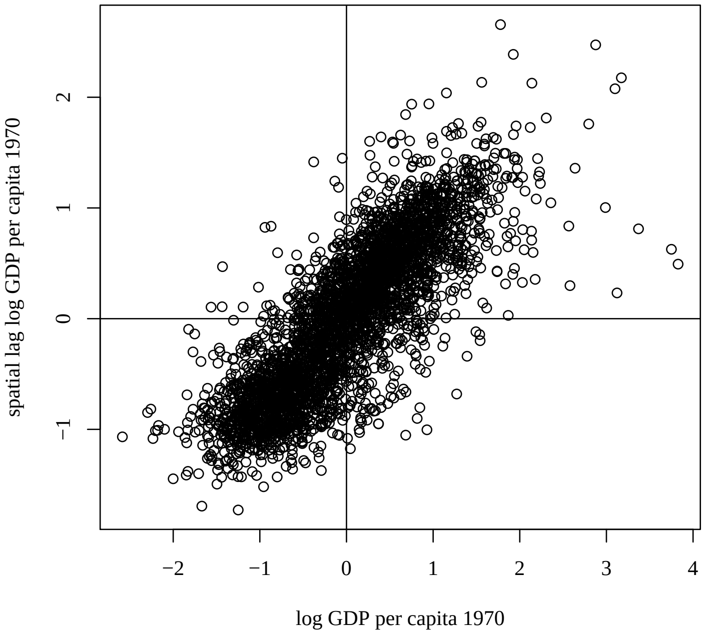


Figure 4: Moran scatterplot – log GDP per capita 1996

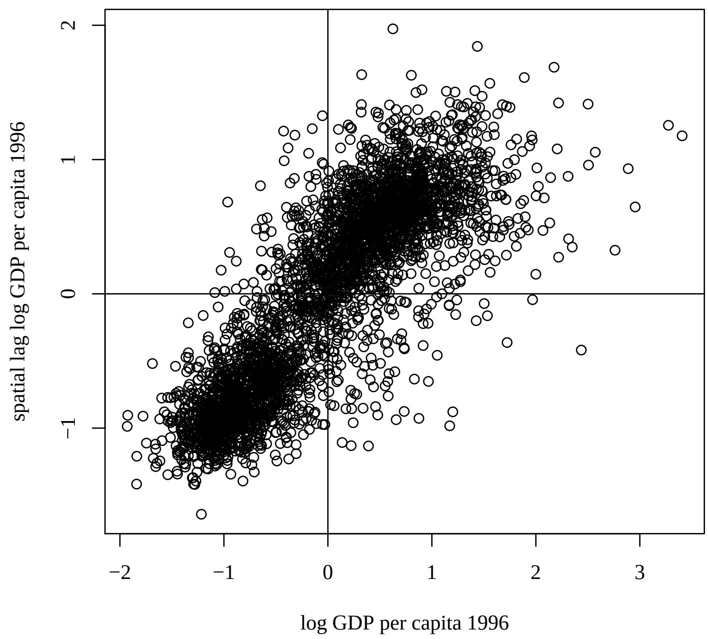


Figure 5: Moran scatterplot – growth 1970-1996

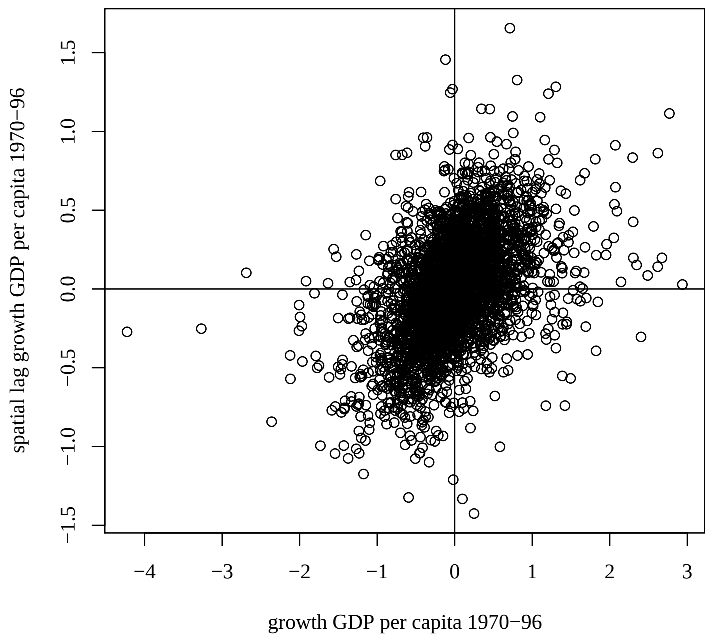


Table 3: Changes in clustering between 1970 and 1996 ; proportion of municipios in HH and LL quadrants with significant LISA, by state

	LL		HH	
	1970	1996	1970	1996
North & Northeast States				
Alagoas (AL)	13.6	58	0	0
Bahia (BA)	15.6	23.5	1.5	1.5
Ceará (CE)	45.7	49.3	0	0
Maranhão (MA)	15.9	61.9	0	0
Paraíba (PB)	41.7	20.8	0	0
Pernambuco (PE)	17.3	6.8	0	0
Piauí (PI)	56.2	58.8	0	0
Rio Grande do Norte (RN)	44.2	64.6	0	0
Sergipe (SE)	8.1	1.4	0	0
Tocantins (TO)	8.8	20.6	0	0
South, Southeast & Center West States				
Espírito Santo (ES)	0	0	1.9	1.9
Goiás (GO)	1.9	1.2	1.2	1.2
Minas Gerais (MG)	4	2.4	2.5	4.4
Paraná (PR)	0	0	4.7	4.3
Rio de Janeiro (RJ)	0	0	17.7	6.5
Rio Grande do Sul (RS)	0	0	51.8	43.1
Santa Catarina (SC)	0	0	13.3	29.4
São Paulo (SP)	0	0	47.6	49.7

Table 4: Percentage of municipios in each state with LISA significant at 5% in each quadrant of the Moran scatterplot – growth 1970-1996

LH: AL (1.1) MG (0.6) PR (0.4) RJ (1.6)	**HH:** BA (3.1) CE (2.2) ES (1.9) GO (3.8) MA (2.7) MG (2.2) PB (1.8) PE (1.2) PI (1.2) PR (13.4) SC (1.1) SP (5.1)
LL: AL (34.1) BA (15.6) MA (14.2) MG (0.7) PE (1.2) PR (1.4) RJ (1.6) RN (2.7) SE (4.1) SP (2.3)	**HL:** AL (4.5) BA (0.9) ES (1.9) MG (0.3) RJ (1.6) RN (0.7) SE (4.1) SP (0.4)

Table 5: Estimation of the standard growth equation and tests of residual spatial dependence

	Absolute convergence	Conditional convergence (1)	(2)
Constant	2.374***	6.078***	5.452***
	(30.95)	(22.92)	(20.39)
Log initial income	-0.233***	-0.565***	-0.635***
	(-21.19)	(-31.16)	(-36.34)
Illiteracy		-1.847***	-0.772***
		(-25.68)	(-8.86)
Urbanization		-0.364***	-0.106
		(-5.51)	(-1.61)
Electricity		0.516***	0.507***
		(6.69)	(6.77)
Agriculture		-0.171***	-0.085
		(-2.7)	(-1.41)
Industry		-0.22***	-0.027
		(-2.79)	(-0.37)
Labour force		-1.171***	0.049
		(-3.92)	(0.17)
Household size		-0.01	0.017
		(-0.45)	(0.81)
Region fixed effects	No	No	Yes
Adj. R^2	0.114	0.322	0.397
I-Moran	0.316***	0.227***	0.177***
LM lag	1642.5***	802.1***	329.8***
Robust LM lag	584.1***	11.9***	38.5***
LM error	2415.6***	1777.4***	1087.2***
Robust LM error	1936.2***	987.2***	795.9***

t-statistics in parentheses.

*, ** and *** : significant at 10%, 5% and 1%.

Table 6: Estimation of the growth equation with externalities across economies

	Spatial lag model	Spatial error model
Constant	4.894***	4.817***
	(48.05)	(43.54)
Log initial income	-0.581***	-0.681***
	(-29.61)	(-38.53)
Illiteracy	-0.762***	-0.688***
	(-10.04)	(-7.25)
Urbanization	-0.187***	-0.224***
	(-2.88)	(-3.44)
Electricity	0.585***	0.467***
	(7.94)	(5.33)
Agriculture	-0.052	-0.217***
	(-0.93)	(-3.76)
Industry	0.001	-0.027
	(0.02)	(-0.38)
Labour force	0.064	0.866***
	(0.35)	(3.82)
Household size	-0.03*	0.086***
	(-1.65)	(5.21)
γ (W*growth rate)	0.428***	
	(4.87)	
λ (W*error term)		0.699***
		(140.45)
Region fixed effect	Yes	Yes
Log likelihood	-710.485	-572.651

Asymptotic t-statistics in parentheses.
*, ** and *** : significant at 10%, 5% and 1%.

Table 7: Estimation of the growth equation (7) and tests of residual spatial dependence

	Spatial cross-regressive model
Constant	4.403***
	(14.36)
Log initial income	-0.676***
	(-36.82)
Illiteracy	-0.659***
	(-7.48)
Urbanization	-0.039
	(-0.58)
Electricity	0.392***
	(5.14)
Agriculture	-0.139**
	(-2.3)
Industry	-0.088
	(-1.17)
Labour force	0.07
	(0.24)
Household size	0.058***
	(2.62)
θ (log W*init.inc.)	0.159***
	(6.85)
Region fixed effects	Yes
Adj. R^2	0.405
I-Moran	0.177***
LM lag	789.1***
Robust LM lag	2.1
LM error	1089.6***
Robust LM error	302.6***

t-statistics in parentheses.

*, ** and *** : significant at 10%, 5% and 1%.

Table 8: Estimation of the growth equations (8) and (9)

	Spatial cross-regressive spatial error model	Spatial cross-regressive spatial lag model
Constant	3.504***	2.215***
	(21.42)	(7.37)
Log initial income	-0.678***	-0.653***
	(-39.16)	(-44.42)
Illiteracy	-0.62***	-0.496***
	(-6.53)	(-6.21)
Urbanization	-0.185***	-0.065
	(-2.89)	(-1.12)
Electricity	0.395***	0.353***
	(4.51)	(4.98)
Agriculture	-0.249***	-0.165***
	(-4.25)	(-3.24)
Industry	-0.057	-0.127*
	(-0.79)	(-1.93)
Labour force	0.837***	0.119
	(3.19)	(0.59)
Household size	0.103***	0.044***
	(5.63)	(2.75)
θ (log W*init.inc.)	0.181***	0.371***
	(6.48)	(13.18)
γ (W*growth rate)		0.613***
		(11.41)
λ (W*error term)	0.681***	
	(121.41)	
Region fixed effect	Yes	Yes
Log likelihood	-559.576	-593.795

Asymptotic t-statistics in parentheses.

*, ** and *** : significant at 10%, 5% and 1%.