

Araujo, Veneziano; Garcia, Renato

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An exam of the spatial patterns of innovation in Brazilian industry: an empirical analysis

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An exam of the spatial patterns of innovation in Brazilian industry: an empirical analysis.

Veneziano de Castro Araujo

PhD candidate at Polytechnic School of University of São Paulo – Brazil

veneziano.araujo@usp.br; venezianoa@gmail.com

Renato Garcia

Professor at Polytechnic School of University of São Paulo – Brazil

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Abstract

The aim of this paper is to exam the spatial patterns of innovative performance in Brazilian industry, taking into account its regional interdependencies, and the impact of the main innovative inputs. There is a huge literature concerning regional innovation and the importance of local inputs in innovative performance. However, most of the studies use data from developed countries. This paper verifies if the role played by innovative inputs in developed countries remain important in developing ones, in which patents are proportionally rare. In this sense, it's applied an empirical model based in the Jaffe's (1989) knowledge production function to Brazilian regions. The model uses patents as a proxy for the innovative output and includes regional variables of local industrial and academic R&D, agglomeration characteristics and some spatial elements such as neighborhood's innovative activities. The main results show the importance of local industrial R&D to regional innovation measured by patents, and, similarly, a relation between patenting activity of the firms and local academic research. With the purpose of evaluate which externality is more important to innovation in Brazilian regions, marshallian or jacobian externalities; the Krugman specialization-diversification index of industrial employment is adopted in the model. The importance of been close to the most innovative regions is assessed with the commonly used spatial lagged variables and the estimation results corroborates the relevance of technological spillovers spatial mediated. Finally, some efforts are made to exam other kinds of proximity as proposed by Boschma (2005) and a network weight matrix based on university-industry collaborative links, such as Ponds et al (2010), is added to the model to test the importance of non spatial proximity. The overall conclusion suggests that in Brazilian case, main innovative inputs seemed in developed countries remain important, but presents also some specificity such as a strong concentration of innovative activities in the Southeast related with the industrial agglomeration and different relative magnitude importance in some local determinants of innovation.

JEL Code: O18 ;O33; R11.

Key-words: Regional innovation – Patents – Spatial analysis – Brazil

Introduction

Several studies tries to assess how several factors determine innovation outcomes. However, geographic elements only gained relevance since the seminal work of Jaffe (1989). Jaffe (1989) used an adapted version of the Griliches' (1979) Knowledge Production Function applied at the level of regions rather than firms. This became the reference model used by many subsequent studies (Acs et

al, 1994; Anselin et al, 1997; Crescenzi et al., 2007; Cabrer Borrás & Serrano-Domingo, 2007, Gonçalves & Almeida, 2009).

Like the original production function, Jaffe's model assumes that some factors determine the production of knowledge through innovation. Largely, these studies use as a measure for the outcome of innovation patents granted or filed in each location. Despite patents still restricted to some specific sectors and do not always represent a real innovation, they are the best measures used for econometric analyzes on innovation from the earlier works (Scherer 1965, Griliches, 1979, e.g.) to more recent ones (Crescenzi et al, 2007; Fritsch & Slavtchev, 2010, e.g.). Patents have the advantage of being universal, granted in all countries, and quite stable criteria.

This paper uses a model based on the knowledge production function to assess the local determinants of innovation, including the efforts of industrial R&D and academic and local industrial structure. We also evaluated the effects of R&D in space using spatial lagged variables. Advantages obtained by a "non-spatial proximity" are also evaluated using like Ponds et al (2010) a measure of interactions of firms and academic research groups. For this purpose, a weight matrix for university-enterprise networks was computed using the Brazilian Directory of Research Groups of the CNPq Lattes database the records of interactions.

Literature Review

Several factors impact the level of innovation in a region, passing by socio-organizational factors and infrastructure. However, certainly the crucial factors for innovation results in a locality are the Research & Development (R&D) efforts from Industry and Universities. These factors, already present in the seminal work of Jaffe (1989), assume that greater the efforts inferred for these activities, the greater the results of innovation. This rationale is extremely straightforward when industrial R&D is higher in a city or region industrial sector, higher is the innovation level measured by patents, new products launched, etc.

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 R&D efforts of a locality can benefit the entire neighboring region and vice versa. Thus, physical proximity would bring a greater advantage for regions close to high innovative regions. That is, 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, 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 R&D that spillovers to its neighbors.

Since the advancement of econometric tools, this phenomenon has been measured by several tools. One of the most used are neighboring matrix to ponder each neighbors' variable for a "metric" of geographical proximity as having common boundaries or the distance between the regions. Several studies showed that be near regions with especially high levels of R&D may be a positive feature. There are many studies that concludes from such measures, that proximity has a positive impact on innovation (Cabrer-Borrás & Serrano-Domingo, 2007; Crescenzi et al, 2007; eg).

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

As for the industrial structure, there are various criteria which indicate various advantages with respect to the sectors in the region. Supported in studies by Marshall (1890), 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 industry diversification is most beneficial for regions because it allow a greater number of radical innovations through which the Jacobs calls "cross fertilization". It occurs because innovations in a given area of knowledge are applied to generating other new industries.

The debate over whether specialized or diversified regions are the most relevant to innovation have generated many of the empirical studies. For this, different indicators were used to measure the relative specialization or diversification of areas, but evidences are conflictive. Some studies points to benefits for many specialized regions (Cabrer-Borrás & Serrano-Domingo, 2007, Henderson 1997, 2003) and other studies presents evidences that diversified regions are more innovative (Audretsch & Feldman, 1999 and Fritsch & Slavtchev, 2007). However, as shown Beaudry & Shiffareova (2009) most of these differences are associated with characteristics of specialization-diversification indexes used such as sector composition or geographical level of analysis.

However, beyond the evidence presented above, the debate on geographical proximity and innovation gained another dimension of analysis. For some authors as Breschi & Lissoni (2009), geographical proximity is not relevant to knowledge flows. From the standpoint of innovation, a company could not only benefit by being geographically close to one location innovative, but also for other types of links that allows the knowledge to circulate easily. It occurs, according to the authors, because people belonging to network related to the research area or the epistemic field ("epistemic networks", as stated by Breschi & Lissoni, 2009). Under this arguments, knowledge flows would be geographically located in the stent that these networks, and consequently the limits of knowledge spread would be membership in groups that share the same knowledge, or epistemic networks (epistemic networks).

Accordingly, Boschma (2005) proposed a classification with five types of proximity, four of them not physical: cognitive, organizational, social and institutional proximity. For this reason, some aimed to assess the role of the physical proximity of other types of proximity (Autant-Bernard et al, 2007; Maggioni et al, 2007; Ponds et al, 2010, for example). Again, the results point to different directions. While the work of Autant-Bernard et al (2007) points out that the social position of agents in the search network is more important than geographical proximity for collaboration of research, the results of Maggioni et al (2007) indicate greater importance of proximity geographical networks against other non-spatial proximity.

As can be seen, the local innovation landscape 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. In addition, further evaluate the role of institutional proximity between companies and university research network as a means of disseminating the results of university research.

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, some additional controls and a variable lagged by a weight matrix of collaboration to measure the role of institutional proximity along the lines of Ponds et al (2007).

Generally, the specification of function is:

$$I_i = f(PD_i, WPD_i, E_i,)$$

Where I_i is the innovation performance of i region (number of patents filed in the region), RD_i , the R&D efforts from firms and universities in i region in the preceding period since it supposes a patented innovation requires several years of research; WRD_i are the R&D spatial effects and E_i 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 & Schiffauerova (2009), the perception of Marshallian or Jacobian advantages. It seems necessary that analysis geographic level is not so large that some regions have more of an important urban center and not so small that one urban

agglomeration is divided in more than one region. If this second case occurs, one could measure internal flows of a metropolis as spatial spillover effects. With this counter, we chose to adopt the microregional level and geographic analysis.

However, Brazilian microregions are highly heterogeneous, especially from the viewpoint of industrial production and innovation levels. With respect to patents, for example, it is important to note what indicates Albuquerque et al (2009). According to this work, the Brazilian patents, as well as other measures of scientific and technological, are significantly more concentrated 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 microregions there were no patents.

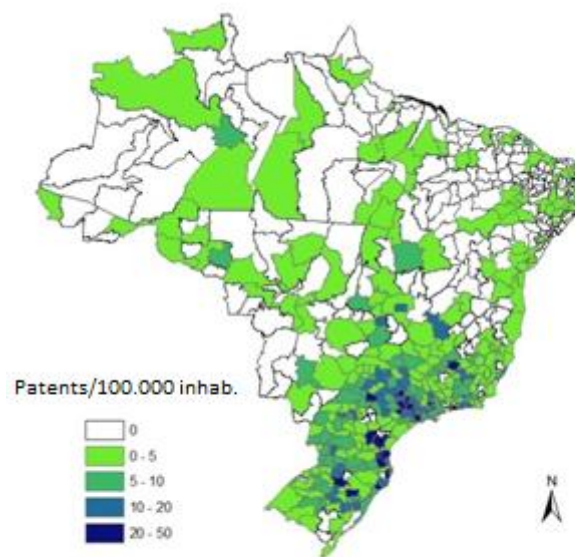


Figure 1 – Patents per 100,000 inhabitant in Brazilian micro-regions, 2001-2005.

In addition, another feature that shows a great discrepancy between the various locations in Brazil is its industrial structure. Brazilian manufacturing and mining sectors presents large regional gaps across the country. 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 region don't have a single active link registered this year in these sectors.

Most of these difficulties could be mitigated with an appropriated cohort, but Brazil hasn't an official statistical selection targeted in industrial centers and urban as the Metropolitan Statistical Areas (MSAs) in United States. To address this, we decided to take a cut of Brazilian micro-regions. Specifically, the model was estimated only for the micro-regions that presents employees in more than half of the 26 divisions (2 digit level) related with manufacturing and mining industries. It is important to note that in this way, the analysis is restricted only minimally industrialized regions. On the other hand, the index of specialization-diversification adopted (Krugman index), would not be biased to regions in which there was a lack of broad industrial sectors allowing to distinguish specialized regions and areas with low industrial presence that may seem specialized in a sector the simple fact of not having an mature industrial park.

In 2001, 304 Brazilian micro-regions present employees in more than 13 divisions. However, for the OLS estimation of the model is necessary to perform a logarithmic transformation of the dependent variable which requires to exclude 34 micro without patents, so the final set has 270 micro-regions.

Although this cohort represents only 48.8% of Brazilian micro-regions, the coverage is more than enough. The set of 270 micro-regions corresponds to 78.6% of the population and 93.4% of national employment. But most surprising is that this concentration is even stronger in terms of innovation, since almost all the patents in the period studied (99.2%) are in these regions. Thus, we can say that the clip used is very complete and meets the needs of the problem.

In view of these observations, the model outlined below.

$$PatPC = R\&DInd + R\&DUniv + Dens + Dens^2 + KI + W_{spat}R\&DInd + W_{spat}R\&DUniv + W_{net}R\&DUniv + Sec + ShrInd + Metro + NNE$$

Results of innovation (PatPc). As several other studies (Borrás & Cabre-Serran-Sunday, 2007 and Montenegro et al, 2011), was adopted as a measure of regional innovation output the number of patents per capita. In this case, we used the patents in the period 2001 to 2005 for every 100,000 inhabitants in a logarithmic form. The other 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.

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. The main aim of this is measure separately the contributions of these various efforts such as the purpose of motivating Jaffe (1989). Due to lack of disaggregated data for firms' expenditure on R&D in Brazil, this paper uses as a proxy for the share of worker with higher degree in manufacturing and mining industries in 2001 (data from RAIS).

Expenditure on University R&D (R&DUniv). It is difficult to have a good proxy for the academic R&D. In general, the available measures are related to workers involved in university research, specifically, this study uses three proxies: number of full-time university professors with master's or doctorate degree (INEP, 2000), number of scholarship for students researchers applying to master's, doctoral or postdoctoral degree (CAPES, 2000) and number of programs *strictu sensu* graduate registered and evaluated in the 2001-2003 triennium (CAPES, 2004).

All three of these proxies have imperfections: university professors may be dedicated only to teaching or the criteria and fellowships for graduate students and recognition of graduate programs may be related to factors political or regulatory motivation. To limit these imperfections, these three variables were combined using principal component analysis that generated a new variable corresponding to the first component called R&DUniv. Although a single component, it corresponds to more than 80% of explanatory power, which are detailed in the Appendix A.1. However, for comparative purposes and also as a way to evaluate these proxies individually, versions of the model with each variable independently were estimated.

Index 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 to a region that can be expressed by the value assumed that the index which varies from 0 to 2, more specialized regions indexes assumes values near 2 and the most diversified ones close to 0. In this case, was used as reference the number of employees in Manufacturing and Mining Industries divisions (2 digit level) in 2001.

Agglomeration (Dens). Inspired by Carlino et al (2007) and trying to control the large voids due to lack of uniformity of Brazilian micro-regions it was used the urban population density. For this, we used the urban area of each micro-region obtained by mapping of EMBRAPA in conjunction with the urban population census of the 2000 (IBGE).

Spatially lagged variables (WspatR&DInd and WspatR&DUniv). Serves to evaluate the role of spatial R&D spillovers using variables lagged by a spatial “Queen” weight matrix.

Effects of university-industry interaction – non-spatial proximity ($W_{netR\&DUniv}$) by assessing the role of other forms of proximity this paper includes a measure lagged by a weight matrix generated by the number of recorded collaborations between companies and university research groups registered in the Directory of Research Groups of the base CNPq's Lattes. This base has been studied by several studies as Rapini et al. (2009), Suzigan et al. (2009) and Garcia et al. (2011). As Ponds et al (2010), in order to include this variable lagged by W_{net} matrix is intended to measure the benefits to local businesses of recurrent interactions with academic groups located at sites with significant academic R&D.

In this paper similarly to Ponds et al (2010), the matrix W_{spat} is defined as follows:

$$W_{spat_{ij}} = \frac{r_{ij}}{\sum_j r_{ij}}$$

Where r_{ij} corresponds to the number of interactions of firms in i region with research groups in j region. Thus, for each pair of regions there is a weight proportional to the degree of accessibility to knowledge developed by universities, or in the terminology of institutional proximity Boschma (2005). Therefore, weighing the academic R&D variable with this matrix, it's possible to assess the relevance of university research efforts in the regions that interact more with the firms.

Controls. In addition to these variables, four controls were included. Similar to Carlino et al (2007) and Gonçalves & Almeida (2009) is an added control for the presence of the sectors most likely to patent (Sec), one for the participation of industry in total employment (ShrInd), as well addition, dummies for the North-Northeast regions (NNE) and the Brazilian metropolitan regions (Metro).

Below are listed the variables present in this work:

Table 1 – Variables description

Variable	Description
PatPC	Patents filed between 2001 and 2005 per 100,000 population in 2000 in the regions. Source: IBGE and INPI.
R&DInd	Industrial R&D of region. Percentage of employees in manufacturing and mining with higher degree in 2001. Source: RAIS 2001.
R&DUniv	Academic R&D of region. Obtained by Principal Component Analysis of RDU_prof, and RDU_bols RDU_prg (listed below). Own elaboration.
Wspat ()	Spatial lagged variable using a weight matrix ("Queen" type), applies to both industrial and university R&D. Own elaboration.
Wnet()	Network lagged variable using a weight matrix created with the number of collaboration between universities and companies reported in the Census Directory of Research Groups of the CNPq in 2008. Only for university R&D. (Elaborated with CNPq, 2008).
KI	Krugman Index of specialization-diversification ¹ . Elaborated with data from RAIS, 2001.
Dens	Population density of urban micro-enterprise. Source: IBGE, 2000 (pop. Urbana) and Embrapa, 2009 (urban area).
Sec	Participation of the sectors most likely to patent the total opposite of Processing and Mining Industries. Source: RAIS, 2001.
ShrInd	Participation of Manufacturing and Mining Industries in the total economically active population. Source: RAIS, 2001.
NNE	Dummy for the North and Northeast. Own elaboration.
Metro	Dummy for metropolitan regions. Own elaboration.
RDU_prof	Number of university teachers with master's or doctoral dedication per capita. Source: INEP, 2000.
RDU_bols	Number of students in master's, doctoral or post-doctoral with fellowship per capital. Source: CAPES, 2000.
RDU_prg	Number of Graduate Programs per capita in Master's or doctorate degree listed in the triennial CAPES evaluation - years 2001-2003. Source: CAPES, 2004

¹ For informations on Krugman index calculus: see Crescenzi et al (2007).

Results

Three versions of the model previously presented were estimated. The first model (1) includes all the variables in the model, with the exception of spatial elements (Wspat) and lagged variables for the weight matrix interactions (Wnet). The second model includes the spatial elements and, finally, the third model also includes variables for university R&D lagged by weight matrix of university-industry interactions. The following are the results of the regressions performed.

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

	1	2	3	
<i>R&DInd</i>	0.05292 (0.01927)***	0.05173 (0.01918)***	0.05110 (0.01911)***	
<i>R&DUniv</i>	0.10288 (0.02345)***	0.10286 (0.02335)***	0.10623 (0.02333)***	
<i>Wspat R&D Ind</i>		5.3593 (2.6079)**	5.1333 (2.599)**	
<i>WspatR&D Univ</i>		0.02010 (0.04978)	-0.0022 (0.05111)	
<i>Wnet P&D Univ</i>			0.02292 (0.01276)*	
Agglomeration	<i>Dens</i>	-3.0150 (2.6919)	-3.7535 (2.7036)	-3.998 (2.6954)
	<i>Dens2</i>	0.17588 (0.1499569)	0.21578 (0.15051)	0.22970 (0.1500)
	<i>KI</i>	-1.3589 (0.21467)***	-1.2530 (0.21934)***	-1.2042 (0.22008)***
	<i>Sec</i>	0.73377 (0.35212)**	0.70806 (0.35052)**	0.69490 (0.34909)**
	<i>ShrInd</i>	2.9348 (0.40615)	2.8852 (0.40601)***	2.8523 (0.40469)***
	<i>NNE</i>	-1.0820 (0.16015)***	-0.98076 (0.16671)***	-0.95571 (0.1665)***
	<i>Metro</i>	0.79611 (0.17595)***	0.80810 (0.17756)***	0.78764 (0.17717)***
	<i>Constant</i>	14.538 (12.066)	17.667 (12.111)	18.619 (12.07)
	<i>R²</i>	0.5656	0.5735	0.5787
	<i>Adjusted R²</i>	0.5506	0.5553	0.5591
<i>Jarque-Bera</i>	.1858 [0.91]	0.0538 [0.97]	0.0825 [0.95]	
<i>White</i>	62.84 [0.12]	69.82 [0.61]	79.51 [0.70]	

*** p < 0.1%; ** p < 1%; * p < 5%; Standart deviation in parenthesis and p-value in brackets

As can be seen, in all cases, both Industrial R&D (R&DInd) and University R&D (R&DUniv) exhibit significant and positive coefficient. This result is expected and indicates that the greater the efforts of local companies' and universities' R&D, higher local levels of patents per capita of the regions.

From the viewpoint of space, the models 2 and 3 indicate that only the industrial R&D (WspatR&DInd) presents a significant spatial spillover effect, since the spatial lag of university R&D (WespR&DUniv) has no significance. This may indicate that, in the Brazilian case, the spillover effects are only related to the dynamics of industrial research. That is, the effects of the industrial R&D held spread out by the surrounding regions so that the level of patents per capita neighboring regions is larger.

However, if spatial effects are not perceived to university research, it is important to note that, when included, the variable that measures the academic R&D weighted by the university-industry

collaborations ($W_{netR\&DUniv}$) coefficient is positive and significant in a similar manner to Ponds et al (2010) results. Thus, one can assume that even if geographical proximity is not an important mean to spread the efforts of university research for firms when there are organizational links, in this case between companies and research groups from a region with higher academic research, there is a perceived benefit to the local patent.

To check the robustness of the evidence related to the Academic Research, we chose to estimate the model 3 for each of the three proxies that make up the variable $R\&DUniv$ (number of professors, number of researchers with fellowship and number of graduate programs). The results of these regressions are present in Appendix A.2 and show a good robustness of this variable since the results remain largely the same. Local university research continues to show positive results, without spatial effects, and interaction with sites of high academic performance shows a positive impact on innovation. The only two notable differences relate to the model (3.1) and may be due to imperfections of the proxy and are $W_{spatR\&DUniv}$ variable coefficient is negative and significant and non-spatial proximity variable ($W_{netR\&DUniv}$) is not significant.

In what concerns the industrial structure, it is noted that the coefficient of the Krugman index (KI) is negative and significant. Since this index takes higher values in regions specialized, the more diverse are the regions, the better their innovative performance. This can be seen as an indication that the advantages of Jacobian type externalities are more important as generators of innovation than Marshallian externalities. However, with regard to agglomeration, it is not possible to detect differences in performance of innovation of the more or less dense regions.

With respect to controls, it is important to note that in all cases is significant. Both the increased presence of the industry as a whole, as the increased participation of sectors that tend to patent more largely explain the innovative performance of regions. Also, note that the North-East have a lower level of patents per capita, while the metropolitan regions have a positive differential in the number of patents per capita.

Conclusions

This paper has shown that the efforts of local industry and university R&D have a positive impact on innovation performance of regions. Furthermore, it was noted the presence of a positive impact of spatial spillovers from industrial R&D in the neighboring regions, which did not occur in the case of university research. On the other hand, it appears that companies can take advantage of university research through non-spatial channels, if measured by the interaction between companies and universities, similar to the tested by Ponds et al (2010). 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.

References

- ACS, Z. J., AUDRETSCH, D.B. & FELDMAN, M. P. (1994). R&D Spillovers and Receipt Firm Size. *Review of Economics and Statistics*, 76 (2), pp. 336-40.
- ALBUQUERQUE E. M., SIMÕES R., BAESSA A., CAMPOLINA B. & SILVA L. (2002) A distribuição espacial da produção científica e tecnológica brasileira: uma descrição de estatísticas de produção local de patentes e artigos científicos, *Revista Brasileira de Inovação*, 1, 225–251.
- ANSELIN, L; VARGA, A; ACS, Z. (1997). Local geographic spillovers between university research and high technology innovations. *Journal of Urban Economics*, v. 42, n. 3, p. 422-448, 1997.
- AUTANT-BERNARD, C.; BILLAND, P.; FRACHISSE, D.; MASSARD, N. (2007). Social distance versus spatial distance in R&D cooperation: Empirical evidence from European collaboration choices in micro and nanotechnologies. *Papers in Regional Science*, Volume 86 Number 3 August 2007.
- BOSCHMA, R. (2005). Proximity and innovation - a critical assessment, *Regional Studies*, vol. 39, no. 1, p. 61-74.
- BRESCHI, S.; LISSONI, F. (2009). Mobility of skilled workers and co-invention networks: an anatomy of localized knowledge flows. *Journal of Economic Geography* 9 (2009) pp. 439–468.
- CABRER-BORRÁS, B., SERRANO-DOMINGO, G., Innovation and R&D spillover effects in Spanish regions: A spatial approach. *Research Policy*, v. 36, p. 1357-1371, jun 2007.
- CARLINO, G. A.; CHATTERJEE, S. & HUNT, R. M. (2007). Urban density and the rate of invention. *Journal of Urban Economics* 61, 389–419.
- CRESCENZI, R.; RODRÍGUEZ-POSE, A. & STORPER, M. (2007) – The territorial dynamics of innovation: a Europe-United States comparative analysis. *Journal of Economic Geography* 7, p. 673-709. Oxford University Press.
- FRITSCH M, SLAVTCHEV V (2007) Universities and innovation in Space. *Ind Innov* 14:201–218.
- GARCIA, R.; ARAUJO, V.; MASCARINI, S.; SANTOS, E. (2011). Os efeitos da proximidade geográfica para o estímulo da interação universidade-empresa. *Revista de Economia, UFPR*.
- GONÇALVES, E.; ALMEIDA, E. S. “Innovation and Spatial Knowledge Spillovers: Evidence from Brazilian Patent Data”. *Regional Studies*, v. 43, p. 513–528, mai. 2009.
- GRILICHES, Z. (1979), Issues in assessing the contribution of research and development to productivity growth. *Bell Journal of Economics*, v. 10, p. 92-116, 1979.
- JACOBS, J., 1969. *The Economies of Cities*. Random House, New York
- JAFFE, A. B., (1989), Real effects of academic research, *American Economic Review* 79(5): 957-970.
- MAGGIONI M, NOSVELLI M, UBERTI E (2007) Space vs. networks in the geography of innovation: A European analysis. *Papers in Regional Science* 86(3).
- MARSHALL, A. (1920). *Principles in Economics*, Macmillan, London.
- MONTENEGRO, R. L., GONÇALVES, E. & ALMEIDA, E. (2011). Dinâmica Espacial e Temporal da Inovação no Estado de São Paulo: Uma Análise das Externalidades de Diversificação e Especialização. *Estudos Econômicos* 41(4) outubro/dezembro de 2011.
- PONDS, R.; VAN OORT, R.; FRENKEN, K. (2010). Innovation, spillovers and university–industry collaboration: an extended knowledge production function approach. *Journal of Economic Geography* 10 (2010) pp. 231–255.
- RAPINI, M.; ALBUQUERQUE, E.; CHAVES, C.; SILVA, L.; SOUZA, S.; RIGHI, H.; CRUZ, W. (2009). University-industry interactions in an immature system of innovation: evidence from Minas Gerais, Brazil. *Science and Public Policy*, 36, p. 373-386.

SCHERER, M. (1965). Firm Size, Market Structure, Opportunity, and the Output of Patented Inventions. The American Economic Review, Vol. 55, No. 5, Part 1, pp. 1097-1125.

SUZIGAN, W.; ALBUQUERQUE, E.; GARCIA, R.; RAPINI, M. (2009). University and industry linkages in Brazil: some preliminary and descriptive results. Seoul Journal of Economics, v. 22, p. 591-611.

Descriptive Statistics

Variable	Mean	Standard dev.	Min	Max
PatPC (log)	1.322958	1.15307	-1.609438	3.907211
P&DInd	3.355232	2.904168	.1767409	23.8053
P&DUniv	.4312574	2.176026	-.4436328	16.89157
WP&DInd	.0312249	.0200477	0	.1336944
WP&DUniv	.2469228	1.0175	-.4436328	6.347449
RP&DUniv	4.256671	3.976005	-.4436328	16.89157
Dens	8.70135	.3981902	7.877733	10.97319
IED (KIndex)	.9423823	.2527221	.3934163	1.651278
Sec	.2431338	.1656125	.0164607	.8635251
ShrInd	.2285816	.1251814	.0206788	.6319789
NNE	.0962963	.295545	0	1
Metro	.1777778	.3830356	0	1

Correlation Matrix

Variable	a	b	c	d	e	F	g	h	I	j	k	l
a.PatPC (log)	1.0											
b.P&DInd	0.3102	1.0										
c. P&DUniv	0.3352	0.2745	1.0									
d. WP&DInd	0.3288	0.0781	0.0675	1.0								
e. WP&DUniv	0.1825	0.0463	0.0418	0.2489	1.0							
f. RP&DUniv	0.2556	0.0533	-0.0104	0.1962	0.3088	1.0						
g. Dens	-0.1611	0.0404	0.0166	-0.1166	-0.0777	-0.1095	1.0					
h.IED	-0.3905	-0.0420	-0.2204	-0.2492	-0.1021	-0.1806	0.0123	1.0				
i. Sec	0.4263	0.4343	0.1368	0.2012	0.1361	0.1507	0.0342	-0.2966	1.0			
j. ShrInd	0.2776	-0.0510	-0.1202	0.0580	0.1295	0.0802	-0.1052	0.2199	0.1095	1.0		
k. NNE	0.3092	0.2489	0.2554	0.0368	-0.1448	0.0396	0.0582	-0.2764	0.1686	-0.1263	1.0	
l.Metro	-0.4356	-0.0848	-0.0351	-0.3290	-0.2632	-0.2232	0.5542	0.0774	-0.2296	-0.2117	0.1109	1.0

Annex

Table A.1 – Principal component analysis– University R&D

Component	Eigenvalue	Difference	Proportion	Cumulative
Comp 1	2.40553	1.88746	0.8018	0.8018
Comp 2	0.518079	0.441693	0.1727	0.9745
Comp 3	0.0763858	.	0.0255	1.0000

Variable	Comp 1	Comp 2	Comp3
Number of professors	0.5112	0.8445	0.1596
Number of researchers with fellowship	0.5938	-0.4813	0.6448
Number of gradute programms	0.6214	-0.2348	-0.7475

Table A.2 – Results (OLS) – Patents per capita (log) other proxies for R&DUniv

	3.1	3.2	3.3
<i>R&DInd</i>	.0486941 (.0193121)**	.0585994 (.0190023)***	.0544171 (.0191199)***
<i>PDU_prof</i>	501.5053 (111.8641)***		
<i>PDU_bols</i>		654.9952 (170.3881)***	
<i>PDU_prg</i>			11912.37 (3001.055)***
<i>W espR&DInd</i>	6.295979 (2.585655)**	4.735914 (2.621557)*	4.675725 (2.611213)*
<i>W espPDU_prof</i>	-444.0305 (264.5202)*		
<i>W espPDU_bols</i>		177.5661 (362.951)	
<i>W espPDU_prg</i>			1079.657 (6337.342)
<i>Wnet PDU_prof</i>	68.59135 (68.16422)		
<i>WnetPDU_bols</i>		149.2636 (87.07129)*	
<i>WnetPDU_prg</i>			3756.634 (1764.66)**
<i>Dens</i>	-2.981019 (2.675722)	-4.26432 (2.721613)	-4.265637 (2.71309)
<i>Dens2</i>	.17383 (.1490194)	.2441255 (.1515175)	.2442356 (.1510371)
<i>KI</i>	-1.207926 (.2188066)***	-1.229387 (.2223837)***	-1.207506 (.2211795)***
<i>Sec</i>	.8445239 (.3506535)**	.5856901 (.3515852)*	.6781576 (.3505932)*
<i>ShrInd</i>	2.942566 (.4036558)***	2.767908 (.4084483)***	2.792533 (.407512)***
<i>NNE</i>	-1.051003 (.1675611)***	-.9512654 (.1670312)***	-.9415093 (.166881)***
<i>Metro</i>	.68814 (.1780391)	.8929737 (.1767433)***	.8126159 (.1783264)***
<i>Constant</i>	13.991 (11.98359)	19.87658 (12.18677)	19.79536 (12.14759)
<i>R2</i>	0.5804	0.5719	0.5750
<i>R2 Ajustado</i>	0.5608	0.5520	0.5552
<i>Jarque-Bera</i>	0.4105 [0.81]	0.1831 [0.91]	0.1742 [0.91]
<i>White</i>	86.24 [0.50]	81.88 [0.63]	80.23 [0.68]

*** p < 0.1%; ** p < 1%; * p < 5%; Standart deviation in parenthesis and p-value in brackets