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Growth Dynamics and Space in Brazil

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Abstract

This paper takes up some of the newly developed tools of spatial econometrics to analyse the importance of geography in regional growth. This perspective is used to characterise growth features in the Brazilian economy. Two strands of empirical literature are brought together to draw the picture of geography as a factor affecting differential economic performance. Firstly, spatial statistics tradition is implemented to examine the spatial dependence of regional per capita income in Brazil for the last six decades. Secondly, the role that geography may have on the determination of growth paths is approached using intradistribution dynamics tools based on the construction of Markov transition matrices and stochastic kernels, for discrete and continuous analysis respectively.

1. Introduction

This paper takes up some of the newly developed tools of spatial econometrics to analyse the importance of geography in regional growth studies (Rey and Montouri 1999, Lopez-Bazo, Vaya, Mora and Surinach 1999, Quah 1996 and 1997b and Rey 1999). This perspective is used to characterise growth features in the Brazilian economy. Two strands of empirical literature are brought together to draw the picture of geography as a factor affecting differential economic performance. Firstly, spatial statistics tradition is implemented to examine the spatial dependence of regional per capita income in Brazil for the last six decades. Secondly, the role that geography may have on the determination of growth paths is approached using intradistribution dynamics tools based on the construction of Markov transition matrices and stochastic kernels, for discrete and continuous analysis respectively.

Traditional empirical growth analysis has developed a number of techniques to discuss the existence or non-existence of beta and sigma convergence¹. Cross sectional and panel data regressions, unit roots and cointegration procedures have been some of the most popular ways of testing for convergence. Nonetheless, most of this literature considers the studied economies in isolation, independently of their locations and links with other economic units. Despite of the fact that theoretical mechanisms that are said to drive regional convergence, such as technological diffusion, factor mobility and transfers of payments, have explicit geographical components, the role of spatial effects in regional studies has been widely ignored (Rey and Montouri 1999). Recently, several works have been developed to put forward the idea that using spatially located data,

¹ For excellent summaries of the different theories and empirical tools see Barro and Sala i Martin (1995) and Durlauf and Quah (1997a).

such as the income per capita of regions or nations, may generate a problem in estimating traditional econometric models to test for convergence. Fingleton (1999) proves that significant spatial dependence and heterogeneity are present in a sample of European regions, what weakens the evidence for convergence. He argues that the vast majority of studies, which have successfully found evidence for convergence, have failed to model for this and, therefore, their results may be misleading. Other studies support this idea, such as Lopez-Bazo, Vaya, Mora and Surinach (LVMS, 1999), that report evidence of spatial patterns in the traditional studies of European regional convergence. Más, Maudos, Pérez (1995) show how Spanish regional output is explained, to some extent, by the accumulation of public capital in neighbouring regions, once private capital and labour contributions are taken into account in the estimation of a regional production function.

Why is space relevant to economic analysis? The concept of space may be important in several ways. Firstly, Sachs (1997) argues that physical geography itself is a factor, in terms of distance from markets, topography, climate, soil quantity, endemicity of disease, rainfall, and other geographical variables which might play a role in determining factor productivity and, hence, the growth potential of an area. Secondly, a whole new branch of theoretical models inserted in the “new geography economy” framework have suggested that, under some particular circumstances (increasing returns, labour mobility, pecuniary externalities), economic activity may agglomerate at some locations, with the striking implication that two regions with similar characteristics may end up developing totally different economic structures (Krugman 1991, Puga 1998). Thirdly, space may be understood in relative terms. Economic growth of a region is bound to be affected by neighbouring economies. Spillovers are at the heart of this perspective. Proximity to a prosperous area necessarily influences

economic performance as does being close to a deprived economic environment. Benabou (1993) and Durlauf (1996) present important theoretical contributions on this issue, pointing out that externalities arise as capital accumulation depends on the spatial location of economic agents.

The main aim of this paper is to estimate how strongly regional per capita income is concentrated in the Brazilian economy and to what extent spillovers are operative. Section 2 introduces the Brazilian case and presents the data employed in the calculations. Section 3 deals with the computation of spatial statistics indexes to measure spatial dependence. Section 4 opens up issues regarding dynamic behaviour from both a discrete and a continuous perspective. Section 5 concludes the paper.

2. Data on Brazilian regional inequality

Brazil is well known for its income inequality, both personal and regional (Baer, 1995, Willumsen and Fonseca, 1996). The richest state presents a per capita income level 7 times higher than the poorest state. Over time the situation has not changed noticeably. In the 70's and early 80's regional inequality seemed to diminish, but since then this process has come to an end or even reversed (Diniz, 1994; Zini, 1996, Azzoni, 2001, Azzoni and Santos, 2000, Azzoni et al, 2000). In 1997, even after controlling for education and other personal characteristics, as well as for job conditions, labour income inequality among the 11 metropolitan areas of the country was still impressive. Controlling for differing cost of living levels does not significantly change this conclusion. Moreover, regional labour income inequality has been quite stable in the 80's and 90's, regardless of extreme variations in inflation rates, in national GDP growth rates and in wage policy in the country (Azzoni and Santos, 2000).

In this paper we deal with yearly per capita income figures for the 20 states of the Brazilian federation in the period 1939-1998 (years 1940-46 are missing). Since some states were separated over time, we work with the 20 states situation of 1939 and not with the present 27 states². For more details on the data, see Azzoni (1997)

3. Spatial Statistics perspective

The spatial statistics literature has made available a number of methods and indicators to capture geographical interlinks (Anselin, 1988, 1995; Griffith, 1996). Two main approaches can be taken to detect spatial dependence. The first stems from the need to derive a measure of overall spatial dependence of a determined variable within a set of spatially located units, as in our case, per capita income of states within a country. The second analyses the correlation between the spatial dependence index and the standard deviation of regional per capita income over time.

The spatial dependence measure is provided by a global statistic such as Moran I^3 , that can be represented by expression (1)

$$I = \frac{n}{S} \frac{\sum_i \sum_j w_{ij} z_i z_j}{\sum_i z_i^2} \quad (1)$$

where n is the number of regions; w_{ij} are the elements of a binary contiguity matrix $W(n \times n)$, taking the value 1 if regions i and j share a common border and 0 if they do not; S is the sum of all the elements of W ; and z_i and z_j are normalised vectors of the log of per capita income of each state. The Moran I is distributed between 1 and -1.

² Amazonas = Acre+Amazonas+Roraima+Rondonia; Mato Grosso=Mato Grosso+Mato Grosso do Sul; Pará = Pará+Amapá; Goiás=Goiás+Tocantins. The Federal District (Brasília) was established in the early 60's and received gradually government employees from other regions in a pace determined by political interests. Since this does not reflect economic reasons, the area was not included in the study.

³ Geary C family statistics have been computed showing very similar results

Values around 1 represent strong and positive spatial dependence (clustering of similar values), whereas values around -1 show negative spatial correlation (clustering of different values).

Figure 1 reports the evolution of Moran I and of the standard deviation of per capita income of Brazilian states. Several facts are worth mentioning. First of all, since the values are always over .4, there is strong evidence of a positive spatial dependence among Brazilian states. This means that the rich (poor) states have a propensity to be close to other rich (poor) states. This situation appears to be quite stable, with an upward shift in the late 80s and in the 90s.

Secondly, there seems to be a certain amount of correlation between the spatial dependence index and the standard deviation of regional per capita income over time. Rey and Montouri (1999) argue that this co-movement may reflect a dynamic characteristic of regional clustering and two possible explanations may support this fact. On the one hand, an increase in spatial dependence could be due to the regions in each cluster becoming more similar. On the other hand, it could also be due to newly formed clusters emerging during a period of increasing income dispersion.

As far as detecting local patterns of spatial association to further explore the spatial aspects of the data, it is important to know not only if the overall regional income of a country is concentrated, but also to identify in which specific states that concentration is stronger and whether those states concentrate high or low values of the variable analysed. Anselin (1995) points out that the degree of spatial association, as a result of the use of global statistics (like the global Moran statistic defined above), ignores the potential instability of local units in the overall sample. New techniques have recently been suggested to treat this kind of instability and to try to recover the rich amount of information it provides (Getis and Ord 1992, Openshaw, Brundson and

Chalton 1991, Openshaw, Cross and Charlton 1990 and Anselin 1993, 1995). We focus on the derivation of local indicators of spatial association (LISA), developed by Anselin (1995), and the interpretation of the Moran Scatterplot (Anselin 1993).

Following Anselin (1995), two properties of LISA, which will condition its interpretation, may be described: a) the LISA for each observation gives an indication of the extent of significant spatial clustering of similar values around that observation, which means that the local indicator L_i should be such that it is possible to infer the statistical significance of the pattern of spatial association at location i ; b) the sum of LISA's for all observations is proportional to a global indicator of spatial association. These two properties are expressed in equation 2,

$$\begin{aligned} \Pr(L_i > \delta_i) &\leq \alpha_i \\ \sum_i L_i &= \lambda \Lambda \end{aligned} \quad (2)$$

where δ_i is a critical value, α_i is the significance level, λ is the scale factor, and Λ is the global indicator of spatial association. The Local Moran and its correspondence to the global statistic are defined as follows

$$\begin{aligned} I_u &= \frac{n}{S} z_i \sum_i w_{ij} z_j / \sum_i z_i^2 \\ \lambda &= S \end{aligned} \quad (3)$$

A first interpretation of LISA as an indicator of local spatial clustering may be obtained by using it as the basis for a test on the null hypothesis of no local spatial association. These local clusters may be identified as the observations for which LISA is significant, based on equation (2). However, LISA distributions are usually unknown. Anselin (1995) suggests a method to generate an empirical distribution for LISA, consisting in the conditional randomisation of the vector z_j . It is conditional in the sense

that z_i remains fixed. The reasoning behind the randomisation procedure lies in the need to assess the statistical significance of the linkage of one state to its neighbours. The generation of the state's i LISA distribution is inferred by the permutation of the neighbours that surround state i (obviously, state i is not used in the permutation). This empirical distribution provides the basis for a statement on the extremeness of the observed LISA. Those values of the empirical distribution that leave $\alpha/2$ of probability on both sides of the derived distribution will set the borderline to assess the significance of the local statistics.

The second interpretation of LISA is the detection of local instability and outliers. Given that the local statistics keep a proportional relation to the global statistic (equation 3), it is possible to find out which observation has a more relevant contribution to the global statistic. In our case, this represents the identification of states whose income clustering is above expectation under a spatially randomly distributed per capita income.

Some extra help in the interpretation of the local statistics is provided by the Moran scatterplot, which is the graphical complement of LISA to visualise local instability. It plots the values of Wz_j on z_i , where W is the row-standardised⁴ first order contiguity matrix and z_i are the standardised values of the analysed variable. In the present context, we would plot the standardised log of per capita income of a state against its spatial lag (also standardised), which is its neighbours' weighted average of the log of income per capita. The Moran scatterplot divides the space in four areas, which correspond to the four types of possible local spatial association between a state and its neighbours; quadrant I: high-income states with high-income neighbours; quadrant II: low-income states surrounded by high-income neighbours; quadrant III: low-income

⁴ In the row standardised matrix the columns sum to 1

states surrounded by low-income neighbours; and, finally, quadrant IV: states with high-income with low-income neighbours (Rey and Montouri 1999). States located in quadrants I and III represent the association of similar values (positive spatial correlation) whereas quadrants II and IV show the association of opposite values (negative spatial correlation). The concentration of states in quadrants I and III is expected in a scenario where rich and poor states cluster separately, generating differentiated areas of high and low-income. If states were located randomly around the origin, occupying indifferently the four quadrants, no pattern of spatial dependence would arise. Nevertheless, instabilities could still be found for individual observations.

Previous work on Brazilian regional income inequality indicates that periods of convergence and divergence are intercalated (Azzoni, 2001). In order to take this into account, we compute decade per capita income averages for each state and construct scatterplots for each decade and for the year 1939. The results are shown in figures 2 to 7. The first relevant phenomenon is the confirmation of the dominance of positive spatial association. In terms of the Moran scatterplot, this means that states are mainly located in quadrants I and III, and this situation has been exacerbated to the extreme in the last decade (Figure 7), where all the states are in quadrants I and III. Although periods of convergence have occurred during the period, it seems that the long-run situation is characterised by an income polarisation with strong spatial influence.

Secondly, a preliminary identification of cluster composition is feasible from these figures. Over time there is a persistent presence of Northeastern states in quadrant III, which could be considered a symptom of a low-income cluster in that part of the country. Southeastern and Southern states populate quadrant I conforming a high-income cluster. Finally, another important issue is whether the growth paths over an almost sixty year period have been, in a way, partially determined by geographical

links. Although this issue will be dealt with more extensively in next section, some insights may be provided. Take for instance the vertical line formed by the states MG, ES, GO and PE in Figure 2. This means that in 1939 these four states shared the same income per capita level. This hypothetical line has rotated clockwise to leave states MG and ES in quadrant I and deepen state PE into quadrant III. In other words, states with fairly similar initial conditions have performed differently due to their regional spatial context.

In order to further explore the existence and composition of clusters, we have also calculated yearly Local Moran indicators. Table 1 reports the time period and the specific states for which the indicator is statistically significant and the quadrant in which the states were located at that point in time. Two important aspects are highlighted in Table 1. First of all, the significant observations are concentrated in quadrants I and III. This is the natural reflection of the previously found pattern of global positive association and of the evidence of the Moran scatterplots. Secondly, the two previously identified clusters were significant for most of the years, indicating their persistence throughout the period. In the Northeast region, the states PI, CE, RN, PB, PE and BA constitute the low-income cluster, whereas in the Southeast region, the states RJ, SP, PR and MG form the high-income cluster. The previously mentioned history about the evolution of PE and MG can also be verified. PE originally stays unclustered up to 1976, when it clusters in the low-income area and remains clustered until the end of the period. MG, in the high-income area, develops similar behaviour.

We can, therefore, suggest that the stability (with a slight upward trend) of the global indicator for spatial association is due, mainly, to the strengthening of these two regional clusters. These clusters are permanent and have been able to attract to their influence peripheral states that were originally unclustered.

4. Dynamics

Implementation of the spatial statistics tools has allowed us to identify global and local patterns of spatial association in a regional economic growth context. It is possible to trace the evolution of the cluster composition and their strength by observing them at different static points in time. The analytical framework to deal with transitional dynamics developed by Quah (1993a) is employed to investigate whether regional clustering has influenced income dynamics. Following Quah, let F_t denote the distribution of income per capita across states at time t . We can define the law of motion $F_{t+1} = M * F_t$ (4)

where M maps one distribution into another, and consequently contains information of the flow from F_t to F_{t+1} . The element M quantifies the mobility or persistency from one period to another.

An easy and common way to approach the model is to discretise distribution F_t into a set of possible values of income per capita relative to the country's mean. An arbitrary number of k possible classes may be defined. The derivation of matrix M is now straightforward as we can compute which states transit from one interval to another. The division in k classes returns a Markov $k \times k$ transition matrix, where the element (i,j) entry is the probability for the state in class i to transit to class j . The main diagonal of this matrix denotes persistence, as it represents the probability for a state to remain in its original class.

There are two important issues here. Firstly, there is no rule of thumb to set the intervals. Quah (1997a) suggests that they are selected so that the k classes host similar number of pairs of observation-years in each row, and this would return what is known

as the uniformly defined matrix. We have followed this approach defining five income class intervals. Secondly, the choice of the time interval may affect the probabilities. Intuitively, the longer the time interval, the higher the probability to move from one income class to another.

Tables 2a and 2b show income transition matrices for one and ten year transition periods respectively. Some insights may be highlighted from these results. First of all, persistence seems to be much higher in the extremes (classes one and five) than in the middle. This means that states with income per capita distanced from the mean tend to remain in that situation, foremost in class five, where 95% and 88% are the probabilities of remaining in the club of the rich states, depending on the transition period considered⁵. Secondly, a greater mobility is found in the middle of the distribution. Most of the transitions are concentrated in classes two, three, and four, which are those around the average. Around 35% of the states in class two manage to ascend to the third class in a ten year time period, whereas 14% are dropped into the first class. Despite the high degree of persistency in class three, almost 52% of the states do not transit in a ten year time period, the other half of the sample moves towards higher or lower classes (30% descend to lower levels and 18% ascend). In class four, persistence is around 69% and there does not seem to be a special pattern of attraction upwards or downwards in the distribution.

The relationship between income distribution and spatially conditioned income distribution is reported in Table 3. A series of income relative to the neighbours' income is computed for every state and is the conditioning series. The matrix is, thus, constructed with pre- and post- conditioned values. If the conditional series had no explanatory power at all, one would expect the poor states to be poor relative to their

surroundings and the rich to be richer than the nearby states. Then, something similar to an identity matrix would emerge. However, if poor states shared a border with similar poor states, their relative income would not depart from the average of the cluster. The mass of probabilities concentrated around classes three and four in the Neighbour relative columns represents this situation. For instance, poor states were only poor relative to their neighbours in 22% of the observations. As shown in Table 3, the matrix is far from being an identity matrix and probabilities are mainly concentrated in classes three and four, although states located in class five do reveal themselves richer than their neighbours. It is important to mention that this is not strictly a transition matrix, as it relates values for a given year and not their evolution over time.

However, several shortcomings of this approach are relevant. Mainly, this sort of analysis does not allow us to answer questions like: why states within the same class (similar income per capita) move in opposite directions? What made some states climb positions towards higher income status whereas others were dragged to the bottom step of the ladder? Rey (1999) proposes a decomposition of the traditional Markov transition matrix ($k \times k$) to provide some insights on these questions. This decomposition aims at capturing the effects of regional context on the transition scheme. It consists of the construction of a ($k \times k \times k$) transition matrix where the transitions between classes of income are conditioned by the spatial lag of the initial period. If the regional context did not matter at all, income transitions would not be affected by the consideration of different spatial lags. In other words, the probability of moving to higher (lower) classes of income should be the same, regardless of the average of the neighbour states' income. This sort of conditioning is different from Quah's space conditioning (Table 3), which tried to answer the question of whether poor (rich) economies were poor (rich)

⁵For the sake of brevity, from this point onwards comments on transition probabilities will make reference to the ten-year transition period matrix, although the one-year matrices are also reported for

relative to their neighbours or not. This addresses the question of whether states' transition in the income distribution is related to the spatial context in which states develop.

Tables 4a and 4b show the calculations for the Brazilian states. Five matrices have been obtained for each time period. Each matrix portrays the transition of one specific initial class to an end class, depending on the initial spatial lag of the states. The first matrix shows movements in the bottom extreme class of the sample (Poor). As noted before, strong persistence is the main feature and the spatial lag of the states does not seem to establish differentiated transitional behaviour. Initial poor states, with poor neighbours, apparently transitioned more easily to higher classes than states with low and middle class neighbours. On the other hand, states with upper and high-class neighbours transitioned up to the fourth income class with a probability of 100%.

The results for the second, third, fourth and fifth classes are more revealing on the influence that the regional context may have in the determination of the transitional pattern. In general terms, states with wealthier surroundings tend to behave better, in the sense that they have a greater chance to move upwards than downwards in the transition matrix. For example, in class four the chances of reaching class five are higher for states with high spatial lag (20% against 5% for states with lower spatial lag). The same argument is valid in the analysis of downward transitions. Class five is a good example of this. The rich states surrounded by states with similar income did not drop to the immediate lower income class as often as states with poorer neighbours (9% vs. 22%).

Tables 5a and 5b summarise the results of this approach. These tables show how, more generally, the existence of a dissimilar surrounding (poorer, same, richer) may influence transition. The message is broadly the same, those states which enjoyed richer neighbours had better chances of an upward transition than those states in a worse

comparison.

regional context. The probability of moving up in the scale if surrounded by richer states is 30%, whereas it drops to 6% for “worse surrounded” states, regardless of their initial situation.

Though strong evidence has been found to prove that proximity to richer (poorer) zones may influence the growth of states, a great amount of arbitrariness is present in the tools implemented. The results of the Markov transition matrices are highly sensitive to the choice of class intervals and transition periods. Different sets of these two variables are bound to return totally different results. Moreover, the construction of a $k \times k$ space conditioned transition matrix brings additional arbitrariness into the analysis when spatial lag intervals are introduced. In fact, when calculating the spatially conditioned transition probabilities we found that in some cases only few observations are available, which makes inference unreliable. This is the case, for instance, of poor states with upper and high spatial lag, where only 3 observations exist.

Quah (1997a) constructs stochastic kernels and contour plots as tools to overcome some of the problems with the application of Markov transition matrices, avoiding the need for discretisation. Stochastic Kernels are the three-dimensional visualisation of a transition probability matrix, where no discretisation has been allowed and class intervals are now transformed into a data continuum⁶. Additional information is presented in the form of contour plots, which are used for better interpretation of the kernels in a two dimensional environment, where the lines on the plot connect points at the same height on the kernel.

Figure 9 is the counterpart of Table 2a, where class transitions are considered unconditionally to study the main characteristics of regional per capita income

dynamics within a ten-year transition period. As previously denoted, persistence has been the key feature in this transition process involving the mass of probability concentrated in the diagonal. However, some mobility has still taken place, as the transition matrices indicate.

Figure 10 plots the income per capita of the Brazilian states relative to Brazil versus the average of the neighbouring state's income. Spatial concentration of the variable would involve the mass of probabilities gathering around 1 in the Neighbour relative axis. This means that states share with their neighbours similar income per capita, regardless of their situation relative to the country. This is precisely what we can deduce from Figure 10, except for very high-income states.

Finally Figures 11, 12, 13, 14 and 15 analyse separately the initial income classes and study their transition conditioned by their spatial lag, this time in a continuum framework. The results are quite consistent with the evidence previously found in the analysis of the Markov transition matrices, achieving a reduction in some of the arbitrariness⁷. These figures have to be examined in a slightly different way than the previous ones. Each pair of kernels and contour plots take one of the five sets of income class, therefore, all the inference will make reference to the states that originally belonged to that class at any point of time. The y-axis represents the standardised spatial lag and the x-axis the end income situation ten years after they entered in the original class. If no regional context influence was to be found there would be a concentration of probability in a straight line at some point of the x-axis, where all states had arrived, regardless of their spatial lag. If neighbourhood had some sort of conditioning effect, probability would tend to be attracted to the bottom left corner (negative influence of a

⁶ Kernels estimates have been calculated nonparametrically, using a Gaussian Kernel with bandwidth set following Silverman (1986). Quah's Tsrf econometric shell was used. For more details on the construction and calculation of the kernels see Quah (1997b)

⁷ Some degree of arbitrariness is still present in the choice of income transition intervals.

bad context) and the upper right corner (positive influence of a good context) in the contour plot.

Class one (Figure 11) presents no traces of regional context influencing a ten-year transition. If any influence is to be noted, it seems that the odds favour states with a worse spatial lag. This result clears up some of the ambiguities found in the transition matrix characterising the first class (table 4a).

Dynamics occurring in class two seem to reflect our intuition about the way states' growth patterns are connected to territorial surroundings. Although persistence is a feature to highlight, it is also true that the probabilities of transition are positively correlated to the initial spatial lag.

The third and fourth classes (Figures 12 and 13), which include states ranging from middle to upper income classes, show very interesting shapes. Two plateaus emerge from the kernels, indicating that the direction of the transition has been sensitive to regional context. This is especially remarkable in class four, where a spatial lag above 1.2 raises significantly the chances of reaching the high-income plateau, and states with spatial lags below 1 are more likely to be trapped in the low-income plateau.

Finally, the richer states (Figure 15) confirm the high persistence detected in the Markov transition matrices and clarify that the possible loss of income position has been suffered by states lacking a relatively wealthy context.

This analysis complements and sometimes unveils dynamic features rather difficult to extract from the use of the transition matrices, where reliable inference is constrained by the correct choice of intervals and transition periods.

It is obvious that transitions are not fully explained by regional context, which would mean the emergence of a picture similar to Figure 9, where the transitions of initially similar states to higher (lower) classes would have been achieved by those with

better (worse) spatial lag. However, it seem that regional context can be a factor to consider when trying to reveal the factors underlying regional convergence.

5. Conclusions

This paper has shown how the evolution of regional income inequality in Brazil has followed a spatial dimension. Strong evidence of spatial clustering in Brazil has been found. Two clusters, a low-income one in the Northeast and a high-income one in the Southeast, have been revealed. These clusters seem to have become stronger over time and states initially unclustered have, slowly, joined the existing clusters.

We have also proved that the growth paths of the Brazilian states have been, partially, determined by their environment. Those states with wealthier neighbours had greater chances of prospering.

It seems feasible that spatial connection may help regional interaction. However, the way in which capital accumulation influences interlinked regions may work differently. Interindustrial links, migration, trade flows, human capital exchange may be the channels that make space important.

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Figure 1: Moran I Vs. Sigma Convergence For Brazilian Regional Per Capita Income (1939-1998).

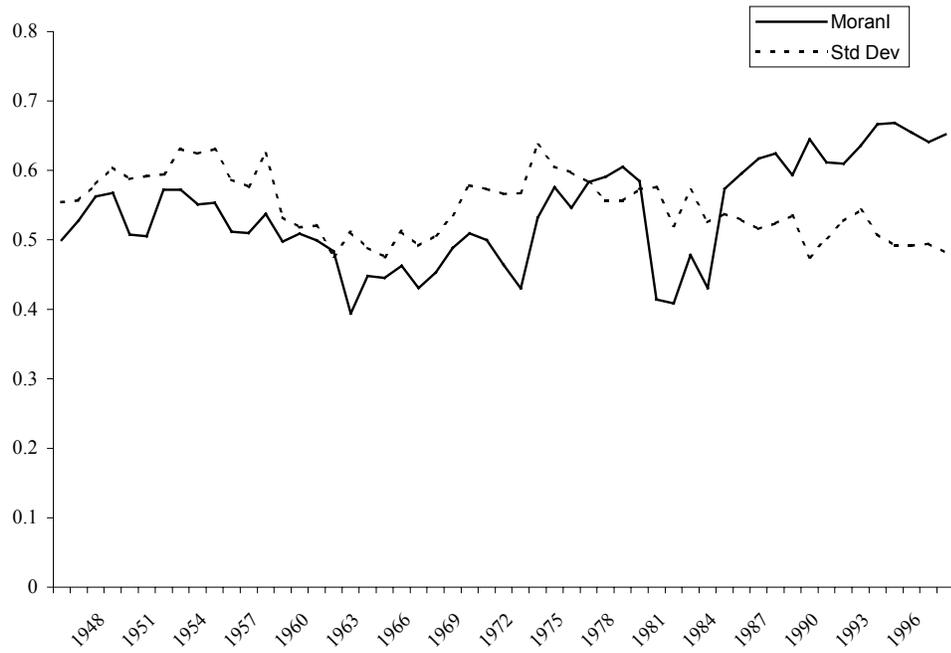


Figure 2: Moran Scatterplot For Brazilian States (1939).

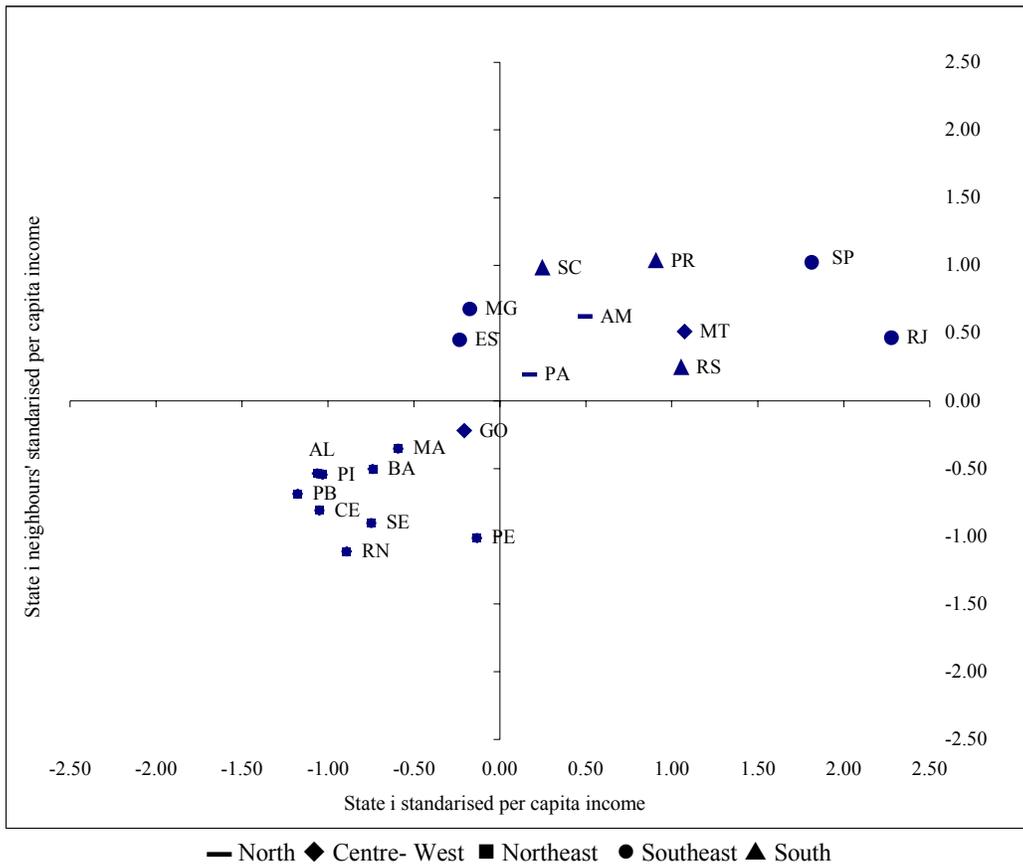


Figure 3 : Moran Scatterplot For Brazilian States (Average Values 1950-1959).

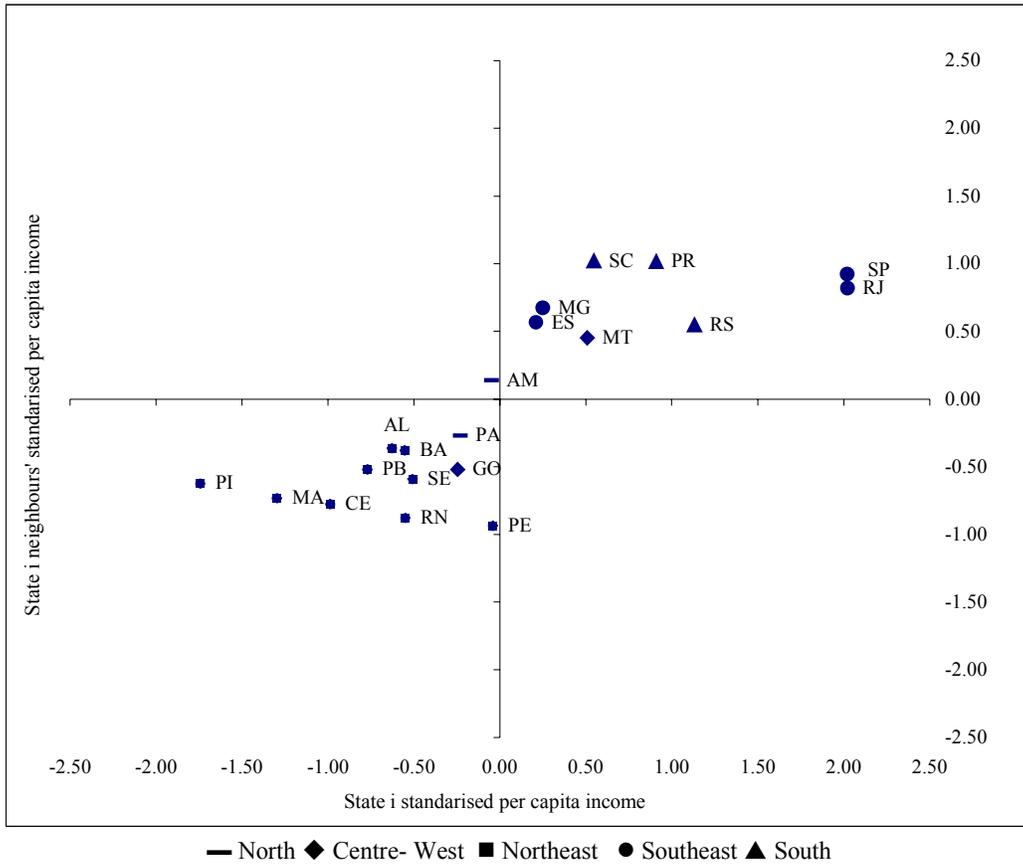


Figure 4 : Moran Scatterplot For Brazilian States (Average Values 1960-1969).

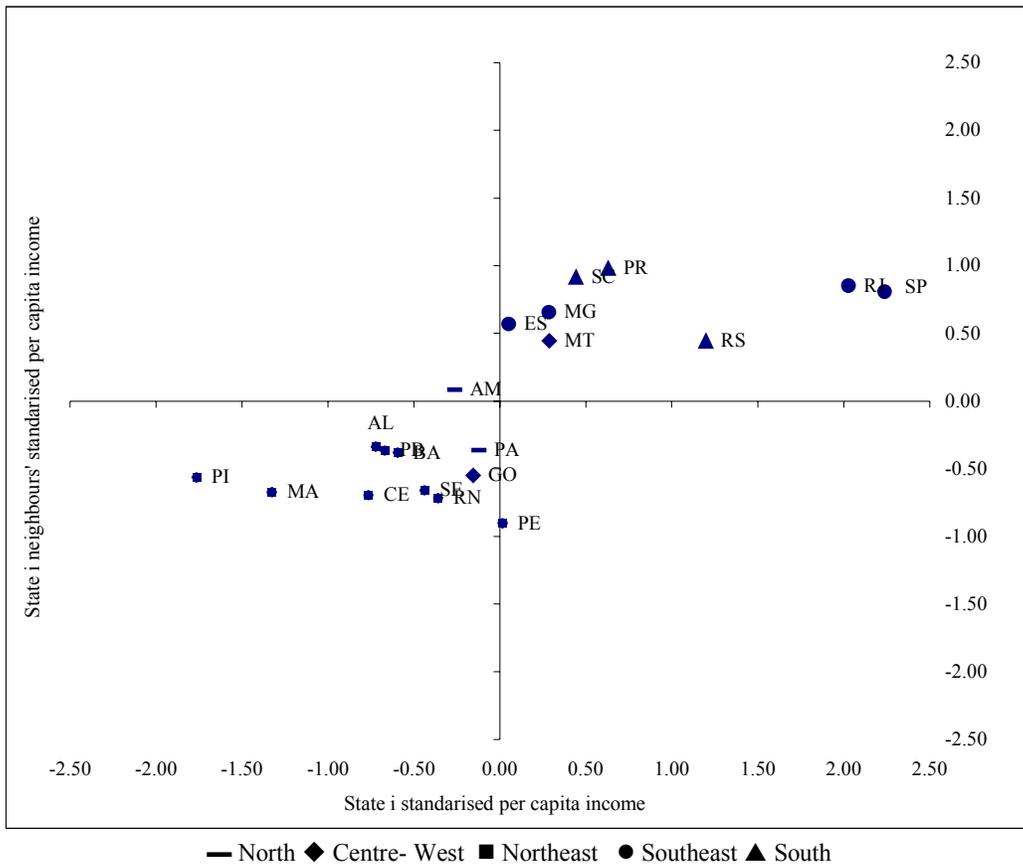


Figure 5 : Moran Scatterplot For Brazilian States (Average Values 1970-1979).

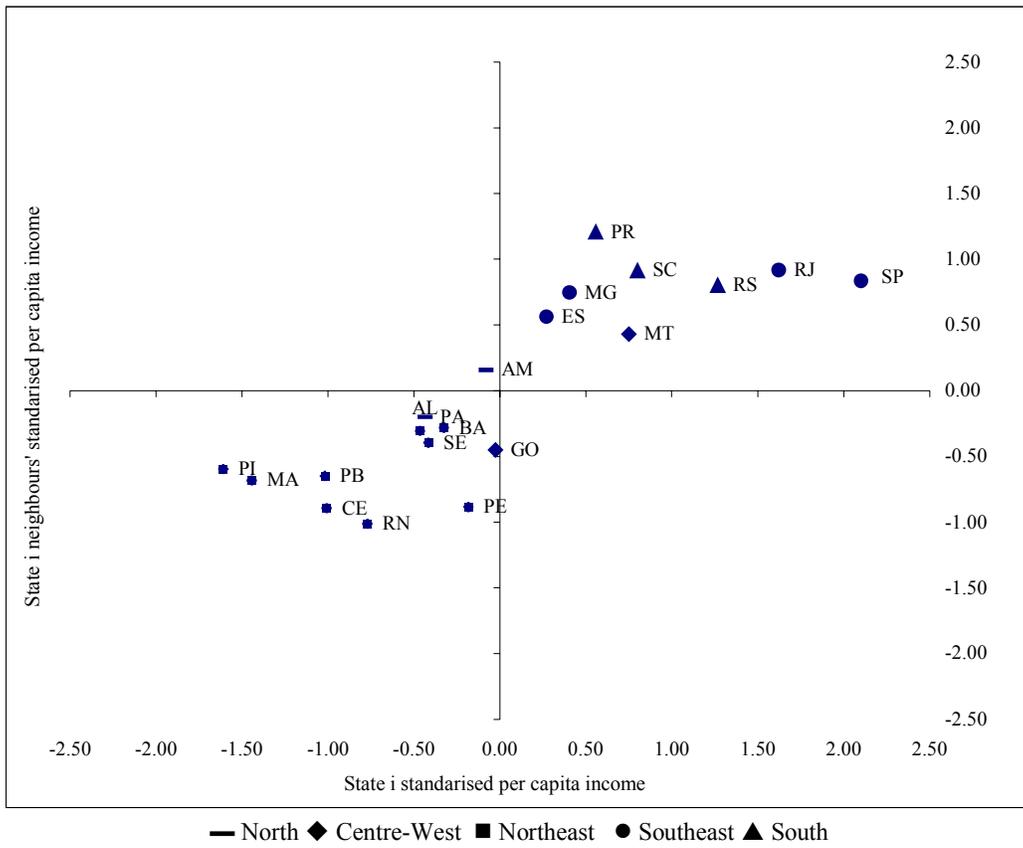


Figure 6 : Moran Scatterplot For Brazilian States (Average Values 1980-1989).

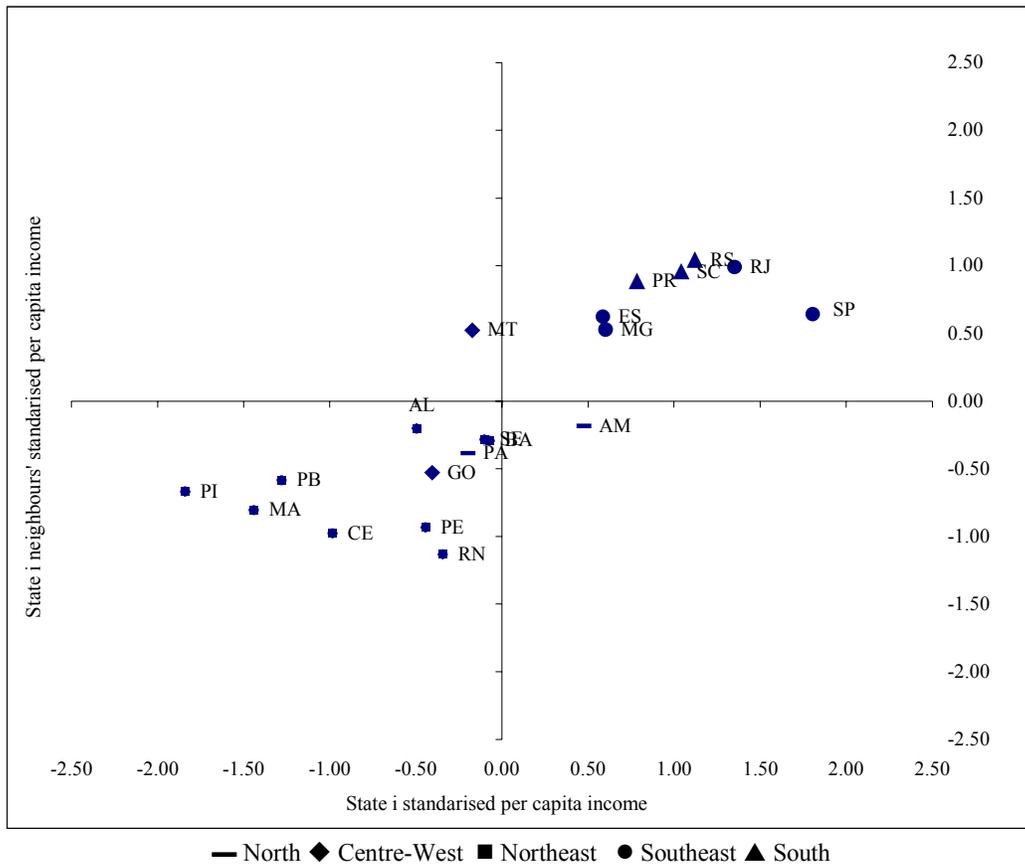


Figure 7 : Moran Scatterplot For Brazilian States (Average Values 1990-1998).

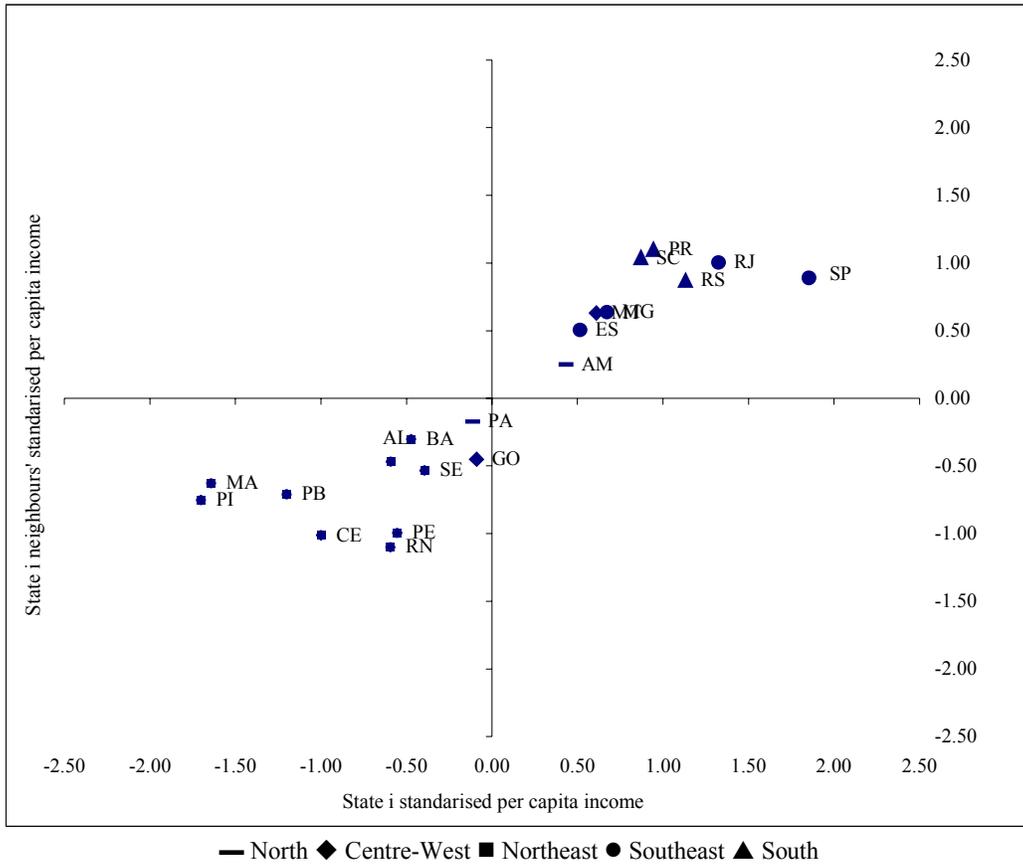


Table 1: Local Moran Significance 1939-1998

10%	I Quadrant	III Quadrant	Total
AM (N)			0
PA (N)		50	1
MA (NE)		49-50, 78, 83-85, 87, 89	9
PI (NE)		47-66, 69-72, 74-98	49
CE (NE)		39, 47-48, 51-59, 61, 69- 83, 85-98	42
RN (NE)		39, 53-54, 58, 69-80, 89, 82-96	23
PB (NE)		39, 79-80, 85-98	18
PE (NE)		76-98	23
AL (NE)		39	1
SE (NE)		39	1
BA (NE)		39, 47-50, 52, 56, 60-63	11
MG (SE)	54, 66-69, 74-81, 83, 85-98		28
ES (SE)	80, 83-86, 88		6
RJ (SE)	47-84, 90-93, 95-98		46
SP (SE)	39, 47-80, 85-98		49
PR (S)	39, 47-55, 58-62, 74-75, 77, 80, 85-98		33
SC (S)	80-90, 93-95		14
RS (S)			0
MT (CW)*	39, 54, 58, 74-79		16
GO (CW)		47-50, 52, 57, 60, 81-84	11
Global	39, 47-98		52
5%	I	III	Total
AM (N)			0
PA (N)			0
MA (NE)		49, 83-84	3
PI (NE)		48-52, 56-63, 74, 78, 80, 82-98	33
CE (NE)		39, 51, 53-55, 57-58, 69-81, 83, 85-98	35
RN (NE)		39, 53, 58, 70-75, 79-80, 93-95	15
PB (NE)		85-90, 94-95	8
PE (NE)		79-80, 82-98	19
AL (NE)			0
SE (NE)		39	1
BA (NE)		39, 52, 61-63	5
MG (SE)	74, 76-80, 86-89, 91-98		18
ES (SE)	83		1
RJ (SE)	48-57, 59, 64-72, 78, 81-83		24
SP (SE)	39, 47-79, 90-98		43
PR (S)	39, 47-50, 52-53, 55, 59, 75, 88, 90-98		20
SC (S)	81		1
RS (S)			0
MT (CW)*	39, 77, 79		4
GO (CW)		47-49, 52, 60, 81-84	9
Global	39, 47-98		52

N=North, NE= Northeast, S=Southeast, S=South, CW=Centre-West

MT psents significant local indicators for years 81-82 where the region was in quadrant II

Table 2a: 1 Year Unconditional Transition Matrix.

<u>Initial</u> <u>Class</u>	<u>Number</u>	<u>End</u> <u>Class</u>				
		P	L	M	U	H
P	200	91%	9%	1%	0%	0%
L	204	8%	77%	14%	1%	0%
M	201	0%	14%	74%	12%	0%
U	205	0%	0%	12%	83%	5%
H	210	0%	0%	0%	5%	95%

Table 2b: Ten Years Unconditional Transition Matrix.

<u>Initial</u> <u>Class</u>	<u>Number</u>	<u>End</u> <u>Class</u>				
		P	L	M	U	H
P	167	75%	18%	5%	2%	0%
L	170	14%	47%	35%	5%	0%
M	170	4%	26%	52%	16%	2%
U	166	2%	2%	11%	69%	14%
H	167	0%	0%	0%	12%	88%

Table 3: Static Space Conditioned Matrix.

<u>Income Class</u>	<u>Number</u>	<u>Neighbour relative</u>				
		P	L	M	U	H
P	203	22%	32%	36%	11%	0%
L	207	0%	1%	50%	44%	3%
M	206	1%	11%	14%	55%	19%
U	210	0%	20%	48%	27%	4%
H	214	0%	0%	14%	36%	50%

First Income Class: Poor (P) 0-0.54 relative to the mean
Second Income Class: Low (L) 0.54-0.70 relative to the mean
Third Income Class: Medium (M) 0.70-0.92 relative to the mean
Fourth Income Class: Upper (U) 0.92-1.35 relative to the mean
Fifth Income Class: High (H) >1.35 relative to the mean.

Table 4a: Dynamic (One Year) Space Conditioned Transition Matrix.

		End Class					
Initial Class	Spatial Lag	Number	P	L	M	U	H
P	P	36	86%	14%	0%	0%	0%
	L	146	93%	7%	0%	0%	0%
	M	15	80%	7%	13%	0%	0%
	U	2	50%	50%	0%	0%	0%
	H	1	0%	0%	0%	100%	0%
L	P	28	14%	75%	11%	0%	0%
	L	91	9%	80%	11%	0%	0%
	M	81	5%	78%	16%	1%	0%
	U	4	0%	25%	50%	25%	0%
	H	0	0%	0%	0%	0%	0%
M	P	25	0%	8%	88%	4%	0%
	L	42	0%	19%	76%	5%	0%
	M	96	0%	17%	76%	7%	0%
	U	25	0%	8%	64%	28%	0%
	H	13	0%	0%	46%	54%	0%
U	P	0	0%	0%	0%	0%	0%
	L	6	0%	0%	67%	33%	0%
	M	12	0%	0%	58%	42%	0%
	U	67	1%	0%	7%	88%	3%
	H	120	0%	0%	7%	87%	7%
H	P	0	0%	0%	0%	0%	0%
	L	0	0%	0%	0%	0%	0%
	M	0	0%	0%	0%	0%	0%
	U	38	0%	0%	0%	11%	89%
	H	172	0%	0%	0%	3%	97%

Table 4b: Dynamic (Ten Years) Space Conditioned Transition Matrix.

		End Class					
Initial Class	Spatial Lag	Number	P	L	M	U	H
P	P	32	41%	41%	16%	3%	0%
	L	120	88%	12%	1%	0%	0%
	M	12	58%	25%	17%	0%	0%
	U	2	0%	0%	0%	100%	0%
	H	1	0%	0%	0%	100%	0%
L	P	17	12%	47%	41%	0%	0%
	L	76	20%	57%	20%	4%	0%
	M	73	8%	40%	47%	5%	0%
	U	4	0%	0%	75%	25%	0%
	H	0	0%	0%	0%	0%	0%
M	P	25	0%	44%	52%	4%	0%
	L	36	14%	33%	53%	0%	0%
	M	71	1%	27%	61%	11%	0%
	U	25	0%	12%	32%	40%	16%
	H	13	0%	0%	38%	62%	0%
U	P	0	0%	0%	0%	0%	0%
	L	6	17%	17%	17%	50%	0%
	M	10	0%	10%	70%	20%	0%
	U	41	7%	2%	12%	73%	5%
	H	109	0%	1%	6%	73%	20%
H	P	0	0%	0%	0%	0%	0%
	L	0	0%	0%	0%	0%	0%
	M	0	0%	0%	0%	0%	0%
	U	37	0%	0%	0%	22%	78%
	H	130	0%	0%	0%	9%	91%

Table 5a: One Year Space Conditioned Transition Probabilities (Summary).

	Number	Down	None	Up
Poorer	151	19%	77%	4%
Same	462	8%	87%	5%
Richer	407	3%	84%	13%

Table 5a: Ten Years Space Conditioned Transition Probabilities (Summary).

	N	Down	None	Up
Poorer	131	37%	56%	6%
Same	350	16%	71%	13%
Richer	359	4%	65%	30%

Figure 9: Ten Year Unconditional Stochastic Kernel And Contour Plot.

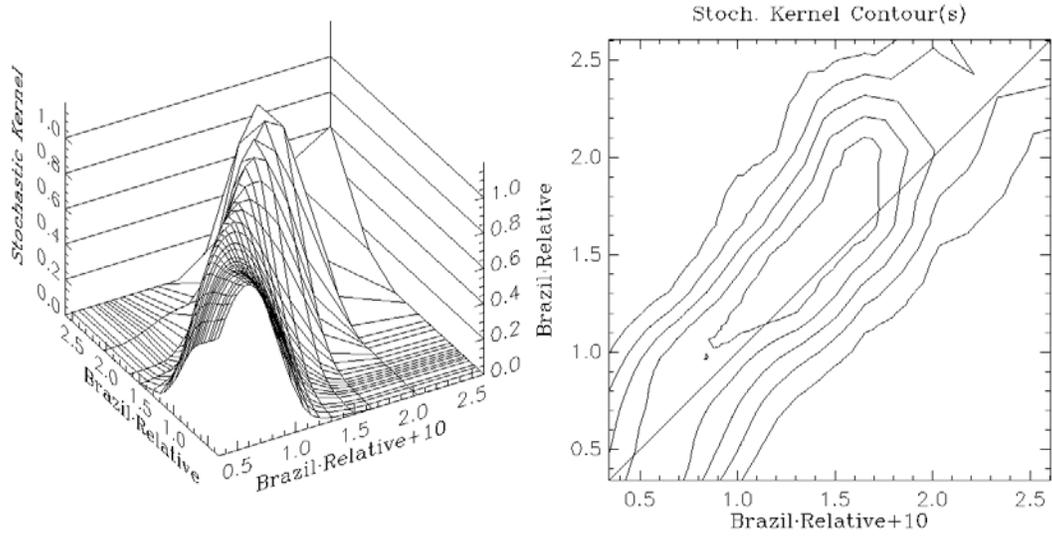


Figure 10: Static Space Conditioned Stochastic Kernel And Contour Plot.

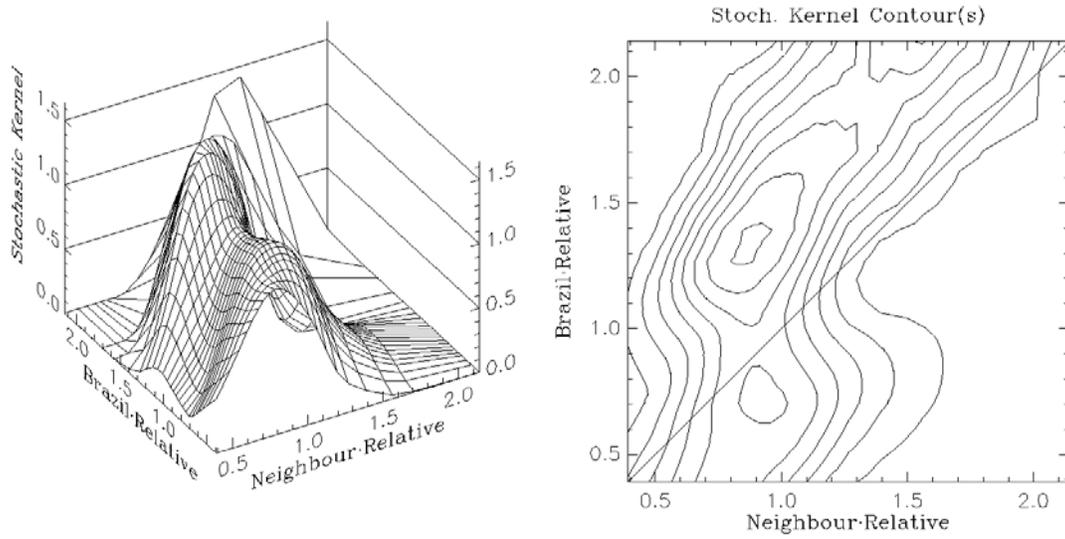


Figure 11: First Class (P) Space Conditioned Dynamics Stochastic Kernel And Contour Plot.

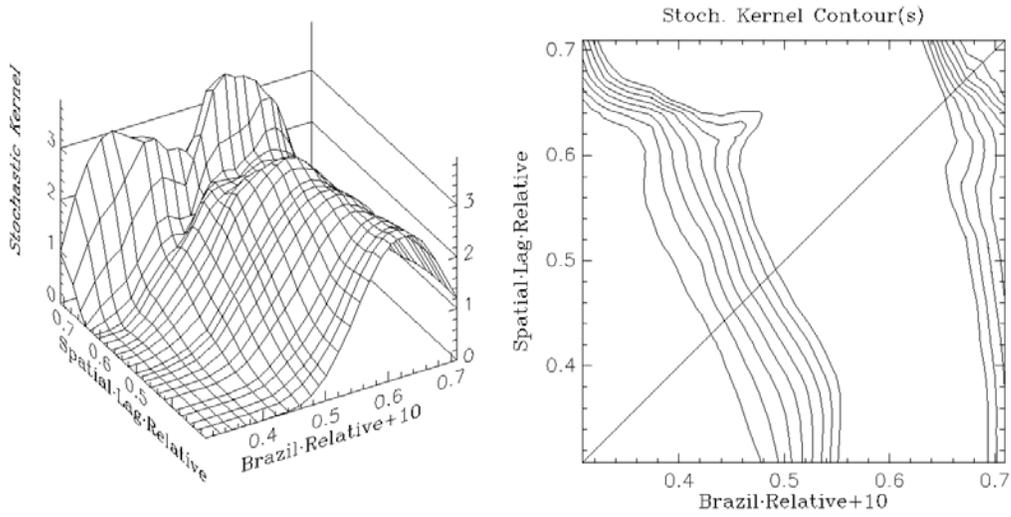


Figure 12: Second Class (L) Space Conditioned Dynamics Stochastic Kernel And Contour Plot.

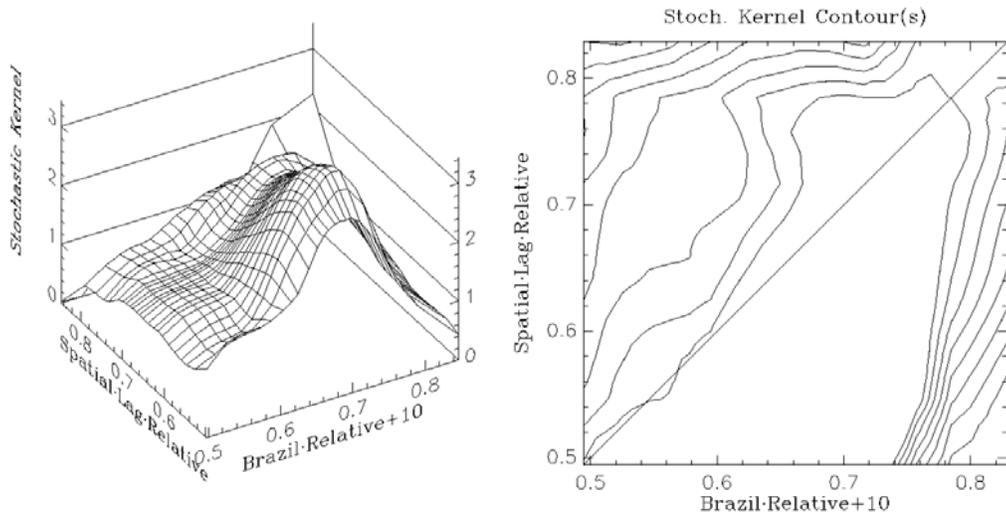


Figure 13 Third Class (M) Space Conditioned Dynamics Stochastic Kernel And Contour Plot.

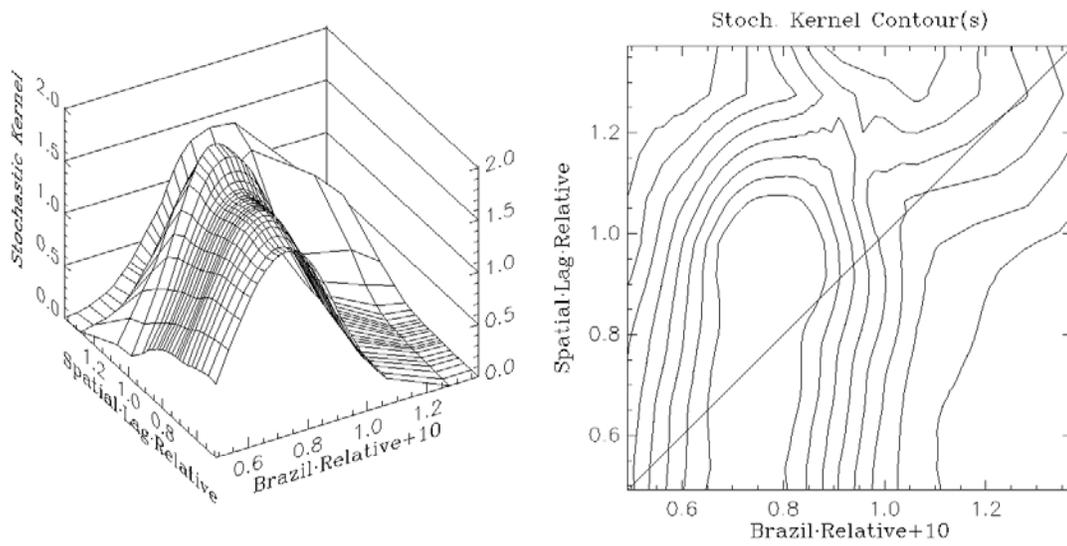


Figure 14: Fourth Class (U) Space Conditioned Dynamics Stochastic Kernel And Contour Plot.

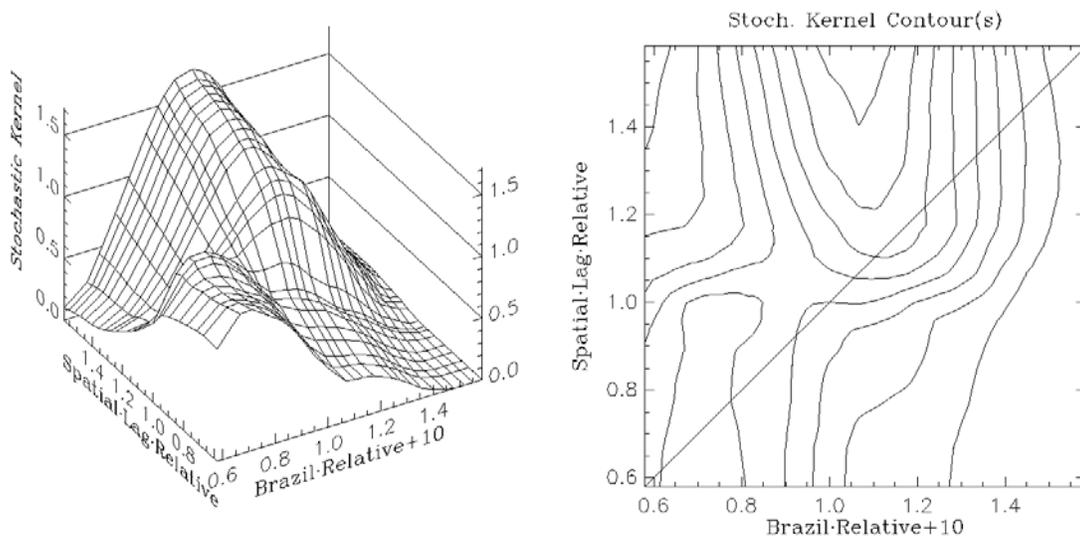


Figure 15: Fifth Class (H) Space Conditioned Dynamics Stochastic Kernel And Contour Plot.

