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# Neighborhood and Efficiency in Manufacturing in Brazilian Regions: a Spatial Markov Chain Analysis

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## ABSTRACT

More competitive regions tend to present higher level of economic growth, with positive reflexes on social aspects. The different economic performances observed among regions are explained mainly by the spatial concentration of the economic activities. This paper aims to analyze the influence of space on the regional competitiveness in manufacturing in Brazil. Data for 137 regions in the period 2000-2006 is used. In each region we have one representative firm for four sectors defined by technological intensity. We estimate stochastic frontiers to calculate regional efficiency, and the efficiency results are then used in Markov Spatial Transition Matrices to analyze the transition of regions between efficiency levels, considering their local spatial context. We found that a good neighborhood (more competitive neighbors) increases the probability of improving the relative efficiency of a region (pull effect). We also found that a bad neighborhood (less competitive) increases the probability of losing relative efficiency (drag effect). In quantitative terms, we found that the pull effect is stronger than the drag effect.

## **1. INTRODUCTION**

Regional dynamic is influenced by spatially specific economic and social aspects, such as human and natural resources and politic and economic environments. The different economic performances observed among the regions can be explained, in parts, by the spatial concentrations of economic activities, particularly in the manufacturing sector. When analyzing the tendencies of the manufacturing sector, we are looking for indications of the future regional growth. According to Baldwin and Martin (2003), forces that stimulate the location of an industry have great possibilities to promote the physical and human capital accumulation in the region. The Spatial Economy literature considers the study of externalities and their transmission through space which are essential to understanding the agglomeration of people and activities. Therefore, in studying the different productive patterns of regions, it is important to consider the spatial distribution of productivity and to measure how the productive level of the neighborhood affects the productive efficiency of a region.

Among the economic activities, we chose to study manufacturing, disaggregated into its sectors. As Rezende and Tafner (2005) argue, innovation is an important variable influencing productivity, and technological advantages constitute the basis for the competitiveness of more developed economies. It is expected that the presence of high technology sectors in the productive structure of a country increases the probabilities of economic and social growth.

This paper investigates how the productive efficiency of a region can be affected by the performance of its neighbors, focusing on Brazilian manufacturing. The paper is organized as follows. After this introduction, the next section describes the database. Section three presents the methodology to obtain the productive regional efficiency estimates, using stochastic frontiers. It also explains the Spatial Markov Chain methodology used to obtain probabilities of changing the relative efficiency situation, conditioned on the efficiency levels of the neighborhood. Section four discusses the empirical results, and section five concludes the paper.

## 2. DATA

The database is composed of manufacturing firms in Brazil. The data source is the annual manufacturing survey (Pesquisa Industrial Anual) developed by IBGE, the Brazilian Statistics Office (PIA). We use an unbalanced panel with three dimensions: a) temporal: annual observations from 2000 to 2006; b) geographical: 137 regions (meso regions); sectoral: four sectors defined on the basis of technological intensity<sup>1</sup>: high (HI), medium-high (MHI), medium-low (MLO) and low (LO). We use value added as the output of firms. The inputs are labor (annual average of employees) and stock of capital. All the monetary variables were deflated by the sector IPA-OG index<sup>2</sup>.

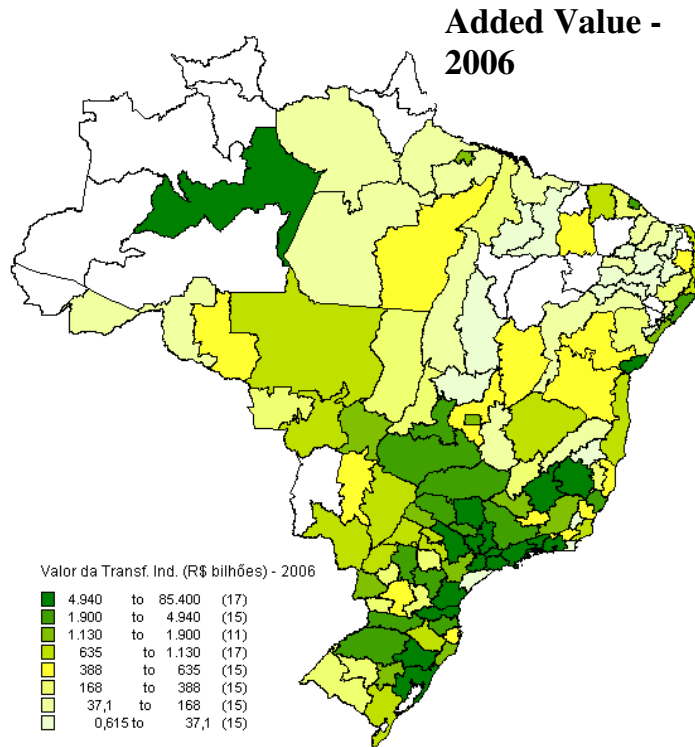
Since confidentiality rules prevent access to data for individual firms, we use a data base specially organized on-demand by IBGE for this study, aggregating the data of output and inputs to the region level. Therefore, we have one representative firm for each region, in each sector, which is constituted by the average of all corresponding firms. Since we have 137 regions and 4 sectors, the maximum number of firms in the sample is 548. Figure 1 shows the regional distribution of value added in 2006. Regions in white were excluded from the sample, since they had zero or very low number of manufacturing plants. A careful study of outliers led to the elimination of some cases (region x sector) with evident data problems.

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<sup>1</sup> Based on spending in R&D and other technological variables, as prepared by De Negri and Salerno (2005), following the OCDE framework. Details in Appendix 1.

<sup>2</sup> FGV data ([www.fgvdados.br](http://www.fgvdados.br))

Figure 1– Regional Distribution of Value Added, 2006



### 3. METHODOLOGY

#### 3.1 Stochastic Frontier

The Spatial Markov Chain (SMC) will be calculated using estimates of productive efficiency obtained from the estimation of stochastic frontiers of production. Assuming certain technology of production, points in the frontier show situations in which it is not possible to increase output without using more inputs. Then, points below the frontier characterize technical inefficient firms and the distance to the frontier is a measure of this inefficiency (AFRIAT, 1972; AIGNER; CHU, 1972; AIGNER et al, 1977; MEEUSEN; Van Den BROECKER, 1977).

We will use the Battese and Coelli (1995) specification of stochastic frontiers, in which the production function is simultaneously estimated with the inefficiency function, which can use exogenous variables that do not belong to the output-input relationship (BATTESE; COELLI, 1995; KUMBHAKAR; LOVELL., 2000; GARDINER et al., 2004). The model can be written as:

$$y_{it} = f(x_{it}; \beta) + v_{it} - u_{it}$$

Where  $y_{it}$ : output of region  $i$  at time  $t$ ,  $x_{it}$ : vector of inputs of region  $i$  at time  $t$ ,  $\beta$ : vector of unknown parameters,  $v_{it}$ : symmetric random error term and  $u_{it}$ : inefficiency term of the region  $i$  at time  $t$ , assuming that  $u_{it} \sim iid N^+(\mu_{it}, \sigma^2)$  and  $\mu_{it} = z_{it}\delta$  where  $\delta$  is the vector of unknown parameters and  $z_{it}$  is the vector of exogenous variables.

The technical efficiency can be obtained by  $TE_{it} = \frac{y_{it}}{f(x_{it}; \beta)}$ . If  $TE = 1$ , the region is fully efficient. If the variables are logged, then  $TE_{it} = \exp(-u_{it})$ . The efficiency estimates are obtained from a Cobb-Douglas model with a trend term in the inefficiency function<sup>3</sup>.

$$y_{it} = \beta_0 + \beta_L L + \beta_K K + (v_{it} - u_{it})$$

$$U_{it} \sim N(\mu_{it}, \sigma_u^2)$$

$$\mu_{it} = \delta_0 + \delta_1 t$$

Table 1 shows the results of the stochastic frontier estimation, with pooled data (each region represented by 4 firms, one for each technology intensity sectors).

**Table 1 - Results of the Stochastic Production Frontier Estimation**

		Coefficient	t stat.	Significance
Production Function	Constant	2.7637	28.69	***
	Ln(employees)	0.3303	15.87	***
	Ln(capital stock)	0.6981	90.463	***
Inefficiency Function	Constant	-8.5300	-2.53	**
	Tendency	-1.2632	-2.66	***
	$\sigma^2$	4.7057	2.83	***
	$\gamma$	0.9771	109.08	***
	Iterations			35
	LR test (3)			236.21
	N			2352
I			337	
T			7	

Significance degrees: \* 10%, \*\* 5%, \*\*\* 1%.

<sup>3</sup> Other specifications were considered, with weaker results.

The stochastic frontier methodology gives one estimate of efficiency to each sector, region and time. Therefore, it is necessary to aggregate the results obtaining a measure of regional efficiency. For that, we applied a system of grades. This system considers the performance of a sector in a region and the role of each sector in the global production of the region. To obtain a high grade, it is necessary that the region be efficient in sectors of high importance for its productive structure. The total grade of the region is given by the weighted average of the grades of the sectors (based on the efficiency estimates) and the participation of each sector in its productive structure. Grades were computed for each year, and the final grade is the arithmetic average of all grades received from 2000 to 2006. The ranking and evolution of the productive efficiency of the regions are computed in the Appendix 2.

### 3.2 Spatial Markov Chain

Rey (2001) explores the Markov spatial transition matrixes when analyzing how the American income distribution evolved on time and space. The Spatial Markov Chains are constructed to evaluate how the efficiency of the neighborhood influences the efficiency in a particular region. The Spatial Markov Chains produce results on the frequency of transitions among classes (or states) considering the spatial dependence in this process. The SMC methodology is a fusion of two theories: i) the Markov chains which analyses the dynamic of processes and ii) the Spatial Econometrics (ROSS, 1996; ANSELIN, 1988). The “Markov Chain” stochastic process specifies that, given the present and past states, any future state of a region is only dependent on the present state. The methodology specifies a vector of states that represents the probabilities of changing among the  $k$  classes of efficiency presented by the regions in some year.

Once the dynamic of the transition process is considered, it is necessary to include the influence of the spatial dependence. The Moran’s I statistic, used to analyze spatial autocorrelation, is given by the expression below.

$$I = \frac{n}{\sum \sum w_{ir}} \frac{\sum \sum w_{ir} (y_i - \bar{y})(y_r - \bar{y})}{\sum (y_i - \bar{y})^2}$$

Where:  $w_{ir}$  is the element of line  $i$  (region) and column  $r$  (other regions) of a  $W$  spatial matrix<sup>4</sup>;  $y$  is the productive efficiency of the region; and  $\bar{y}$  is the mean of the productive efficiency. We use a Queen type of a binary spatial matrix of a first order contiguity. This means that, considering a region in line  $i$  of the matrix, all the columns assume value equal to one if they are neighbors of  $i$  (if they have a common border with the  $i$  region) and zero otherwise.

However, the Moran's  $I$  ignores the possibility of local instabilities, since it calculates a global indicator. The LISA (Local Indicator of Spatial Analysis) is a local index that identifies the presence of spatial agglomerations and calculates an indicator to each location, and verifies its significance through similar values with the analyzed region. The LISA is given by the expression below<sup>5</sup>.

$$I_i = \frac{(y_i - \bar{y}) \sum_r w_{ir} (y_r - \bar{y})}{\sum_i (y_i - \bar{y})^2}$$

Where the variables are the same as defined by the Moran's  $I$ . LISA analyzes the state of a region in relation to the total space, given the state of its neighbors. As so, it is a relative measure that classifies each region in one of the four kinds of behaviour: HH (LL) when the value of the region and its neighbors is high (low), and LH (HL) when the value of the region is low (high) and its neighbors is high (low).

We allow that all the regions to change to different states of efficiency, always maintaining the same spatial structure. The SMC shows how this changing process occurs, considering spatial and dynamics aspects. Each element of the SMC matrix

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<sup>4</sup> Each line and column of the  $W$  matrix represents a region. Each cell assumes a value depending of the relation between the region in line  $i$  and the regions of the column  $r$  to this line. If the regions of the line and column are neighbors, the cell assumes a value different from zero.

<sup>5</sup> According to Anselin (1995), a LISA indicator should satisfy two propositions. First, it gives an indication of the extension of the spatial agglomeration (cluster) to each observation and similar values to its neighborhood and second, the sum of the LISAs of all the observations should be proportional to a global indicator of spatial association.



indicates the probability that a region belonging to the  $a$  state in period  $t$  can move to a  $b$  state in period  $t+1$ , given the state of its neighbors.

The first step is to decide the number of classes in which the productive efficiency is evaluated. The probability of transition among classes is conditional to the initial efficiency class of the neighbors resulting in the transition spatial matrix of Markov (REY, 2001). If there exists  $k$  classes of efficiency, the matrix dimension will be  $k \times k \times k \times k$  (the possible initial and final states of the region and the possible states of the neighbors). Therefore, the SMC studies the dynamics of the transition among states in two moments in time, considering the spatial characteristics of the regions.

The efficiency state of the neighbors is calculated using a  $W$  matrix of spatial weights and the result is divided according to the number of the  $k$  classes chosen. If four classes are assumed, we obtain four different behaviors to the regions: HH, HL, LH and LL. The Table 2 exemplifies a case of SMC considering  $k=2$  and two moments in time  $t_0$  (initial) e  $t_1$  (final).

**Table 2 - Spatial Markov Matrix - Example**

Spatial Dependence	State	$T_1$	
	$t_0$	L	H
L	L	$P_{LL/L}$	$P_{LH/L}$
	H	$P_{HL/L}$	$P_{HH/L}$
H	L	$P_{LL/H}$	$P_{LH/H}$
	H	$P_{HL/H}$	$P_{HH/H}$

Each cell of the matrix indicates probabilities of transition among states. The first cell,  $P_{LL/L}$ , indicates the probability of a region that has low efficiency in  $t_0$  ( $P_{LL/L}$ ) to stay in the same state in  $t_1$  ( $P_{LL/L}$ ), given that its neighbors have low efficiency ( $P_{LL/L}$ ). The probability  $P_{LH/L}$  from the first row and second column indicates the probability of a region that has low efficiency in  $t_0$  ( $P_{LH/L}$ ) to move to a higher efficiency state in  $t_1$  ( $P_{LH/L}$ ), given the low efficiency state of its neighbors ( $P_{LH/L}$ ). This means that the region is successful, since not only enhanced its efficiency in relation to the mean, but also did this involved in a low efficient environment. It is possible to apply this analysis in time, substituting successively the  $t_0$  e  $t_1$  periods and calculating the corresponding probabilities.

We decided to perform a more detailed analysis, defining four classes ( $k=4$ ): from the mean to one standard deviation (H), higher than one standard deviation (HH), from the mean to less than a standard deviation (L) and lower than a standard deviation (LL).

Since we are dealing with neighborhood, it is important to include all the regions in the analysis, even if they do not have efficiency estimates (regions with absence of some sector). To consider these observations, the SMC is modified to include an extra class, comprising the zero-cases. Thus, instead of dealing with  $k=4$  classes, we use  $k+1=5$  classes. The regions characterized by the absence of a sector are denominated NaN (not a number). The rest of them are calculated as explained above, using the mean and standard deviation<sup>6</sup>. If the entire neighborhood is NaN, the spatial dependence also assumes NaN. But if just one neighbor is different from NaN, we use the spatial dependence estimate of the efficiency. NaN in  $t_0$  e  $t_1$  indicates that the sector is absent in the region for both periods, while NaN in the spatial dependence means that the sector is absent in the neighborhood of the region.

#### 4. EMPIRICAL RESULTS

The transition spatial Markov matrix is analyzed considering the productive efficiencies estimated in the previous section. The results are presented in Table 3. The first column is an indicator of the line of the matrix, and it is designed to facilitate the location of the results explained in the text. In the SMC methodology, the transition of efficiency states it is considered between two consecutive moments in time. Hence, if the period is from 2000 to 2006, there are six possible transitions. To each pair of years, we compute the transition cases. The same behavior case of the next consecutive pair of years is summed, and then we calculate the probabilities. Therefore, with  $n$  region,  $k$  classes and  $t$  years, there are  $(t-1)*k*n$  possible cases of transitions.<sup>7</sup>

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<sup>6</sup> The mean and the standard deviation are calculated ignoring the NaN observations.

<sup>7</sup> At most, there are 137 regions and five sectors (HI, MHI, MLO, LO and absence of a sector NaN). From 2000 to 2006, we have  $t-1=6$ . Therefore, it is possible to obtain, at most,  $137*5*6= 4110$  cases of transitions.

Table 3 shows the number of cases of a certain kind of transition. For example, line 9 indicates the probability of transition of a region that started  $t_0$  with H efficiency, to move to the other classes of efficiency, given that it is surrounded by LL neighbors. Considering the pairs of consecutive years from 2000 to 2006, there are 54 cases (line 9 column 4) of regions that presented this type of behavior. The same logic is repeated to the tables in Appendix 3, which show the results for each sector of technology intensity. The lines 1 to 5, 6, 11, 16 and 21 and the NaN column are not of interest to the analysis because they show cases where there is not an indication of productive efficiency (they are all NaN cases). The main diagonal (in yellow) represents situations where there is no relative change in the efficiency of the regions.

**Table 3 – SMC Matrixes – pooled data**

Line	$t_0$	Neighborhood condition	Num. Cases	$t_1$				
				NaN	LL	L	H	HH
1	NaN	NaN	397	1.0000	0.0000	0.0000	0.0000	0.0000
2	LL		8	0.0000	0.5000	0.2500	0.2500	0.0000
3	L		8	0.0000	0.2500	0.2500	0.5000	0.0000
4	H		60	0.0000	0.0167	0.0667	0.9000	0.0167
5	HH		4	0.0000	0.0000	0.0000	0.7500	0.2500
6	NaN	LL	135	0.9926	0.0074	0.0000	0.0000	0.0000
7	LL		69	0.0000	0.6957	0.2319	0.0725	0.0000
8	L		47	0.0000	0.3191	0.3404	0.3404	0.0000
9	H		54	0.0000	0.0741	0.1852	0.6852	0.0556
10	HH		10	0.0000	0.1000	0.0000	0.4000	0.5000
11	NaN	L	199	0.9899	0.0101	0.0000	0.0000	0.0000
12	LL		114	0.0088	0.5877	0.3070	0.0965	0.0000
13	L		153	0.0000	0.1961	0.4706	0.3333	0.0000
14	H		264	0.0000	0.0379	0.2008	0.7235	0.0379
15	HH		23	0.0000	0.0000	0.0000	0.3043	0.6957
16	NaN	H	551	0.9964	0.0018	0.0000	0.0018	0.0000
17	LL		85	0.0000	0.4118	0.2941	0.2706	0.0235
18	L		189	0.0000	0.1217	0.4286	0.4444	0.0053
19	H		825	0.0012	0.0206	0.1103	0.8412	0.0267
20	HH		73	0.0000	0.0411	0.0000	0.5342	0.4247
21	NaN	HH	40	1.0000	0.0000	0.0000	0.0000	0.0000
22	LL		3	0.0000	0.0000	0.6667	0.3333	0.0000
23	L		5	0.0000	0.2000	0.4000	0.4000	0.0000
24	H		17	0.0000	0.0000	0.1176	0.8235	0.0588
25	HH		3	0.0000	0.0000	0.0000	0.3333	0.6667

Lines 6 to 10 represent regions whose neighbors have very low productive efficiency (LL). Lines 11 to 15 represent cases of L neighbors; lines 16 to 20 represent neighbors with efficiency between the mean up to one standard deviation (H); lines 21 to 25 represent neighbors with efficiency beyond one standard deviation (HH). In general, the

yellow cells hold the larger values of the lines, meaning that inertia (that is, probability of the region to stay in the same class of efficiency) is very high. Table 4 shows the probability of the regions to stay in the same class of efficiency, independently of their neighborhood<sup>8</sup>. The probability of staying in the same class is high, especially for regions classified as H-efficient.

**Table 4 – Probability of staying in the same class of efficiency**

	LL	L	H	HH
All sectors	0.4238	0.4099	0.7684	0.5718
High Intensity	0.3929	0.4170	0.7712	0.0000
Medium High	0.3684	0.5588	0.5962	0.2322
Medium Low	0.4560	0.4045	0.8174	0.3250
Low Intensity	0.4513	0.4532	0.7122	0.6699

Table 5 summarizes the simulated SMC matrixes. We count all the cases of getting better and worse. Then, considering the cases of regions that could get better, we counted the ones that actually did get better. Dividing the two values, we obtained the probability of the region to achieve a better class of efficiency (and the same logic is applied to the worsen cases, *mutatis mutandis*).

The next step is to consider all the cases of regions whose neighbors were classified in better classes of efficiency and, among these, count the cases of regions that enhanced their situation. We calculate the probability of moving to better classes of efficiency, given that the region is surrounded by higher efficiency neighbors (the same logic is applied to the worsen cases, *mutatis mutandis*).

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<sup>8</sup> We obtained the values of table 4 by calculating the mean of the inertial behavior for all classes of efficiency of their neighbors.

**Table 5 – Results of the SMC matrixes**

Getting better

	Cases of regions that could get better	Cases of regions that got better	Probability of getting better	Cases of regions with better neighbors	Cases of regions with better neighbors and that got better	Probability of getting better with better neighbors
All sectors	1.825	310	0.1699	413	187	0.4528
High Intensity	314	57	0.1815	86	33	0.3837
Medium High	292	50	0.1712	70	32	0.4571
Medium Low	576	97	0.1684	143	59	0.4126
Low Intensity	633	113	0.1785	166	72	0.4337

Getting worse

	Cases of regions that could get worse	Cases of regions that got worse	Probability of getting worse	Cases of regions with worse neighbors	Cases of regions with worse neighbors and that got worse	Probability of getting worse with worse neighbors
All sectors	1.663	311	0.1870	471	146	0.3100
High Intensity	299	57	0.1906	89	28	0.3146
Medium High	268	50	0.1866	82	15	0.1829
Medium Low	529	92	0.1739	169	48	0.2840
Low Intensity	591	115	0.1946	187	60	0.3209

In general, the probability of a region deteriorating its efficiency situation is higher than the probability of getting better: 18.7% versus 17.0%. But, if regions are surrounded by neighbors with better efficiency, they have 45.3% chances of getting better (almost three times more than when the neighborhood is not considered). This result is higher than the probability of a region to get worse if it is surrounded by neighbors with worse efficiency (31.0%), meaning that bad neighborhood almost doubles the chances of failure. Therefore, we conclude that the *pull effect* (that is, the effect of a good neighborhood in enhancing efficiency) is higher than the *drag effect* (effect of a bad neighborhood in retracting the efficiency)

Some sectoral patterns are observed in the simulation by technological intensity sector. The probability of getting better is higher in the High Intensity sector, while the probability of getting worse is higher in the Low Intensity sector. Besides, this sector seems to be the more negatively influenced by the neighbors, since it is the one that has the largest probability of getting to a worse efficiency if it is surrounded by less efficient neighbors; the probability of the High Intensity sector is almost the same. The most successful sector, when surrounded by more efficient neighbors, is the Medium High

Intensity sector, which also presents low relative probability of getting worse when surrounded in a less efficient neighborhood.

These results show that the neighborhood has an important influence in the regions' efficiency and that the *pull effect* is bigger than the *drag effect*. This pattern is maintained to all 4 sectors. The difference between these effects is larger for the Medium High Intensity (0.27 pp), indicating that this is the sector with lower instability in relation to the possibility of its regions to benefit from the *pull effect*. With less than half of the value, it is followed by the Medium Low Intensity and Low Intensity sectors (0.13 and 0.11 pp, respectively).

## 5. CONCLUSION

In this paper we analyzed how the efficiency of a region can be affected by the state of efficiency of its neighborhood. To do so, we first obtained the efficiency estimates by applying the stochastic frontier methodology to the manufacturing data in Brazil. The regional efficiency was explored through the effect of the proximity of a region to a good or bad neighborhood, using the Spatial Markov Chain methodology.

The most important conclusion is that we could obtain a measure that indicates that the neighborhood affects the performance of the regions. When the analysis does not consider the neighborhood, there is a higher probability of the regions to get worse. But when they are surrounded by a good neighborhood (of high efficiency), they have almost three times more chances of getting a better performance. On the other hand, the bad neighborhood enhances almost two times the chances of failure. This indicates that the *pull effect* (good neighborhood enhancing the efficiency) is bigger than the *drag effect* (bad neighborhood decreasing the efficiency), since regions with more efficient neighbors have 45.3% of chances to increase their efficiency, while regions with less efficient neighbors have 31.0% of chances to decrease their efficiency.

This pattern is maintained to all the levels of technology intensity sectors. The difference between the effects is bigger for the Medium High Intensity sector (0.27 pp),

indicating that it is the sector with less instability when beneficiating of the *pull effect*. It is followed by the Medium Low and Low Intensity sectors.

The most successful sector when surrounded by efficient neighbors is the Medium High Technology Intensity sector. The regions with Low Intensity sector seems to be the most negatively affected by their neighbors, since it is the sector with higher probability of getting worse if surrounded by less efficient neighbors.

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## Appendix 1 – Classification of the technological intensity sectors

Classification	CNAE 1.0 Code (IBGE)
High technology intensity	35 (Other Vehicles)
	33 (Medical and hospital equipments)
	31(Electrical equipments)
	322, 323 (Electronic equipments)
	30 (Computer hardware equipments)
	29 (Machines and equipments)
	341 to 343, 345 (Vehicles)
	232 (Oil refinery)
Medium-High technology intensity	24 (Chemical products)
	321(Basic electronic products)
	211 (Cellulose and paper plant)
	16 (Tobacco)
	344 (Vehicles accessories)
	369 (Diverse products)
Medium-Low technology intensity	25 (Rubber and plastic products)
	28 (Metal products)
	27 (Steel)
	212 to 214 (Paper and packages)
	26 (Products of on metal minerals)
	19 (Leather and shoes)
Low technology intensity	17 (Textile)
	15 (Food and Beverages)
	361 (Furniture products)
	18 (Clothes and accessories)
	20 (Wood products)
	22 (Edition and printing)
	231, 233, 234 (Alcohol and nuclear energy)

**Appendix 2 – Evolution (%) of the efficiency by mesoregion from 2000 to 2006**

Mesoregion		Position 2001	Position 2006	Evolution (%)	Mesoregion		Position 2001	Position 2006	Evolution (%)	Mesoregion		Position 2001	Position 2006	Evolution (%)
PA	1505	1	1	0.00	BA	2907	33	33	7.00	TO	1701	91	71	45.85
BA	2901	1	1	0.00	SC	4201	17	34	-6.31	SC	4202	45	72	-24.07
RJ	3304	1	1	0.00	PA	1506	71	35	60.84	PE	2603	93	73	49.51
MT	5102	1	1	0.00	SP	3511	46	36	7.67	RS	4303	50	74	-15.76
GO	5202	1	1	0.00	ES	3203	68	37	52.19	PR	4109	54	75	-15.49
GO	5204	89	1	173.59	SP	3512	41	38	5.16	RS	4301	43	77	-28.58
RO	1102	102	1	400.00	MS	5002	84	39	75.02	PR	4106	39	78	-29.98
BA	2905	13	2	10.61	SP	3513	4	40	-29.87	MT	5101	57	79	-17.07
MT	5105	16	3	13.76	CE	2303	47	41	2.24	SP	3510	60	80	-18.17
AM	1303	3	4	-0.23	BA	2906	11	42	-24.68	PI	2202	99	81	65.54
MA	2101	10	5	4.13	MG	3106	88	43	81.38	BA	2903	73	82	-2.97
AL	2702	7	6	-0.34	SP	3501	32	44	-11.19	RS	4304	34	83	-42.37
MG	3107	44	7	35.11	PB	2503	92	45	92.07	SE	2803	87	84	8.14
MG	3105	56	9	59.78	SP	3502	49	46	5.54	SC	4203	67	85	-17.30
PR	4110	23	10	14.52	SC	4205	21	47	-18.26	RN	2404	80	86	2.94
SP	3507	2	11	-6.84	MA	2102	58	48	14.63	AC	1202	103	87	100.00
RJ	3305	38	12	30.45	RS	4302	27	49	-18.38	CE	2301	18	89	-51.04
SP	3506	66	13	76.37	PE	2605	72	50	43.56	SE	2802	52	90	-33.33
ES	3201	53	14	49.19	AL	2703	28	51	-18.84	PR	4101	69	92	-14.61
RJ	3306	6	15	-5.83	SP	3504	62	52	12.11	PR	4102	82	93	0.00
PA	1503	64	16	64.91	RN	2402	76	53	42.65	RS	4306	83	94	0.00
RJ	3302	74	17	101.28	SP	3503	59	54	8.29	PR	4104	61	95	-33.05
MS	5003	96	18	183.43	SP	3505	42	55	-12.10	RS	4307	86	96	-7.13
MG	3108	19	19	6.34	GO	5205	14	56	-31.32	MS	5004	24	97	-55.65
DF	5301	25	20	6.63	RO	1101	1	57	-40.00	MG	3111	48	98	-48.81
SP	3509	9	21	-7.94	SC	4206	77	59	37.81	PR	4103	55	99	-45.93
SP	3515	35	22	15.75	MG	3109	63	60	9.06	PB	2504	97	100	2.89
SC	4204	15	23	-2.22	MG	3112	70	61	27.51	MG	3102	90	102	-23.08

Mesoregion	Position 2001	Position 2006	Evolution (%)	Mesoregion	Position 2001	Position 2006	Evolution (%)	Mesoregion	Position 2001	Position 2006	Evolution (%)			
PR	4105	20	24	4.52	ES	3204	65	62	9.20	PE	2604	94	103	-23.63
RJ	3301	30	25	6.34	MT	5104	40	63	-18.73	SP	3514	22	104	-69.50
ES	3202	8	26	-13.50	RJ	3303	5	64	-40.99	CE	2302	36	105	-71.92
PA	1501	79	27	100.00	GO	5203	51	65	-7.81	CE	2305	31	106	-73.53
PA	1502	1	28	-20.00	MG	3103	100	66	118.94	RN	2401	95	107	-38.87
PB	2501	37	29	12.68	MG	3110	85	67	39.45	RN	2403	1	108	-80.00
BA	2904	75	30	82.95	MG	3101	98	68	95.34	MG	3104	81	111	-50.00
GO	5201	1	31	-20.00	SP	3508	12	69	-40.30	PR	4108	78	112	-52.39
RS	4305	26	32	0.78	PR	4107	29	70	-32.30	MT	5103	101	113	-4.37

### Appendix 3 – Spatial Markov Chain Matrixes

High Technology Intensity							Medium High Technology Intensity								
t <sub>0</sub>	Spatial Dependence	Num. Cases	t <sub>1</sub>					t <sub>0</sub>	Spatial Dependence	Num. Cases	t <sub>1</sub>				
			NaN	LL	L	H	HH				NaN	LL	L	H	HH
NaN	NaN	198	1.0000	0.0000	0.0000	0.0000	0.0000	NaN	NaN	157	1,0000	0,0000	0,0000	0,0000	0,0000
LL		7	0.0000	0.8571	0.1429	0.0000	0.0000	LL		5	0,0000	0,4000	0,2000	0,4000	0,0000
L		13	0.0000	0.0769	0.5385	0.3846	0.0000	L		7	0,0000	0,1429	0,2857	0,5714	0,0000
H		21	0.0000	0.0000	0.2381	0.7143	0.0476	H		20	0,0000	0,1000	0,1500	0,7500	0,0000
HH		1	0.0000	0.0000	0.0000	1.0000	0.0000	HH		0	0,0000	0,0000	0,0000	0,0000	0,0000
NaN	LL	38	1.0000	0.0000	0.0000	0.0000	0.0000	NaN	LL	45	0,9778	0,0222	0,0000	0,0000	0,0000
LL		0	0.0000	0.0000	0.0000	0.0000	0.0000	LL		4	0,0000	0,5000	0,5000	0,0000	0,0000
L		7	0.0000	0.1429	0.7143	0.1429	0.0000	L		4	0,0000	0,2500	0,5000	0,2500	0,0000
H		7	0.0000	0.0000	0.2857	0.5714	0.1429	H		8	0,0000	0,1250	0,1250	0,7500	0,0000
HH		1	0.0000	0.0000	0.0000	1.0000	0.0000	HH		0	0,0000	0,0000	0,0000	0,0000	0,0000
NaN	L	64	1.0000	0.0000	0.0000	0.0000	0.0000	NaN	L	115	1,0000	0,0000	0,0000	0,0000	0,0000
LL		7	0.0000	0.5714	0.2857	0.1429	0.0000	LL		14	0,0000	0,5000	0,3571	0,1429	0,0000
L		25	0.0000	0.0400	0.4800	0.4800	0.0000	L		17	0,0000	0,4118	0,2941	0,2941	0,0000
H		65	0.0000	0.0154	0.2154	0.7231	0.0462	H		57	0,0000	0,0175	0,0702	0,8772	0,0351
HH		4	0.0000	0.0000	0.0000	1.0000	0.0000	HH		7	0,0000	0,0000	0,0000	0,5714	0,4286
NaN	H	163	1.0000	0.0000	0.0000	0.0000	0.0000	NaN	H	177	0,9887	0,0056	0,0000	0,0056	0,0000
LL		16	0.0000	0.5000	0.3750	0.1250	0.0000	LL		19	0,0000	0,4737	0,1579	0,3684	0,0000
L		57	0.0000	0.1579	0.4737	0.3684	0.0000	L		34	0,0000	0,1176	0,4412	0,4412	0,0000
H		124	0.0000	0.0403	0.1129	0.7903	0.0565	H		132	0,0076	0,0227	0,1515	0,7576	0,0606
HH		5	0.0000	0.0000	0.0000	1.0000	0.0000	HH		6	0,0000	0,1667	0,0000	0,3333	0,5000
NaN	HH	5	1.0000	0.0000	0.0000	0.0000	0.0000	NaN	HH	3	1,0000	0,0000	0,0000	0,0000	0,0000
LL		2	0.0000	0.5000	0.5000	0.0000	0.0000	LL		0	0,0000	0,0000	0,0000	0,0000	0,0000
L		0	0.0000	0.0000	0.0000	0.0000	0.0000	L		2	0,0000	0,0000	1,0000	0,0000	0,0000
H		4	0.0000	0.0000	0.0000	1.0000	0.0000	H		1	0,0000	0,0000	1,0000	0,0000	0,0000
HH		0	0.0000	0.0000	0.0000	0.0000	0.0000	HH		0	0,0000	0,0000	0,0000	0,0000	0,0000

## (cont.) Spatial Markov Chain Matrixes

Medium Low Technology Intensity								Low Technology Intensity							
t <sub>0</sub>	Spatial Dependence	Num. Cases	t <sub>1</sub>					t <sub>0</sub>	Spatial Dependence	Num. Cases	t <sub>1</sub>				
			NaN	LL	L	H	HH				NaN	LL	L	H	HH
NaN	NaN	30	1.0000	0.0000	0.0000	0.0000	0.0000	NaN	NaN	12	1.0000	0.0000	0.0000	0.0000	0.0000
LL		0	0.0000	0.0000	0.0000	0.0000	0.0000	LL		0	0.0000	0.0000	0.0000	0.0000	0.0000
L		0	0.0000	0.0000	0.0000	0.0000	0.0000	L		0	0.0000	0.0000	0.0000	0.0000	0.0000
H		6	0.0000	0.0000	0.0000	1.0000	0.0000	H		0	0.0000	0.0000	0.0000	0.0000	0.0000
HH		0	0.0000	0.0000	0.0000	0.0000	0.0000	HH		0	0.0000	0.0000	0.0000	0.0000	0.0000
NaN	LL	41	1.0000	0.0000	0.0000	0.0000	0.0000	NaN	LL	18	1.0000	0.0000	0.0000	0.0000	0.0000
LL		16	0.0000	0.6875	0.1875	0.1250	0.0000	LL		15	0.0000	0.7333	0.2000	0.0667	0.0000
L		8	0.0000	0.1250	0.6250	0.2500	0.0000	L		24	0.0000	0.2083	0.5000	0.2917	0.0000
H		19	0.0000	0.0000	0.0526	0.8947	0.0526	H		17	0.0000	0.1176	0.3529	0.4706	0.0588
HH		5	0.0000	0.2000	0.0000	0.4000	0.4000	HH		4	0.0000	0.2500	0.0000	0.0000	0.7500
NaN	L	60	0.9833	0.0167	0.0000	0.0000	0.0000	NaN	L	54	0.9815	0.0185	0.0000	0.0000	0.0000
LL		32	0.0000	0.5313	0.3438	0.1250	0.0000	LL		63	0.0000	0.6508	0.2222	0.1270	0.0000
L		51	0.0000	0.1765	0.4706	0.3529	0.0000	L		42	0.0000	0.3095	0.4048	0.2857	0.0000
H		102	0.0000	0.0196	0.2059	0.7353	0.0392	H		91	0.0000	0.0440	0.1648	0.7473	0.0440
HH		10	0.0000	0.0000	0.0000	0.5000	0.5000	HH		11	0.0000	0.0909	0.0000	0.4545	0.4545
NaN	H	77	1.0000	0.0000	0.0000	0.0000	0.0000	NaN	H	39	1.0000	0.0000	0.0000	0.0000	0.0000
LL		38	0.0000	0.6053	0.2632	0.1053	0.0263	LL		19	0.0526	0.4211	0.2105	0.1579	0.1579
L		67	0.0000	0.0746	0.5224	0.3731	0.0299	L		76	0.0000	0.0921	0.4079	0.4737	0.0263
H		237	0.0000	0.0295	0.0970	0.8397	0.0338	H		278	0.0000	0.0072	0.1151	0.8309	0.0468
HH		25	0.0000	0.0400	0.0000	0.5600	0.4000	HH		40	0.0000	0.0500	0.0500	0.4250	0.4750
NaN	HH	4	1.0000	0.0000	0.0000	0.0000	0.0000	NaN	HH	22	1.0000	0.0000	0.0000	0.0000	0.0000
LL		1	0.0000	0.0000	0.0000	1.0000	0.0000	LL		1	0.0000	0.0000	1.0000	0.0000	0.0000
L		0	0.0000	0.0000	0.0000	0.0000	0.0000	L		2	0.0000	0.0000	0.5000	0.5000	0.0000
H		5	0.0000	0.0000	0.0000	0.8000	0.2000	H		5	0.0000	0.0000	0.2000	0.8000	0.0000
HH		0	0.0000	0.0000	0.0000	0.0000	0.0000	HH		1	0.0000	0.0000	0.0000	0.0000	1.0000