**Local determinants of innovation and spatial dependence - A Spatial Tobit model applied to Brazilian Micro-regions**

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**Abstract**

This paper analyses the spatial patterns of innovation, its spatial interdependencies and the role of some local determinants of innovation in Brazilian micro-regions. Specifically, it evaluates how local firms’ R&D, regional academic research, agglomeration level and local industrial specialization or diversification affect regional innovation and the presence of spatial dependence in regional innovation. This purpose is achieved a Spatial Data Analysis and the estimation of an econometric model using the number of patents per capita as a measure of local innovative outputs. Similar to studies using other countries data, the Spatial Analysis shows that innovation is not homogeneously distributed in the Brazilian geography and it’s especially concentrated in South and Southeast Regions, where the main industrial clusters are located. The empirical model adopted is based on the Knowledge Production Function applied to regions and is estimated using a Spatial Autoregressive Tobit (SAR-Tobit) with Brazilian patent data as an innovation output proxy. The use of a Spatial Tobit model allows to deal more appropriately with a large number of Brazilian regions without patents. It’s an important point to a study applied for a developing country where industrialized and rural areas coexist. Moreover, several additional tests were performed to ensure the quality of inferential results. The estimation of the model of this work indicates that higher levels of regional industrial R&D imply greater innovation measured by patents. Another model’s finding is that local university research impacts positively on industrial innovation confirming that academic research can foster firm’s innovation. Both results are important to reaffirm that industrial and academic innovative activities play an important role also for local innovation in developing countries. Moreover, denser and diverse cities tend to present a better innovative performance than smaller and specialized ones. A specific extension of the model points that the association of these two factors are an important driver of local innovation what indicates Jacobian advantages for regional innovation in Brazil. Finally, in regards of spatial dynamics, local innovation is positively affected by the proximity of the most innovative micro-regions and it can point to the presence of interregional knowledge spillovers associated to innovative activities.

JEL Code: O18; O33; R11.

Key-words: Innovation; Spatial Tobit; Patents; Brazil

**Resumo**

Este trabalho tem por objetivo analisar padrões espaciais da inovação, suas interdependências e o papel de alguns determinantes locais da inovação nas microrregiões do Brasil. Especificamente, avalia-se como a P&D das empresas locais, a pesquisa universitária da região, o nível de adensamento urbano e a relativa especialização ou diversificação do sistema produtivo local afetam a inovação regional. Para isso, foi realizada uma Análise Exploratória de Dados Espaciais e a estimação de um modelo econométrico utilizando como medida do resultado de inovação o número de patentes por habitante das microrregiões. É possível notar que a inovação está desigualmente distribuída pelo espaço geográfico e se concentra especialmente nas Regiões Sul e Sudeste, onde se encontram os principais clusters inovativos. O modelo empírico adotado se baseia na Função de Produção de Conhecimento aplicada às regiões e é estimado por meio de um Tobit Espacial Autorregressivo (SAR-Tobit). O uso de um modelo SAR-Tobit permite lidar de modo mais adequado com um grande número de regiões sem patentes, além disso, foram feitos diversos testes adicionais que buscam assegurar a qualidade dos resultados inferenciais. A estimação do modelo desse trabalho indica que maiores níveis regionais de P&D industrial e da pesquisa universitária implicam em maior inovação, medida pelas patentes. Ao mesmo tempo, as regiões adensadas e diversificadas tendem a apresentar um melhor desempenho inovativo. Uma extensão específica do modelo aponta que a associação desses dois fatores é um importante determinante da inovação local o que aponta para a existência de vantagens Jacobianas para a inovação regional no Brasil. Por fim, a inovação local é afetada positivamente pela proximidade de microrregiões mais inovadoras, o que corrobora a existência de transbordamentos de conhecimento inter-regionais da inovação.

**Palavras-chave:** Inovação; Spatial Tobit; Patentes; Brasil

**Área 10 – Economia Regional e Urbana**

**Introduction**

Firm’s innovation is strongly dependent to local context. The emergence of some regions with high innovative performance mainly in North America and Europe, such as Silicon Valley in United States and Badden-Wurttemberg in Germany drove the attention of academics to how some factors determine regional innovation output and putted the location and geography in the focus of several studies on innovation.

This topic gained more relevance in the innovation econometric literature since the seminal work of Jaffe (1989) that used an adapted version of the Griliches’ (1979) Knowledge Production Function (KPF) applied to geographic units. KPF models became the reference model used by many later studies (Acs et al, 1994; Anselin et al, 1997; Crescenzi et al., 2007; Fritsch and Slavtchev, 2007).

Similar to the original production function, the Knowledge Production Function assumes that some factors determine the production of knowledge through innovation. Largely, these studies use patents granted or filed in each location as a proxy for local innovation output. Despite patents are restricted to some specific sectors and do not always represent a real innovation, they were considered the best measure for econometric models on innovation since earlier works (Scherer 1965, Griliches, 1979, e.g.) and still as the standard in more recent studies (Crescenzi et al, 2007; Fritsch and Slavtchev, 2007, e.g.). Patents present the significant advantage of being universal, since they are granted in all countries, and present a quite stable award criteria.

This paper uses a model based on the knowledge production function to assess the local determinants of innovation in Brazil, including local R&D (industrial and academic) and industrial level of agglomeration and relative specialization. Spatial dependence was also analyzed using an autoregressive model that includes a lagged dependent variable in the model with different specifications of proxy, variables and spatial weight matrixes to reduce possible bias.

**Literature Review**

Local Research & Development (R&D) efforts – industrial and academic, private or public – have crucial importance Despite in regional innovation level. These factors, present in the seminal work of Jaffe (1989), are used due to an extremely straightforward reasoning that assumes that greater these efforts, the greater the innovation outputs.

In the case of academic R&D, the new knowledge generated by universities and research centers is utilized by companies for various mechanisms, intended or not, as the hiring of workers trained in Universities’ research groups, the generation of a new spinoff company, or formal collaborative contracts.

However, a fundamental element for the geographical analysis of innovation is the role of the proximity of regions particularly innovative. Since Jaffe (1989), several studies indicated that innovative efforts in certain locality can benefit the entire neighboring region and vice versa. Thus, physical proximity would bring an advantage for regions close to high innovative regions. That is, innovative process in a company in a given location can benefit from university research efforts near or projects developed by companies in neighboring regions. On the other hand, isolated individual firms would be more difficult to enjoy the innovative results of the most dynamic region for it to be more geographically distant. Under this view, one important factor was the proximity to regions with higher levels of patents that spillover to its neighbors.

Since the advancement of econometric tools, this phenomenon has been measured by several tools. One of the most used are neighboring weight matrix to ponder each neighbors’ variable for a ‘metric’ of geographical proximity as having common boundaries, the distance between regions, or others. Several studies showed that the proximity to regions with especially high levels of patents can benefit the local innovative level as pointed by several studies (Fischer and Varga, 2003; Gonçalves and Almeida, 2009, e.g.).

In addition, a series of studies on innovation has been evaluating the role of concentration and industrial structure for innovation (Carlino et al., 2007). For these studies, the spatial concentration presents clear advantages for innovation by allowing more interactions between the parts and economies of scale.

Regarding the industrial structure, there are various criteria that indicate various advantages for specialized or diversified regions. Supported by Marshall (1890) findings, many authors advocate the best innovative performance of regions specialized in a given economic activity. Under this view, specialized regions would have a set of specialized suppliers, skilled workers and a greater flow of informal knowledge among employees. These factors collaborate for greater productivity and innovative performance among local enterprises.

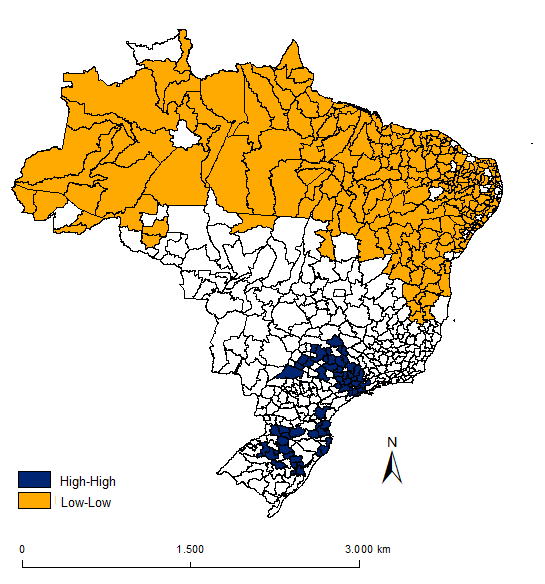
On the other hand, some studies argue - as proposed by Jacobs (1969) - that the most beneficial for regions is a diversification of industrial activities. The knowledge transfers between different sectors would allow a greater number of radical innovations through which the author calls "cross fertilization". This argument is supported by a higher number of new firms and industries in bigger diversified cities.

The debate over whether specialized or diversified regions are the most important to innovative purposes presents empirical support for both hypothesis. On the one hand, different indicators were used to measure the relative regional specialization or diversification. Some results points to benefits for specialized regions (Cabrer-Borrás and Serrano-Domingo, 2007, Henderson 1997, 2003) and some for diversified regions (Audretsch and Feldman, 1999 and Frtisch and Slavtchev, 2007). However, as shown by Beaudry and Shiffareova (2009) most of the differences in these findings are associated with the use of different specialization-diversification indicators, sector composition or geographical level of analysis.

As can be seen, the panorama of the local innovation is extremely broad and diverse and yet demands many insights. Accordingly, this paper tries to make a deeper analysis of the role of various factors on local innovation and assess their spatial effects with a Brazilian regional dataset of patents.

**Innovation in Brazil: Spatial Patterns**

An initial analysis of regional distribution of innovative activities can be done using a LISA (Local Indicator of Spatial Autocorrelation) of patents per capita in Brazilian Micro-regions. Using a statistical indicator, the LISA technique classifies high-high regions that delimitates a cluster of highly innovative regions (with high levels of patents per capita) surrounded by similar ones. In the opposite, LISA also present low-low regions, with the lowest innovative regions that has similar neighbors. In the map below, high-high and low-low regions in Brazil are presented. The variable analyzed is the patents per capita between 2001 and 2005.



The LISA Map shows a great concentration of highly innovative regions in the South-Southeast Brazilian regions that has a great proportion of industrial production. This pattern is also in line with the concentration of innovative and technological activities in Brazil described by Albuquerque et al (2002) and Gonçalves and Almeida (2009). This is also an important element to the model estimated.

Some papers analyze the innovation in Brazil in a spatial perspective. Albuquerque et al. (2002) describes the distribution of technological and scientific activities in Brazil. Based in the location of patents, the authors show a strong spatial concentration of innovative activities point that only ten municipalities in Brazil detain more than 53% of patents in an eleven years period (1990-2000) and this concentration was mainly located in the South and Southeast regions, a similar spatial profile was obtained by Gonçalves (2007). Albuquerque et al (2002) also points that the concentration of innovative activities is higher than the production concentration similar to the results of Audretsch and Feldman (1996) for United States.

One important study that uses KPF for Brazilian Regions is Gonçalves and Almeida (2009) that runs a Spatial Autorregressive model to 558 Brazilian micro-regions. Results point that agglomeration level and academic research are important determinants of and level of industrialization are important determinants of local innovation.

**Data and Method**

This paper’s model is based on the original specification of the production function of knowledge of Jaffe (1989) with spatial elements and some additional controls.

Generally, the specification of function is:

Where ***Iit***is the innovation performance of region ***i*** in (number of patents filed in the region), ***RDit-1***, the R&D efforts from firms and universities in ***i*** region in the preceding period since it supposes an innovation requires some time to became a mature innovation in terms of formalization in most cases patents are used as proxy and ***Eit*** characteristics of the local productive structure (level of agglomeration and specialization/diversification in industry), and controls.

Before detailing the model, it seems important to make some methodological considerations. The first concerns the geographical level of aggregation chosen because it directly affects the measurement of spatial effects of research and, as indicated by Beaudry and Schiffauerova (2009), the perception of Marshallian or Jacobian advantages. It seems necessary that the spatial units of analysis are not too large that they have more than one important urban center, and not too small that an important urban center is split in more than one geographical area to avoid that one could measure as a spatial spillover effects what is actually due to internal flows of a metropolis. With this counter, we chose to adopt the micro-regional level as the geographic level of analysis.

However, Brazilian micro-regions are highly heterogeneous, especially from the viewpoint of industrial production and innovation. Regarding patents, for example, it is important to note that Albuquerque et al. (2002) point that patents, as well as other measures of scientific and technological levels, are significantly more concentrated in Brazil than production and population. In addition, there are large gaps in terms of patents in Brazil, as can be seen in the illustration below that shows the grouping of micro according to their level of per capita patents filed between 2001 and 2005. During this period, 229 of the 558 Brazilian micro-regions there were no patents.

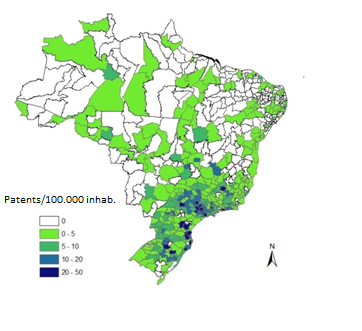


Figure 1 – Patents per 100,000 inhabitant in Brazilian micro-regions, 2001-2005.

In addition, another feature that shows a great discrepancy between the various locations in Brazil is its industrial structure. There are large gaps across the country coexisting industrial areas and rural ones. Many micro-regions have only a few hundred employees in the corresponding 2 digits division in 2001, and even two micro-regions in the Northern part don’t have a single active link registered this year. Therefore, it seems appropriate to adopt as an object of this study all the Brazilian micro-regions, as would be compared with industrialized regions.

Most of these difficulties could be mitigated with an appropriated cohort, but Brazil hasn’t an official statistical selection of targeted in industrial centers and urban as the Metropolitan Statistical Areas (MSAs) in the United States. To address this, we decided to use a Spatial Tobit Model that can deal with a high proportion of zero-patent regions. This option is in line with the solution adopted by Autant-Bernard and LeSage (2011) that treats the patent statistics as a measure censored in zero modeled by a Spatial Tobit.

The model is outlined below.

Local Innovation (PatPC). As several other studies (Moreno et al, 2005 and Montenegro et al, 2011), we adopt patents per capita of each region as proxy of local innovation. In this work, we chose to use a pooled regression with patents in the period 2004 and 2005 for every 100,000 inhabitants in each Brazilian micro-region. Independent variables were selected to represent the efforts that led to these patents were therefore used data from the years immediately preceding that period. This assumes that the patents involved in innovative efforts take years to generate as a result of a patent.

Spatially lagged Local Innovation (WPatPC). The autoregressive term was included in the model to evaluate the role of spatial spillovers of innovative results to neighbors. The spatial weight matrix use is a k-nearst matrix for 15 neighbors but we also did additional tests with three other spatial matrixes to check robustness of our results.

Expenditure on Industrial R&D (R&DInd). Although some studies have only the value-added spent on R&D or just the Industrial R&D, like Crescenzi et. al. (2007), this paper separates industrial and academic R&D efforts. This approach permits to evaluate separately the contributions of both R&D efforts to local innovation. Due to lack of disaggregated data for firms’ expenditure on R&D in Brazil, this paper uses as a proxy number of workers occupied in R&D functions in total local employment divided per total population (data from RAIS).

Expenditure on University R&D (R&DUniv). It is also difficult to have a good proxy for the academic R&D. In general, the available measures are related to number of researcher in university, specifically, this study uses two proxies: the relative number of full-time university professors (INEP) and of students applying to master's, doctoral or postdoctoral degree in graduate programs (CAPES).

Both proxies present imperfections. University professors may be dedicated only to teaching activities or graduate students may be related to educational policy motivation and is not related directly with research. To limit these imperfections, these two variables were combined using principal component analysis (PCA) generating a new variable corresponding to the first component labeled R&DUniv. This single component fits our needs because corresponds to more than 80% of explanatory power of the both variables, which is detailed in the Appendix A.

Indicator of specialization and diversification – Kugman Index (KI). To assess when more specialized or diversified regions have better innovative performance, was used the Krugman index in a similar way as Crescenzi et al (2007). This heterogeneity index measures the industrial structure of a region that can be expressed by a value that varies from 0 to 2. In more specialized regions, the index assumes values near 2 and in more diversified ones, the index is close to 0. In this case, was used as reference the number of employees in Manufacturing and Mining Industries (2 digit level) in 2004 or 2005.

Agglomeration (Dens). As attested by Carlino et al (2007), local innovative level is frequently related to agglomerative advantages: denser regions tend to present higher innovative performance. In this way, an additional variable with the population density using the population census (IBGE) was introduced in the model.

Controls. In addition to these variables, four controls were included. Similar to Carlino et al (2007) we added a control for the participation of manufacturing industry in total employment (ShrInd) and presence of some sectors more prone to patent (Sec). The model also includes a dummy for the North, Northeast and Center-West regions (N) assuming that they are less innovative and dummies for Brazilian metropolitan regions (Metro) assuming that great urban centers are more prone to innovate.

Table 1 – Variables description

|  |  |
| --- | --- |
| Variable | Description |
| PatPC | Patents filed in 2004 or 2005 per 100,000 population in the regions. Source: INPI. |
| R&DInd | Industrial R&D of region. Percentage of employees in manufacturing and mining working acting in R&D activities per total employees. Source: RAIS 2003/2004. |
| R&DUniv | Academic R&D of region. Obtained by Principal Component Analysis of RDU\_prof, and RDU\_stu (listed below). Own elaboration. |
| KI | Krugman Index of specialization-diversification[[1]](#footnote-1). Elaborated with data from RAIS, 2004/2005. |
| Dens | Population density of microregions. Source: IBGE |
| ShrInd | Participation of Manufacturing and Mining Industries in the total economically active population. Source: RAIS, 2004/2005. |
| Sec | Share of top 9 sector in local employment. Source: RAIS, 2004/2005 |
| NNE | Dummy for the North, Northeast and Center-West. Own elaboration. |
| Metro | Dummy for metropolitan regions. Own elaboration. |
| RDU\_prof | Number of university professors with full dedication per 10.000 inhabitants. Source: INEP, 2003/2004. |
| RDU\_stu | Number of students in master, doctoral or post-doctoral programs per 10.000 inhabitants. Source: CAPES, 2003/2004. |

**Results**

Three versions of the model previously presented were estimated with pooled data for two years (2004 and 2005) with a total sample with 1,116 observations (558 micro-regions x 2 years). The first OLS model estimated (1) includes all variables less spatial elements, the second model estimated is a SAR (2) that includes the autoregressive term for patents and finally a SAR-Tobit (3) as presented in Table 2 below.

Table 2 - Results of regression– Patents per capita (log)

|  |  |  |  |
| --- | --- | --- | --- |
| ***N = 1,116*** | 1. **OLS** | 1. **SAR** | **(3) SAR-Tobit** |
| ***WPatPC*** |  | 0,52\*\*\*  [105,979] | 0,295\*\*\*  [5,258] |
| ***R&DInd*** | 0,138\*\*\*  [6,25] | 0,118\*\*\*  [5,764] | 0,144\*\*\*  [3,991] |
| ***R&DUniv*** | 0,432\*\*\*  [8,477] | 0,401\*\*\*  [8,477] | 0,477\*\*\*  [6,298] |
| ***Dens*** | 0,123\*\*  [2,781] | -0,008  [-0,194] | 0,226\*\*  [2,631] |
| ***KI*** | -0,321\*  [-2,09] | -0,569\*\*\*  [-3,993] | -3,082\*\*\*  [-9,911] |
| ***ShrInd*** | 5,993\*\*\*  [10,906] | 3,941\*\*\*  [7,737] | 9,531\*\*\*  [9,265] |
| ***Sec*** | 2,899\*\*\*  [7,05] | 2,193\*\*\*  [5,749] | 3,498\*\*\*  [4,701] |
| ***NNE*** | 2,214\*\*\*  [6,125] | 2,494\*\*\*  [7,438] | 2,551\*\*\*  [4,547] |
| ***Metro*** | -0,922\*\*\*  [-5,737] | -0,004  [-0,027] | -1,152\*\*  [-3,455] |
| ***Adj-R2*** | 0,4664 | 0,4899 | - |
| ***LM-SAR*** | 180.48\*\*\* |  |  |

\*\*\* p < 0.1%; \*\* p < 1%; \* p < 5%; t-stat in brackets

From a special perspective, models 2 and 3 coefficients show spatial spillover effects. This indicates that, in Brazil, the spatial proximity to regions with high patent levels is associated with high innovative performances. The positive and significant coefficient of spatial lagged dependent variable is similar to Fischer and Varga (2003). It also corroborates Gonçalves and Almeida (2009) results for Brazil and is in line with the concentration of innovative activities in Southern Brazilian micro-regions.

Both Industrial R&D (R&DInd) and University R&D (R&DUniv) exhibit significant and positive coefficient. This result is expected and confirms that the greater the efforts of local companies’ and universities’ R&D, higher local levels measured by patents per capita.

Regarding industrial structure, Krugman index (KI) coefficient is negative and significant. Krugman index takes higher values in regions specialized, so more diverse are the regions, better their innovative performance. Additionally, population density is positively correlated with innovation indicating that denser cities are associated with more innovation. So, summing this two results, our model present same indication to jacobian externalities are more important as generators of innovation than Marshallian ones.

All controls have the expected signal and are significant. Metropolitan regions, with higher share of industrial activities and specific sector with higher propensity to patent tend to be present higher levels of patents per inhabitant. Micro-regions not located in the South and Southeast presents lower levels of patents per capita.

These results about industrial structure indicate two general lines. First, diversified regions present more innovative results than specialized ones. Secondly, two of the models show that denser regions are positively related to innovation. However, in one agglomeration coefficient was not significant.

Several studies claim that the degree of diversification is closely associated to agglomeration. At the same time, we can point out that regions with little industrial presence have more specialized indices for the values ​​of Krugman Index due to the very composition of these indices. At the same time, for a region to be considered diversified, it have to present at least few employees in each industrial division, making it difficult for a region with little employment is appointed as varied by these indicators.

So, it is relevant to consider in detail the cases in which the diversification and agglomeration occur simultaneously. This can be accomplished by including a simple interaction between variables in the model. Thus, the interaction would distinguish the effect of diversification and agglomeration together, the effect of diversification and agglomeration per se. However, for it to be made ​​a variable linking diversification and agglomeration is more intuitive to use the specialization indicator in the opposite direction, as a measure of diversification.

To perform this additional test, we inverted the Krugman index multiplying it by -1. Thus, this new indicator labeled here "- KI" ranges from -2 to 0. This means that the most specialized regions take the value closest to -2 and diverse close to 0. The estimation results of these models are shown below.

Regresion results – SAR-Tobit

|  |  |  |
| --- | --- | --- |
| ***N = 1,116*** | **-KI** | **Interaction** |
| **WPatPC** | 0,294\*\*\*  [4,956] | 0,275\*\*\*  [4,956] |
| **R&DInd** | 0,142\*\*\* [3,874] | 0,152\*\*\*  [4,287] |
| **R&DUniv** | 0,478\*\*\*  [6,354] | 0,472\*\*\*  [6,251] |
| **Aglom** | 0,227\*\*  [2,608] | 0,050  [0,478] |
| **-KI** | 3,083\*\*\*  [9,928] | 0,468  [0,466] |
| **-KI\*Aglom** | - | 1,622\*\*  [2,677] |
| **ShrInd** | 9,533\*\*\*  [9,240] | 9,531\*\*\*  [9,257] |
| **Sec** | 3,476\*\*\*  [4,571] | 3,055\*\*\*  [3,923] |
| **Metro** | 2,563\*\*\*  [4,531] | 2,897\*\*\*  [5,253] |
| **NNE** | -1,156\*\*\*  [-3,475] | -1,273\*\*\*  [-3,818] |

\*\*\* p < 0.1%; \*\* p < 1%; \* p < 5%; t-stat in brackets

As expected, the inversion of KI causes a reversal of the sign of the index of specialization or diversification and others coefficients are similar to the original model. In the final model, the interaction term of agglomeration and diversification (-KI \* Aglom) the interaction term is positive and significant, suggesting that the density of the regions and diversification have significant and positive effects on innovation only when occurring concomitantly. In this model, the diversification and agglomeration *per se* are not significant, although they maintain their initial signal. All other results remain the same.

This find reduce the importance of diversification and agglomeration per se but reinforce the perception that the Jacobian advantages are especially linked to major agglomerated and diversified centers as suggested by Storper and Venables (2004). Thus, one can point to the diversification and agglomeration of the regions creates together these local special conditions that provide higher innovation performance.

To ensure that all results presented above were correct, others models were tested. To avoid influence in the choice of the spatial weight matrix we runt three additional estimations with different matrix an all inferences remain the same. As stated before, Brazil is a vast country with huge differences regarding economic development. To control this, we runt another model only with the South and Southeast regions and the main results remain the same. Finally, to ensure that our choices in certain variables influence the results, we runt several models with a different variable with a more restrict selection of patents, a different specialization index (Herfindhal-Hirschman index) and different proxy for academic R&D and again main results remain the same. The results of these additional models are presented in the Annex B.

**Conclusions**

This paper findings shows that local industry and university R&D efforts have a positive impact on innovation performance of regions. Furthermore, model results presents an impact of spatial spillovers from neighboring regions with higher patent levels and it appears that local companies can take advantage of these proximity. Finally, we noticed an important role in the agglomeration of innovation regions and localities of the most diversified industrial point of view have better innovative performance.

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Annex A

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Component | Eigen value | Difference | Proportion | Cumulated |
| Comp 1 | 1.76428 | 1.52857 | 0.8821 | 0.8018 |
| Comp 2 | 0.235716 | 0 | 0.1179 | 0.9745 |

|  |  |  |
| --- | --- | --- |
| Variable | Comp 1 | Comp 2 |
| Graduate programs | 0.7071 | 0.7071 |
| Full professors | 0.7071 | -0.7071 |

Annex B

Regresion results – Different Spatial Weight Matrixes

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| ***N = 1,116*** | **Original Estimation** | **20-nearest**  **(A)** | **Inverso da distância**  **(B)** | **Rainha**  **(C)** |
| **WPatPC** | 0,295\*\*\*  [5,258] | 0,102\*\*\*  [2,578] | 0,281\*\*\*  [4,995] | 0,154\*\*\*  [3,569] |
| **R&DInd** | 0,144\*\*\*  [3,991] | 0,153\*\*\*  [4,368] | 0,144\*\*\*  [3,889] | 0,145\*\*\*  [3,958] |
| **R&DUniv** | 0,477\*\*\*  [6,298] | 0,492\*\*\*  [6,534] | 0,488\*\*\*  [6,417] | 0,506\*\*\*  [6,620] |
| **Aglom** | 0,226\*\*  [2,631] | 0,266\*\*  [3,115] | 0,242\*\*  [2,819] | 0,256\*\*  [3,033] |
| **KI** | -3,082\*\*\*  [-9,911] | -3,192\*\*\*  [-10,629] | -3,189\*\*\*  [-10,314] | -3,066\*\*\*  [-10,083] |
| **ShrInd** | 9,531\*\*\*  [9,265] | 10,886\*\*\*  [10,504] | 9,599\*\*\*  [9,195] | 10,193\*\*\*  [9,850] |
| **Sec** | 3,498\*\*\*  [4,701] | 3,710\*\*\*  [4,986] | 3,604\*\*\*  [4,723] | 3,578\*\*\*  [4,671] |
| **Metro** | 2,551\*\*\*  [4,547] | 2,365\*\*\*  [4,325] | 2,35\*\*\*  [4,232] | 2,381\*\*\*  [4,311] |
| **NNE** | -1,152\*\*  [-3,455] | -1,934\*\*\*  [-6,156] | -1,183\*\*\*  [-3,44] | -1,812\*\*\*  [-5,880] |

\*\*\* p < 0.1%; \*\* p < 1%; \* p < 5%; t-stat in brackets

Regresion results – Different Spatial Weight Matrixes

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| ***N = 1,116 (556 D model)*** | **Original Estimation** | **South and Southeast only**  **(D)** | **Different Spec/Div Index (HH)**  **(E)** | **Different Proxy for Univ. R&D**  **(F)** |
| **WPatPC** | 0,295\*\*\*  [5,258] | 0,298\*\*\*  [4,055] | 0,333\*\*\*  [6,142] | 0,275\*\*\*  [4,940] |
| **R&DInd** | 0,144\*\*\*  [3,991] | 0,107\*\*  [2,742] | 0,114\*\*  [3,111] | 0,137\*\*\*  [3,707] |
| **R&DUniv/ RDU\_prof (F)** | 0,477\*\*\*  [6,298] | 0,440\*\*\*  [5,528] | 0,517\*\*\*  [6,669] | 0,074\*\*\*  [5,425] |
| **Aglom** | 0,226\*\*  [2,631] | 0,249  [1,829] | 0,03  [0,358] | 0,257\*\*  [3,044] |
| **KI / HH (E)** | -3,082\*\*\*  [-9,911] | -3,436\*\*\*  [-8,309] | -5,678\*\*\*  [-7,190] | -3,197\*\*\*  [-10,261] |
| **ShrInd** | 9,531\*\*\*  [9,265] | 12,026\*\*\*  [8,272] | 8,302\*\*\*  [7,598] | 9,441\*\*\*  [9,007] |
| **Sec** | 3,498\*\*\*  [4,701] | 3,049\*\*  [3,053] | 1,869\*  [2,375] | 3,394\*\*\*  [4,369] |
| **Metro** | 2,551\*\*\*  [4,547] | 2,92\*\*\*  [4,028] | 3,481\*\*\*  [6,431] | 2,806\*\*\*  [5,064] |
| **NNE** | -1,152\*\*  [-3,455] | - | -1,641\*\*\*  [-5,073] | -1,286\*\*\*  [-3,844] |

\*\*\* p < 0.1%; \*\* p < 1%; \* p < 5%; t-stat in brackets

1. For informations on Krugman index calculus: see Crescenzi et al (2007). [↑](#footnote-ref-1)