Spatial externalities between Brazilian municipios and their neighbours

Philippe de Vreyer, Gilles Spielvogel

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5 Spatial Externalities between Brazilian Municipios and Their Neighbors

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5.1 Introduction

Economic growth is not a uniform process through space. Within countries, some regions grow more rapidly than others and these differences may result in poorer regions catching up with wealthier regions, or, alternatively, increasing income gaps. Brazil offers a good example of a country with regions of very different levels of development. The Northeast region in particular is much less developed than the southern part of the country. Home of 28 percent of the population in 2000, the Northeast produced only 13 percent of the GDP in 2001, whereas the Southeast region produced 57 percent of the GDP, with 43 percent of the population. As a result, per capita income was only 47 percent of the national average while that of the Southeast was 34 percent above average. The poorest state, Maranhão, in the Northeast, had a per capita income level about six times lower than the richest state, São Paulo. And the Northeast is not catching up with the southern regions: in 1937, the per capita income of São Paulo was five times that of Piauì in the Northeast (Azzoni and Servo 2002).

Poorer, the Northeast is also more unequally developed than other regions of Brazil. The wealthiest state in the 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 Center-West, South, and Southeast.

The Northeast has not always been the poorest part of Brazil. At the beginning of the nineteenth century, the Northeast, specializing in the production of sugar, cotton, and tobacco, dominated the Brazilian exports and, in terms of living standards, was not less developed than Rio de Janeiro. During the nineteenth century, however, economic activities developed much more rapidly in the Southeast, and the Northeast has never been able to catch up. This resulted from the increasing competition that Brazilian producers of cotton and sugar faced from English, French, and Dutch colonies and from a switch in comparative advantage in favor of coffee. According to Leff (1972), labor and capital productivity were higher in the coffee sector than in the traditional Northeast exporting sectors. As coffee was easier to produce in the south of the country, capital and labor moved out of the Northeast.[1] The developing production and exportation of coffee has rapidly necessitated the building of transport infrastructures. This mostly benefited São Paulo and its region: from 15,000 inhabitants in 1860, the population of São Paulo rose to 20,000 in 1872 and to about 40,000 in 1886. With this population growth came an increasing concentration of incomes and the development of financial institutions and public services. The conditions for a sustained industrial development were then set and, at the beginning of the twentieth century, the region of São Paulo became the most industrialized part of the country.

While the southern part of the country was taking off, concern for the relative backwardness of the Northeast was on the Brazilian government's agenda. In 1877, after a severe drought, federal public agencies planned water storage and irrigation programs. Since then, they have hired public works labor gangs, built roads and electric plants, promoted and subsidized industry, encouraged labor migration, and called for land reform, thus making the Northeast "one of the world's most important examples of large-scale regional planning" (Goldsmith and Wilson 1991). Unfortunately, despite these efforts, the Northeast has never been able to catch up with the Center-South, mostly because its numerous and poorly educated population serves as a labor reservoir to the industrialized South, and because institutional reforms have not followed the burgeoning economic development. The concern for the low economic development of the Northeast might well be a concern for the development of Brazil as a whole. Goldsmith and Wilson (1991) see in Northeastern underdevelopment major restraints on true development and modernization of Brazil, because 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.

In this paper we document and analyze 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. We use Theil index decomposition to analyze 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 analyze 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 over time, whereas municipios with a GDP per capita higher than average tend to be grouped in the South.

This observation leads us, in the second part of our empirical analysis, to analyze the process of growth in per capita GDP. The emergence of poverty traps and polarized development could result from the existence of externalities across neighboring 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 neighboring municipios. We find evidence of positive externalities across the Brazilian municipios, which could explain the emergence of poverty traps.

The next section presents a short literature survey of recent growth studies in Brazil. Section 5.3 presents the data. Section 5.4 gives the results of the Theil index decompositions and of the spatial statistical analysis. In section 5.5, we briefly present a theoretical model of growth with spatial externalities and expose the results of our econometric estimations. Finally, section 5.6 concludes.

5.2 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 matter not only for growth within a given city or region, but also for growth between neighboring regions (Lopez-Baso, Vaya, and Artis 2004).

Growth at a given location may affect the growth of neighbors through several channels. First, due to technological externalities, a locality may benefit from improved economic conditions in another locality. For instance, if some firms in a locality have developed innovative processes, knowledge spillovers may favor the diffusion of new technologies to firms at neighboring 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 center may improve matching on the labor market, thus reducing costs and increasing labor 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 neighboring 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 labor markets.

Understanding how local growth may spread to neighbors 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 the good from the bad channels may help in designing more efficient policies. Land and transportation policies are also closely related issues: 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 improve these policies.

In the recent years, several papers have analyzed 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 analyzing 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.[2] The methods used in that paper are standard in the sense that, as most surveys studying regional convergence at that time, it did not consider the issue from 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 take 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, Vaya, and Artis (2004) for Europe; and Magalhães, Hewings, and Azzoni (2000) for Brazil. Recent papers on this topic are therefore using spatial econometric methods. Abreu, de Groot, and Florax (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 neighbors have a greater chance of moving up 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 clusters. Intradistribution dynamics are 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 global convergence. Indeed, their 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 constitutes progress: first, it permits us 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 labor 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 neighborhood. Lall and Shalizi offer two alternative explanations for this result. One is that productivity growth in one locality is likely to attract capital and labor from the neighboring 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 in the Northeast to increase the scale of production, productivity enhancements in any location are likely to result in productivity or profitability reductions in neighboring 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.

5.3 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 has 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 a 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 twenty-seven states in Brazil is then obtained by adding up the proxies for the municipal value added. In a third step, IPEA calculates each municipality's share 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 several difficulties with the use of these data. First, Brazil is today made up of 5,561 municipios. In 1970, there were only 3,951 municipios. The permanent creation of new municipalities through the redistricting of existing units has been particularly intense in the North (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 Mínimas Comparáveis* (minimum comparable areas, hereafter AMC. See IPEA's website for details[3]). 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 reals. 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 GDP 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. Third, according to household surveys, informal employment represents up to 40 percent of total employment in the country (Soares 2004). However, since the local GDP data we use are derived from economic censuses and surveys, they typically do not take the informal sector into account. It must therefore be kept in mind that our analysis deals with the formal sector only.

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 to 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 3,487 AMC over a total of 3,659 (our sample represents more than 95 percent of the Brazilian AMC). As a result, the mean size of AMC in the sample is 1,052 square kilometers, while it is 2,310 square kilometers if all AMC are included (the mean size of out-of-sample AMC is 28,398 square kilometers). Our sample of AMC comprises all of the Northeast, Southeast, and South regions, plus the states of Tocantins (region North) and Goias, and the Federal District of Brasilia (region Center-West). Though our sample accounts for only 43 percent of the Brazilian territory, it represented more than 90 percent 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 5.1.

Table 5.1
Description of the variables used and summary statistics

		Brazil		Sample	
Variable	Description (sources)	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 sectorin GDP, 1970 (IPEA)	0.16	0.17	0.16	0.17
Services		0.38	0.15	0.38	0.15
Labor 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	

5.4 Inequalities between Municipios

5.4.1 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.[4] 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 subindexes (Shorrocks 1984). If we use the AMC as the basic unit of observation, and since each AMC belongs to one of the twenty-seven Brazilian states and each state belongs to one of the five regions (North, Northeast, Center-West, Southeast, and South), the familiar Theil index $(GE(1))$ can be written 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

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

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

Table 5.2
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

between AMC in state j in region i. The weighted sum of within-state indexes forms the within-state component of the global index, and the weighted sum of between-state indexes forms the intermediate between-state component.

In the top panel of table 5.2, 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 5.2 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.

5.4.2 Exploratory Spatial Data Analysis

In this section we use statistical measures of global and local spatial association to investigate the dependence of per capita incomes across municipios. 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:

$$I = \frac{n}{S_0} \sum_i \sum_j w_{ij} z_i z_j \Big/ \sum_i z_i^2 = \frac{n}{S_0} \frac{z'Wz}{z'z}, \tag{5.1}$$

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 capita in municipio i]. We have computed the Moran's I statistic using several definitions for the weight matrix W: first- and higher-order binary contiguity matrices (up to the fourth-order) and distance-based neighborhood matrices with different distance bounds (100, 150, 200, and 300 kilometers). For the first-order contiguity matrix, $w_{ij} = 1$ if i and j share a common border and 0 otherwise. For the nth order contiguity matrix, $w_{ij} = 1$ if i and j share a common border or if j shares a border with a $(n-1)$th order neighbor 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 (5.1) 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.[5]

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

$$I_i = \frac{n z_i \sum_j w_{ij} z_j}{\sum_i z_i^2} \tag{5.2}$$

and we have $I = (1/S_0) \sum_i I_i$. 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.[6] The LISA for each municipio therefore gives a indication of significant spatial clustering of similar values around that observation. A 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 neighbors.

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 neighbors. Regions with a high

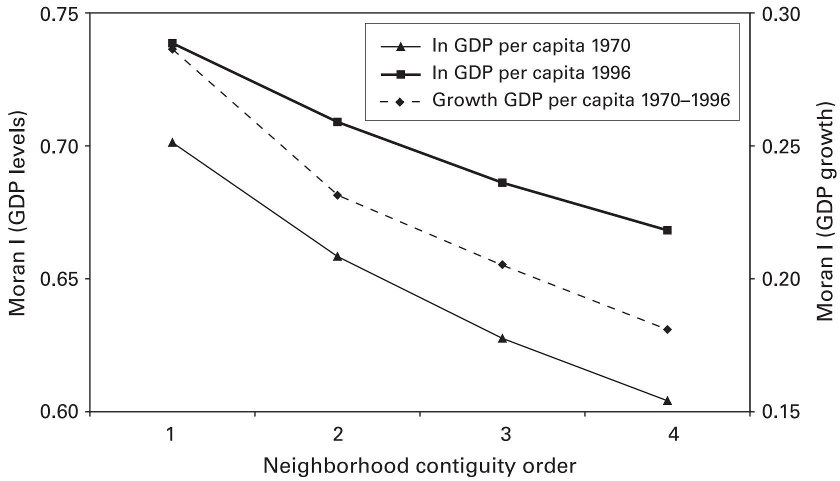

Figure 5.1
Moran's *I*, contiguity-based neighborhoods.

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 (respectively negative) spatial autocorrelation indicating the spatial clustering of similar (respectively 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 5.1 and 5.2, which present the values of the Moran's *I* for the different variables and for the different neighborhood concepts used.

In all cases, we find highly significant (1 percent) 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 (low) values of per capita GDP are localized close to other municipios with relatively high (low) per capita GDP more often than if their localization were purely random. This tendency appears to reinforce over time, since the Moran

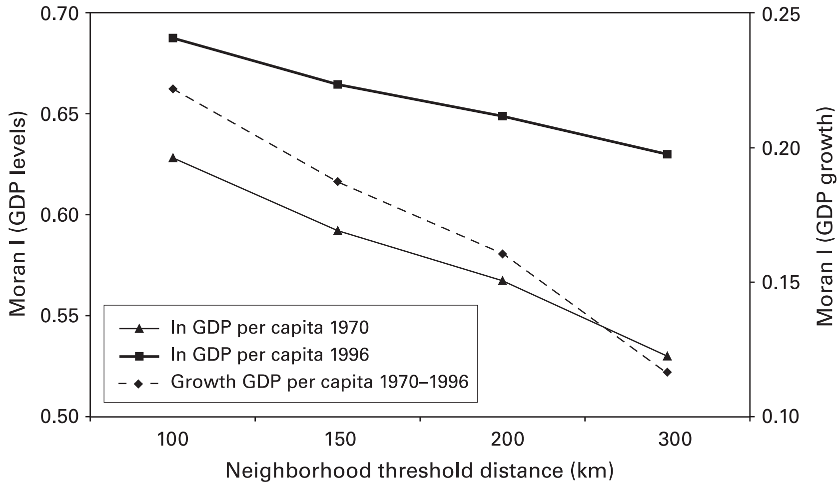

Figure 5.2
Moran's *I*, distance-based neighborhoods.

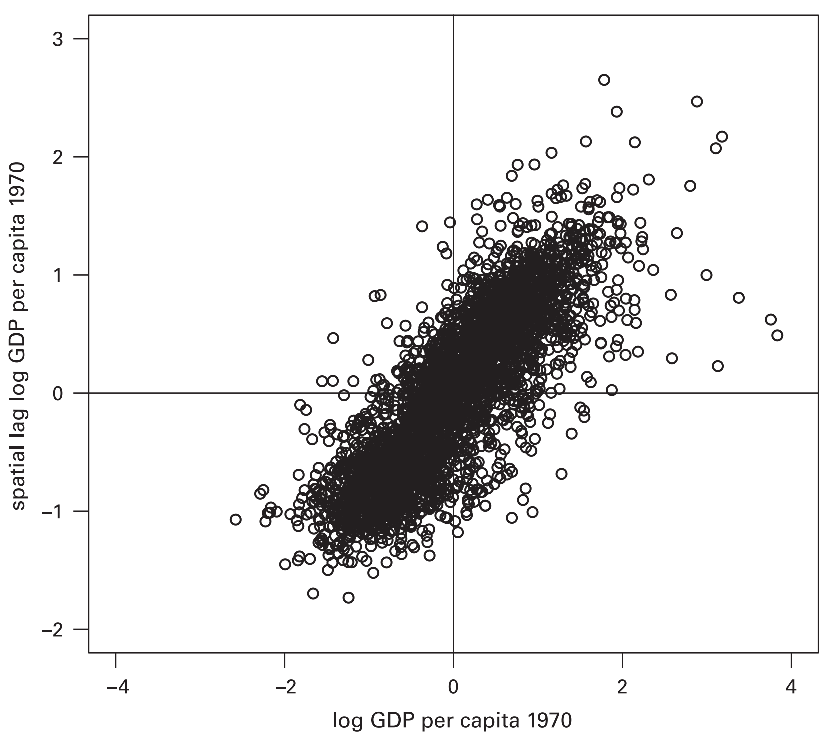

Figure 5.3
Moran scatterplot—log GDP per capita 1970.

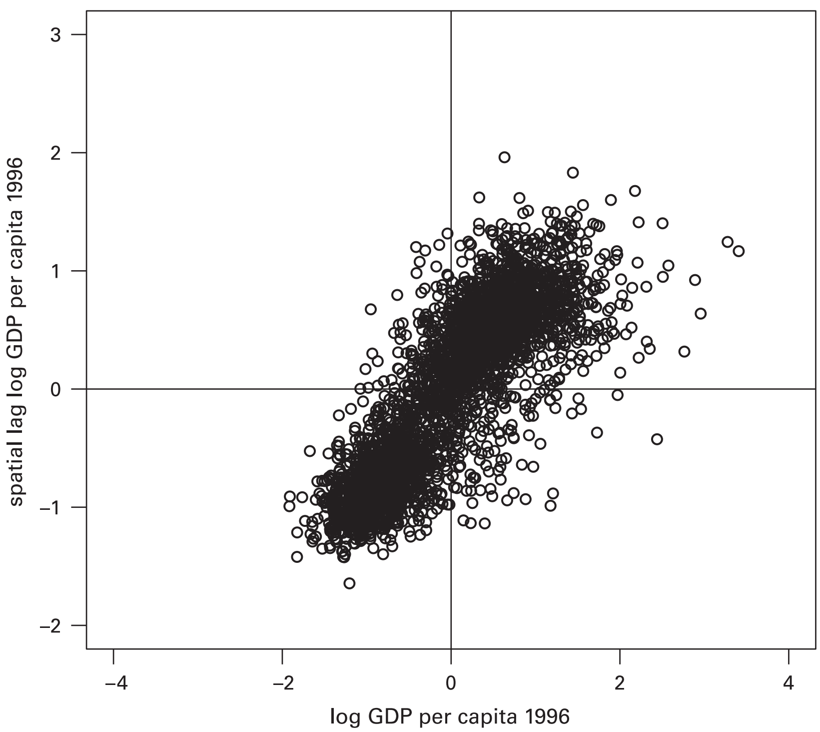

Figure 5.4
Moran scatterplot—log GDP per capita 1996.

statistic is found to be higher in 1996 than in 1970 for all the neighborhood 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 5.3, 5.4, and 5.5 give a visual representation of this association. Figures 5.3 and 5.4 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. Table 5.3 summarizes the results of figures 5.3 and 5.4 and shows, by state and for both years 1970 and 1996, the percentage

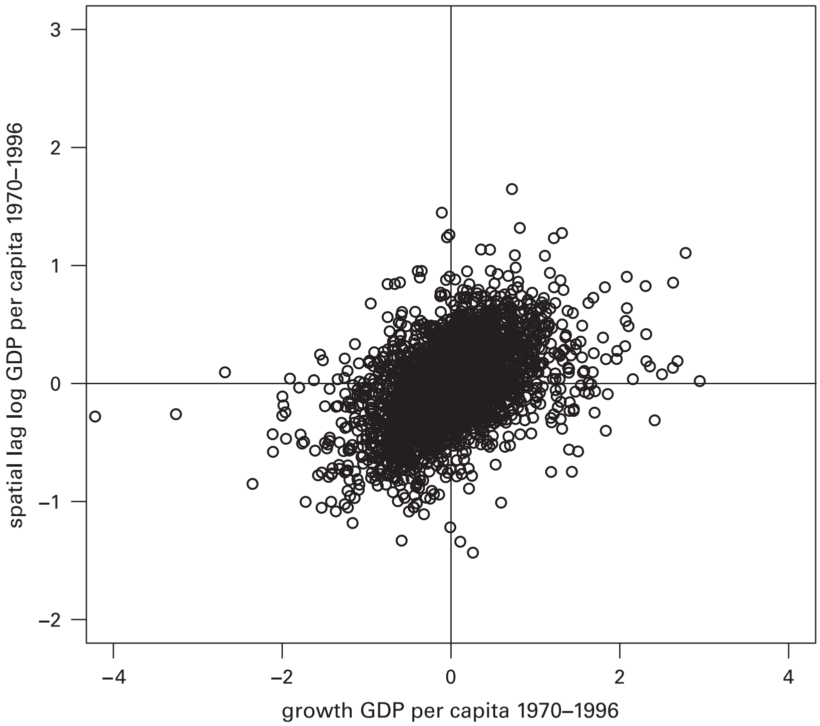

Figure 5.5
Moran scatterplot—GDP per capita growth 1970–1996.

of municipios located in quadrants HH or LL, with a LISA statistic significant at the 5 percent 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 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 increased in Brazil as a whole, but this dynamic appears to be mainly due to the Northeast's specific growth pattern.

Table 5.3
Changes in clustering between 1970 and 1996; percentage of municipios in HH and LL quadrants with significant LISA, by state

	LL		HH	
	1970	1996	1970	1996
North and 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, and 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

The Moran scatterplot for growth is presented in figure 5.5 together with the states percentage of significant LISA statistics in table 5.4. The pattern is not as clear as with the GDP per capita levels. The percentage of municipios with a significant LISA statistic is 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 neighboring municipios is Paraná (PR), located in the South.

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 municipio level, but with a different

Table 5.4
Percentage of municipios in each state with LISA significant at 5% in each quadrant of the Moran scatterplot—growth 1970–1996

	LL	HH	LH	HL
North and Northeast states				
Alagoas (AL)	34.1	0	1.1	4.5
Bahia (BA)	15.6	3.1	0	0.9
Ceará (CE)	0	2.2	0	0
Maranhão (MA)	14.2	2.7	0	0
Paraíba (PB)	0	1.8	0	0
Pernambuco (PE)	1.2	1.2	0	0
Piauí (PI)	0	1.2	0	0
Rio Grande do Norte (RN)	2.7	0	0	0.7
Sergipe (SE)	4.1	0	0	4.1
Tocantins (TO)	0	0	0	0
South, Southeast, and Center-West states				
Espírito Santo (ES)	0	1.9	0	1.9
Goiás (GO)	0	3.8	0	0
Minas Gerais (MG)	0.7	2.2	0.6	0.3
Paraná (PR)	1.4	13.4	0.4	0
Rio de Janeiro (RJ)	1.6	0	1.6	1.6
Rio Grande do Sul (RS)	0	0	0	0
Santa Catarina (SC)	0	1.1	0	0
São Paulo (SP)	2.3	5.1	0	0.4

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 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.

5.5 Spatial Dependence and Convergence between Municipios

In this section, we first present a theoretical model of growth that allows for externalities accross economies. This is largely illustrative though, since in our econometric empirical investigations we shall not test this structural model, as our data do not bear enough information. We will be looking for evidence of externalities across municipalities, but we will not be able to identify the nature of these externalities.

5.5.1 Spatial Dependence in Growth and Level of Income: Some Theoretical Developments

In a recent paper Lopez-Bazo, Vaya, and Artis (2004) presented a simple model of growth that allows for externalities across economies. Output, Y, is produced using labor, L, and both physical and human capital, K and H. 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 labor 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 neighboring 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 $k_{\rho it}$ ($h_{\rho it}$) denotes the average physical (human) capital ratio in the neighboring 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 neighboring municipios increases technology in municipio i by $\gamma\tau_k$ percent. Thus, under this assumption, a municipio benefits from investments made by its neighbors.

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 neighboring municipios. As pointed out by Lopez-Bazo, Vaya, and Artis, 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.

5.5.2 Estimating *β*-convergence between Municipios

These assumptions on technological spillovers across municipios lead to the following empirical growth equation (see Lopez-Bazo, Vaya, and Artis 2004 for details):

$$g = c - (1 - e^{-\beta T}) \ln y_0 + \frac{(1 - e^{-\beta T})\gamma}{1 - \tau_k - \tau_h} \ln y_{\rho 0} + \gamma g_\rho + u \tag{5.3}$$

where g is the per capita GDP growth rate, T is the length of the period (26 years in our case), 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 neighboring municipios, and u is a random term that is assumed to be 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 neoclassical 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 neighboring municipios at the beginning of the observation period and the average growth rate in the neighborhood have a positive effect on the steady-state growth rate. Growth will be higher in municipios surrounded by neighbors with high initial per capita GDP and high rates of growth.

We complete equation (5.3) 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:

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

This inclusion is also necessary in order to control for similarities between neighboring 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 labor force; the mean size of households, which helps control for sociocultural 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

$$g = c + \alpha \ln y_0 + \theta \ln(Wy_0) + \gamma Wg + X\delta + u. \tag{5.4}$$

We estimate several versions of the model presented in equation (5.4), starting with the standard OLS specification ($\gamma = \theta = 0$) and then including spatial lag variables. Note that according to our structural model, $\gamma = 0$ implies $\theta = 0$ in this 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 residuals follow a spatially autoregressive process:

$$\begin{aligned} g &= c + \alpha \ln y_0 + \theta \ln(Wy_0) + X\delta + \varepsilon \\ \varepsilon &= \lambda W\varepsilon + u. \end{aligned} \tag{5.5}$$

The results are presented in tables 5.5 to 5.8. Table 5.5 shows the results obtained when spillovers across municipios are neglected ($\gamma = \theta = \lambda = 0$). Table 5.6 shows the estimation results when spillovers across municipios are allowed, but initial per capita GDP of neighbors has no effect ($\theta = 0$). In table 5.7, growth in municipios can depend upon initial GDP of neighboring municipios ($\theta \neq 0$), but every other kind of spillovers are neglected ($\gamma = \lambda = 0$). Finally, in table 5.8, estimates of models (5.4) and (5.5) are shown.

Starting with table 5.5, we first 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. As the fit we obtain is 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. Column 3 shows the results when regional fixed effects are included. The coefficients of the regional dummies are found to be significant and the regression fit is largely improved. For this model, the point estimate of the yearly rate of convergence between municipios is 3.9 percent.[7] It is interesting to note that the

Table 5.5
Estimates for the standard growth equation and tests of residual spatial dependence

	Absolute convergence	Conditional convergence (1)	Conditional convergence (2)
Constant	2.374***	6.078***	5.452***
	(30.95)	(22.92)	(20.39)
Log initial income	−0.233***	−0.565***	−0.635***
	(−21.2)	(−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)
Labor force		−1.171***	0.049
		(−3.92)	(0.17)
Household size		−0.01	0.017
		(−0.45)	(0.81)
Regional dummies (ref.: North)	No	No	Yes
Northeast			−0.425***
			(−5.59)
Southeast			0.038
			(0.5)
South			0.185**
			(2.33)
Center-West			0.203**
			(2.45)
Adj. R^2	0.114	0.322	0.397
AIC	5420.02	4496.25	4087.02
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***

Note: t-statistics in parentheses.
*, ** and ***: significant at 10 percent, 5 percent and 1 percent.

coefficients of four of our control variables vanish when regional dummies are included. This is because there are large differences in the mean values of these variables between regions. In other words, in the regression without regional dummies, the level of urbanization, the shares of the primary and the secondary sector, and the proxy for the size of the labor force capture the effect of geographical location on growth. However, as we will see, some of these variables contribute on their own to the explanation of municipios growth, once spatial interaction effects are controlled for.

Results obtained in section 5.4.2 clearly indicate that levels and growth of per capita GDP are spatially clustered. For this reason, we compute various tests of residual spatial autocorrelation using the weight matrices defined earlier. 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 test results reported in table 5.5 are obtained using the second-order contiguity matrix; the first-order matrix leads to similarly significant results. Lagrange multiplier (LM) tests are used to obtain a more precise idea of the kind of spatial dependence involved (Anselin and Bera 1998). We first conducted the tests 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 (5.4) reduces to the simple conditional convergence model 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:

$$
\begin{aligned}
g &= c + \alpha \ln y_0 + X\delta + \varepsilon \\
\varepsilon &= \lambda W \varepsilon + u.
\end{aligned}
\tag{5.6}
$$

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 us 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 cutoffs). 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 nonspherical. 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. The results reported in table 5.6 were obtained with the second-order contiguity matrix since the log-likelihood was systematically higher for models estimated with this weight matrix. Interestingly, in terms of this criterion, the spatial error model is superior to 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 neighborhood 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 percent for the spatial lag model and 4.4 percent for the spatial error model, which is substantially higher than the rate estimated in the initial model.

We now relax the assumption that the initial level of income in neighboring 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):

$$g = c + \alpha \ln y_0 + \theta \ln(Wy_0) + X\delta + u. \tag{5.7}$$

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 5.7. Compared to the initial model (table 5.5), the inclusion of the spatially lagged initial income improves the estimation. We find a significant positive impact of the initial income of the neighborhood on growth and an estimated rate of convergence of 4.3 percent 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 pres-

Table 5.6
Estimates for 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)
Labor 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)
Regional dummies (ref.: North)	Yes	Yes
Northeast	−0.236***	−0.068
	(−3.07)	(−0.62)
Southeast	0.087	0.365***
	(1.28)	(3.34)
South	0.197***	0.497***
	(2.85)	(4.31)
Center-West	0.186**	0.361***
	(2.5)	(3.05)
Log likelihood	−1917.485	−1777.207
AIC	3864.98	3584.41
I-Moran	0.066***	−0.018

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

Table 5.7
Estimates for the growth equation (5.7) 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)
Labor force	0.07
	(0.24)
Household size	0.058***
	(2.62)
θ (log W*init.inc.)	0.159***
	(6.85)
Regional dummies (ref.: North)	Yes
Northeast	−0.422***
	(−5.58)
Southeast	−0.02
	(−0.26)
South	0.111
	(1.4)
Center-West	0.157*
	(1.9)
Adj. R^2	0.405
AIC	4042.28
I-Moran	0.177***
LM lag	789.1***
Robust LM lag	2.1
LM error	1089.6***
Robust LM error	302.6***

Note: t-statistics in parentheses.
*, ** and ***: significant at 10 percent, 5 percent and 1 percent.

ence of a spatial-dependent error process) cannot be rejected. This result points to the spatial cross-regressive spatial error model as the correct specification (equation (5.5)). For the sake of completeness, we also the estimate the spatial cross-regressive spatial lag model which corresponds to our structural model (equation (5.4)).

Estimation results for these models, using the second-order contiguity matrix, are presented in table 5.8. As indicated by Akaike's information criterion (Aic), both models clearly outperform the spatial cross-regressive model of equation (5.7). We obtain a point estimate of 4.4 percent for the yearly rate of convergence between municipios in the spatial cross-regressive spatial error model and of 4.1 percent 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 (5.5), one gets:

$$g = (I - \lambda W)c + \alpha \ln y_0 + \theta \ln(Wy_0) + \lambda Wg + X\delta - \lambda\alpha W \ln y_0 \\ - \lambda\theta W \ln(Wy_0) - \lambda WX\delta + u. \tag{5.8}$$

This equation is directly comparable to equation (5.4). Several comments are in order. First, the values of γ and λ are found to be quite close to each other in table 5.8, which indicates that both models predict a quite similar impact of the neighbors' growth on the growth of a given municipio. Second, provided that $\ln(Wy_0)$ and $W \ln y_0$ are close enough,[8] the overall impact of the initial income of neighbors 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 neighbors, 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

Table 5.8
Estimates for the growth equations (5.4) and (5.5)

	Spatial cross-regressive spatial lag model	Spatial cross-regressive spatial error model
Constant	2.215***	3.504***
	(7.37)	(21.42)
Log initial income	−0.653***	−0.678***
	(−44.42)	(−39.16)
Illiteracy	−0.496***	−0.62***
	(−6.21)	(−6.53)
Urbanization	−0.065	−0.185***
	(−1.12)	(−2.89)
Electricity	0.353***	0.395***
	(4.98)	(4.51)
Agriculture	−0.165***	−0.249***
	(−3.24)	(−4.25)
Industry	−0.127*	−0.057
	(−1.93)	(−0.79)
Labor force	0.119	0.837***
	(0.59)	(3.19)
Household size	0.044***	0.103***
	(2.75)	(5.63)
θ (log W*init.inc.)	0.371***	0.181***
	(13.18)	(6.48)
γ (W*growth rate)	0.613***	—
	(11.41)	
λ (W*error term)	—	0.681***
		(121.41)
Regional dummies (ref.: North)	Yes	Yes
Northeast	−0.143**	−0.071
	(−2.02)	(−0.66)
Southeast	−0.027	0.25**
	(−0.41)	(2.16)
South	0.031	0.363***
	(0.46)	(2.96)
Center-West	0.07	0.301**
	(0.97)	(2.48)
Log likelihood	−1799.41	−1764
AIC	3630.8	3560
I-Moran	0.0102**	−0.017

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

that poor municipios tend to catch up with richer ones over time (a usual result of β-convergence regressions), the average income level of neighbors has a positive impact on growth. Other things being equal, a municipio located in a relatively poor neighborhood will therefore have lower income growth. Moreover, the growth of the neighbors 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.

5.6 Conclusion

This chapter shows that the presence of spatial externalities in Brazilian municipalities' growth process 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 β-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 neighboring municipios affect 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.

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 into account 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 implies 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 of the externalities at work among Brazilian municipios. Indeed, while the theoretical model we used explicitly focused 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 chapter, could certainly improve our understanding of local growth in Brazil.

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Notes

1. The reallocation of labor has been far from complete, mostly because of high migration costs. This induced coffee producers in the south to encourage and finance migration from Europe.

2. 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.

3. http://www.ipeadata.gov.br.

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

5. 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 neighboring values. Values of I larger (smaller) than the expected value under the hypothesis of no spatial autocorrelation, $E(I) = -1/(n-1)$, indicate positive (negative) spatial autocorrelation; that is, the clustering of similar (dissimilar) attribute values.

6. Due to global spatial autocorrelation, we use Bonferroni pseudosignificance 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 pseudosignificance level that is equal to $1-(1-a)^{1/k}$. However, this requires the local statistics to be multivariate normal, which is unlikely to be the case with LISA. The chosen pseudosignificance level does not require this assumption.

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

8. Which is the case, with a correlation of 0.99.

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