Regions and Innovation: Determinants and its Spatial Dependence in Brazil

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Abstract

This paper analyses the spatial patterns and spatial interdependencies of innovation and the role local determinants of innovation play 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. In order to analyse these factors, an empirical model based on the Knowledge Production Function was estimated using a Spatial Autoregressive Tobit (SAR-Tobit) with Brazilian patent data. The results indicate that higher levels of regional industrial R&D imply greater innovation and that greater university research at a regional level positively impacts industrial innovation. Moreover, agglomerated and diverse regions present better innovative performance. Regarding spatial dynamics, the proximity of the most innovative micro-regions positively affects local innovation, which shows the existence of interregional knowledge spillovers that are associated with innovative activities.

JEL Code: O18; O33; R11.

Key-words: Regional innovation; Patents; Brazil; Spatial Tobit

1. Introduction

The location of innovation and the role of proximity in knowledge flows have received increasing attention in the regional science and economic geography literatures. Assessing innovation from a regional perspective assumes that innovative activities are influenced by the local context; in certain circumstances, location can enhance or limit firms' innovation. This phenomenon occurs because the knowledge and skills necessary for innovation become more easily accessible in locations where more accumulated knowledge are concentrated and a high number of qualified professionals frequently interact.

Geographical proximity among agents can facilitate the assimilation of complex knowledge used in innovative activities. In this way, it is important to analyze the role of local knowledge spillovers and the local context as drivers of regional innovation. Through knowledge spillovers, knowledge created and accumulated due research activities in firms and universities may benefit the innovative activities of nearby firms. These interregional spillovers are important determinants of local innovation and can be evaluated with different spatial econometric specifications (Greunz, 2003; Fischer and Varga, 2003; Crescenzi et al., 2007; Autant-Bernard and LeSage, 2011).

Innovation activity is not evenly distributed geographically; rather it is concentrated in certain regions. Several empirical studies show that innovation is even more spatially concentrated than manufacturing (Audretsch and Feldman, 1996; Crescenzi et al., 2007; Corsatea and Jayet, 2014) and that denser urban areas are more innovative (Carlino et al., 2007). Another point that is often made in the literature and that demands further analysis is how regional sectoral specialization or diversification generates different advantages (Marshallian or Jacobian ones) and how it propagates by the means of spatial spillovers in innovation (Beaudry and Schiffauerova, 2009).

This paper contributes to the literature by presenting new empirical evidence on this subject and analysing the relation of innovation and agglomeration and regional specialization. Additionally, it contributes by performing an empirical analysis using data from Brazil, because there is little empirical evidence from developing countries. The empirical model is based on the knowledge production function and was estimated by a Spatial Autoregressive Tobit.

The remainder of the paper introduces a literature review about regional determinants of innovation (Sect. 2) and presents an exploratory Spatial Data Analysis that confirms the spatial concentration of innovation in Brazil – mainly in the South-Southeast regions – which reinforces the relevance of a spatial econometric approach (Sect. 3). Then, the model adopted and its variables are described with several methodological remarks (Sect. 4) and the estimation results are analysed (Sect. 5) and checked for robustness and alternative specifications (Sect. 6). Finally, concluding remarks are presented (Sect. 7).

2. Regional Determinants of Innovation

Innovation does not occur in the same manner in different locations. Remarkably, it depends on firms' local environment because firms not only use internal resources to innovate but also employ external local factors to foster innovation. Knowledge creation and diffusion are strongly related to space. Knowledge is embodied in academic and industrial researchers and the tacit dimension of knowledge attests that knowledge exchange occurs with higher efficiency and lower costs through face-to-face contacts (Storper and Venables, 2004). Furthermore, when a given region possesses a great concentration of highly qualified professionals, a rich and complex local knowledge base is created and intensifies local knowledge spillovers and benefit firm innovation. Innovation is facilitated by interaction, cooperation and a collective learning process (Capello and Lenzi, 2013). Geographical proximity is frequently associated to other types of proximity, such as cultural, social or technological proximity, which strengthen these benefits (Paci et al., 2014). Regions with an accumulated knowledge and skill base will perceive advantages in innovation due to better use or access to specific and complex knowledge related to industrial or academic research.

Local industrial and academic R&D activities play a crucial role in regional innovation, as the seminal study of Jaffe (1989) has shown. There is an extremely straightforward reasoning for this finding: as the resources applied to innovative activities (studies, laboratories, funds, etc.) increase, local innovation increases. A region with a high number of researchers can provide more efficiently assets related to innovation such as specialized services or skilled professionals. It implies in more and better opportunities for technology transfers or R&D cooperation. This environment also affords the attraction of new qualified workers and improves absorptive capacity of the firms.

In the case of academic R&D, the new knowledge generated by universities and research centres is utilized by companies for various mechanisms, intentional or not, such as hiring qualified researchers from universities' research groups, generating new spinoff firms, or creating formal collaborative contracts.

Geographical proximity plays a crucial role in fostering innovation. Innovative processes in a firm in a given location can benefit from nearby firms and university research in the same region due to spatial knowledge spillover mechanisms (Duranton and Puga, 2000; Crescenzi et al., 2007). This physical proximity advantage also extends to neighbouring locations, so regions that are close to highly innovative regions also experience benefits. Instead, it is more difficult for isolated individual firms to benefit from the innovation of the most geographically distant.

According to this view, being located in a region with a high number of innovative firms or near a region with greater innovations allows the firm to exploit important benefits from spatial intra and interregional knowledge spillovers in its innovative activities. In fact, evidence of both types of spatial spillovers are present in the literature (Autant-Bernard and LeSage, 2009) and several studies show that innovative activities in a certain locality can benefit the entire neighbouring region and vice versa (Fischer and Varga, 2003; Moreno et al., 2005, Crescenzi et al., 2007).

In addition, other studies on regional innovation have evaluated the role of agglomeration in innovation showing that spatial agglomeration presents clear advantages for innovation by allowing external scale economies and more interactions between local agents (Moreno et al., 2005; Carlino et al, 2007).

Regarding local sectoral specialization, many studies have found evidence that regions specialized in a given economic activity innovate more (Cabrer-Borrás and Serrano-Domingo, 2007, Henderson 1997, 2003). These evidences are theoretically linked to Marshallian externalities that indicate that regional specialization implies in a great number of specialized suppliers, a vast pool of skilled workers and a larger stock of industry-specific knowledge that flows better locally. Specialization reduces transaction costs and facilitates communication intensifying knowledge spillovers. Together these factors contribute to more innovations among local enterprises in that industry.

In contrast, other studies present evidence that the diversification of industrial activities is the most beneficial for innovation in regions (Feldman and Audretsch, 1999 and Fritsch and Slavtchev, 2007). These activities are closely related to the Jacobian advantage which poses that knowledge transfers between different sectors allow a greater number of radical innovations through what the author calls ‘cross fertilization’. It occurs due to the higher complementarities of firms’ knowledge bases that generate synergic advantages in innovation. Knowledge creation and learning often depend on a combination of diverse, complementary capabilities among heterogeneous agents (Capello and Lenzi, 2013). This argument is supported by a higher number of new firms and industries in more diversified cities (Duranton and Puga, 2001).

Despite the vast number of works related to this topic, the debate on whether specialized or diversified regions are the most important for innovation remains open and the comparing these results is a complex task because of their different specialization-diversification indicators, sector composition or geographical levels of analysis (Beaudry and Shiffareova; 2009).

As shown, while the panorama of local innovation is extremely broad and diverse, many questions remain open that require further empirical evidence. Therefore, this paper attempts to conduct a deeper analysis of the role of various factors on local innovation and assesses their spatial interregional spillovers effects. To do that, this paper uses a Brazilian regional dataset of patents is used and a Spatial Autoregressive Tobit model was used in order to capture the regional spillover effects on innovation and explicitly control for regions that do not produce any patents.

3. Regional Distribution of Brazilian Innovative Activities

Regional innovation is extremely concentrated in South and Southeast regions of Brazil (Gonçalves and Almeida, 2009) where manufacturing activities are clustered and population density, GDP per capita and workforce education levels are higher than national average. Although Brazil is a developing country, this scenario is quite similar to that in developed countries such as France (Corsatea and Jayet, 2014) and the United States (Carlino et al., 2007).

This can be verified with an analysis of the regional distribution of innovative activities performed with the test of autocorrelation of patents per capita in Brazilian micro-regions between 2001 and 2005. This test rejects the null hypothesis of no spatial autocorrelation (Annex A.1) and the positive result of Moran index indicates that more innovative regions are spatially clustered and, consequently, that regions with lower innovation levels are clustered generating a spatially heterogeneous distribution of innovation in Brazil. The LISA map (Local Indicator of Spatial Autocorrelation) shows a great concentration of highly innovative regions in the Southern regions of Brazil, converging to the spatial concentration of manufacturing.

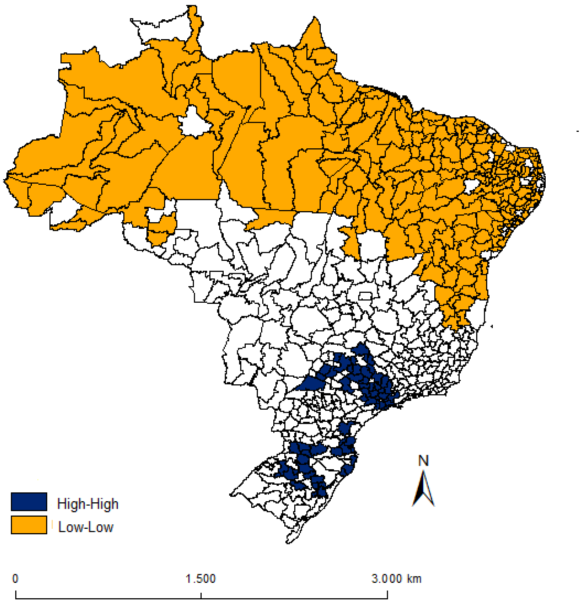

Figure 1 – LISA Map – High-high and low-low - patents per 100,000 inhabitants in Brazilian micro-regions, 2001-2005.

4. Methodology and Model Specification

The role of geography in innovation was first shown by Jaffe (1989) who applied an adapted version of the Griliches' (1979) Knowledge Production Function (KPF) to geographical units. Later, this set of econometric models was improved with spatial econometrics tools and more specific data that were more spatially disaggregated (Acs et al., 1994; Anselin et al., 1997; Crescenzi et al., 2007; Fritsch and Slavtchev, 2007).

Patents granted or patent applications in each location were largely used as a proxy for local innovation output. Although patents are restricted to specific sectors and do not always represent real innovation, they have been considered the best measure in econometric models on innovation since the earliest works (Scherer 1965, Griliches, 1979). Recent studies have also used patents as the standard proxy for innovation (Crescenzi et al., 2007; Fritsch and Slavtchev, 2007, Corsatea and Jayet, 2014). One of the main advantages of the use of patents is that they are universal, easy to count and present stable criteria.

In this paper, the model is based on the Knowledge Production Function, with spatial elements and additional controls. The general specification of the function as follows:

$$I_{it} = f(RD_{i,t-1}, E_{it}, Controls);$$

where $\boldsymbol{I_{it}}$ is the innovation performance of region $\boldsymbol{i}$ measured by the number of patents filed in the region; $\boldsymbol{RD_{it-1}}$ is the R&D expenditure from firms and universities in region $\boldsymbol{i}$ in the preceding period; and $\boldsymbol{E_{it}}$ represents the characteristics of the local productive structure (level of agglomeration and specialization of local economy). This time-lag structure allows us to take into account the delay between research and its results are sufficient mature in terms of formalization to file a patent as adopted in other studies (Corsatea and Jayet, 2014; Paci et al., 2014).

Before detailing the model, it is important to note several additional methodological remarks. For the geographical level of aggregation, this study adopted the micro-regional level, which is similar to EU NUTS-3. This option is justified because the geographical area of analysis should not be so large that it has more than one relevant urban centre, and it should not be so small that an important urban centre is split into more than one geographical area. Additionally, the regional spatial effects should not be mixed into the internal flows of a metropolis.

The spatial distribution of patents shows a high spatial concentration in Brazil, demonstrated by the patents per capita (Figure 2. In addition, large geographical gaps can also be noted, because 229 of the 558 micro-regions produced no patents in the 2001-2005 period.

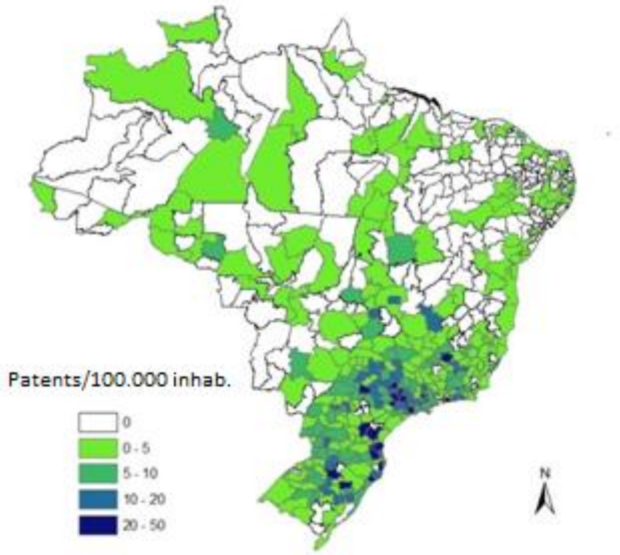

Figure 2 – Patents per 100,000 inhabitant in Brazilian micro-regions, 2001-2005.

Most of these measurement issues can be mitigated with an appropriated cohort, but Brazil does not have an official statistical selection of targeted industrial and urban centres, such as the Metropolitan Statistical Areas (MSAs) in the United States. To address this issue, this study used a Spatial Tobit Model that can address a high proportion of zero-patent regions because it treats patent statistics as a measure censored to zero and modelled by a Spatial Tobit and allows explicitly controlling for regions that do not produce any patents (Autant-Bernard and LeSage, 2011; Kang and Dall'erba, 2015).

Regarding spatial dependence, a Spatial Autoregressive (SAR) model was used because it allows the analysis of spatial dynamics and the effects of inter-regional innovation spillovers in spatial autoregressive term [1]. The complete model is outlined as follows, and the descriptions of variables are presented in Table 1.

$$PatPC_{i,t} = WPatPC_{i,t} + R\&DInd_{i,t-1} + R\&DUniv_{i,t-1} + Dens + KI + ShrInd + Sec + Metro + NNE$$

[1] This specification provides an adequate specification of externalities in diffusion process of innovation Paci et al. (2014).

Table 1 – Variables description

Variable	Description
PatPC	Patents filed in 2004 or 2005 per 100,000 inhabitants in the regions. Source: Brazilian Patent Office.
R&DInd	Industrial R&D of region. Percentage of employees in manufacturing and mining working acting in R&D activities per total employees. Source: Ministry of Labor 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[2]. Elaborated with data from Ministry of Labor, 2004/2005.
Dens	Population density of micro-regions. Source: Brazilian Statistical Bureau.
ShrInd	Participation of Manufacturing and Mining Industries in the total economically active population. Source: Ministry of Labor, 2004/2005.
Sec	Share of top 9 sector in local employment. Source: Ministry of Labor, 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: Brazilian Ministry of Education, 2003/2004.
RDU_stu	Number of students in master, doctoral or post-doctoral programs per 10.000 inhabitants. Source: Brazilian Ministry of Education, 2003/2004.

Source: author' own elaboration.

Local Innovation (PatPC). The dependent variable is patent applications per capita for each region, a proxy for local innovation (Moreno et al., 2005; Crescenzi et al 2007; Autant-Bernard and LeSage, 2011; Kang and Dall'erba 2014; Corsatea and Jayet, 2014; Paci et al., 2014). Patent grants often take several years to be defined and the number of years may vary expressively between technological classes, so the application date is more stable and closer to the time that knowledge is created (Kang and Dall'erba (2014). Locational information on patent assignees were obtained and aggregated in micro-regional level.

Spatially Lagged Local Innovation (WPatPC). The autoregressive term was included in the model in order to evaluate the role of spatial spillovers in innovation to neighbours. A standard spatial weight matrix with a k-nearest matrix for 15 neighbours was used. Additional estimations were made with another spatial weight matrix as a robustness check.

Industrial R&D Expenditures (R&DInd). The proxy for industrial R&D expenditures at the regional level is related to human capital: the share of workers occupied in R&D. The source is the Brazilian Ministry of Labour. This proxy is used because of the lack of data on R&D expenditures at the firm level. Previous studies include either industrial and academic R&D expenditures or just industrial R&D (Crescenzi et. al., 2007; Sebestyén and Varga; 2013). In this paper the option was to include industrial and academic R&D expenditures separately in order to measure their individual contribution to local innovation (Fritsch and Slavtchev (2007; Kang and Dall'Erba, 2015).

University R&D Expenditures (R&DUniv). Data on academic expenditures on R&D are not available in Brazil. So, in order to measure academic R&D, two different proxies are chosen. First, the share of full-time university professors at the regional level, and second the number of graduate students applying to master's, doctoral and postdoctoral degrees. However, both

[2] The calculus of Krugman index can be found in Crescenzi et al (2007).

proxies present imperfections, because university professors may be dedicated only to teaching activities and graduate students may be employed in other activities not directly related to research. To limit these imperfections, these two variables were combined using principal component analysis, generating a new variable corresponding to the first component, labelled R&DUniv. This single component corresponds to more than 80% of the explanatory power of both variables (Appendix A.1).

Indicator of specialization and diversification - Krugman Index (KI). In order to assess whether more specialized or diversified regions are more innovative, the Krugman index was used as a measure for the region's industrial structure (Crescenzi et al., 2007). The Krugman index varies from 0 to 2: most specialized regions assume values near 2 and the most diversified regions close to 0. The index uses the number of employees in the manufacturing industry (at 2-digit level).

Agglomeration (Aglom). Previous studies show that local innovation is frequently related to agglomerative advantages (Moreno et al., 2005). Therefore, denser regions tend to demonstrate higher innovative performance. In this way, an additional variable for the population density using the population census was introduced to the model.

Controls. Four controls were included: first, the share of manufacturing in total employment (ShrInd) (Carlino et al., 2007; Gonçalves and Almeida, 2009); second, the presence of certain industries is more prone to patents (Sec); third, dummies for the North, Northeast and Centre-West regions (N); and fourth, dummies for Brazilian metropolitan regions (Metro).

5. Results

Three versions of the model were estimated with pooled data for two years (2004 and 2005) with a total sample of 1,116 observations (558 micro-regions x 2 years). The first is an OLS (model 1) that includes all the variables but without spatial factors. The second estimated model is a SAR model (2) that includes the autoregressive term for patents. And finally the SAR-Tobit model (3, Table 2). The results remain mainly the same.

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

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

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

Both Industrial (R&DInd) and University (R&DUniv) R&D exhibit significant and positive coefficients, as expected, which means that patents at the local level grow when local companies' and universities' R&D expenditures increase. Previous empirical studies that use similar specification found that both local industrial and academic R&D are local determinants of innovation (Fritsch and Slavtchev, 2010; Kang and Dall'erba, 2015).

Regarding the local industrial structure, the Krugman index (KI) coefficient is negative and significant. KI takes higher values in specialized regions; therefore, as regions become more diversified, their innovative performance improves. This evidence shows the importance of local benefits of diversification for local innovation, in line with previous studies (Greunz, 2003, Fritsch and Slavtchev, 2007; Corsatea and Jayet, 2014). Additionally, population density is positively correlated with innovation, indicating that denser cities are more innovative. This result also confirms previous studies on the U.S. (Carlino et al., 2007), Europe (Moreno et al., 2005) and Brazil (Goncalves and Almeida, 2009).

From a spatial perspective, the positive and highly significant parameter of the spatially lagged dependent variable (WPatPC) suggests that knowledge flows between spatially proximate regions are important sources of innovation. Therefore, more innovative neighbours implies in more innovation in the region, probably through spatially mediated spillovers. The positive and significant coefficient of the spatial lagged dependent variable confirms Gonçalves and Almeida's (2009) previous results but better deals with the reality that some regions presents zero patent in some years and correcting the potential downward bias in a samples censored to zero (LeSage and Pace, 2009).

All controls present the expected signals and are significant. Metropolitan regions, with higher shares of industrial activities and specific sectors with greater propensities to patent, present higher levels of patents per inhabitant – similar to previous studies (Moreno et al., 2005; Carlino et al., 2007; Gonçalves and Almeida, 2009). Finally, micro-regions not located in the South and Southeast present lower levels of patents per capita confirming the importance of the regional heterogeneity of innovation in Brazil with a lower innovation pattern outside the main industrial areas.

In order to ensure the accuracy of the main results, other model specifications were tested. To ensure that the weight matrix specifications are appropriate and the results are not particularly sensitive to the form adopted in the weight matrix, the original model was estimated again with alternative spatial weight matrices[3]. The results, presented in the Annex, remain the same, even in terms of the coefficients (original signal and significance level) and the magnitude of the coefficients is quite similar (LeSage and Pace, 2010).

Table 4 – Regression results – Patents per capita (log) – Alternative independent variables and cohort.

	PatInvPC (I)	**PatnUnivPC (II)**	**HH (III)**	**Professors (IV)**	**S-SE (V)**	**2001-2005 (VI)**
$WPatPC_t$	0,180**	0,301***	0,333***	0,275***	0,298***	0,258***
	[2,856]	[5,480]	[6,142]	[4,940]	[4,055]	[6,992]
$P\&DInd_{t-1}$	0,099***	0,136***	0,114**	0,137***	0,107**	-
	[4,407]	[3,698]	[3,111]	[3,707]	[2,742]	
Eng			-		-	0,009**
						[3,000]
$P\&DUniv_{t-1}$	0,384***	0,373***	0,517***	-	0,440***	0,366***
	[7,765]	[4,845]	[6,669]		[5,528]	[7,618]
$Prof$			-	0,074***	-	-
				[5,425]		
$Aglom$	0,154**	0,246**	0,03	0,257**	0,249	0,283***
	[2,793]	[2,921]	[0,358]	[3,044]	[1,829]	[5,400]
IED(KI)	-2,042***	-3,150***	-	-3,197***	-3,436***	-3,131***
	[-9,818]	[-10,120]		[-10,261]	[-8,309]	[-15,105]
$IED(HH)$			-5,678***	-	-	-
			[-7,190]			
$ShrInd$	5,167***	9,498***	8,302***	9,441***	12,026***	9,043***
	[7,697]	[9,065]	[7,598]	[9,007]	[8,272]	[14,108]
Sec	1,753***	3,502***	1,869*	3,394***	3,049**	3,360***
	[3,657]	[4,529]	[2,375]	[4,369]	[3,053]	[7,279]
$Metro$	1,331***	2,487***	3,481***	2,806***	2,92***	2,675***
	[3,763]	[4,476]	[6,431]	[5,064]	[4,028]	[8,186]
NNE	-0,84***	-1,138***	-1,641***	-1,286***	-	-1,205***
	[-3,875]	[-3,424]	[-5,073]	[-3,844]		[-5,730]

*** p < 0.1%; ** p < 1%; * p < 5%; estatística t em colchetes.

Alternative specifications were also tested with changes in the dependent variable (models I and II). First, the total number of patents per capita was replaced by a more restrict proxy the number of invention patents per capita because they embody higher quality intellectual property (Ying (2008). Second, a model with total patents excluding university patents. Although the total number of university patents is of little significance, it is important to check that the positive impact of R&D University on the total level of patent remains after this exclusion (the new variables are listed in Table A.4 in the Annex).

[3] The alternative weight matrices are: k-nearest with the 20 nearest neighbours (instead of the 15 included in the main model), and the inverse of distance and Queen. According to LeSage and Pace (2010), little change in the results is expected, even with such different matrices.

Regressions with alternative specifications that use only invention patents (PatInvPC – Model I) and without university patents (PatnUnivPC – Model II) present the same results as the original model, showing that the empirical results are robust to more specific innovation types and when university patents are removed.

Two other variables were also changed (Models III and IV). In model III, the Krugman index was replaced by the Herfindahl-Hirschman index (HH) as the proxy for industrial specialization of the regions. It intended to assess whether the effects found for the specialization or the diversification of regions with the Krugman index remain with an alternative specialization index. In model IV, the proxy for University R&D was replaced by the number of full-time doctorate professors per inhabitant. This approach is justified because, although the university research proxy is particularly appropriate, it is composed of the association of two indicators and is therefore difficult to interpret. The test with a more direct indicator can help verify the robustness of the results. Again, the results remained the same.

Finally, two additional regressions were estimated: one only for South and Southeast regions (model V) and another for all Brazilian micro-regions but for a longer period of time (model VI). The South and Southeast cohort is supported by the extensive innovation gaps in the northern portion of Brazil evident in the previous LISA analysis and the heterogeneity in the spatial dimensions of the regions. Finally, the model VI includes five years of patents (2001-2005) and allows to guarantee that the results are not restricted to specific factors or to the short time frame of two years (2004-2005), but rather remain over a longer period. However, to accomplish this estimation, it is necessary to have another independent variable for the level of Industrial R&D because the original proxy is not available for periods before 2003. Therefore, although it is a weaker proxy, the share of engineers in the total employees at the regional level was used because data are available for the whole period.

Overall, results from these models confirm former results: positive and significant coefficients for industrial and academic R&D; a significant and positive autoregressive term (WPatPC); and a negative and significant specialization index. Signs and significance of the controls remained the same; the only exception was the level of agglomeration (Aglom) which was not significant in two models (III and V).

6.1 Agglomeration and Diversification

It is important to take a specific look at the results on the industrial structure of the regions. First, the main results show that diversified regions are more innovative than specialized ones. Second, agglomerated regions are positively related to innovation, which shows the role of the agglomeration of resources in the urban areas in fostering innovation.

Previous studies indicate that the degree of diversification is closely associated to agglomeration (Duranton and Puga, 2000). Therefore, it is relevant to consider in detail the cases in which diversification and agglomeration occur simultaneously, which can be accomplished by including a simple interaction between the variables in the model. Thus, the interaction would distinguish the effect of diversification and agglomeration together and the sole effect of both diversification and agglomeration. In order to link diversification and agglomeration, the specialization index was built in the opposite direction, by inverting the Krugman index and multiplying it by -1. Thus, this new indicator,"- KI", ranges from -2 to 0, which means that the most specialized regions take the value closest to -2 and the most diverse closest to 0. The estimation is presented in Table 6.

Table 6 – Regression results – Patents per capita (log).

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

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

Obviously, the inversion of KI causes a reversal of the sign of the specialization index, and other coefficients remain similar to the original model. But the inclusion of the interaction term (-KI * Aglom) changes the results. The diversification and agglomeration *per se* are not significant, although they maintain their initial signs and 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 at the same time.

This finding reduces the importance of diversification and agglomeration *per se* and reinforces the perception that Jacobian advantages are especially linked to major agglomerated and diversified centres (Storper and Venables, 2004). Thus, the occurrence of diversification and agglomeration in a region creates these special local conditions, which provide greater innovation performance.

6. Conclusions

Innovation depends on a wide range of factors. Specifically, several elements that can benefit the innovation results must be considered when analysing this phenomenon from the regional point of view. For this reason, many studies have sought to explore how and why different local factors can allow a better innovative performance.

To assess this topic, the empirical analysis in this paper involved estimating a model based on the Jaffe-Griliches Knowledge Production Function (KPC) using a Spatial Autoregressive Tobit (SAR-Tobit) estimation. The adoption of a Spatial Tobit is justified by the large number of Brazilian micro-regions that did not register any patents in this period because it allows us to adequately address the observations of regions without patents. In this way, it is possible to obtain the estimated results without the potential downward bias that would occur with a sample censored to zero and to assess the spatial dynamics and the effects of inter-regional innovation spillovers.

The empirical results show that the local R&D level is positively related to innovation in the region which points to the importance of local firms' research as a main component of regional innovation. Additionally, there is a positive association between university research and the number of patents per capita which corroborates several studies that report academic research as an important factor of local patenting.

With regard to local characteristics, the estimation results show that agglomeration and diversification imply in higher innovation corroborating the advantages of agglomeration are also important in the Brazilian case. Additionally, because diverse regions tend to have higher numbers of patents is an evidence of Jacobian advantages for innovation in Brazil.

An alternative estimation with an interaction term between density and diversity indicated that urban agglomeration and diversification are beneficial for innovation only when they occur at the same time. Therefore, agglomeration and diversification *per se* do not generate benefits for companies to innovate, but the combination of these two factors does. This result indicates that large, diversified urban centres generate significant benefits for innovation, supporting Storper and Venables's (2004) view that companies in locations with these characteristics have largely favourable conditions for innovation.

Regarding spatial effects, the autoregressive term indicated a positive effect of the proximity of particularly innovative regions. This finding points to the occurrence of inter-regional spillovers of innovative activity, indicating that companies in a particular region can benefit from effects of proximity to the innovations of a neighbouring locality.

In short, two main contributions derive from this work. First, spatial interregional spillovers are important drivers of regional innovation in Brazil reaffirming benefits for firms in locations near innovative regional poles. Second, this study corroborates the evidence that Jacobian externalities are beneficial for innovation since local industrial diversification and agglomeration are beneficial for local innovation.

Our results lead to several implications for policy design. Regional policy should take into account diverse innovation patterns that arise from differences in the presence of certain local drivers of innovation. The finding that diverse and dense regions present a particularly positive dynamics than other regions suggests the need to adopt specific policies for each of these scenarios and confirms the need to move away from a "one size-fits-all" policy approach to innovation.

Policy makers can develop measures to take advantage of the more favorable conditions for innovation, offered by large diversified centers. At the same time, for specialized and less densely populated regions a different schedule is needed because these locations do not have the same favorable terms of densification and diversification for innovation and therefore particularly depend on the formation of local skills and capabilities geared toward innovation.

Finally, for research agendas, this work points to the relevance of further studies that deeply address the relation between agglomeration and diversification not only for innovation but also for productivity and economic growth.

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Annex A.1

Global Moran I - patents/10.000 inhab. all micro-regions Brazil (2001-2005).

Year	Moran Index	t stat	Std deviation	Marginal prob.
2005	0,3869	17,3	0,0224	0,000
2004	0,4136	18,4	0,0255	0,000
2003	0,4014	17,9	0,0224	0,000
2002	0,2885	13,5	0,0213	0,000
2001	0,3514	16,0	0,0220	0,000

Annex A.2

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 A.3

Table 3 – Regression results – Patents per capita (log) – Different Weight Matrices

n = 1116	**20-nearest (A)**	**Inverse distance (B)**	**Queen (C)**
WPatPC	0,102*** [2,578]	0,281*** [4,995]	0,154*** [3,569]
R&DInd	0,153*** [4,368]	0,144*** [3,889]	0,145*** [3,958]
R&DUniv	0,492*** [6,534]	0,488*** [6,417]	0,506*** [6,620]
Aglom	0,266** [3,115]	0,242** [2,819]	0,256** [3,033]
KI	-3,192*** [-10,629]	-3,189*** [-10,314]	-3,066*** [-10,083]
ShrInd	10,886*** [10,504]	9,599*** [9,195]	10,193*** [9,850]
Sec	3,710*** [4,986]	3,604*** [4,723]	3,578*** [4,671]
Metro	2,365*** [4,325]	2,35*** [4,232]	2,381*** [4,311]
NNE	-1,934*** [-6,156]	-1,183*** [-3,44]	-1,812*** [-5,880]

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

Annex A.4

Additional dependent variables.

Variable	Description	Source
$PatIndPC_t$	Ivention Patents Filed per 10.000 inhabitants in micro-region.	INPI and IBGE.
$PatnUnvPC_t$	Total Patents Filed excludin Academic Patents per 10.000 inhabitants in micro-region.	INPI and IBGE.
Eng	Industral R&D– Engineers per 10.000 workers in micro-region.	RAIS.
$Prof$	University R&D– Full-time PhD Professors per 10.000 inhab.	INEP and IBGE.
HH	Herfindhal-Hirschman Index – employment CNAE 1.0 Manufacturing and Extrative Industries.	RAIS.