



Cooperative Research Networks in Brazil: University Interactions to Regional Innovation Effects

Bernardo França Santos¹;
Carlos Fernando Ferreira Lobo²;
Márcia Siqueira Rapini³;
Igor Santos Tupy⁴;

Resumo: Este artigo realiza uma análise espacial e regional das Redes Cooperativas de Pesquisa (RCPs) e seu impacto nos Sistemas Territoriais de Inovação (STI) no Brasil, levando em consideração seus recortes regionais. Entende-se que o desenvolvimento e a maturação dos STIs dependem da transmissão de conhecimento entre seus agentes, de maneira que as interações entre universidade, indústria e governo, podem ter efeitos econômicos detectáveis sobre a inovação. Utilizando um banco de dados regionalizado para as Regiões Imediatas do Brasil, que inclui dados de grupos de pesquisa acadêmica (proxy para a universidade), parceiros externos (proxy para a economia) e produção tecnológica/inovativa (patentes), foram aplicados métodos de Análise Exploratória de Dados Espaciais. Os resultados dos indicadores de autocorrelação espacial (Índice de Moran e LISA) revelam uma intensa concentração de ativos de CT&I (Ciência, Tecnologia e Inovação), com a formação de clusters de alta atividade em inovação e aprendizado no Sul-Sudeste e de baixa atividade no Norte-Nordeste. Modelos de regressão espacial (SAR-Tobit) confirmam a existência de efeitos de transbordamento entre regiões vizinhas e sugerem a importância dos parceiros interativos (empresas e governo) e dos grupos de pesquisa que possuem cooperações externas como fatores associados à produção de patentes, reforçando a importância das Redes Cooperativas de pesquisa. Conclui-se que os produtos inovadores são marcados por desigualdades regionais enraizadas na evolução histórica da economia brasileira, sendo a dimensão espacial um fator crucial para a compreensão e formulação de políticas industriais e de inovação. Além disso, levando em consideração a discussão teórica sobre a inovação enquanto um processo sistêmico, acumulativo e dependente de instituições formais e informais, entende-se que fatores chave como a transmissão do conhecimento tácito estejam presentes nessas Redes, através de seus vários tipos de proximidade, entre elas a geográfica.

Palavras-chave: Sistemas Territoriais de Inovação; Redes Cooperativas de Pesquisa; Geografia da Inovação; Análise Espacial; Econometria Espacial

Código JEL: O18; R11; C21

¹ Doutorando em Economia pela UFMG/Cedeplar. E-mail: bernardofs@cedeplar.ufmg.br

² Diretor e Professor do Instituto de Geociências IGC/UFMG. E-mail: carlosfflobo@gmail.com

³ Professora titular do departamento de Economia Cedeplar/ UFMG. E-mail: msrapini@cedeplar.ufmg.br

⁴ IPEA. E-mail: igor.tupy@ipea.gov.br

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Abstract: This article conducts a spatial and regional analysis of Cooperative Research Networks (RCPs) and their impact on Territorial Innovation Systems (TIS) in Brazil, considering their regional divisions. It is understood that the development and maturation of ITSs depend on the transmission of knowledge among their agents, such that interactions between universities, industry, and government can have detectable economic effects on innovation. Using a regionalized database for Brazil's Immediate Regions, which includes data from academic research groups (a proxy for university) and external partners (proxy for economy) and technological production (patents), Spatial Exploratory Data Analysis methods was applied. The results of spatial autocorrelation indicators (Moran's I and LISA) reveal an intense concentration of STI (Science, Technology, and Innovation) assets, with the formation of clusters of high activity in innovation and learning in the South-Southeast and low activity in the North-Northeast. Spatial regression models (SAR-Tobit) confirm the existence of spillover effects between neighboring regions and highlight the importance of interactive partners (firms and government) and research groups with external collaborations as factors associated with patent production, reinforcing the importance of Cooperative Research Networks. The conclusion is that innovative products are marked by regional inequalities rooted in the historical evolution of the Brazilian economy, with the spatial dimension being a crucial factor for understanding and formulating industrial and innovation policies. Furthermore, considering the theoretical discussion on innovation as a systemic, cumulative process dependent on formal and informal institutions, it is understood that key factors such as the transmission of tacit knowledge are present in these Networks, through their various types of proximity, including geographical proximity.

Keywords: Territorial Innovation Systems; Cooperative Research Networks; Geography of Innovation; Spatial Analysis; Spatial Regression.

1. Introduction

Brazil's Cooperative Research Networks (CRNs) constitute a form of knowledge transfer between universities and the economy, encompassing the distribution and movement of activities in Science, Technology, and Innovation (STI). They have a fundamental spatial dimension, divided between geographic proximity, which facilitates local interactions, and other types of proximity (non-geographic) that connect distant places (Boschma, 2005).

The literature on innovation has consolidated the view that contemporary economic development, marked by the Information and Knowledge Economy (IKE), is intrinsically linked to a country or region's ability to produce and disseminate innovations. This capacity is the result of a complex institutional arrangement, known as the National Innovation System (NIS) (Lundvall, 1992), in which multiple actors (firms, government, universities) interact systemically. In this context, we present what the literature recognizes as Brazilian university collaborations within innovation systems (Rapini; Chiarini; Stein, 2023). We understand these interactions more broadly than the traditional UIL (University–Industry Links), although this dimension is also included. University collaborations and their role in the Innovation System emerge as a central mechanism, particularly in late-industrializing countries like Brazil, where universities and the public sector often take a proactive role in innovative activities (Suzigan and Albuquerque, 2008).

However, the distribution of these interactions and their outcomes is not homogeneous across space. The Geography of Innovation demonstrates that knowledge, especially in its tacit dimension, has a "spatially sticky" nature, favoring the formation of clusters and shaping regional inequalities (Gertler, 2003). Therefore, the analysis of National Innovation Systems must incorporate the territorial dimension, understanding dynamics at multiple scales, such as Regional Innovation Systems (RIS) (Cooke; Morgan, 1998) or, more broadly, Territorial Innovation Systems (TSI) (Fernandes, 2016).

This article's main objective is to conduct a spatial analysis of the effects of Cooperative Research Networks on innovation in Brazil, focusing on autocorrelation patterns and spillover effects between Immediate Regions (IR). The aim is to answer the question: How are research cooperation activities and STI assets distributed across Brazil? Is there evidence of spatial dependence and knowledge spillovers between regions? What factors associated with CRN explain patent production at the regional level?

To this end, the article is structured as follows: Section 2 presents a brief review of the theoretical framework on the Geography of Innovation and Territorial Innovation Systems. Section 3 details the methodology, database construction, and spatial analysis methods employed. Section 4 presents and discusses the results of the autocorrelation and spatial regression models. Finally, the concluding remarks summarize the findings and their implications for regional development and innovation policies.

2 THEORETICAL FRAMEWORK

2.1 Geography of Innovation and Territorial Systems

The Geography of Innovation is an interdisciplinary field that investigates the spatial dimensions of knowledge production, dissemination, and use, as well as innovation⁵. To understand the complexity of the theoretical framework that has shaped the inclusion of space in innovation-driven economic development models, it is necessary to revisit the authors who underpin Urban Regional Science. The fundamental assumptions of Geography of Innovation are the recognition of agglomeration economies and the importance of tacit knowledge, as well as the dispersion characteristics across the territory (Tunes, 2020; Garcia, 2021; Gertler, 2003).

Agglomeration economies, whether through specialization (Marshall, 1890) or diversification (Jacobs, 1969), create positive externalities that reduce costs and foster economic dynamism within a given urban-industrial region. Tacit knowledge, in turn, is uncodified knowledge acquired through experience and face-to-face interaction (Nelson; Winter, 1982; Storper; Venables, 2004), making

⁵ It is necessary to present the geography of innovation as a field of research embedded within a broader approach: evolutionary economic geography. The latter is governed by a series of assumptions of evolutionary economics that encompass not only the importance of innovation (and novelty), but also the dynamic nature of economic transformation and the importance of path dependence and institutions (Boschma; Martin, 2010).

geographic proximity a crucial factor for its sharing and, consequently, for innovation (Rodríguez-Pose & Crescenzi, 2009). These principles explain why, even in a globalized world, innovative activities tend to be geographically concentrated, forming clusters or Territorial Innovation Systems (TIS). The concept of TIS, proposed by Fernandes (2016) and similar approaches, as territorial innovation models (TIM - Moulaert; Sekia, 2003; Tunes, 2016), advances the concepts of National Innovation Systems (NIS) and Regional Innovation Systems (RIS) by incorporating a political interpretation of the territory. The territory is viewed not as a passive receptacle but as an active participant, a space of intricate relationships, synergies, and disputes among diverse agents.

Analyzing a TIS involves understanding the interaction between the knowledge production sub-network (universities and research centers) and the knowledge exploitation sub-network (firms), mediated by an institutional framework (government, funding agencies, local culture). In Brazil, a country characterized by profound regional inequalities and an NIS classified as "immature" or "underdeveloped" (Albuquerque, 1999; Fernandes et al., 2023), analyzing TISs, especially at the regional scale, is essential to uncovering the barriers and potentials for development. The heterogeneity of the Brazilian territory gives rise to the coexistence of Regional Innovation Systems (RISs) at different stages of maturity, ranging from "learning regions" and "regions of scarcity" to a few mature systems whose dynamics are key to understanding the broader national framework (França-Santos; Barreto, 2025).

2.2. Brazilian Cooperative Research Networks

Networks are a hallmark of the contemporary historical period (Castells, 1999). They emerged from the technological revolution associated with Information and Communication Technologies (ICTs) and the political and economic processes of market expansion and territorial penetration of mercantile logic. Beyond the effects of contemporaneity and globalization (Benko, 1996; Santos, 2000), the evolution of accumulation models (Fordism to Post-Fordism) has reshaped production structures, labor relations, and spatial organization, reinforcing the importance of connectivity and coordination through networks.

A more comprehensive understanding of networks, however, requires going beyond their seasonal or static features to capture their dynamics within geographical space. This dynamic movement, materialized through the interplay of "fixes and flows" (Santos, 1996), reveals networks as both infrastructure and process: anchored in spatial "fixes" such as organizations, facilities, and regions, yet constantly transformed by the "flows" of information, capital, and knowledge that traverse them.

Brazilian Cooperative Research Networks might be understood as a knowledge network (Oslo Manual, OCDE, 2018). **Its cooperation is a form of tacit knowledge transmission relevant to the innovation process.** Therefore, network measures enable the identification of appropriate inputs to the innovation process that are not captured by traditional indicators, such as patents and articles (Rodríguez-Pose, 2013; Glänzel et al., 2019).

Table 1 - University collaborations, 2016, Brazil.

The University in Cooperative Research Networks			
Nature	RCP Aggregations¹		
	S&T Is²	Groups	Links
Private	211 (46,4%)	1770 (14,9%)	3832 (13,6%)
Public	244 (53,6%)	10118 (85,1%)	24349 (86,4%)
Total	455	11888	28181
Public/Private Ratio	1,16	5,72	6,35

¹N, Frequency (%); ² Mainly Higher Education Institutions.
Source: Directory of Research Groups (CNPq, 2016) and MCTI (2023).

Here are the statistical details that describe the University and its various partners, as provided

in the CRN data from the Directory of Research Groups (CNPq, 2016). The data highlight the predominant participation of public universities, especially on the knowledge supply side, whereas the demand side shows substantial heterogeneity across partners and links. Since both the number of groups and partners, as well as the intensity of their connections, are relevant to our analysis, it is notable that the private sector consistently participates within these networks. This aspect will be discussed further below.

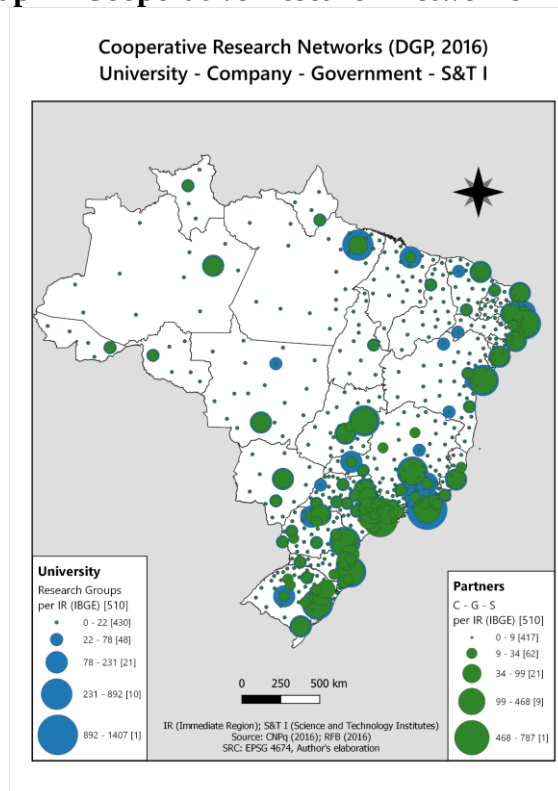
Table 2 - University collaboration partners, 2016, Brazil.

Partners within Cooperative Research Networks			
S&T I ²	Legal Nature	Partners	Links
		1174 (19,9%)	18461 (65,5%)
	Private	611 (52%)	2402 (13%)
	Public	543 (46,3%)	16016 (86,8%)
Public Sector		762 (12,9%)	3607 (12,8%)
	Federal Government	139 (18,2%)	919 (25,5%)
	Federative Entities	390 (51,2%)	1178 (37,2%)
	State-owned and Mixed companies	233 (30,6%)	1510 (41,9%)
Private Sector		3800 (64,6%)	5801 (20,6%)
	Companies	2860 (75,3%)	4222 (72,8%)
	Non-profit Organizations	940 (24,5%)	1579 (27,2%)
Others		150 (2,5%)	312 (1,1%)
Total		5886	28181

¹N, Frequency (%); ² Science and Technology Institutions: disaggregated by department; minor dominance of HEIs; 20 ICTs undefined, hence totals may not sum to 100%.
Source: Directory of Research Groups (CNPq, 2016) and Federal Revenue Service (Brazil, 2016).

The following cartographic representations illustrate these spatial patterns, providing an intuitive view of how cooperative research networks develop and evolve across territory. Some observations regarding these illustrations of the CRN: Map 2 depicts the flows of intermunicipal cooperation (and their regional origins) to understand the patterns of extra-local interaction. As one moves away from the more concentrated regions, particularly around the state of São Paulo, the proportional lines become more translucent and sparser. Furthermore, the density of these lines decreases with distance, as expected (Fernandes et al., 2022; Garcia et al., 2011), raising the question of proximity.

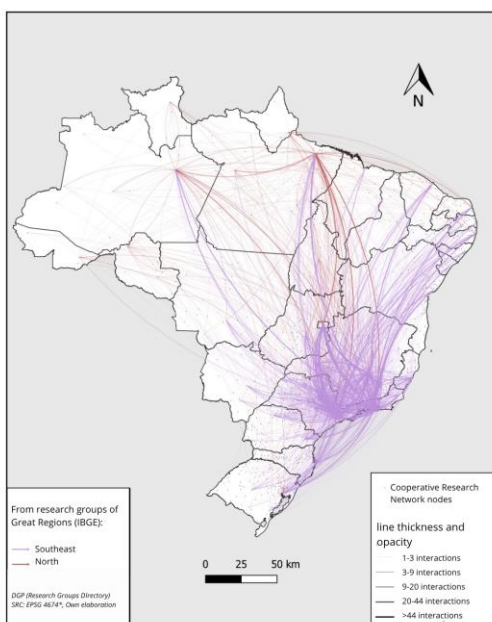
Map 1 - Cooperative Research Networks - fixes



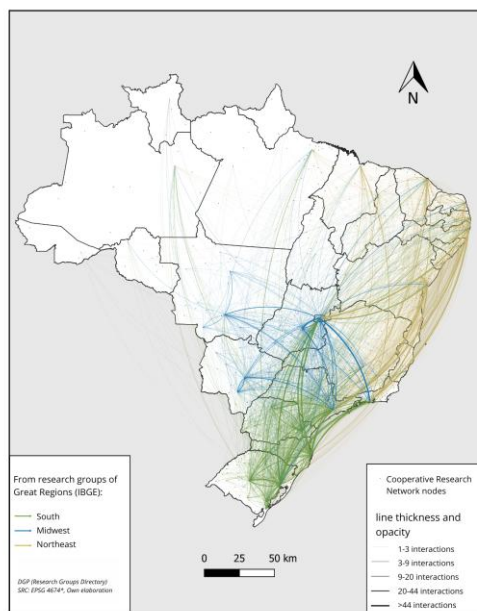
Source: CNPq Research Group Directory (DGP), 2016. Author's elaboration.

Map 2 - Cooperative Research Networks - fluxes

Cooperative Research Networks - Proportional flows
Visualization 1 (Southeast and North) (DGP, 2016)



Cooperative Research Networks - Proportional flows
Visualization 2 (South, Northeast and Midwest) (DGP, 2016)



Source: CNPq Research Group Directory (DGP), 2016. Author's elaboration.

Table 3 – CRN and territory boundaries**Geographical proximity of interactions**

By spatial unit (n = 28,181 interactions)								
Municipality	n	%	Ratio (x/x')	State	n	%	Ratio (x/x')	
a. Same	7643	27,1%	0,37	a. Same	15525	55,1%	1,23	
b. Different	20538	72,9%	2,69	b. Different	12656	44,9%	0,82	
Immediate Region (IBGE)	n	%	Ratio (x/x')	Major Region (IBGE)	n	%	Ratio (x/x')	
a. Same	10345	36,7%	0,58	a. Same	19677	69,8%	2,31	
b. Different	17836	63,3%	1,72	b. Different	8504	30,2%	0,43	

Source: Research Groups Directory (CNPq, 2016). Author's elaboration.

As observed in Table 3, cooperation becomes increasingly restricted as it moves from the local scale to the national scale defined by administrative and regional boundaries. This clearly illustrates how a lack of geographical proximity can be a barrier to interactions, the literature highlights that various other forms of proximity exist and are important for establishing the links of learning, co-work, generation, and dissemination of knowledge that are so crucial to innovation systems.

Regarding the limits of local knowledge spillovers, Knobens and Oerlemans (2006), Torre (2008), and Boschma (2005) emphasize that innovation dynamics are shaped by multiple dimensions of proximity beyond mere geographical (or euclidean) closeness (Garcia, 2021). These dimensions are organizational, social, institutional, and cognitive. They are fundamental for the "sharing of knowledge and fostering of interactive learning processes" (Garcia, 2021, p. 282). Although geographical proximity favors innovation, technology generation, and the development of communities, universities, and companies, it may, by itself, be insufficient to ensure the effective transmission of information and knowledge among those involved.

For cooperation to occur, it is necessary to develop not only one of these proximities between the agents involved; this has been systematically observed in studies on university-industry interaction in Brazil (Garcia et al., 2011; Callari; Rapini, 2017; Rapini et al., 2024). It is crucial for this work to recognise that Cooperative Research Networks necessarily encompass these other proximities, not only in long-distance flows, but also in short-distance ones.

Table 3 shows that 63.3% of interactions occur between different Immediate Regions (IRs). However, it is well established that most interactions take place within relatively short geographical distances (Callari; Rapini, 2017), which tend not to exceed the boundaries of Brazil's Major Regions (IBGE); interactions across these broader regions account for only 30.2%. This evidence implies that: **(i)** the Immediate Region approach is particularly suitable for capturing the strictly local sphere of interactions characterized by close geographical proximity; **(ii)** most interactions occur over short- to medium-range distances, which are still sufficiently large to limit a full cartographic representation of Cooperative Research Networks (CRNs), as illustrated in Map 2; **(iii)** knowledge networks operate through multiple dimensions of proximity, meaning that their geographical configuration is neither straightforward nor easily mapped, especially in a large and heterogeneous territory such as Brazil; and **(iv)** as suggested by the Oslo Manual (OECD, 2018), these networks may have strong effects on innovation outcomes, although they remain insufficiently understood within economic geography, particularly from a regional perspective.

3. METHODOLOGY

This study employs a multi-stage methodology based on Exploratory Spatial Data Analysis (ESDA), which comprises “a set of complementary techniques to describe and visualize spatial distributions, flag spatial outliers, detect spatial dependence, and suggest its regimes or other forms of instability” (Lopes et al., 2022, p.3; Almeida 2012; Anselin 2005). In addition, social network analysis and spatial econometric methods are applied to investigate potential relationships between variables and the regional dynamics of innovation in Brazil.

3.1. Data and Unit of Analysis

A unique database was constructed for the 510 Immediate Regions (IRs) of Brazil, the official 2017 small-scale regional division from the Brazilian Institute of Geography and Statistics (IBGE). The IR was chosen as the spatial unit because it represents functional economic territories, capturing daily commuting flows and socioeconomic cohesion more effectively than purely administrative boundaries such as municipalities. The database integrates information from multiple sources for the period around 2016.

The primary data source is the 2016 census of the Directory of Research Groups (DGP) from the National Council for Scientific and Technological Development (CNPq). This comprehensive survey captures self-reported collaborations between university-based research groups and external organizations. We extracted variables for the number of Research Groups engaged in partnership and their partners.

Table 3 – Display of the set key-variables

- Research Groups – Groups that reported information about partners in the Directory of Research Groups (2016 census); (“grpspct”). - Partners – Organizations linked to a CNPJ (National Registry of Legal Entities) reported by the research group leader in the DGP questionnaire (2016). Partner information is cross-referenced with the CNPJ database (RFB, 2016); (“ptrrspct”). - <i>Firms</i> – Partners classified as firms or companies from both public, mixed and private sectors; (“firmsspct”). - Publications – Sum of all bibliographic outputs (international, national, book chapters, and books) reported by the research leader in the DGP (2016); (“pub_pct”). - <i>International Publications</i> – As reported by the DGP; (“int. publication”). - Patents – Includes invention patents (PI), utility models (MU), and certificates of addition (C) filed at INPI from 01/01/2016 to 12/31/2018. Source: BADEPI_v9.0_Patentes (INPI, 2022). (“patentspct”). - Origin Degree – Number of outward (university side) collaboration links from each IR to partners in other IRs; (“gra_rgm”). - Eigenvector – Centrality score weighting links to well-connected IRs more heavily; (“egnvctr”).
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Source: Author’s elaboration.

To avoid spurious correlations arising from the colocalization of related economic and innovative factors, a set of control variables was selected and described above, considering the most common determinants of innovation identified in the literature (e.g., Jaffe, 1989; Audretsch & Feldman, 1996; Araujo & Garcia, 2019).

We work with per-capita indicators to normalize for city/region size and mitigate scale effects and heteroskedasticity. This is standard in regional innovation studies because inventive output and S&T inputs scale with population and employment; per-capita (or intensity) measures make cross-region comparisons more meaningful and reduce spurious correlation with size. (Crescenzi & Rodríguez-Pose 2011; Garcia et al., 2011)

Table 4 – Display of the control variables

Dimension	Variable / Proxy	Description (shortened)
Socioeconomic (IBGE)	Metropolitan Area (rm)	Dummy indicating legally defined Metropolitan Area (IBGE, 2016).
	Industrial VA (va_ind)	Sectoral value added (% of local GDP).
	GDP per capita (pib_pc), Population (pop)	Measures income level and population size.
Labor and Employment (RAIS, 2016)	Technological Occupations (potec_p)	Share of workers in technology-intensive occupations.
	Skilled Labor (mdo_educ_sup_perc)	Workers with higher education (%).
	Krugman Index (KI)	Regional specialization/diversification index.
Higher Education (INEP, 2016)	HEIs and Federal Universities (IES, iespc, federal)	Number of higher education institutions (total, per capita, and a dummy for federal presence).
	STEM Graduates (STEM, stem_pg)	Graduates in Science, Technology, Engineering, and Math (% of total graduates).

Source: Author's elaboration.

3.2. Exploratory Spatial Data Analysis - from network metrics to econometric models

Following ESDA default techniques (Anselin, 2005; Almeida, 2012), Global Moran's I was calculated for each key variable to assess the overall degree of spatial clustering across the entire country. Subsequently, Local Indicators of Spatial Association (LISA) were computed to identify the specific locations of significant spatial clusters, mapping regions as High-High, Low-Low, or spatial outliers (High-Low, Low-High).

Dyadic collaboration data was modeled as a directed inter-regional network in which the 510 Immediate Regions (IRs) serve as nodes, and each collaboration from an origin IR to a destination IR is represented by a directed edge. From this graph, standard centrality metrics were computed, following the classic literature of network metrics (Bonacich, 1987; Bonacich & Lloyd, 2001), to capture each IR's structural position in national knowledge flows. All metrics were empirically tested in econometric and spatial econometric specifications, and two were retained based on model fit: eigenvector centrality score and origin degree.

In directed networks, degree centrality counts the number of ties, focusing on out-degree in this case, which is the number of collaborations an IR initiates, thereby within the University's knowledge supply-side. This is a simple yet informative measure of a region's outward reach in the collaboration system. Eigenvector centrality weights connections by the importance of one's partners, assigning higher scores to IRs that collaborate with already well-connected IRs; it proxies embeddedness in the "core" of the network. These measures are widely used in regional innovation studies to characterize the position of places within collaboration networks (e.g., Balland et al., 2019; Calignano et al., 2021). Thus, the calculated network centrality metrics were included as key explanatory variables to assess their influence on regional innovation.

To model the determinants of patenting activity, we employed a standard SAR (Spatial Autoregressive Model) and a Spatial Tobit Model. This approach was chosen for two main reasons: (i) the dependent variable (patents) is censored at zero for a large number of regions, which would bias standard methods (Autant-Bernard and LeSage, 2011; Araujo & Garcia, 2019), and (ii) ESDA results confirmed the presence of strong spatial dependence. The model incorporates a spatial lag of the

dependent variable to explicitly account for spillover effects from neighboring regions.

Thereby, the final model specification is:

$$y = \rho W y + X\beta + \varepsilon, \varepsilon \sim N(0, \sigma^2 I)$$

for the SAR (Spatial Autoregressive model), and

$$y^* = \rho W y^* + X\beta + \varepsilon, y_i = \max(c_L, \min(y_i^*, c_U)),$$

for the Spatial Tobit (Censored SAR) — Latent-variable formulation. This model set lower/upper censoring limits; here we use left-censoring at $c_L = 0$ for patents per capita.

- y : $n \times 1$ vector of the dependent variable (patents per capita).
- W : $n \times n$ row-standardized spatial-weights matrix (distance- or KNN-based).
- X : $n \times k$ matrix stacking key variables and controls; β : $k \times 1$ coefficient vector.
- ρ (rho): spatial autoregressive parameter; σ^2 : variance of ε ; I : identity matrix.
- ε : disturbance term; in the Spatial Tobit, the latent outcome y^* is censored to produce observed

y .

Two neighborhood specifications were used: a K-nearest neighbors (KNN, where $K = 8$) matrix and a distance-based matrix. Both are standard in applied spatial econometrics and regional innovation studies (LeSage & Pace, 2009; 2014). They were selected on theoretical and practical grounds to ensure robustness to the heterogeneity in size and shape of Brazil's Immediate Regions. Distance captures the decay of interaction with space, while KNN ensures a bounded, comparable number of neighbors across regions. In addition, we assessed model fit (LM/Lagrange Multiplier diagnostics for OLS; AIC and residual autocorrelation for SAR; and predictive performance/significance for spatial Tobit) and therefore report both matrices side by side, highlighting the specification that yields the best empirical performance.⁶

4. RESULTS AND DISCUSSION

4.1 - Spatial autocorrelation

Our first results confirm what a large body of prior research has emphasized about Brazil: innovation activities are spatially concentrated and regionally uneven [Diniz; Gonçalves, 2005; Gonçalves et al., 2011]. Given Brazil's historical settlement patterns, the strong coastal and metropolitan concentration of population and industry, and the territorial-administrative configuration of its geographic units, contiguity-based spatial weight matrices tend to yield moderate, yet statistically meaningful, values of Moran's Index. In this context, $I \approx 0.30$ – 0.40 already indicates strong clustering for socio-economic outcomes at the regional scale; values above ≈ 0.40 can be considered high.

A key pattern is the increase in spatial dependence as we move from university-side variables (research groups, publications) to society/industry-side variables (partners, firms, patents). This suggests that S&T assets hosted by public institutions, more directly shaped by policy and infrastructure (universities, research institutes), are spatially broader, whereas cooperative research networks and market-oriented outcomes (firm participation, co-operation ties, patenting) are more concentrated in fewer metropolitan areas and depend more strongly on localized externalities (dense supplier-client bases, specialized labor, and knowledge spillovers).

⁶ Two methodological decisions warrant clarification (Elhorst, 2014): 1) Spatial lag of covariates models (SLX/SDM) are not emphasized in the working paper, as the focus of the analysis is on endogenous spatial interaction within Immediate Regions and knowledge spillovers from innovation outcomes themselves, rather than from their assumed explanatory drivers. Moreover, exploratory estimations including WX terms did not materially improve inference; 2) SEM (Spatial Error) Tobit models are not estimated due to software limitations (Rstudio 4.3.3 packages), thus model selection relies on theoretical considerations and diagnostic evidence. Furthermore, robust LM tests in OLS favored SAR over SEM formulations, supporting the interpretation of spatial dependence as substantive rather than residual, which is also followed for the censored-based model (SAR-Tobit).

Table 4 – I Moran of CRN and STI regional dataset (*per capita*)

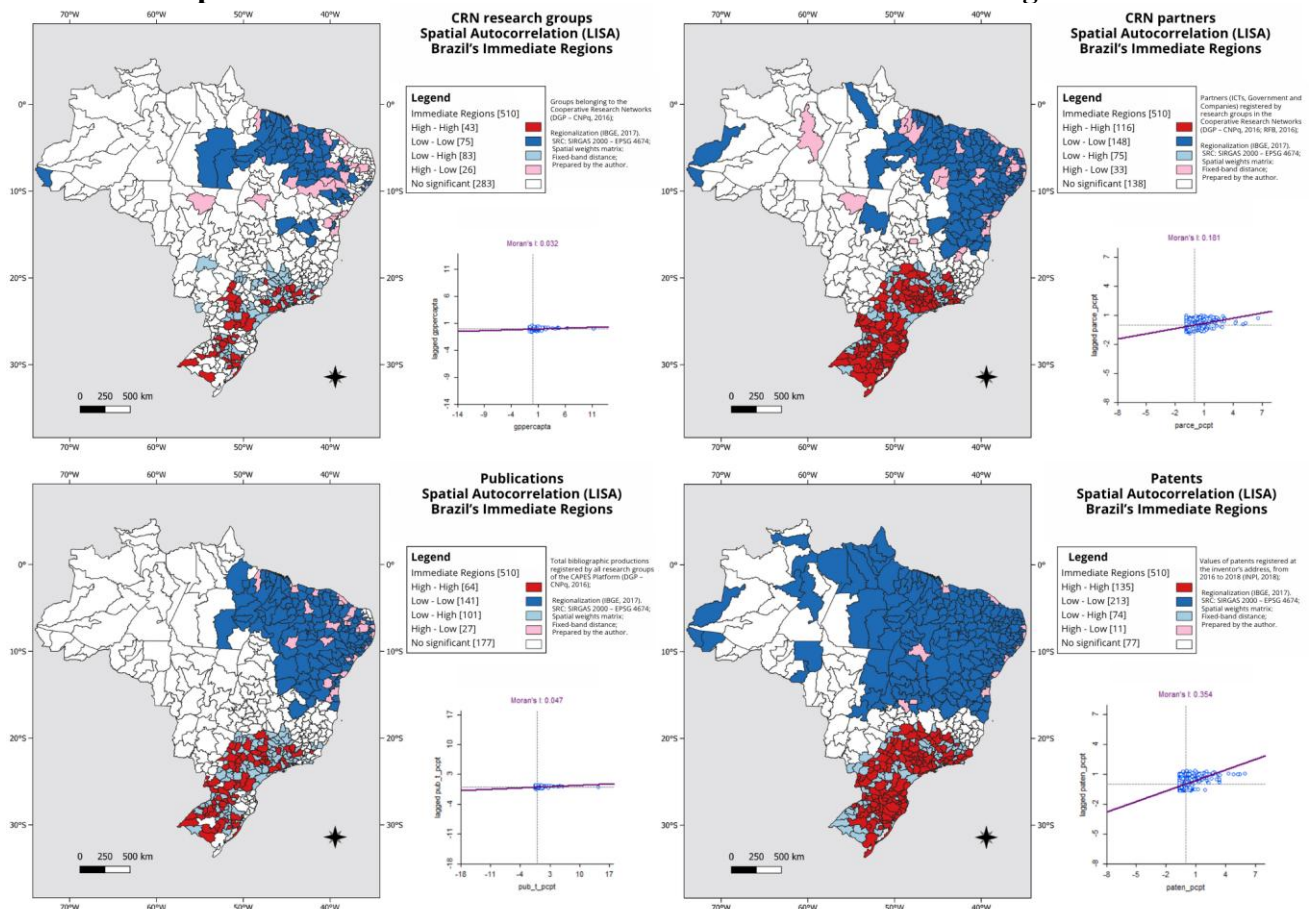
Variáveis (<i>per capita</i>)	Spatial Autocorrelation – CRN and STI in Brazil ¹	
	I Moran (KNN ²)	I Moran (dist_inv)
Groups	0,054(**)	0,03(**)
Publication	0,056(**)	0,046(***)
Int. Publication	0,045(**)	0,03(**)
Partners	0,255(***)	0,182(***)
Firms	0,275(***)	0,185(***)
Patents	0,434(***)	0,353(***)

¹ Immediate Regions (IBGE); ² KNN matrix = 8; testes de significância *p*-value <0,1 (*); <0,5 (**); <0,01(***)

Author's calculations based on the study dataset

To visualize the regional distribution of CRN and STI assets considered in this paper, we follow standard ESDA procedures and present LISA (Local Indicators of Spatial Association) maps. As mentioned, the LISA results also show that overall agglomeration intensifies as we move from public research infrastructure (research groups, publications; comparatively less clustered) to firm-side knowledge absorption and innovation outputs (partners, firms, patents; more spatially dependent and concentrated). LISA maps pinpoint these clusters in space, revealing a pattern that is strongly regionalized in Brazil, especially along the university-to-industry gradient.

Map 3 – LISA's of CRN and STI of 510 brazilian Immediate Regions



Source: Author's elaboration based on the study dataset

In the econometric models, it is important to primarily examine the spatial dependence among patents, as this will provide a spatial basis for the independent variable “patents” (ρ_{WY}). Thus, “patents” shows the highest value, indicating that the spatial models specified in the methodology should be useful for understanding their geographical distribution. Additionally, Moran’s I was computed on the randomized quantile residuals in the next section, econometric model selection (a non-spatial Tobit model), indicating the presence of residual spatial dependence (Moran’s I ≈ 0.11). Although this value is substantially lower than that observed for the patent variable itself, it remains statistically significant, suggesting the need for spatial econometric models.

Consistent with long-standing findings for Brazil, assets associated with the National Innovation System (NIS) tend to be denser and more spatially clustered in the South–Southeast regions. In these areas, the predominance of High–High clusters shapes what Gonçalves (2007) termed a “technological corridor”, which, in the present context, can be understood as a learning and innovation corridor. This pattern reflects the geographical contiguity of multiple Regional Innovation Systems and/or Learning Regions that have reached a certain degree of maturity (Cooke, Uranga & Etzebarria, 1997; Cooke & Morgan, 1998; Rolim, 2005).

In parallel, the presence of some Low–High clusters alongside these corridors suggests not only intra-regional heterogeneity but also a relatively standard urban hierarchy. Such a structure helps explain why more complex innovation-related infrastructures are not present in all Immediate Regions, despite their geographical proximity to highly innovative cores. This interpretation is consistent with central place theory (Christaller, 1933) and with more recent contributions on Brazilian urban hierarchy and innovation systems (Diniz et al., 2006; Gonçalves, 2007). This pattern is particularly evident for variables associated with universities and science and technology institutions (research groups and scientific publications) and is less pronounced for industry-related variables, including firms and patents.

In the broader North–Northeast regions, the spatial pattern is characterized predominantly by Low–Low clusters, underscoring the relevance of scarcity in terms of learning and innovation assets. These patterns are directly connected to Brazil’s historical development trajectory and territorial formation (Cano, 1998; Furtado, 2007; Fernandes, 2016). At the same time, a few isolated “islands” of learning and innovation emerge, indicating localized and somewhat disconnected instances of Regional Innovation Systems or Learning Regions that diverge from the prevailing macro-regional pattern. This suggests that these Immediate Regions do not benefit substantially from geographical spillovers arising from neighboring areas, pointing instead to the role of alternative drivers, such as institutionally driven historical trajectories and targeted government interventions. Notably, stronger performance is observed in state capitals and in selected inland regions that benefited from higher-education expansion policies, including REUNI, PROUNI and FIES (Santos; Amaral, 2023)

Overall, the spatial patterns identified in this analysis regarding the geographical distribution of innovation assets, inputs and outputs are fully aligned with the established empirical literature on Brazilian regional innovation dynamics (e.g., Diniz; Gonçalves, 2005; Gonçalves, 2007; Gonçalves & Fajardo, 2011; Garcia et al., 2011).

4.2 - Spatial econometric models - the effects of CRN on regional innovation

The first model selection is intentionally broad with respect to the cooperative research network (CRN). The key regressor partners aggregate at least three partner types, spanning distinct organizational profiles (including other research centers, public organizations, and private firms), capturing heterogeneous collaboration channels. We also include publications per capita to represent a more formal and codified knowledge flow from universities into the economy. Completing the key block, the two network metrics (as defined in the methodology) capture whether network position affects innovation outcomes across Immediate Regions.

Table 5 – Econometric (spatial) models of selection 1

Selection 1 = publication + partners + networks (n = 510)					
Dependent = patents per capita					
Variables	OLS	Matrix 1 (KNN = 8)		Matrix 2 (inverse distance)	
		SAR	Spatial Tobit*	SAR	Spatial Tobit*
Intercept	-43.430 (12.180)***	-30.239 (11.197)**	-58.68 (13.76)***	-28.197 (11.198)**	-57.32 (14.43)***
Key variables					
pub_pct	0.0008 (0.0009)	0.0009 (0.0008)	0.0015(0.001).	0.0009 (0.0008)	0.0016(0.001).
ptnrspct	1.376 (0.197)***	1.096 (0.180)***	1.221 (0.222)***	1.032 (0.18)***	1.16 (0.232)***
gra_rgm	25.290 (14.030).	20.908 (12.715).	-5.739 (15.880)	22.735 (12.713).	-5.116 (16.060)
egnvctr	-9.710 (6.443)	-9.885 (5.840).	-8.534 (7.105)	-10.785 (5.891).	-9.893 (6.987)
Controls					
potec_pc	0.410 (0.636)	0.651 (0.577)	-0.016 (0.734)	0.839 (0.576)	0.311 (0.760)
mdc_pct	-0.037 (0.093)	-0.023 (0.085)	-0.120 (0.113)	-0.027 (0.085)	-0.135 (0.112)
federal	-1.672 (1.142)	0.281 (1.050)	1.025 (1.289)	0.316 (1.051)	1.178 (1.302)
rm	1.885 (0.606)**	0.972 (0.555).	1.448 (0.706)*	1.060 (0.554).	1.543 (0.704)*
KI	-0.589 (1.751)	0.948 (1.589)	-5.397 (2.137)*	1.154 (1.594)	-4.861 (2.166)**
log(pop)	0.469 (0.519)	0.971 (0.471)**	2.051 (0.598)***	1.003 (0.471)**	2.128 (0.606)***
log(gdp_pc)	4.072 (0.822)***	1.792 (0.783)**	3.798 (0.973)***	1.482 (0.789).	3.508 (1.030)***
va_ind	-0.009 (0.036)	-0.016 (0.032)	-0.016 (0.041)	-0.010 (0.032)	-0.016 (0.043)
Tests & parameters					
ρ (rho)	—	0.462 (0.051)***	0.401 (0.051)***	0.523(0.058)***	0.448 (0.057)***
σ (sigma) / sige	—	σ=5.17	sige=38.87	σ=5.17	sige=38.92
R ² / AIC	Adj R ² =0.518	AIC=3167.2	—	AIC=3167.1	—
LR (rho)	RSlag = 20.28***	LR = 73.12***	—	LR=73.18***	—

Note: β (standard errors in parentheses); p-value (t-test) < 0.10 (.), < 0.05 (.), < 0.01 (.), < 0.001 (.). *137/510 left censored values. Source: Author's calculations based on the study dataset.

The results indicate: 1) Spatial effects. Both spatial-weighting specifications yield positive and significant spatial autoregressive parameters (ρ), reinforcing the choice of spatial models. The Lagrange Multiplier (LM) diagnostics applied to the OLS residuals indicate robust significance for the lag alternative and comparatively weaker support for the error alternative, which is the standard indication to prefer SAR over SEM. 2) Comparison across matrices: differences between the two spatial weight matrices are small in magnitude. Matrix 2 yields slightly higher estimates of spatial dependence (ρ), whereas Matrix 1 yields marginally lower residual dispersion (measured by σ in the SAR models and by sige, the variance of the latent error term, in the spatial Tobit specifications). Although these differences are insufficient to claim overall superiority of one matrix in terms of model fit, the results suggest that Matrix 2 more effectively captures spatial spillover dynamics under the corresponding specifications. Importantly, coefficient signs and substantive conclusions remain stable across matrices; therefore, results are reported side by side

3) Key effects. The variable “partners” is consistently positive and statistically significant across OLS, SAR, and Spatial Tobit. Consistent with the literature that favors limited-dependent spatial models when censoring is present (e.g., LeSage & Pace, 2009; Araújo & Garcia, 2019), we place greater weight on the Spatial Tobit coefficients. Within this framework, beyond partners, publications per capita show at most a small positive effect on regional patenting, while other covariates in the key block are not robustly significant.

Selection 2 targets the economic side of CRN interactions through the key regressor firms per capita. These variable proxies the productive base and absorptive capacity of each region, its ability to recognize, assimilate, and exploit external knowledge, which is central to how innovation systems

operate. In parallel, research groups per capita captures a core engine of regional learning: the diffusion of tacit knowledge, repeatedly emphasized in the evolutionary economics literature as a primary cognitive input to innovation (Nelson & Winter, 1982; Foray, 2004). Regional and urban innovation studies argue that these localized learning processes justify spatial approaches to innovation outcomes (Storper & Venables, 2004; Rodríguez-Pose & Crescenzi, 2009). Community-centered organizations, such as research groups, are especially informative because they embody multiple forms of proximity, including cognitive, organizational, social, institutional, and geographical, which facilitate the transmission of tacit knowledge (Storper, 2005; Boschma, 2005; Garcia, 2021).

Table 6 – Econometric (spatial) models of selection 2

Dependent = patents per capita		Selection 2 = groups + firms + networks (n = 510)			
Variables	OLS	Matrix 1 (KNN = 8)		Matrix 2 (inverse distance)	
		SAR	Spatial Tobit*	SAR	Spatial Tobit*
Intercept	-44.428 (12.232)***	-33.241 (11.333)**	-62.860 (14.923)***	-30.07 (11.282)**	-60.745 (14.29)***
Key variables					
grpspct	0.0360 (0.0804)	0.1000 (0.0734)	0.1813 (0.0922)*	0.0762 (0.0730)	0.1586 (0.0891)*
firmspct	2.10 (0.289)***	1.495 (0.268)***	1.533 (0.330)***	1.499 (0.267)***	1.532 (0.3222)***
gra_rgm	27.055 (14.54).	20.208 (13.265)	-7.534 (17.077)	22.452 (13.203).	-5.9961 (16.684)
egnvctr	-10.250 (6.488)	-10.017 (5.918).	-8.353 (7.160)	-10.933 (5.893).	-10.2775 (7.420)
Controls					
potec_pc	0.338 (0.635)	0.638 (0.580)	0.085 (0.738)	0.800 (0.577)	0.311 (0.743)
mdc_pct	-0.021 (0.093)	-0.016 (0.085)	-0.129 (0.114)	-0.017 (0.085)	-0.129 (0.118)
federal	-0.470 (1.171)	0.962 (1.079)	1.551 (1.381)	1.063 (1.074)	1.8106 (1.313)
rm	2.023 (0.60)***	1.148 (0.555)*	1.651 (0.683)*	1.188 (0.552)*	1.642 (0.701)*
KI	-0.877 (1.754)	0.778 (1.602)	-5.462 (2.172)*	0.984 (1.600)	-4.665 (2.223)**
log(pop)	0.294 (0.525)	0.897 (0.479).	2.008 (0.650)***	0.917 (0.478).	2.128 (0.618)***
log(gdp_pc)	4.486 (0.81)***	2.272 (0.782)***	4.371 (1.026)***	1.851 (0.785)**	3.915 (0.997)***
va_ind	-0.0363 (0.036)	-0.0373 (0.0326)	-0.0437 (0.0416)	-0.0307 (0.032)	-0.0402 (0.043)
Tests & parameters					
ρ (rho)	—	0.453 (0.051)***	0.400 (0.053)***	0.520 (0.058)***	0.460 (0.056)***
σ (sigma) / sige	—	$\sigma=5.215$	sige=39.81	$\sigma=5.191$	sige=39.37
R ² / AIC	Adj R ² =0.507	AIC=3175.2	—	AIC=3171.0	—
LR (rho)	RS=20.28***	LR=67.14***	—	LR=71.32***	—

Note: β (standard errors in parentheses); p-value (t-test) < 0.10 (.), < 0.05 (), < 0.01 (), < 0.001 ().

*137/510 left censored values. Source: Author's calculations based on the study dataset.

The overall model fit and spatial diagnostics do not substantially differ from Selection 1, thus, our conclusions about the preferred specification, the choice of spatial weights, and the behavior of the control block remain the same. The main difference lies in the magnitude and significance of the CRN proxies variables: research groups per capita (replacing publications) and firms per capita (replacing general partners).

First, substituting groups for publications strengthens the evidence that the supply side of knowledge (research groups) matters, both in terms of and extent to which networked (more tacit) knowledge influences regional innovation outcomes. Second, substituting firms for partners indicates that the productive sector's (profit-based) absorptive capacity is even more decisive for enhancing innovation. In short, Selection 2 sharpens the university-to-economy channel: group density amplifies the availability and circulation of knowledge, while firm density captures the local ability to internalize and exploit it.

At the same time, it is noteworthy that goodness-of-fit statistics and diagnostic measures perform slightly better under Selection 1, as indicated by lower AIC values, smaller standard errors (σ and sige),

and higher adjusted R^2 . This difference can be attributed to the underlying sampling distribution⁷ of the key variables across specifications. Publications and partners per capita are intrinsically more pervasive across Immediate Regions than research groups and firms per capita. By contrast, the more concentrated distribution of groups and firms leads to higher variability and, consequently, larger standard errors, reducing overall model efficiency. Thus, the same feature that yields stronger and more significant coefficients for the key variables in Selection 2 also limits the model's overall explanatory power (Wooldridge, 2010; LeSage & Pace, 2009).

Another important point concerns the behavior of the network metrics across both selections and nearly all models. It is unlikely that these metrics capture a real effect of CRNs on regional patenting. The origin degree appears with a positive sign but only a low significance level ($p < 0.10$) in OLS and SAR; in the Spatial Tobit (recommended approach given censoring) it is not significant, so we do not reject the null hypothesis. A similar pattern holds for eigenvector centrality, which, in some cases, even shows an unexpected inverse association; this is unlikely to be meaningful.

These were the only metrics that showed any significance in the tests. Our hypothesis is that the actual effects of CRNs are less about interregional flows per se and more about the presence of TIS agents and institutions in the regions (absorptive capacity, long-term interactions, and organizational presence). This likely occurs, first, because although networks matter, they are not as dense or pervasive as the typical networks analysed with such methods, especially given Brazil's wide and continental territory.

Second, because agglomeration economies associated with the co-location of key CRN agents (fixed and concentrated in some regions) are highly relevant, which generate some multicollinearity that affects the performance of the network regressors; and third, because non-existence of geographical proximity appears to constrain innovation effects of other forms of proximity that networks capture. This means that drivers of distant interregional interaction (organizational, institutional, social, or cognitive proximities) may be insufficient to transmit the tacit knowledge underlying patents.

Concluding Remarks

The results show that Brazil's Cooperative Research Networks (CRNs) play an uneven yet important role by enhancing regional innovation systems. Innovation assets and processes are spatially concentrated in the South–Southeast, while large areas in the North–Northeast remain peripheral, revealing persistent territorial inequalities. University collaborations towards industry foster spillovers but remain highly dependent on pre-existing regional structures. This occurs because innovation is widely acknowledged to be driven by cumulative learning processes and historical path dependency, an understanding rooted in the evolutionary economics tradition (Dosi; Freeman; Fabiani, 1994), to which regional scholars largely subscribe (Boschma, 2005; Martin & Sunley, 2006; Rodriguez-Pose & Crescenzi, 2009).

It is increasingly acknowledged that many processes of technological and economic change involve path-dependence and dynamic increasing returns. This has to do with knowledge indivisibilities; the incremental and 'cumulative' nature of learning; standardization requirements; network externalities; interactions that are spatially 'local'; and other sources of positive feedbacks 93 (Dosi; Freeman; Fabiani, 1994, p. 26).

That said, and understanding innovation as a systemic and social process (Arocena & Sutz, 2003; Lundvall, 2005), albeit with important geographical dimensions (Tunes, 2020), two major mechanisms fostering Regional Innovation Systems (at the Immediate Region scale) were identified: first, regarding evolutionary institutions and the social and physical technologies associated with them⁸ (Nelson, 2008; Lemos & Cario, 2015), University–Industry Links (UIL) are interpreted as a proxy for informal, tacit,

⁷ Sample distributions of the key variables, along with matrix correlation and pairwise scatterplots are reported in the Appendix at the end of the paper.

⁸ Following Nelson (2008), technologies (social and physical) are understood as sets of institutions, routines, organizational arrangements, and social practices that co-evolve with economic and technological change. In this sense, “social technologies” refer to the institutionalized patterns of interaction that structure agents' behavior within innovation systems.

and immaterial social technologies, expressed through agents' interactions within innovation systems. Although such institutions are difficult to capture and measure (Rodriguez-Pose, 2013), they are crucial for understanding the development of Regional Innovation Systems (RIS). Using the research group database (CNPq, 2016), this study identified an institutional effect suggesting the need to jointly develop intangible aspects alongside the physical infrastructure of an RIS, based on its existing endpoints: universities, firms, and government are all necessary in this process.

Second, evidence, such as spatial autoregressive parameters (ρ -rho), which are consistently significant across models, suggests that geographically bounded technological spillovers are always present, manifesting as neighboring regions' patenting activity. The lack of significance of network parameters does not invalidate the role of other forms of proximity discussed by Boschma (2005). However, it indicates that geographic proximity may be even more restrictive within a National Innovation System such as Brazil's, characterized by learning shortages and regionally concentrated deficiencies, given the continental scale of its territory.

Thus, the evidence suggests that local absorptive capacity (Schiller; Lee, 2015), particularly as represented by research groups and firms, is more important for innovation outcomes than network centrality itself. Geographic and institutional proximity thus remain crucial drivers of learning and knowledge diffusion, underscoring the need for policies that strengthen endogenous capabilities and reduce regional asymmetries within Brazil's innovation system.

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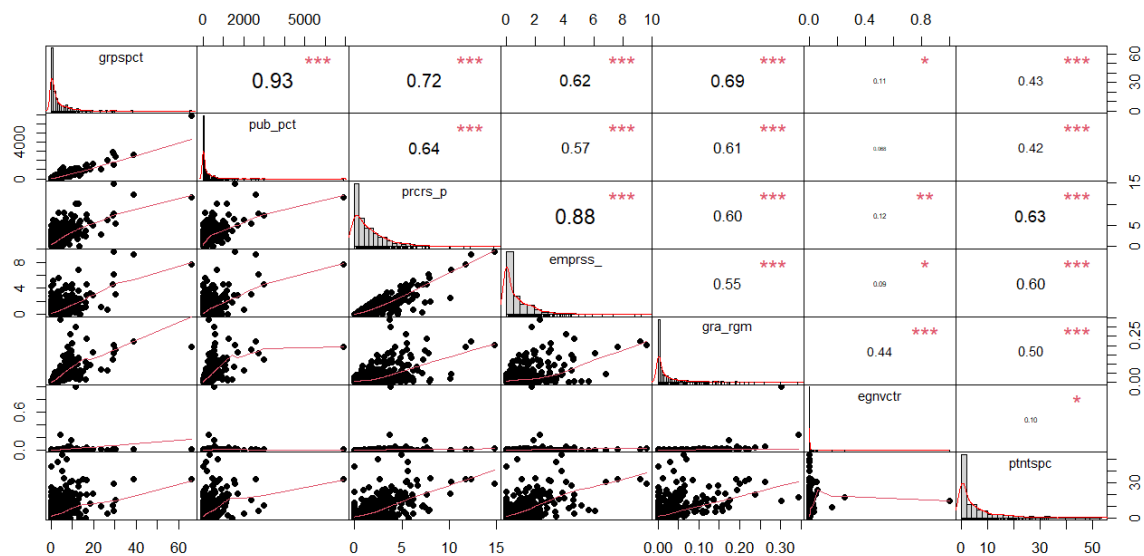
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Appendix

Image 1 - Correlation matrix, distributions and pairwise scatterplots of key variables



Note: “firmspct” as “emprss_” and “prtnrspct” as “prcrs_p”
Source: Author’s calculations based on the study dataset.