Regional technological capabilities and co-invention networks in the technological diversification process: evidence from Brazil

Mariane Santos Françoso *[1]
(corresponding author marianef@unicamp.br)
Vanessa de Lima Avanci *
Alysson Fernandes Mazoni *

*InSySPo, Department of Science and Technology Policy, Institute of Geosciences, UNICAMP

Abstract

This paper contributes to the literature on regional diversification investigating how the regional endowment of technological capabilities and co-invention networks contribute to the emergence of new technological specializations in regions. The empirical analysis employs patenting data from Brazil and quantitative analysis on the microregional level. Our results indicate that having internal capabilities that can be applied to new cognitive close technologies, cohesive internal co-inventor collaborations, and a control position in interregional networks contribute to technological diversification. Moreover, our results suggest that less developed regions benefit from interregional collaboration in general, even if it does not involve controlling positions.

Keywords: technological diversification, technological capabilities, co-invention networks, relatedness.

Resumo

Este artigo contribui para a literatura sobre diversificação regional investigando como a dotação regional de capacitações tecnológicas e as estruturas de redes de co-invenção contribuem para o surgimento de novas especializações tecnológicas nas regiões. A análise empírica utiliza dados de patenteamento no Brasil e análise quantitativa em nível microrregional. Nossos resultados indicam que ter capacitações internas que podem ser aplicadas a novas tecnologias cognitivamente próximas, redes internas coesas de colaboração e uma posição de controle em redes inter-regionais contribuem para a diversificação tecnológica regional. Além disso, nossos resultados sugerem que as regiões menos desenvolvidas se beneficiam da colaboração inter-regional em geral, mesmo que esta não envolva posições de controle.

Palavras-chave: diversificação tecnológica, capacitações tecnológicas, redes de co-invenção, *relatedness*.

JEL: O30, R11

Área ANPEC: Área 9 - Economia Industrial e da Tecnologia

[1] The authors acknowledge support by The São Paulo Research Foundation (FAPESP) in connection to the São Paulo Excellence Chair "Innovation Systems, Strategy and Policy" (InSySPo) at the University of Campinas (grant number 2020/12676-2).

1. Introduction

This paper investigates the role of the regional endowment of technological capabilities and co-invention network structures in the emergence of new technological specializations in regions. We consider a region specialized in a technology when its share of patents in a given technology is higher than the share in Brazil. The development of new technologies in regions has been discussed in the literature as a path-dependent process in which new technologies requiring similar technological capabilities as those already present in the region are more likely to be developed (Boschma et al., 2015; Hidalgo et al., 2007; Hidalgo et al., 2018; Neffke et al., 2011). The rationale behind it is that regional diversification is like a branching process in which local knowledge is used to support the development of new technologies cognitively close to those in which the region is already specialized.

Many works have explored this argument, emphasizing the endogenous dynamics involved in the regional diversification process. They empirically show that the regional endowment of knowledge and technological capabilities is crucial to developing new economic specializations (Balland et al., 2019; Neffke et al., 2011). At the same time, another stream of literature has extensively pointed out the benefits of inter and intraregional co-invention networks for regional innovation performance (Bathelt et al., 2004; Broekel & Mueller, 2018; Graf & Kalthaus, 2018). However, the impact these networks' configurations may have on technological diversification has not yet been widely discussed in a branching process context. Recently, some attempts have been made on this matter, especially regarding the role of external linkages (Balland & Boschma, 2021; Barzotto et al., 2019; Whittle et al., 2020). Nevertheless, the role of co-invention network structures at the inter- and intraregional levels is still unclear for distinct kinds of regions.

In this vein, this work investigates the relative role of regional technological capabilities and co-invention network structures in technological diversification, addressing their differential roles in regions with distinct economic development levels. To do so, we used patent data from Brazil (2000 – 2019) and designed two types of networks: one based on interregional and the other based on intraregional co-invention linkages. We then conduct an econometric analysis on the microregional level, focusing on four main variables: centrality degree, betweenness, transitivity, and technology flexibility. Centrality degree is the number of connections a region establishes with others, capturing the region's access to external knowledge. Betweenness shows how well-positioned a region is in the interregional co-invention flows occurring in Brazil, meaning that the region has a control position in the network formation, as it intermediates knowledge flows between other regions. Transitivity shows how well knowledge disseminates inside a region based on the network's cohesiveness. Technology flexibility captures the average cognitive closeness of the regional technological capabilities to the technologies in which the region is not specialized.

Our results indicate that technology flexibility, betweenness, and transitivity contribute to regional technological diversification. At the same time, the centrality degree only has a positive and statistically significant effect when interaction terms regarding the regional development level are included in the analysis. It means regions generally benefit from their local knowledge and technological capabilities endowment, cohesive internal collaborations, and interregional networks' control positions. Less developed regions benefit from interregional connections *per se*, regardless of involving control positions or not. These results may have policy implications, as they indicate that less developed regions may achieve technological diversification by balancing their unfavorable internal condition with external linkages.

The rest of the paper is structured as follows. In section 2, we discuss the theoretical framework on which our analysis is based. In section 3, we present our methodology. In section 4, we show and discuss our econometric results. Finally, in section 5, we draw some conclusions and policy implications based on our quantitative analysis.

2. Diversification as a branching process and co-invention networks

Many scholars have sought to explain structural change by considering the role of knowledge and innovation (Foray & Lundvall, 2009; Nelson & Winter, 1982). In this sense, technological capabilities and learning are perceived as important factors to enable or hinder such a process (Abramovitz, 1986; Fagerberg & Srholec, 2018; Keun, 2012). Different branches of literature have extensively studied how structural change takes place and the different aspects that facilitate such a phenomenon.

The evolutionary economic geography argues that structural change is like a branching process, in which regional capabilities and cognitive proximity are crucial aspects. The fundamental premise is that technologies require different knowledge and capabilities to be developed. These assets can be recombined and deployed in new, cognitively close (related) technologies. Therefore, places with a greater variety of technological capabilities and knowledge have more opportunities and flexibility for recombination (Boschma, 2017; Frenken et al., 2007; Hidalgo et al., 2018). As some knowledge and capabilities are geographically bounded and challenging to transfer, regions with a dense economic structure, counting many sectors, companies, technologies, and institutions, have better possibilities for knowledge recombination, spillovers, and learning (Feldman & Kogler, 2010; Storper & Venables, 2004).

These arguments have been empirically addressed in many works, in which relatedness, local knowledge, and technological capabilities appear as central features of regional diversification. Empirical evidence shows that the development of new industries, technologies, and products is strongly impacted by locally available knowledge and capabilities. Cognitive close industries, technologies, and products, related to the existing regional portfolios, are more likely to be developed because at least part of the resources they require is already locally available. Diversification is then characterized as a branching process in which emerging activities build on the existing ones (Alonso & Martín, 2019; Essletzbichler, 2015; Neffke et al., 2011; Petralia et al., 2017; Xiao et al., 2018).

The literature on the geography of innovation has documented the importance of inter- and intraregional linkages between organizations for learning and innovation (Bathelt et al., 2004; Giuliani, 2005). Dense intraregional flows enable knowledge to spill over among local actors, whose contact is facilitated by physical proximity, trust relationships, and a shared institutional environment (Boschma & Ter Wal, 2007; Cao et al., 2022). Despite the favorable condition that physical proximity implies, being geographically close is not sufficient to ensure knowledge flows and learning. Local agents must be deliberately engaged in networks for local spillovers to occur. Then, observing the internal network structures is paramount to understanding how local knowledge and capabilities are recombined and deployed in new applications (Audretsch & Feldman, 1996; Breschi & Lenzi, 2015; Cassi & Plunket, 2014; Jaffe et al., 1993; Kauffeld-Monz & Fritsch, 2013).

In regions where members are strongly connected in research and innovation networks, face-to-face contact and reciprocity foster knowledge transmission, as information spills over faster and more accurately across groups (Coleman, 2009; Strumsky & Thill, 2013). However, the repeated connections between the same local partners may harm innovation and learning, as the local actors are not exposed to nonredundant knowledge, which may limit knowledge recombination possibilities (Fitjar & Rodríguez-Pose, 2017).

Accessing external knowledge and technological capabilities via interregional linkages enables contact with a more extensive knowledge pool and increase a region's capacity to adapt to technological changes (Bathelt et al., 2004; Graf, 2011). Interregional knowledge flows can potentially stimulate opportunities for local knowledge application, as local assets can be recombined with external knowledge accessed through networks (De Noni et al., 2018). Studies have already shown that high innovation performance regions are those in which local organizations connect not only with one another but also with external ones (Giuliani & Bell, 2005; Morrison, 2008). Nevertheless, establishing external linkages is not trivial and is influenced by network structures and similarities between nodes (Broekel & Mueller, 2018; Crespo & Vicente, 2016; Françoso & Vonortas, 2022).

Interregional flows are considered highly relevant for regions. However, some authors go a step further and argue that in addition to interregional flows *per se*, having a strategic and control position within networks is essential. This idea builds on the fact that a strategic position in networks impacts the economic performance of agents, as it implies a position to enable network formation or disarticulation. Hence, some regions are not only connected to several other regions but are in strategic and control positions, ensuring knowledge flows between different regions in the network, acting as intermediaries (Dosso & Lebert, 2020).

Only a few works addressing regional diversification as a branching process have focused on the potential role played by inter- and intraregional co-invention network structures. Network-related learning has been widely discussed in the literature as a way to renew the local knowledge stock, increase productivity and avoid lock-in (Bathelt et al., 2004; Lengyel & Eriksson, 2017; Tóth & Lengyel, 2021). We argue that investigating co-invention networks at the inter and intraregional levels may contribute to the technological diversification analysis. Networks are perceived as a way to assess a region's position in a particular technological space, as well as the region's potential to pursue external partnerships and restructure internal collaboration dynamics (Dosso & Lebert, 2020). Besides, less developed regions may count on a thin set of knowledge and technological capabilities, which may impose external sourcing. Therefore, addressing how (and if) inter and intraregional network structures impact technological diversification, especially in their case, may broaden the scope for regional policies targeting technological diversification in those regions.

Addressing interregional flows, Barzotto et al. (2019) found a positive impact of interregional collaboration in technological diversification. This impact demonstrated particular relevance for lagging regions, as they would be able to compensate for their low levels of capabilities and limited knowledge stock. However, they found that the positive returns of external collaboration diminish in regions characterized by higher levels of technological capabilities. Similarly, Balland & Boschma (2021) found that interregional connections accessing complementary knowledge positively affected the development of new technological specializations. External connections appeared to be especially relevant for the technological diversification of lagging regions. Whittle et al. (2020) found a positive correlation between regional technological diversification and interregional collaboration, highlighting that the latter has a more significant influence if the region connects to a diverse set of other regions.

Incorporating not only external flows but also intraregional cooperation dynamics into the analysis, Santoalha (2019) points out that both intra- and interregional collaborations have a positive impact on technological diversification. However, more and least developed regions have distinct benefits from them. While in most developed regions, intra- and interregional collaborations are beneficial, for the least developed ones, they depend on each other because external collaboration will only result in benefits if there are intense internal connections.

3. Methodology

3.1. Data

To conduct our analysis, we used patent data from the Intellectual Property Statistical Database - BADEPI v.8.0, compiled by the Brazilian National Institute of Industrial Property (INPI). We extracted data on invention patents and utility models applications with at least one Brazilian inventor. We assigned patents to microregions[2] according to the inventor's location. When a patent included inventors from different microregions, we assigned the patent to both microregions. To classify the technological domains of patents, we used the International Patent Classification (IPC) at the subclass level. Our database includes 113.121 applications, divided into four nonoverlapping 5-year periods: 2000-2004, 2005-2009, 2010-2014, and 2015-2019.

It is well known that patent data do not represent all inventive activity, as patenting propensity varies across sectors. However, patents provide valuable information on inventors and inventions (Acs et al., 2002; Barzotto et al., 2019). Moreover, empirical evidence indicates that the ability to patent in a particular technology is a good predictor of locally available knowledge and capabilities, which may be translated into new economic activities and scientific developments (Pugliese et al., 2019).

We also use microregion-specific data, such as GDP *per capita*, population density, the ratio of employers with tertiary education, number of patents *per* thousand inhabitants, and manufacturing specialization, which were gathered from The Institute for Applied Economic Research (IPEA) and the Annual Social Security Information Report (RAIS).

3.2. Regional technology endowment and co-invention networks

To account for the co-invention network structures, we employ betweenness, centrality degree (interregional level), and transitivity (intraregional level). To capture the regional technological endowment dimension of the branching process, we employ the measure of technological flexibility.

---

[2] The Brazilian Institute of Geography and Statistics (IBGE) provides a spatial classification of the Brazilian territory.

Networks are relational structures in which linkages connect different nodes. We followed Araújo et al. (2019), and to avoid multicollinearity problems, we adopted two network perspectives: inter- and intraregional networks. For interregional networks, we calculated two measures (betweenness and centrality degree), but they will be inserted separately in the following econometric analysis. To design the interregional networks for each period, we connected the microregions through inventors' co-invention; that is, microregions are the nodes, and the linkages are defined by the presence of inventors from different regions in the same patent application. In the intraregional networks, we assess the connections between inventors within the regions.

Both betweenness and centrality degree are centrality measures, capturing nodes' influence in the network. Nevertheless, they communicate different features. The centrality degree of a node is the number of connections it has in the network (Newman et al., 2011). In our case, it is the number of connections a region has with other regions, evidencing if it has access to knowledge externally produced.

Betweenness shows how well-positioned regions are to access external knowledge. This measure is based on the number of shortest paths (geodesic) between every pair of nodes in the network (Freeman, 1977). Nodes with high betweenness values lie in intermediating positions for the greatest number of shortest paths between the other nodes. Thus, it is considered a position of control over the transmission of information in a network, capturing the intermediate position of regions as crucial nodes to enable interregional flows (Araújo et al., 2019; Barrat et al., 2004; Dosso & Lebert, 2020). The betweenness of node u is given by the following expression:

$$Betweenness\ centrality\ (u) = \Sigma_{u \neq v \neq w} \frac{\sigma_{v,w}(u)}{\sigma_{v,w}}$$

Where $\sigma_{v,w}(u)$ is the total number of shortest paths from node v to node w that passes through node u.

Transitivity shows how well knowledge may spill over inside the region based on local inventors' cooperation patterns. It measures the intraregional network cohesiveness, meaning the formation of communities, based on local inventors' connections (Barrat et al., 2004; Funk, 2014). To characterize the transitivity of a regional network, it is necessary to take the total number of triangles on the graph divided by the number of connected triples in the graph (Luce & Perry, 1949; Newman, 2003). In intraregional networks, a "triangle" is a trio of inventors, each connected to the others, and a "connected triple" is a single inventor connected to two others. The transitivity index takes values between 0 and 1, with small values indicating poor transitivity and values close to one indicating great transitivity.

$$Trasitivity = \frac{3 \times number\ of\ triangles}{number\ of\ connected\ triples}$$

Technological flexibility reflects the region's knowledge and technological capabilities. This measure is proxied by the average relatedness density of regions to all technologies that are not part of their technology portfolio. Hence, this measure accounts for the regional knowledge endowment and relatedness between technologies. Technological flexibility relies on the fact that regions are more likely to diversify into technologies requiring the same knowledge and capabilities as those in which the region is already specialized. Therefore, the higher its technological flexibility is, the better the conditions for a region to diversify into new technologies because it means that its knowledge and technological capabilities can be applied to the development of new technologies in which the region is not specialized yet (Balland et al., 2015).

To calculate technological flexibility, we used the EconGeo R package (Balland, 2017). First, we calculated the relatedness between technologies and the revealed technological advantage (RTA) of regions. A region has RTA in a given technology if this technology is overrepresented in the region when compared to the reference, Brazil. Being overrepresented means that the ratio of patents share of technology i in region r is greater than in Brazil. Then, this variable is turned into a binary, assuming the value of 1 when the share of a technology in the region is greater than in Brazil, and 0 otherwise. We assume that if RTA=1 the region is specialized in the technology and possesses the knowledge and technological capabilities necessary to develop it.

Next, we calculate the relatedness between technologies. The idea behind this index is that technologies appearing in the same patent document are cognitively close to each other, as they were combined in the same application. To calculate relatedness, we followed Balland et al. (2019) and used the colocation of IPCs in patent documents, using a 'technology x patent document' incidence matrix. Thus, technology relatedness measures the normalized frequency with which two IPCs appeared on the same patent document.

As technological flexibility is a region-specific measure, we calculate the relatedness density of each technology in each region. Relatedness density is a ratio measure showing for a given region r the proportion of technologies related to a given technology i in which the region has RTA (Balland et al., 2019). We used a 'region x technology' matrix to perform this calculation. Regions with fewer than 15 patents were excluded from the analysis to prevent high RTAs based on very small absolute numbers of patents.

$$Relatedness\ density_{i,r,t} = \frac{\sum_{j \in r, j \neq i} \phi_{ij}}{\sum_{j \neq i} \phi_{ij}} * 100$$

The relatedness density in technology i in region r at time t is calculated using the relatedness $\phi_{i,j}$ of technology i to all other technologies j in which the region has RTA divided by the total sum of technological relatedness of technology i to all the other technologies j in the reference region, Brazil, at time t. This measure varies between 0 and 100. It has a maximum value of 100 when a region is specialized in all technologies to which a given technology i is related.

3.3. Econometric approach

Our dependent variable is technological diversification. First, we use the total number of new technology specializations (RTA) acquired by a region in period t compared to period t-1. One may say this is a biased indicator, as regions with fewer technological specializations would have more opportunities to develop new ones. Hence, we followed Santoalha (2019) and weighted the number of entries by the potential of new entries as a robustness check. Due to the distinct nature of dependent variables, we employ negative binomial and ordinary least squares (OLS).

Our main variables of interest are centrality degree, betweenness, transitivity, and technological flexibility. To avoid multicollinearity problems, we run a model using centrality degree and other with betweenness. The first will show the impact of external connections in the diversification process, while the other shows the impact of controlling positions in interregional networks for diversification.

We also control some region-specific features, such as population density, to account for agglomeration economies; GDP *per capita*, to account for economic development; the ratio of employees with tertiary education as a *proxy* for human capital; and patents per thousand inhabitants as a *proxy* for inventive capacity. Considering that we are using patents to measure technological diversification and that manufacturing sectors are more prone to patenting than others, we introduce a control for manufacturing specialization (De Noni et al., 2018). Hence, for regions specialized in manufacturing sectors, this control variable will assume the value of 1. To define manufacturing specialization, we used the number of employees in manufacturing sectors: if a region has a larger share of employees in manufacturing sectors than the reference, Brazil, it is considered to be specialized in manufacturing.

The microregions are located in different Brazilian states, which may have their institutions and practices to encourage research and innovation, such as funding agencies, specific credit lines, and tax incentives. To control for the possible heterogeneity between states, we insert state-fixed effects. All independent variables are lagged by one period to avoid endogeneity. As we excluded regions with fewer than 15 patents *per* period, we only included regions that appeared in two subsequent periods in our estimations.

Finally, we added interaction terms to capture the different effects of co-invention network structures in regions with different development levels. First, assuming that less developed regions have a thin set of knowledge and capabilities which diminishes their possibility to apply them to new technologies, we interacted technological flexibility with betweenness, centrality degree, and transitivity. Second, assuming that different development levels are reflected in different GDP *per capita*, we interacted this variable with our three network structures' variables.

We report clustered errors at the region level. Table 1 summarizes the main features of our dataset.

Table 1 – Summary of variables

Variable	Mean	Std. Dev	Min	Max	Tec flexibility	Tertiary education/emp	(log) Density	(log) GDP per cap	Betweenness	Patents/thous	Transitivity	Centrality
Tec flexibility	15.37	8.664	2	42								
Tertiary educ/emp	0.132	0.0466	0.0341	0.409	0.466							
(log) Density	4.667	1.261	1.896	8.734	0.7033	0.4295						
(log) GDP per cap	2.957	0.391	1.741	4.427	0.348	0.183	0.194					
Betweeness	7,98E+18	1,17E+19	0	7,48E+19	0.315	0.149	0.1902	0.0990				
Patents/thous	0.214	0.184	0.0186	1.200	0.436	-0.000900	0.1211	0.300	0.178			
Transitivity	0.621	0.415	0	1	0.417	0.281	0.2740	0.137	0.159	0.167		
Centrality	21.9	61.07	0	650	0.4951	0.3510	0.4887	0.3167	0.0565	0.3102	0.1327	
Manufacturing	0.689	0.459	0	1	-0.135	-0.468	-0.275	0.0165	0.002	0.236	-0.137	-0.136

Source: Authors' draft

4. Results and discussion

This section presents the results and discussion of the quantitative analysis regarding the acquisition of new technologies, both in terms of the absolute number of new specializations and considering the potential of new entries. Table 2 shows the results for the estimations using betweenness as the interregional network measure, while table 3 displays results with the centrality degree as the interregional network indicator.

Table 2 – Econometric results with betweenness

	N. of entries					
Tec flexibility	0.3065*** (0.0330)	0.3450*** (0.0357)	0.3234*** (0.0375)	0.3595*** (0.0385)	0.3346*** (0.0452)	0.3914*** (0.0457)
(log) Density	0.0773*** (0.0177)	0.0842*** (0.0230)	0.0722*** (0.0170)	0.0778** (0.0225)	0.0767*** (0.0176)	0.0857*** (0.0230)
(log) GDP per cap	0.1035* (0.0417)	0.1361* (0.0568)	0.1157** (0.0410)	0.1533** (0.0577)	0.1012* (0.0453)	0.1263* (0.0556)
Tertiary educ/emp	0.0643** (0.0202)	0.0247 (0.0253)	0.0596** (0.0202)	0.0257 (0.0249)	0.0603** (0.0203)	0.0234 (0.0251)
Patents/thous	0.0352 (0.1275)	0.0517 (0.1150)	0.0186 (0.1211)	0.0186 (0.1123)	0.0333 (0.1268)	0.04185 (0.1201)
Betweeness	0.0379* (0.0174)	0.0333 (0.0173)	0.0552** (0.0180)	0.0496** (0.0174)	0.1252* (0.0483)	0.1253** (0.0444)
Transitivity	0.0637*** (0.0173	0.0529** (0.0165)	0.0493* (0.0215)	0.0402 (0.0217)	0.1067* (0.0477)	0.0624 (0.0419)
Manufacturing	0.01168* (0.0466)	0.1230* (0.0480)	0.1133* (0.0456)	0.1225** (0.0473)	0.1304** (0.0470)	0.1372** (0.0488)
cons	2.9476*** (0.1719)	3.0209*** (0.1953)	2.964*** (0.1671)	3.0281*** (0.1902)	2.9544*** (0.1802)	3.0355*** (0.1899)
inter1 (bet & tec flex)			-0.0560*** (0.0141)	-0.0473** (0.0151)		
inter2 (trans & tec flexi)			-0.0173 (0.0327)	-0.0148 (0.0306)		
inter3 (tec flex & gdpc)					-0.0007 (0.0016)	-0.0015 (0.0014)
inter4 (bet & gdpc)					-0.0041* (0.0020)	-0.0044* (0.0020)
inter5 (trans & gdpc)					-0.0022 (0.0024)	-0.0005 (0.0020)
pseudo R^2	0.1210	0.1496	0.1240	0.1523	0.1229	0.1523
Period fe	No	Yes	No	Yes	No	Yes
State fe	No	Yes	No	Yes	No	Yes
Wald chi2	1042.48***	.	1093.27***	.	1198.38***	.
Obs	435	435	435	435	435	435

*p<0.05, **p<0.01, ***p<0.001

	(log) potential of entry					
Tec flexibility	0.4121*** (0.0368)	0.4364*** (0.0408)	0.4270*** (0.0432)	0.4501*** (0.0448)	0.4007*** (0.0502)	0.4588*** (0.0527)
(log) Density	0.0898*** (0.0185)	0.1114*** (0.0256)	0.0858*** (0.0183)	0.1057*** (0.0257)	0.0867*** (0.0185)	0.1080*** (0.0262)
(log) GDP per cap	0.1127* (0.0431)	0.1438* (0.0668)	0.1224** (0.0425)	0.1571* (0.0680)	0.1118* (0.0482)	0.1351* (0.0654)

Tertiary educ/emp	0.0591** (0.0219)	0.0284 (0.0306)	0.0558* (0.0224)	0.0296 (0.0304)	0.0513* (0.0220)	0.0252 (0.0304)
Patents/thous	0.0441 (0.1521)	0.0693 (0.1541)	0.0305 (0.01463)	0.0428 (0.1501)	0.0294 (0.1514)	0.0441 (0.1605)
Betweeness	0.0367* (0.0185)	0.0324 (0.0190)	0.0515* (0.0201)	0.0457* (0.0198)	0.1645** (0.0548)	0.1617** (0.0503)
Transitivity	0.0565** (0.0193)	0.0429* (0.0189)	0.0416 (0.0264)	0.0286 (0.0265)	0.1121* (0.0537)	0.0632 (0.0487)
Manufacturing	0.1142* (0.0495)	0.1274* (0.0550)	0.1135* (0.0500)	0.1283* (0.0553)	0.1262* (0.0499)	0.1425* (0.0556)
cons	-3.556*** (0.1812)	-3.5611*** (0.2216)	-3.539*** (0.1756)	-3.5508*** (0.2166)	-3.5395*** (0.1928)	-3.5149*** (0.2158)
inter1 (bet & tec flex)			-0.0511*** (0.0173)	-0.0441* (0.0186)		
inter2 (trans & tec flexi)			-0.0170 (0.0376)	-0.0172 (0.0362)		
inter3 (tec flex & gdpc)					0.0012 (0.0016)	-0.0002 (0.0017)
inter4 (bet & gdpc					-0.0061* (0.0024)	-0.0062* (0.0022)
inter5 (trans & gdpc)					-0.0028 (0.0027)	-0.0011 (0.0024)
R^2	0.7124	0.7767	0.7175	0.7804	0.7183	0.7826
Period fe	No	Yes	No	Yes	No	Yes
State fe	No	Yes	No	Yes	No	Yes
F-test	190.42***	.	166.5***	.	156.73***	.
Obs	435	435	435	435	435	435

*p<0.05, **p<0.01, ***p<0.001

All estimations' results are similar in signal and statistical significance. Technological flexibility, betweenness, and transitivity positively affected the acquisition of new technological specializations. Hence, having a control position in interregional flows and cohesive internal structures contribute to technological diversification, as well as having knowledge and capabilities locally available, which can be redeployed in new technology applications.

The positive effect of betweenness shows that regions with an intermediate position in the interregional co-invention networks are better able to specialize in new technologies. Betweenness' positive effect shows that regions holding a control position in the network flows diversify more. It is probably because this position reflects their prominence in overall knowledge generation in the country. The positive coefficient of transitivity shows that regions characterized by intense collaboration and reciprocal internal relationships are more successful in diversifying into new technologies. It is probably because cohesive structures reflect the easiness with which knowledge is transmitted along local agents, fostering knowledge spillover within regions (Araújo et al., 2019). Therefore, even when the regional endowment of technological capabilities is controlled, the co-invention network structures are essential to support technological diversification. The importance of regional positioning in interregional co-invention networks, as well as intraregional cohesive interactions, corroborates other studies that found a positive correlation between those network features and inventive activity (Araújo et al., 2019; De Noni et al., 2018; Santoalha, 2019; Strumsky & Thill, 2013).

Nevertheless, the magnitude of the effect of the network indicators is smaller than the effect of technological flexibility. It means that although co-invention network structures contribute to technological diversification, they are not as capable of impacting diversification as technological flexibility. This result dialogues with other studies that found a positive relationship between diversification and relatedness, evidencing that most countries, including Brazil, follow a related regional diversification pattern (Françoso et al., 2022; Galetti et al., 2021). New specializations are developed based on locally available knowledge and technological capabilities in this branching process. Therefore, the local endowment of knowledge and technological capabilities is fundamental to understand regional technological diversification trajectories.

Next, we focused on the effects of co-invention network structures on regions with different development levels. The negative and statistically significant impact of interactive term 1 (betweenness and technological flexibility) shows a substitution mechanism between the two variables, as the impact of one increases when the impact of the other decreases. Interactive term 4 (betweenness and GDP *per capita*) also presents a negative and statistically significant coefficient, meaning that the lower the GDP *per capita*, the higher the betweenness effect.

Less developed regions present few technological specializations, which implies few locally available knowledge and technological capabilities, reducing the possibilities of local assets' application to new technologies. Hence, their technological diversification prospects are not that good based on their internal technological capabilities. However, those regions may resort to their interregional network position to develop new technological specializations. Our results indicate that having a control position in interregional co-invention networks positively impacts the technological diversification in those regions.

It may sound counterintuitive that less developed regions may have an intermediate role in co-invention networks, controlling knowledge flows. However, it is worth mentioning that the connections are based on inventors' relationships with other inventors outside their regions. Thus, even in a less developed region, inventors may have key intermediate relationships with other inventors outside their regions. This result may indicate the importance of those inventors for less developed regions.

One may speculate that the importance of betweenness is due to the access to external knowledge that an intermediate position implies. Thus, we also run regressions with centrality degree instead of betweenness. Results are displayed in table 3.

Table 3 - Econometric results with centrality degree

	N. of entries					
Tec flexibility	0.3188*** (0.0325)	0.3527*** (0.0347)	0.3011*** (0.0375)	0.3307*** (0.0389)	0.3024*** (0.0511)	0.3530*** (0.0524)
(log) Density	0.0862*** (0.0184)	0.0923*** (0.0228)	0.0760*** (0.0181)	0.0851** (0.0221)	0.0833*** (0.0185)	0.0880*** (0.0236)
(log) GDP per cap	0.1129** (0.0424)	0.1443* (0.0573)	0.0993* (0.0415)	0.1453** (0.0553)	0.1008* (0.0440)	0.1370** (0.0525)
Tertiary educ/emp	0.0716** (0.0210)	0.0332 (0.0267)	0.0672** (0.0214)	0.0355 (0.0258)	0.0656** (0.0209)	0.0209 (0.0263)
Patents/thous	0.0785 (0.1289)	0.0936 (0.1195)	0.0148 (0.1236)	0.0130 (0.1213)	0.0489 (0.1306)	0.0415 (0.1235)
Centrality	-0.0326*** (0.0087)	-0.0237** (0.0089)	0.1860* (0.0728)	0.1816 (0.1046)	0.2262* (0.0919)	0.3044** (0.1040)
Transitivity	0.0612*** (0.0174)	0.0504** (0.0168)	0.0472* (0.0209)	0.0381 (0.0214)	0.0988* (0.0437)	0.0534 (0.0383)
Manufacturing	0.1223** (0.0467)	0.1258** (0.0481)	0.1214** (0.0463)	0.1295** (0.0477)	0.1338** (0.0476)	0.1409** (0.0495)
cons	2.8653*** (0.1814)	2.9390*** (0.2010)	3.0210*** (0.1812)	3.0428*** (0.2030)	2.9345*** (0.1844)	3.0484*** (0.1896)
inter6 (cent & tec flex)			-0.0961** (0.0326)	-0.0893* (0.0455)		
inter2 (trans & tec flexi)			-0.0176 (0.0322)	-0.0159 (0.0300)		
inter3 (tec flex & gdpc)					-0.0002 (0.0016)	-0.0007 (0.0015)
inter7 (cent & gdpc					-0.0071** (0.0024)	-0.0088** (0.0020)
inter5 (trans & gdpc)					-0.0019 (0.0022)	-0.0008 (0.0018)
pseudo R^2	0.1204	0.1488	0.1225	0.1511	0.1220	0.1518
Period fe	No	Yes	No	Yes	No	Yes
State fe	No	Yes	No	Yes	No	Yes
Wald chi2	1591.9***	.	1407.9***	.	1508.17***	.
Obs	435	435	435	435	435	435

*p<0.05, **p<0.01, ***p<0.001

	(log) potential of entry					
Tec flexibility	0.4239*** (0.0358)	0.4475*** (0.0396)	0.3983*** (0.0423)	0.4154*** (0.0444)	0.3791*** (0.0568)	0.4339*** (0.0612)

(log) Density	0.0899*** (0.0196)	0.1087*** (0.0263)	0.0783*** (0.0195)	0.1007*** (0.0258)	0.0869*** (0.0196)	0.1037*** (0.0261)
(log) GDP per cap	0.1121* (0.0433)	0.1467* (0.0666)	0.0952* (0.0421)	0.1435* (0.0638)	0.1118* (0.0461)	0.1347* (0.0604)
Tertiary educ/emp	0.0613** (0.0224)	0.0276 (0.0316)	0.0579* (0.0228)	0.0323 (0.0308)	0.0533* (0.0223)	0.0127 (0.0319)
Patents/thous	0.0573 (0.1591)	0.0810 (0.1624)	-0.0028 (0.1516)	-0.0056 (0.1587)	0.0202 (0.1600)	0.0182 (0.1662)
Centrality	-0.0048 (0.0185)	0.0007 (0.0123)	0.2573** (0.0201)	0.2670* (0.1204)	0.3486** (0.0957)	0.4250** (0.1200)
Transitivity	0.0573** (0.0195)	0.0434* (0.0192)	0.0428 (0.0256)	0.0291 (0.0256)	0.1080* (0.0494)	0.0564 (0.0442)
Manufacturing	0.1177* (0.0493)	0.1310* (0.0551)	0.1176* (0.0500)	0.1363* (0.0550)	0.1303* (0.0501)	0.1501** (0.0563)
cons	-3.560*** (0.1922)	-3.5503*** (0.2319)	-3.3791*** (0.1919)	-3.4159*** (0.2342)	-3.4730*** (0.1972)	-3.4048*** (0.2192)
inter6 (cent & tec flex)			-0.1164** (0.0358)	-0.1182* (0.0530)		
inter2 (trans & tec flexi)			-0.0156 (0.0368)	-0.0157 (0.0349)		
inter3 (tec flex & gdpc)					0.0013 (0.0025)	-0.0003 (0.0032)
inter7 (cent & gdpc					-0.0098*** (0.0025)	-0.0115*** (0.0021)
inter5 (trans & gdpc)					-0.0025 (0.0024)	-0.0006 (0.0021)
R^2	0.7098	0.7748	0.7155	0.7801	0.7156	0.7820
Period fe	No	Yes	No	Yes	No	Yes
State fe	No	Yes	No	Yes	No	Yes
F-test	239.63***	.	181.23***	.	216.03***	.
Obs	435	435	435	435	435	435

*p<0.05, **p<0.01, ***p<0.001

Table 3 shows that centrality has a negative effect on technological diversification. This result probably reflects the fact that regions that diversify the most have more internal capabilities. With varied knowledge and technological capabilities, they rely more on their own resources and less on external sourcing. This result was similar to Barzotto et al. (2019) and Santoalha (2019) found in Europe.

However, once the regional development level is considered, the centrality degree is positive and has a statistically significant effect on the number of new technological specializations, while the interactive terms are negative and statistically significant. The negative sign indicates a substitution mechanism between low technology flexibility and centrality degree and between centrality degree and GDP *per capita*, meaning that the effect of centrality degree is higher when the effects of technology flexibility and GDP *per capita* are lower. This substitution effect was also encountered when we used the betweenness measure.

Results in tables 2 and 3 indicate that, generally, having controlling and intermediate positions in interregional networks, rather than establishing numerous connections, is important for diversification. Notwithstanding, once the regional development level is considered, both the intermediate position and the number of connections are important for diversification. Interregional linkages enlarge the pool of knowledge locally available, enabling local organizations and inventors to tap into nonredundant knowledge and broadening the possibilities of knowledge recombination, which may lead to technological diversification. In the case of less developed regions with a thin set of local knowledge and technological capabilities, interregional flows may alleviate their local endowment limitation by mobilizing external resources through networks.

In all regressions, density, GDP *per capita*, and specialization in manufacturing also showed positive and statistically significant results. It implies that agglomeration economies, economic development, and specialization in manufacturing sectors are also important factors for technological diversification. The ratio of employees with tertiary education was positive; however, it presented a statistically significant coefficient only in some cases.

The fact the interactive terms involving transitivity did not present statistical significance evidence that less developed regions struggle to specialize in new technologies relying only on their internal knowledge flow dynamics. The small variety of knowledge, technological capabilities, and local agents harms knowledge recombination possibilities, and cohesive structures are not able to compensate for the thin local knowledge and technological capabilities endowment. Hence, these regions must establish linkages outside their boundaries.

Conclusion

This paper aims to investigate how the regional endowment of technological capabilities and co-invention network structures contribute to the technological diversification process. To do so, we employed Brazilian patent data from 2000 to 2019 and conducted a quantitative analysis. Our main variables of interest are technological flexibility, which captures the regional technological endowment; betweenness, which accounts for control and intermediate positions in co-invention interregional networks; centrality degree, accounting for the number of interregional linkages; and transitivity, accounting for intraregional networks' cohesiveness. With this analysis, we intend to contribute to the regional diversification literature that has emphasized the role of regional knowledge and technological capabilities endowment in diversification but has not extensively studied the role of inter and intraregional co-invention network structures in acquiring new technological specializations.

Our results indicate that regional technological endowment and co-invention network structures at the inter- and intraregional levels are essential for technological diversification. We can see that high intraregional transitivity and high betweenness in interregional networks are important in all contexts. At the same time, centrality is only statistically significant and positive when interaction terms regarding the regional development level are included. Our results suggest a substitution mechanism between technology flexibility and betweenness, and GDP *per capita* and betweenness. This effect also holds when we change betweenness for centrality degree. It means that less developed regions with lower technological endowments benefit from establishing interregional co-invention linkages in general, regardless of control and intermediate positions.

Our analysis dialogues with findings from two strands of literature. First, the literature on evolutionary economic geography which has empirically shown that the diversification process is path-dependent and strongly impacted by the relatedness between different sectors, technologies, and products, as the current knowledge and capabilities regionally available will support the development of new ones. Furthermore, this result also dialogues with studies focused on the geography of innovation, in which the flows between physically close and distant agents contribute to enhancing knowledge recombination and production, encouraging learning and innovation.

We showed that when these two perspectives are combined, the regional endowment of technological capabilities, as well as co-invention network structures, are important for developing new technological specializations, although to different extents. Yet, our study suggests that regions with different levels of development benefit in different ways from participating in co-invention networks. In general terms, regions benefit from a cohesive internal structure of collaboration and controlling positions stemming from the intermediation of interregional linkages. Less developed regions, which have fewer internal technological capabilities and fewer possibilities for redeploying existing knowledge in new technology applications, benefit from interregional collaboration *per se*, even if it does not involve a controlling position.

Our results add to the debate on regional diversification policies, especially in less developed regions. Designing place-based policies can be especially challenging for these regions because less developed regions have few technological specializations, implying little locally available knowledge and technological capabilities. This thin economic setting provides few insights for policymakers into which technological options are the best to pursue. However, including network-related aspects, the scope of the policy can be broadened by including practices that favor the connection within regions and with external actors. Additionally, our focus on an unequal Global South economy provides further evidence on the role of technological capabilities and co-invention network structures in the technological branching process, as most empirical evidence produced so far has concentrated on the European regions.

Although our study sheds light on how technological capabilities and co-invention network structures impact technological diversification, it presents some limitations and new research questions. The present work generally discusses co-invention network structures' importance to diversification, disregarding whether the knowledge externally accessed through networks is supplementary or complementary to the local knowledge base, that is, how related to the local technological portfolio is the knowledge externally accessed. Besides, we do not assess the interplay between different kinds of networks (scientific and technological, for instance) in technological development. Although these analyses are beyond the scope of the present paper, we understand that they could contribute to policy design and should be further explored in future research.

Bibliography:

Abramovitz, M. (1986). Catching Up, Forging Ahead, and Falling Behind. *The Journal of Economic History*, *46*(2). https://doi.org/10.1017/S0022050700046209

Acs, Z. J., Anselin, L., & Varga, A. (2002). Patents and innovation counts as measures of regional production of new knowledge. *Research Policy, 31*(7). https://doi.org/10.1016/S0048-7333(01)00184-6

Alonso, J. A., & Martín, V. (2019). Product relatedness and economic diversification at the regional level in two emerging economies: Mexico and Brazil. *Regional Studies*, *53*(12). https://doi.org/10.1080/00343404.2019.1605441

Araújo, I. F., Gonçalves, E., & Taveira, J. G. (2019). The Role of Patent Co-

inventorship Networks in Regional Inventive Performance. In *International Regional Science Review* (Vol. 42, Issues 3–4). https://doi.org/10.1177/0160017618770717
Audretsch, D. B., & Feldman, M. P. (1996). R&D Spillovers and the Geography of Innovation and Production. *American Economic Review*, *86*(3). https://doi.org/10.2307/2118216
Balland, P. A. (2017). *Economic Geography in R: Introduction to the EconGeo package* (No. 17; 09).
Balland, Pierre Alexandre, & Boschma, R. (2021). Complementary interregional linkages and Smart Specialisation: an empirical study on European regions. *Regional Studies*, *55*(6). https://doi.org/10.1080/00343404.2020.1861240
Balland, Pierre Alexandre, Boschma, R., Crespo, J., & Rigby, D. L. (2019). Smart specialization policy in the European Union: relatedness, knowledge complexity and regional diversification. *Regional Studies*, *53*(9). https://doi.org/10.1080/00343404.2018.1437900
Balland, Pierre Alexandre, Rigby, D., & Boschma, R. (2015). The technological resilience of US cities. *Cambridge Journal of Regions, Economy and Society*, *8*(2). https://doi.org/10.1093/cjres/rsv007
Barrat, A., Barthélemy, M., Pastor-Satorras, R., & Vespignani, A. (2004). The architecture of complex weighted networks. *Proceedings of the National Academy of Sciences of the United States of America*, *101*(11). https://doi.org/10.1073/pnas.0400087101
Barzotto, M., Corradini, C., Fai, F. M., Labory, S., & Tomlinson, P. R. (2019). Enhancing innovative capabilities in lagging regions: An extra-regional collaborative approach to RIS3. *Cambridge Journal of Regions, Economy and Society*, *12*(2). https://doi.org/10.1093/cjres/rsz003
Bathelt, H., Malmberg, A., & Maskell, P. (2004). Clusters and knowledge: Local buzz, global pipelines and the process of knowledge creation. *Progress in Human Geography*, *28*(1). https://doi.org/10.1191/0309132504ph469oa
Boschma, R. (2017). Relatedness as driver of regional diversification: a research agenda. *Regional Studies*, *51*(3). https://doi.org/10.1080/00343404.2016.1254767
Boschma, R., Balland, P. A., & Kogler, D. F. (2015). Relatedness and technological change in cities: The rise and fall of technological knowledge in US metropolitan areas from 1981 to 2010. *Industrial and Corporate Change*, *24*(1). https://doi.org/10.1093/icc/dtu012
Boschma, R., & Ter Wal, A. L. J. (2007). Knowledge networks and innovative performance in an industrial district: The case of a footwear district in the South of Italy. *Industry and Innovation*, *14*(2). https://doi.org/10.1080/13662710701253441
Breschi, S., & Lenzi, C. (2015). The Role of External Linkages and Gatekeepers for the Renewal and Expansion of US Cities' Knowledge Base, 1990–2004. *Regional Studies*, *49*(5). https://doi.org/10.1080/00343404.2014.954534
Broekel, T., & Mueller, W. (2018). Critical links in knowledge networks–What about proximities and gatekeeper organisations? *Industry and Innovation*, *25*(10). https://doi.org/10.1080/13662716.2017.1343130
Cao, Z., Derudder, B., Dai, L., & Peng, Z. (2022). 'Buzz-and-pipeline' dynamics in Chinese science: the impact of interurban collaboration linkages on cities' innovation capacity. *Regional Studies*, *56*(2). https://doi.org/10.1080/00343404.2021.1906410
Cassi, L., & Plunket, A. (2014). Proximity, network formation and inventive performance: in search of the proximity paradox. *Annals of Regional Science*,

53(2). https://doi.org/10.1007/s00168-014-0612-6
Coleman, J. S. (2009). Social capital in the creation of human capital. In *Knowledge and Social Capital*. https://doi.org/10.1086/228943
Crespo, J., & Vicente, J. (2016). Proximity and Distance in Knowledge Relationships: From Micro to Structural Considerations based on Territorial Knowledge Dynamics (TKDs). *Regional Studies*, *50*(2). https://doi.org/10.1080/00343404.2014.984671
De Noni, I., Orsi, L., & Belussi, F. (2018). The role of collaborative networks in supporting the innovation performances of lagging-behind European regions. *Research Policy*, *47*(1). https://doi.org/10.1016/j.respol.2017.09.006
Dosso, M., & Lebert, D. (2020). The centrality of regions in corporate knowledge flows and the implications for Smart Specialisation Strategies. *Regional Studies*, *54*(10). https://doi.org/10.1080/00343404.2019.1619923
Essletzbichler, J. (2015). Relatedness, Industrial Branching and Technological Cohesion in US Metropolitan Areas. *Regional Studies*, *49*(5). https://doi.org/10.1080/00343404.2013.806793
Fagerberg, J., & Srholec, M. (2018). National innovation systems, capabilities and economic development. In *Innovation, Economic Development and Policy: Selected Essays*. https://doi.org/10.1016/j.respol.2008.06.003
Feldman, M. P., & Kogler, D. F. (2010). Stylized facts in the geography of innovation. In *Handbook of the Economics of Innovation* (Vol. 1, Issue 1 C). https://doi.org/10.1016/S0169-7218(10)01008-7
Fitjar, R. D., & Rodríguez-Pose, A. (2017). Nothing is in the Air. *Growth and Change*, *48*(1). https://doi.org/10.1111/grow.12161
Foray, D., & Lundvall, B. Å. (2009). The knowledge-based economy: From the economics of knowledge to the learning economy. In *The Economic Impact of Knowledge*. https://doi.org/10.1016/b978-0-7506-7009-8.50011-2
Françoso, M. S., Boschma, R. A., & Vonortas, N. S. (2022). *Regional diversification in Brazil: the role of relatedness and complexity* (22.06; Papers in Evolutionary Economic Geography). http://econ.geo.uu.nl/peeg/peeg2206.pdf
Françoso, M. S., & Vonortas, N. S. (2022). Gatekeepers in regional innovation networks: Evidence from an emerging economy. *The Journal of Technology Transfer*, *47*(1). https://doi.org/10.1007/s10961-022-09922-4
Freeman, L. C. (1977). A set of measures of centrality based upon betweenness. *Sociometry*, *40*, 35–41.
Frenken, K., Van Oort, F., & Verburg, T. (2007). Related variety, unrelated variety and regional economic growth. *Regional Studies*, *41*(5). https://doi.org/10.1080/00343400601120296
Funk, R. J. (2014). Making the most of where you are: Geography, networks, and innovation in organizations. *Academy of Management Journal*, *57*(1). https://doi.org/10.5465/amj.2012.0585
Galetti, J. R. B., Tessarin, M. S., & Morceiro, P. C. (2021). Skill relatedness, structural change and heterogeneous regions: evidence from a developing country. *Papers in Regional Science*. https://doi.org/10.1111/pirs.12629
Giuliani, E. (2005). Cluster absorptive capacity: Why do some clusters forge ahead and others lag behind? In *European Urban and Regional Studies* (Vol. 12, Issue 3). https://doi.org/10.1177/0969776405056593
Giuliani, E., & Bell, M. (2005). The micro-determinants of meso-level learning and innovation: Evidence from a Chilean wine cluster. *Research Policy*, *34*(1). https://doi.org/10.1016/j.respol.2004.10.008

Graf, H. (2011). Gatekeepers in regional networks of innovators. *Cambridge Journal of Economics*, *35*(1). https://doi.org/10.1093/cje/beq001

Graf, H., & Kalthaus, M. (2018). International research networks: Determinants of country embeddedness. *Research Policy, 47*(7). https://doi.org/10.1016/j.respol.2018.04.001

Hidalgo, C. A., Winger, B., Barabási, A. L., & Hausmann, R. (2007). The product space conditions the development of nations. *Science*, *317*(5837). https://doi.org/10.1126/science.1144581

Hidalgo, César A., Balland, P. A., Boschma, R., Delgado, M., Feldman, M., Frenken, K., Glaeser, E., He, C., Kogler, D. F., Morrison, A., Neffke, F., Rigby, D., Stern, S., Zheng, S., & Zhu, S. (2018). The Principle of Relatedness. In *Springer Proceedings in Complexity*. https://doi.org/10.1007/978-3-319-96661-8_46

Jaffe, A. B., Trajtenberg, M., & Henderson, R. (1993). Geographic localization of knowledge spillovers as evidenced by patent citations. *Quarterly Journal of Economics*, *108*(3). https://doi.org/10.2307/2118401

Kauffeld-Monz, M., & Fritsch, M. (2013). Who Are the Knowledge Brokers in Regional Systems of Innovation? A Multi-Actor Network Analysis. *Regional Studies*, *47*(5). https://doi.org/10.1080/00343401003713365

Keun, L. (2012). Schumpeterian analysis of economic catch-up: Knowledge, path-creation, and the middle-income trap. In *Schumpeterian Analysis of Economic Catch-Up: Knowledge, Path-Creation, and the Middle-Income Trap*. https://doi.org/10.1017/CBO9781107337244

Lengyel, B., & Eriksson, R. H. (2017). Co-worker networks, labour mobility and productivity growth in regions. *Journal of Economic Geography*, *17*(3). https://doi.org/10.1093/jeg/lbw027

Luce, R. D., & Perry, A. D. (1949). A method of matrix analysis of group structure. *Psychometrika*, *14*(2). https://doi.org/10.1007/BF02289146

Morrison, A. (2008). Gatekeepers of knowledge within industrial districts: Who they are, how they interact. *Regional Studies*, *42*(6). https://doi.org/10.1080/00343400701654178

Neffke, F., Henning, M., & Boschma, R. (2011). How Do Regions Diversify over Time? Industry Relatedness and the Development of New Growth Paths in Regions. *Economic Geography*, *87*(3). https://doi.org/10.1111/j.1944-8287.2011.01121.x

Nelson, R. R., & Winter, S. G. (1982). An Evolutionary Theory of Change. In *Massachusetts, Belknap Harvard*.

Newman, M., Barabási, A. L., & Watts, D. J. (2011). The structure and dynamics of networks. In *The Structure and Dynamics of Networks*.

Newman, M. E. J. (2003). The structure and function of complex networks. In *SIAM Review* (Vol. 45, Issue 2). https://doi.org/10.1137/S003614450342480

Petralia, S., Balland, P. A., & Morrison, A. (2017). Climbing the ladder of technological development. *Research Policy*, *46*(5). https://doi.org/10.1016/j.respol.2017.03.012

Pugliese, E., Cimini, G., Patelli, A., Zaccaria, A., Pietronero, L., & Gabrielli, A. (2019). Unfolding the innovation system for the development of countries: coevolution of Science, Technology and Production. *Scientific Reports*, *9*(1). https://doi.org/10.1038/s41598-019-52767-5

Santoalha, A. (2019). Technological diversification and Smart Specialisation: the role of cooperation. *Regional Studies*, *53*(9). https://doi.org/10.1080/00343404.2018.1530753

Storper, M., & Venables, A. J. (2004). Buzz: Face-to-face contact and the urban economy. *Journal of Economic Geography*, *4*(4). https://doi.org/10.1093/jnlecg/lbh027

Strumsky, D., & Thill, J. C. (2013). Profiling U.S. metropolitan regions by their social research networks and regional economic performance. *Journal of Regional Science*, *53*(5). https://doi.org/10.1111/jors.12048

Tóth, G., & Lengyel, B. (2021). Inter-firm inventor mobility and the role of co-inventor networks in producing high-impact innovation. *Journal of Technology Transfer*, *46*(1). https://doi.org/10.1007/s10961-019-09758-5

Whittle, A., Lengyel, B., & Kogler, D. F. (2020). Understanding Regional Branching Knowledge Diversification via Inventor Collaboration Networks. *Papers in Evolutionary Economic Geography*.

Xiao, J., Boschma, R., & Andersson, M. (2018). Industrial Diversification in Europe: The Differentiated Role of Relatedness. *Economic Geography*, *94*(5). https://doi.org/10.1080/00130095.2018.1444989