
# O efeito da proximidade industrial sobre a diversificação tecnológica regional: evidências do Brasil

Danielle Evelyn de Carvalho[1];
João Prates Romero[2];

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**Resumo:** O objetivo deste estudo é analisar como a densidade de encadeamentos industriais influencia o processo de diversificação tecnológica no nível das classes tecnológicas das regiões intermediárias do Brasil. Foram estimados modelos MQO, Probit e Logit para 133 regiões intermediárias brasileiras em 119 classes tecnológicas, no período de 2006 a 2021. O estudo evidencia o papel do relacionamento entre as classes tecnológicas e a estrutura industrial na diversificação tecnológica. Ademais, observamos que a complexidade tecnológica reduz as chances de entrada e diversificação de uma região. No entanto, a probabilidade de diversificação aumenta quando as tecnologias se relacionam ao sistema industrial local, independentemente de sua complexidade. Também constatamos que a proximidade tecnológica não afeta a diversificação em áreas de menor renda per capita, enquanto a proximidade industrial apresenta relação positiva. Além disso, a densidade de relações industriais mostra-se mais relevante para a diversificação tecnológica em patentes de empresas do que em patentes de universidades. Esses resultados contribuem para a compreensão da dinâmica entre tecnologia e indústria em um país em desenvolvimento.

**Palavras-chave**: Diversificação regional; Tecnologia; Proximidade Industrial; Complexidade.

**Código JEL:** O33; R11; L60

**Área Temática:** Redes e sistemas urbanos, regionais e nacionais

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## The effect of industry relatedness on regional technological diversification: evidence from Brazil

**Abstract:** The objective of this study is to analyze the influence of industrial relatedness density on the process of technological diversification at the level of technological classes in Brazil's intermediate regions. MQO, Probit, and Logit models were estimated for the 133 Brazilian intermediate regions in 119 technological classes between 2006 and 2021. This study highlights the influence of the relationship between technological classes and industrial structure on technological diversification. Furthermore, we find a region's chances of entry and diversification are reduced by technological complexity. However, the probability of diversification increases when technologies are related to the local industrial system, despite their complexity. We also find that technological relatedness does not affect technology diversification in areas with lower per capita income, but industrial relatedness has a positive relationship. In addition, the density of industrial relationships is more important for technological diversification

[1] CEDEPLAR/UFMG. E-mail: danielle-evelyn@hotmail.com.
[2] CEDEPLAR/UFMG. E-mail: jpromero@cedeplar.ufmg.br.

with patents from company applicants than from university applicants. These findings contribute to understanding the dynamics of the relationship between technology and industry in a developing country.

**Keywords:** Regional diversification; Technology; Industrial Relatedness; Complexity.

## 1. Introduction

Diversification is crucial for regional economic development. Jacobs' pioneering work (1969) emphasized the importance of cities with greater productive diversification for knowledge externalities and economic growth. Some decades later, Glaeser et al. (1992) provided new evidence of the importance of productive diversification for regional growth.

Nonetheless, as Nooteboom (2000) pointed out, knowledge is more easily shared between sectors if their cognitive distance is not too great. Fruitful interactions between agents from different activities require a relatively close cognitive distance, that is, some degree of relatedness. Consequently, as shown by Frenken, Oort and Verburg (2007), regions with a greater variety of related industries have more learning opportunities and, consequently, more local knowledge spillovers, which results in higher employment growth.

Similarly, the first studies on the geography of innovation highlighted the importance of geographical location and the concentration of agents as drivers of innovative activity (Jaffe, 1989; Feldman, 1993; Audretsch & Feldman, 1996; Baptista & Swann, 1998). Geographical proximity facilitates interaction and learning from new combinations and knowledge, directly impacting innovation (Asheim & Gertler, 2005; Doloreux, 2002). Schumpeter (1985) argued that the generation of innovations results from new combinations of existing knowledge, which is why regions with greater technological diversity tend to present higher innovation rates. Duranton and Puga (2001) referred to the regions with these characteristics as "nursery cities" because they facilitate research and experimentation in innovation.

Following the growing literature on the importance of related industrial diversification for regional growth (Frenken et al., 2007; Neffke et al., 2011; Freitas et al., 2024), several works have also explored the importance of related technological diversification for technological competitiveness (Rigby, 2013; Boschma et al., 2015; Balland et al., 2018). These studies have shown the diversification process is not random. Regions specialize in new technologies or sectors related to their pre-existing technological and productive competencies. However, it is essential to note that analyses mainly consider the influence of a single type of capacity on new specializations within the same knowledge in the regions.

Following the rapid developments in the literature on related diversification, it is intuitive to suspect that industrial and technological capacities might be complementary or even, to some extent, substitute sources of relevant knowledge for technological development. For example, the rise of the organic chemicals industry in Germany resulted from the German industry's pressure on the government to create institutions responsible for technological development that worked in conjunction with the production system. Universities have advanced the scientific and technological knowledge in chemistry to develop synthetic dyes. The companies, therefore, set up laboratories within their industries so that scientists could work on the discovery and development of new products, also with the help of funding from the German government (Chandler, 1990; Murmann, 2003; Nelson, 2008). Thus, in addition to the diversity of technological knowledge that enables the generation of externalities and innovation, productive structures might provide complementary knowledge and pressure institutions to technological development.

Nonetheless, few papers still have explored the interplay between industrial and technological relatedness for technological upgrading. According to the evidence found by Aarstad et al. (2016) and Tavassoli and Carbonara (2014), regions with more related industries are associated with more innovative firms. Recent research suggests effective learning from production experience can lead to innovation (Berger, 2013; Locke & Wellhausen, 2014; Eum & Lee, 2019; Eum & Lee, 2022). Moreover, studies such as Feldman (1993) and Audretsch and Feldman (1996) have also shown an important relationship between the location of innovation production and the geographic concentration of manufacturing sectors. But most importantly, these works have observed that related industries are the most relevant for innovative activities.

This literature is even scarcer when it comes to evidence for developing countries. In the case of Brazil, a notable exception is Mascarini et al. (2023), who examined the effect of a related and unrelated variety of industries on regional innovation. However, the analysis conducted is at the regional level, i.e., it examines the effect of regions with related and unrelated varieties on the number of patents in the region. Pavitt (1984) and Malerba (2002) have already pointed out that the propensity to patent is known to vary widely across industries. For this reason, our estimates include sectoral dynamics in the technological diversification of regions, which is one of the contributions of this paper.

Therefore, the objective of this paper is to assess whether a region has a greater probability of diversifying into new technological classes if its productive structure is composed of industries related to the targeted technological classes. The relatedness density between industries and technologies was calculated based on the co-occurrence of industries and technologies in the region, according to the measure proposed by Hidalgo et al. (2007). Industrial sectors were associated with technology classes using the Algorithmic Link with Probabilities (ALP) proposed by Lybbert e Zolas (2014). Employment and patent data for 133 Brazilian intermediate regions were used to measure industrial and technological relatedness in each technology class, covering the period from 2006 to 2021.

The remainder of the paper is organized as follows. Section 2 provides an overview of the literature, highlighting relevant and similar contributions. Section 3 describes the indicators used, the database, and the econometric specifications. Section 4 presents a descriptive analysis and the results of the econometric tests, while section 5 provides concluding remarks.

## 2. Literature Review

### 2.1. Determinants of Regional Technological Diversification

Innovation processes are influenced by geographically localized knowledge and the proximity of agents and institutions (Audretsch & Feldman, 1996; Feldman, 1993; Jaffe, 1989; Asheim & Gertler, 2005; Doloreux, 2002). Therefore, regions with a more diversified knowledge base are likely to have greater innovation potential.  According to Neffke et al. (2011), cities with a wide range of industries have a greater diffusion of ideas across sectors, becoming repositories of knowledge through the diversity of economic activities in which people are employed. As a result, ideas are recombined, creating new opportunities for innovation. New knowledge can be produced by recombining pre-existing resources or knowledge components. A broader variety of knowledge can facilitate the generation of new ideas and innovations (Schumpeter, 1985). This is consistent with Jacobs' (1969) argument that cities with many different industries would experience more innovation because exchanging knowledge between sectors would lead to more new products and processes.

However, there must be some common ground for knowledge to be exchanged between agents and recombined.  Excessive cognitive distance can constrain understanding and hinder the exploitation of collaborative opportunities. The challenge, therefore, is to find partners who are cognitively distant enough to bring new ideas to the table but not so distant as to prevent mutual understanding (Nooteboom et al., 2007). Boschma (2005) suggests that moderate cognitive distance is critical in preventing lock-in, especially in contexts where access to diverse knowledge is critical for product innovation. Consequently, an "ideal region" would have a high concentration of industries and different technologies but with some coherence in the industrial and technological profile (Neffke, 2009).

The factors influencing the amount of knowledge and capabilities in a region and their implications for the region's diversification pathways have been widely studied in the last decade. Recent research has revealed that local industries often emerge from the existing regional industrial framework and benefit from the available skills and resources (Neffke et al., 2011; Essletzbichlera, 2015; Freitas et al., 2024). Evidence suggests that diversification into new activities tends to be related to the location's pre-existing knowledge and capabilities, which aligns with the relatedness principle (Hidalgo et al., 2018). This principle is observed for different types of capabilities (technological, industrial, scientific, etc.), the spatial level (regions, cities, countries, etc.), or period of analysis (Neffke et al., 2011; Essletzbichlera, 2015; Rigby, 2013, Boschma et al., 2015; Balland et al., 2018; Freitas et al., 2024).

Regarding regional technological capabilities, the pioneering work of Rigby (2013) examined technological diversification through the entry into and exit from patent technological classes in US cities between 1975 and 2005 using OLS and logit models. Boschma et al. (2015) conducted similar analyses for US cities between 1981 and 2010 and Balland et al. (2018) for 282 European regions between 1985 and 2009. These studies have calculated the relationship between technologies in a variety of forms. Rigby (2013) used the co-occurrence between citations of pairs of technology classes, while Boschma et al. (2015) used the co-occurrence between technological classes in cities. On the other hand, Balland et al. (2018) calculate technological proximity through the co-occurrence of technological classes in each patent document. Nevertheless, the results are convergent despite the different calculation methods of the relationship between technological classes. Rigby (2013), Boschma et al. (2015), Balland et al. (2018) found that technological diversification in regions is influenced by the proximity of technologies to the local knowledge portfolio, that is, the proximity to the set of existing technological specializations.

However, in all these studies, the investigation refers to a single type of knowledge that condition the technological specialization in regions (Neffke; Henning; Boschma, 2011; Rigby, 2015; Boschma; Balland; Kogler, 2015; Balland et al., 2018; Freitas; Britto; Amaral, 2024). Nonetheless, different types of knowledge influence technological diversification (Pugliese et al., 2019). Aarstad, Kvitastein and Jakobsen (2016) and Tavassoli and Carbonara (2014) show that related and unrelated industrial knowledge affects the process of innovative knowledge generation. Tavassoli and Carbonara (2014) are amongst the first to test the relationship between related variety in industries and regional innovation, distinguishing between related and unrelated varieties. The authors estimate a negative binomial model of regional knowledge production in Sweden for 2002–2007. The results show that both varieties generate innovation, although related variety has a greater impact. Aarstad, Kvitastein and Jakobsen (2016) associate related industrial variety with innovation at the f irm level in Norway. By estimating a multilevel model for the period 2008-2010, they found that related industrial variety positively affects a firm's propensity to innovate, while unrelated variety had no significant result on innovation. The central hypothesis of these studies is that regions with economic activities more closely related to the pre-existing set of local capabilities are more likely to exploit, recombine, and transform the knowledge of these related sectors into innovation.

Regarding studies for Brazil, Mascarini et al. (2023) analyze the effect of related and unrelated industrial varieties on innovation in Brazilian micro-regions between 2002 and 2017. The results show that related varieties are associated with an increase in different types of patents in Brazilian regions. The scope of this study is limited to the regional level (Mascarini et al., 2023). However, it has been observed that different technology classes have differing characteristics, opportunities, links with industrial sectors, and determinants of diversification. (Pavitt, 1984; Malerba, 2002). Therefore, the sectoral dimension of diversification into technological classes is one of the main contributions of this work.

In general, however, there are still very few studies relating industrial relations to diversification in technological classes. Considering that the construction of technological and productive capacities is relevant to economic development, studying this relationship for developing countries, especially those with large regional dimensions and inequalities, such as Brazil, is even more important.

In this context, the hypotheses to be tested are the following:

*Hypothesis 1*: Regions are more likely to develop new specializations in technological classes related to their industrial knowledge base.

*Hypothesis 2*: Regions are less likely to lose specializations in technological classes related to their industrial knowledge base.

*Hypothesis 3*: Regions with low per capita income are more likely to develop specializations in technological classes related to their industrial knowledge base.

*Hypothesis 4*: Regions are more likely to new develop specializations in complex technological classes when related to their industrial knowledge base.

## 3. Methodology

### 3.1 Database

To carry out the empirical investigation proposed in this paper, employment data were gathered from RAIS (Annual Social Information Report), and patent data were gathered from INPI (National Institute of Industrial Property). In addition, GDP per capita and population data were obtained from IBGE (Brazilian Institute of Geography and Statistics), all for the period 2006-21.

Patents have been widely used as a proxy for innovative activity (Griliches, 1979) and in the analysis of innovation at the regional level (Jaffe, 1989; Feldman, 1994; Feldman & Florida, 1994; Acs et al., 2002). However, there are limitations to using this indicator to measure innovation. As Griliches (1979, p. 296) highlights, *"[...] not all inventions are patentable, not all inventions are patented, and the inventions that are patented differ greatly in 'quality', in the magnitude of inventive output associated with them"*. Similarly, Albuquerque (2004) emphasized the limitations of the use of patents since not all knowledge generated is codifiable, nor is every invention patentable for various reasons, such as legal restrictions, other appropriability mechanisms, and so on. In addition, different sectors have different propensities to patent, so it is important to consider technology classes when analyzing technological diversification, not just regional characteristics.

On the other hand, despite the above-mentioned limitations, patents have several advantages for analyzing technological change due to the large amount of data available, accessibility, industrial applicability, and objective and stable criteria (Griliches, Andersson & Lööf, 2012). For this reason, we choose to use patent databases to measure technological knowledge, in line with Françoso et al. (2024) and Mascarini et al. (2023).

The INPI patent database, the inventor database is most often used due to its more equitable distribution across the country. On the other hand, the applicant database focuses on the addresses of applicant institutions, resulting in a greater concentration in large urban centers. The inventors' database was used for the general estimates, entry/exit, and in the regions' income divisions, while the applicants' database was used for the estimates with divisions of patents applied by companies and universities/research institutions. The patent count considers both the address of the inventor/applicant and the technological classification (IPC) of the patent. For example, if a patent has two inventors in the region and is classified into two technological classes, it is counted four times in the database. This procedure is adopted because the knowledge generated by the patent is not divisible and is generated for each location or technological class to which it belongs.

Employment data by sector from RAIS were used to measure Industry Relatedness Density. Several studies at the Brazilian regional level use employment data because of its large territorial coverage and high degree of specificity (Freitas et al., 2024; Françoso et al., 2024). The foreign trade data used by Hidalgo et al. (2007) and Hidalgo and Hausmann (2009) are less suitable for regional analysis in the Brazilian context. This is because several regions in Brazil do not participate in import and export activities, which results in the loss of important information. Moreover, trade data is often reported in places different from their production localities, while trade within the country is also not considered.

RAIS employment data and INPI patent data have different classification systems, which are not directly related. The CNAE sector classification is used for employment data, and the IPC classification is used for patents. Therefore, it is necessary to adopt a methodology to relate the two sets of data, translating sectoral employment into technology classes. Previous studies have used the *Algorithmic Link with Probabilities (ALP)* concordance table to analyze the relationship between production and knowledge (Dosi et al., 2021; Eum & Lee, 2019) by translating data between SITC, ISIC, and NAICS from/for IPC (Lybbert & Zolas, 2014). The first step in this process was to make the 2-digit ISIC Rev. 4 compatible with the 2-digit CNAE 2.0. The CNAE is a classification derived from the CIIU/ISIC that has a very close correspondence to the International Classification, except for two CNAE product classes, which were subdivided into different division correspondences[3]. Finally, a translation of the 2-digit CNAE 2.0 was

[3] 15.40-8 of the CNAE code - manufacture of parts of footwear, of any material - is equivalent to 2219 (if it's rubber), 2220 (if it's plastic), 1520 (if it's leather) and 1629 (if it's wood); 20.29-1 of the CNAE code - manufacture of organic chemical products not elsewhere specified - is equivalent to 1910 (manufacture of coke oven products) and 2011 (manufacture of basic chemical products). In order to check whether these incompatibilities would alter the results obtained by the regressions,

obtained for the technological classes (IPC) of patents at the 3-digit level using ALP.

Our panel consists of data for 133 Brazilian intermediate regions and 119 patent technology classes at the three-digit level from 2006-2021. We average the data into non-overlapping 4-year periods (2006-2009, 2010-2013, 2014-2017, 2018-2021), except for patent data, where the number of patents by technology class was summed for every four years and region due to the high incidence of zero values and large fluctuations over the years, as is common in the context of an underdeveloped economy. This division, with a range of years, is commonly used in research on technological diversification, as highlighted in previous works (Rigby, 2013; Boschma, 2015).

### 3.2 Measuring Technological and Industrial Relatedness

Several recent studies have used co-occurrence measures to understand industry relatedness (Bryce & Winter, 2009; Freitas, 2024; Hidalgo et al., 2007; Teece et al., 1994). Co-occurrence measures the relationship between two industries or technologies by assessing whether they are frequently found together in the same region. For example, Hidalgo et al. (2007) use the number of times two industries reveal comparative advantage (co-occurrence) in the same country to analyze productive diversification trajectories. Similarly, Teece et al. (1994) and Bryce and Winter (2009) use the number of times a firm has plants in two different sectors (co-occurrence) to analyze the process of intra-firm diversification.

This paper adopts co-occurrence measures to capture the relatedness density between sectors and between technologies in a region. This measure was initially developed by Hidalgo et al. (2007) and applied to exports (Hausmann et al., 2014), industries (Freitas, 2019; Hausmann & Klinger, 2007; He et al., 2015; Neffke et al., 2011) and technologies (Boschma et al., 2015). The main idea behind this method is that a country or region is more likely to have a revealed comparative advantage in products that use similar knowledge and production capacities (Hausmann & Klinger, 2007). More specifically, the relatedness approach is based on co-occurrence analysis, where the proximity between activities is revealed by the probability of their co-occurrence in a country or region (co-location).

Regarding industrial proximity, due to the unavailability of output information by sector at the regional level for Brazil, employment data were used to identify the specialization of sectors in each region, as in Freitas et al. (2024). In this case, Revealed Comparative Advantage (RCA) and Revealed Technology Advantage (RTA) were used to identify the co-occurrence of specialized technologies in a location. Only the labor of tradable industries[4] was taken into account. Labor data was transformed into technology classes to calculate RCA of production in each technology class. In addition, patent data were used to calculate RTA in each technology class. The calculation of these ratios is formalized as follows:

$$RCA_{r,c} = \frac{\frac{emp_{r,c}}{emp_r}}{\frac{emp_c}{emp}} \qquad (1)$$

where: $emp_{r,c}$ is employment in the intermediate region $r$ in the technological class $c$; $emp_r$ is total employment in the intermediate region $r$; $emp_c$ is total employment in the technological class $c$; and $emp$ is total employment in the country.

For patent data, the quotient is calculated as follows:

$$RTA_{r,c} = \frac{\frac{pat_{r,c}}{pat_r}}{\frac{pat_c}{pat}} \qquad (2)$$

several estimations were made in which the correspondences varied. For example, three models were estimated in which 15.40-8 corresponded to divisions 22, 15, and 16. The same was done for the product 20.29-1, which corresponds to both division 19 and 20. Thus, there were no significant changes in the estimated models. The estimates in this study retained the correspondence of 15.40-8 for Division 22 and 20.29-1 for Division 20.

[4] The main reason for this is that the specialization of tradable industries is more likely to reflect the intrinsic endowments and capacities of the location. The industries used for the calculation are the 39 divisions of the CNAE 2.0. The divisions are grouped into sections: A (Agriculture, Livestock, Forestry, Fishing and Aquaculture), B (Extractive Industries), C (Manufacturing), D (Electricity and Gas), E (Water, Sewerage, Waste Management and Decontamination Activities - minus 39, which are decontamination and waste management services) and F (Construction).

where $pat_{r,c}$ is the number of patents in technology class $c$ in region $r$; $pat_r$ is the total number of patents in region $r$; $pat_c$ is the number of patents in technology class $c$; and $pat$ is the total number of patents.

These calculations compare the shares of employment or patents in each technology in the intermediate regions with the share of the same technology in the country. An RCA or an RTA greater than 1 means the region has a higher concentration on the technology class than other regions. Formally:

$$RCA_{r,c} = \begin{cases} 1, & if\ RCA_{r,c} \geq 1 \\ 0, & otherwise \end{cases} \quad (3)$$

$$RTA_{r,c} = \begin{cases} 1, & if\ RTA_{r,c} \geq 1 \\ 0, & otherwise \end{cases} \quad (4)$$

The RCA and RTA calculations calculate the probability that a technology is co-located with another technology. To calculate the relatedness between each pair of technologies in the region, the conditional minimum probability that a region has a specialization in one technology and a co-specialization in another was employed, as in equations (5) and (6). The minimum probability is used to avoid bias due to the prevalence of employment or patents for certain technologies in certain regions, as in Hausmann and Klinger (2007) and Hidalgo et al. (2007). The following equations measure the co-location between two technologies $c$ and $d$ with employment and patent data, respectively:

$$\theta_{c,d} = \min\{P(RCA_{r,c} = 1\ |RCA_{r,d} = 1), P(RCA_{r,c} = 1|RCA_{r,d} = 1)\}, \forall\ c \neq d \quad (5)$$

$$\varphi_{c,d} = \min\{P(RTA_{r,c} = 1\ |RTA_{r,d} = 1), P(RTA_{r,c} = 1|RTA_{r,d} = 1)\}, \forall\ c \neq d \quad (6)$$

where θ is the industrial relatedness and φ is the technological relatedness in each technology class $c$. In this way, two proximity index matrices are obtained based on the analysis of the co-occurrence of technologies $c$ in the intermediate region $r$ for employment and patent data.

The next step is to connect the relatedness to the regional specialization structure of sectors or technologies using the relatedness density indicator. The relatedness density was created by Hausmann and Klinger (2007) and is measured as the degree of proximity between an activity and the industrial and technological structure of the region. For the purposes of this analysis, the relatedness density is defined as the sum of the relatedness connecting a technology $c$ with all other technologies in which the region specializes (with RCA or RTA equal to or greater than 1). If the region has an RCA or an RTA equal to or greater than one in most of the classes related to technology $c$, then the relatedness density will be close to 100, which is considered high. On the other hand, if the region has only a small proportion of classes related to the $c$ technology with an RCA or an RTA equal to one, then the relatedness density will be low, close to 0. Thus, the Industrial Relatedness Density (RD) of the $c$ technology in a $r$ region is calculated as:

$$Industrial\ RD_{c,r} = \frac{\sum_{c\in r, c\neq d} \theta_{c,d}}{\sum_{c\neq d} \theta_{c,d}}\ X\ 100 \quad (7)$$

where $\theta_{c,d}$ is the industrial relatedness $c$ concerning technology $d$ calculated with employment data, moreover, the Technological Relatedness Density (RD) of the technology $c$ in a $r$ region is calculated as:

$$Technological\ RD_{c,r} = \frac{\sum_{c\in r, c\neq d} \varphi_{c,d}}{\sum_{c\neq d} \varphi_{c,d}}\ X\ 100 \quad (8)$$

where $\varphi_{c,d}$ is the technological relatedness $c$ with respect to technology $d$ calculated with patent data.

### 3.3 Empirical model

In order to understand the relationship between Industrial RD and the technological specialization of each region, entry and exit into technologies were estimated according to the following equations:

$$\begin{aligned} Y_{r,c,t} = \beta_0 + \beta_1 Technological\ RD_{r,c,t-1} + \beta_2 Industrial\ RD_{r,c,t-1} \\ + \beta_3 TCI_{c,t-1} + \beta_4 (Industrial\ RD_{r,c,t-1} * TCI_{c,t-1}) \\ + \beta_5 GDP_{pc_{r,t-1}} + \beta_6 Pop_{r,t-1} + \tau_r + \gamma_c + \pi_t + \epsilon_{r,c,t} \end{aligned} \quad (9)$$

where $Y_{r,c,t}$ represents the three dependent variables used in the estimated models: $RTA_{r,c,t}$, $Entry_{r,c,t}$ and $Exit_{r,c,t}$. $RTA_{r,c,t}$ is the degree of specialization in a given technology $c$ in region $r$ at time $t$. The variable *Entry* is set to 1 if a region $r$ was not specialized in technology class $c$ at time *t-1* ($RTA < 1$) but becomes specialized in $c$ at time $t$ ($RTA \geq 1$). It takes the value 0 if the region $r$ was not specialized at *t-1* and is not specialized at $t$. Thus, this variable only considers the subset of technologies in which the region was not competitive at the time ($RTA < 1$). On the other hand, the variable *Exit* follows the opposite logic. It takes the value 1 if region $r$ was specialized in a technological class $c$ at time *t-1* ($RTA \geq 1$) but has ceased to be so at time $t$ ($RTA < 1$). The value 0 is assigned if the region $r$ was specialized at time $t$ and remains specialized at time $t$. Therefore, for the variable *Exit*, the observations are limited to cases where the region is specialized in the technological class $c$ ($RTA \geq 1$) at time *t-1*. Formally the definitions are as follows:

$$Entry_{r,c,t} = I(c \notin PF(r,t) \cap i \ \in PF(r,t+1) \tag{10}$$

$$Exit_{r,c,t} = I(c \in PF(r,t) \cap i \notin PF(r,t+1) \tag{11}$$

where PF stands for Probability Function.

Rigby (2013), Kogler et al. (2015), Boschma et al. (2015) and Balland et al. (2018) found different probabilities of entry and exit into technology classes depending on their relatedness to the technological classes in which the region is specialized in. Thus, it is expected that the higher the Technological RD, that is, the closer the knowledge of a given technology is to the region's technological knowledge, the higher will be the probability of specialization (entry) in that technology class, and the lower the probability of exit from that technology class in the region.

Industrial $RD_{r,c,t-1}$ is the main variable of interest analyzed in this paper. It is based on Jacobs (1969) and Neffke (2009), which argue that a greater variety of ideas and innovative possibilities are found in places with a more diversified industrial fabric. In addition, studies such as Feldman (1993) and Audretsch and Feldman (1996) have shown that there is an important relationship between the location of innovation production and the geographical concentration of manufacturing industries. But above all, they have observed that related industries are the most important for innovative activities. Thus, local industrial structures are important for the existence of regional knowledge spillovers.

$TCI_{r,c,t-1}$ is the Technology Complexity Index of each technology $c$ at time *t-1*. The starting point for the calculation is the diversification of an economy (the number of technologies in which a region is specialized in) and the ubiquity of technologies (the number of regions specialized in that technology). More diversified regions generally tend to specialize in less ubiquitous technologies, which tend to require a greater variety of resources. These are more complex technologies that tend to be developed in a few economies and that facilitate diversification in the long run[5].

$GDP_{pc_{r,t-1}}$ is the per capita gross domestic product (in constant reais) of the intermediate region $r$ in the year *t-1*. According to Petralia et al. (2017), the level of economic development influences the technological diversification of a place. $Pop_{r,t-1}$ is the population of the intermediate region $r$ in the year *t-1*. Urban characteristics are very relevant to knowledge generation and industrial concentration (Duranton & Puga, 2004). The advantages of urban agglomeration include greater urban diversity in terms of production, facilities, skills, tastes, needs and cultures which generates a spill-over of ideas from one sector to other economic activities located in the same urban area. According to Jacobs, large cities are natural incubators for new businesses and ideas of all kinds. The author stresses that the diversity of sectors within a geographical region promotes knowledge externalities and innovation and economic growth. This justifies using the population variable to measure its potential impact on technological diversification in Brazil.

Finally, the data were organized into a panel of 119 technological classifications (IPC) in the 133 Brazilian intermediate regions for the years 2006 and 2021, covering four periods (2006-2009, 2010-2013, 2014-2017, and 2018-2021), resulting in a panel of 63,308 observations. However, for the estimation of the entry and exit models, the panel is smaller. For the Entry dummy variable, only those technology classes that have the potential to enter the region in the subsequent period are considered. This implies that the RTA must be 0 in the initial periods. As a result, the subsample used for the entry model consists of 36,136 observations. For the Exit dummy variable, the technology classes that could potentially leave the portfolio of intermediate regions in the

[5] More details on how to calculate this variable can be found in Hausmann and Kingler (2007).

following period were considered (RTA ≥ 1), resulting in a subsample of 7,963 observations. Estimates in this study were made using OLS, Probit, and Logit models. Estimates were divided into income groups based on the per capita income of intermediate regions. We considered the average per capita income for the entire period and divided the sample into three groups with similar regions: high-income, with 45 regions; middle-income; and low-income, with 44 regions for each group.

## 4. Results

### 4.1 Descriptive analysis

Figures 1. A, 1.B, 1.C, 1.D and 1.E show that average Industrial RD, Technological RD, RTA, Entry and Exit present similar regional distributions. This indicates that regions with a greater average Industrial RD (which can be interpreted as a measure of industrial cohesion) present also a greater Technological RD (technological cohesion) and a stronger specialization, facing higher entry and lower exit probabilities.

There are differences in diversification potential between the different Brazilian regions. The highest values of Industrial RD, Technological RD, RTA and Entry are concentrated in the south-eastern and southern regions of the country, especially around São Paulo and its metropolitan area, which is a more industrially consolidated part of the country. On the other hand, regions in the Northeast and North offer much more limited opportunities for diversification and a low percentage of specialization and entry in new technology classes. The spatial distribution of innovative activities in Brazil shows profound imbalances, both between regions and within regions, as has already been discussed in various works (Gonçalves & Almeida, 2009; Santos & Mendes, 2023).

In this sense, there is still a high concentration of technological and industrial activities in some regions and locations in Brazil. Moreover, this concentration can perpetuate regional disparities since entry and exit are conditioned by the regions' capabilities. This is driven by path dependence, which means that regions have inputs of technological classes related to their pre-existing stocks of knowledge, and regions with more capabilities have a greater chance of entering new technology classes.

**Figure 1. Average Industrial RD, Technological RD and RTA, entry and exit rates in Brazilian regions between 2006 and 2021**

Source: Authors' elaboration.

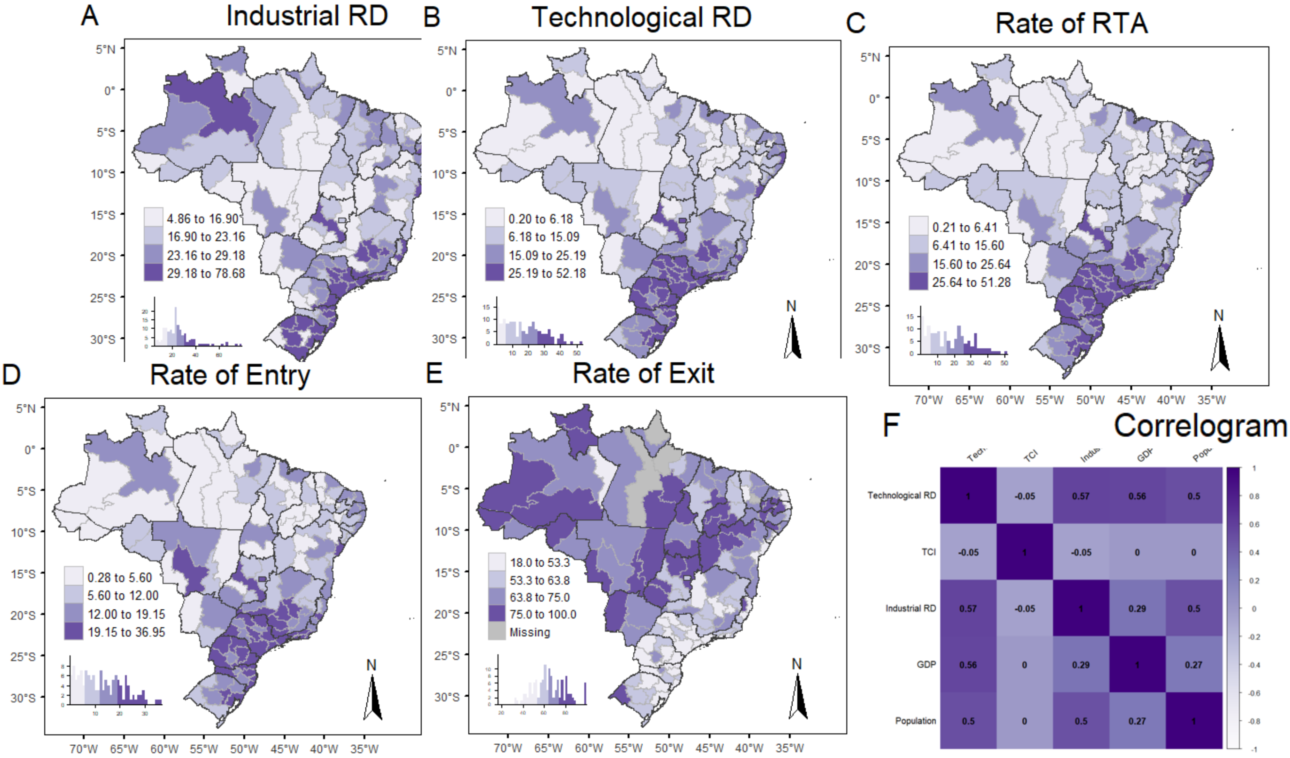
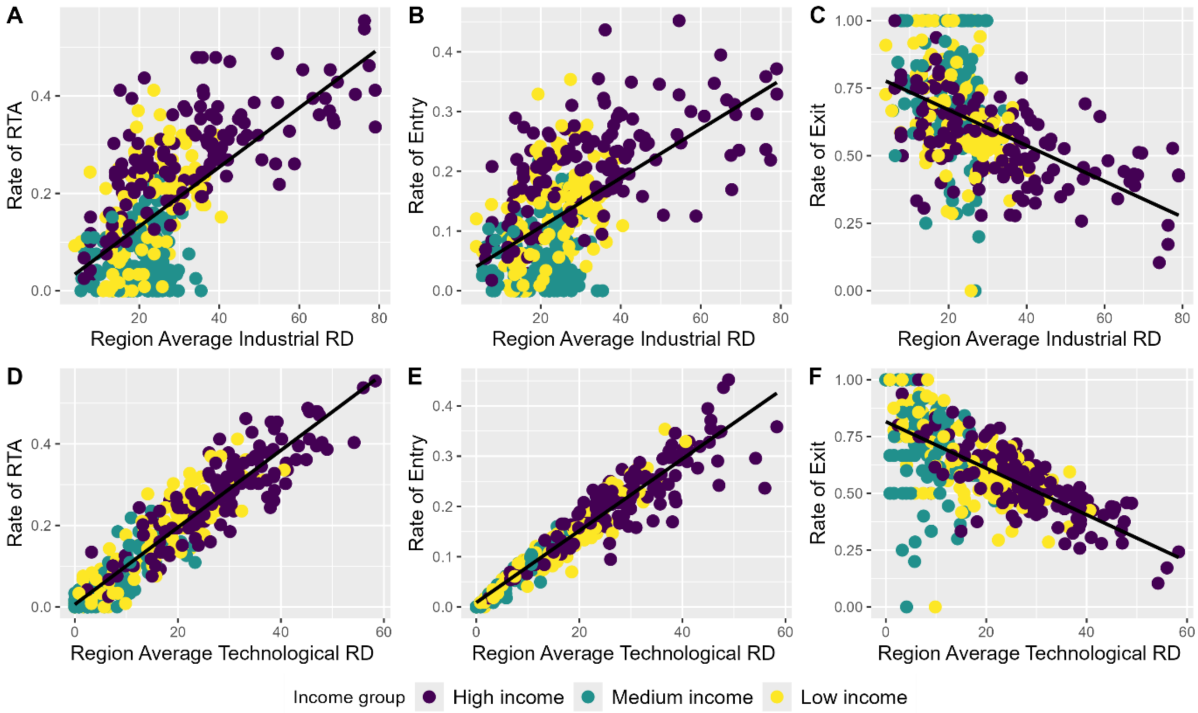


Figure 1.F illustrates the intensity of the correlations between the independent variables used in the models. Mostly, the correlations are positive, indicating a relationship between the variables used in the estimations. The strongest correlations are between Technological RD and Industrial RD (0.57) and Technological RD and GDP per capita (0.56). This result can be explained by the fact that economies and technological classes with more technological knowledge integration also tend to be closer regarding productive knowledge. In addition, regions with higher Technological RD are economies with more advanced technological knowledge, suggesting a tendency towards higher GDP per capita. Finally, it is important to note that no relevant multicollinearity between the independent variables could affect the results found in the estimations.

**Figure 2. Relationship between RTA, entry and exit with the average Industrial RD in Brazilian regions between 2006 and 2021**

Source:




Authors' elaboration.

Following Boschma et al. (2015), Figures 2.D, 2.E, and 2.F show, respectively, the average RTA and the entry and exit rates of the technology classes in the portfolio of the intermediate regions relative to the average Industrial RD in each of them. The color of the dots indicates the income group to which each region belongs. The analyses in Figures 2.A and 2.B show a positive correlation between the RTA and Entry with the regional average Industrial RD. However, at the extremes of Industrial RD within the highest per capita income group, where regions show greater dispersion along the line, indicating a less consistent relationship. On the other hand, for the Exit rates of the technological classes (Figure 2.C), there is a negative relationship with the average Industrial RD of the regions.

### 4.2 Main results

This section presents the results of the estimations described in equation (9). The models were estimated using OLS, Probit, and Logit as in Boschma et al. (2015). It should be noted that the coefficients of the Logit and Probit estimates are not directly comparable with those of the OLS estimates. Still, their signs and significance levels can be compared. All regressions were corrected for heteroscedasticity using robust standard errors. All estimates include fixed effects for region, technology, and period to control for characteristics that may influence technological specialization.

As discussed before, it is expected: (i) a positive coefficient on Industrial RD in the $RTA_{t+1}$ and $Entry_{t+1}$ models (hypothesis 1); (ii) a negative coefficient for Industrial RD in the $Exit_{t+1}$ models (hypothesis 2); (iii) in low-income regions, a positive coefficient for Industrial RD and no significance for Technological RD (hypothesis 3); and (iv) a positive and significant coefficient for the interaction variable between Industrial RD and TCI (hypothesis 4).

The results presented in Table 1 show that technological capabilities, measured by Technological RD, affect the diversification into new technological classes in Brazilian regions, a result already found for the United States by Rigby (2015) and Boschma et al. (2015), and for European regions by Balland et al. (2018). The direction of the effects of all variables is consistent in all specifications, with only TCI losing significance in model (III).

Most importantly, the results reported in Table 1 indicate that Industrial RD is positively associated with technological diversification in Brazilian regions. As found by Aarstad et al. (2016), Tavassoli and Carbonara (2014) and Mascarini at al. (2023), regions with a more related industrial variety are more likely to exploit, recombine and transform the knowledge of these related sectors, thus promoting greater regional innovation. However, our results show this relationship at a more disaggregated level. In this way, we found that technological classes that relate to the region's industrial portfolio are more likely to specialize in that technology in the region. Moreover, as expected, the coefficient for Industrial RD is lower than the coefficient for Technological RD. This means that the latter has a stronger influence on the specialization into new technology classes because it involves the same type of knowledge and skills.

In addition, estimations IV and V showed that technology complexity is negatively related to specialization in these technologies. This demonstrates that the more complex the technology class, the more difficult it is for regions to specialize in them. This was also found by Balland et al. (2018). According to the authors, this is called the ’diversification dilemma’ because complex knowledge, although necessary for development, is more challenging to develop. And often, technologies related to regional capabilities have a lower level of complexity. However, the interaction between the Industrial RD and technology complexity presents a positive and significant coefficient in all estimates. This shows that even if a technology is more difficult to master, the probability of specialization in it increases if it is related to the industrial capabilities of the region.

**Table 1: Determinants of technological diversification in Brazilian regions**

| | *Dependent variable:* $RTA_t$ | | | | |
|---|---|---|---|---|---|
| | *OLS* | | | *Probit* | *Logit* |
| | (I) | (II) | (III) | (IV) | (V) |
| Technological $RD_{t-1}$ | 0.010*** | 0.010*** | 0.010*** | 0.035*** | 0.063*** |
| | (0.0005) | (0.0006) | (0.0006) | (0.0020) | (0.0035) |
| Industrial $RD_{t-1}$ | | 0.003*** | 0.003*** | 0.013*** | 0.023*** |
| | | (0.0003) | (0.0003) | (0.0012) | (0.0021) |
| $TCI_{t-1}$ | | | -0.004 | -0.080*** | -0.168*** |
| | | | (0.0044) | (0.0250) | (0.0454) |
| Industrial $RD_{t-1}$ * $TCI_{t-1}$ | | | 0.0002*** | 0.004*** | 0.008*** |
| | | | (0.0001) | (0.0005) | (0.0009) |
| $GDPpc_{t-1}$ (log) | | | 0.0606*** | 0.464*** | 0.883*** |
| | | | (0.0192) | (0.1050) | (0.194) |
| $Population_{t-1}$ (log) | | | -0.018 | -0.120 | -0.302 |
| | | | (0.0667) | (0.4150) | (0.775) |
| Constant | 0.304*** | 0.235*** | -0.0916 | -3.689 | -5.934 |
| | (0.0307) | (0.0314) | (0.9920) | (6.092) | (11.38) |
| Observations | 47,481 | 47,481 | 47,481 | 46,053 | 46,053 |
| $R^2$ | 0.17 | 0.17 | 0.170 | | |
| Wald $chi^2$ | | | | 6988.14 | 6403.68 |
| Pseudo $R^2$ | | | | 0.20 | 0.20 |

Source: Authors’ elaboration.

Note: Robust standard errors in parentheses. $*p < 0.1$; $**p < 0.05$; $***p < 0.01$. All regressions include region, period and technological class fixed effects.

Table 2 shows that the probability of entry is increased when the technology class is related to local technological and industrial capabilities. Moreover, the probability of exit is decreased for technological classes related to the technological and industrial competences of the region. The values enclosed in square brackets illustrate the impact of industrial and technological relatedness density on the probability of entry and exit through the average marginal effects. An increase of 10 in Technological RD increases in 20% the probability of entry, while an increase of 10 in Industrial RD increases this probability in only 1%. Conversely, an increase of 10 in Technological RD reduces in 43% the probability of exit, while a similar increase in Industrial RD reduces this probability in 3%. In addition, the probability of entry decreases with the level of complexity of the technology class. However, even if the technology is more complex, when it is related to local industries, it shows a positive sign for the entry. The region's per capita income also has positive and negative relationships with technology entry and exit, respectively, as Balland & Boschma (2021) found.

**Table 2: Determinants of entry and exit into new technological classes in Brazilian regions**

| | *Dependent variable:* | | | | | |
|---|---|---|---|---|---|---|
| | $Entry_t$ | | | $Exit_t$ | | |
| Technological $RD_{t-1}$ | 0.259*** | 0.257*** | 0.254*** | -0.240*** | -0.240*** | -0.245*** |
| | (0.0058) | (0.0058) | (0.0059) | (0.0076) | (0.0075) | (0.0078) |
| | [0.020] | [0.020] | [0.020] | [-0.042] | [-0.042] | [-0.043] |
| Industrial $RD_{t-1}$ | | 0.015*** | 0.013*** | | -0.016*** | -0.017*** |
| | | (0.0029) | (0.0029) | | (0.0042) | (0.0042) |
| | | [0.001] | [0.001] | | [-0.003] | [-0.003] |
| $TCI_{t-1}$ | | | -0.339*** | | | 0.122 |
| | | | (0.0610) | | | (0.0995) |
| | | | [-.027] | | | [0.021] |
| Industrial $RD_{t-1}$ * $TCI_{t-1}$ | | | 0.013*** | | | -0.006*** |
| | | | (0.0014) | | | (0.0018) |
| | | | [0.001] | | | [-0.001] |
| $GDPpc_{t-1}$ (log) | | | 1.391*** | | | -1.728*** |
| | | | (0.303) | | | (0.436) |
| | | | [0.110] | | | [-0.302] |
| $Population_{t-1}$ (log) | | | 0.072 | | | 3.079* |
| | | | (1.105) | | | (1.727) |
| | | | [0.006] | | | [0.537] |
| Constant | -4.319*** | -4.606*** | -19.04 | 2.695*** | 3.048*** | -22.14 |
| | (0.319) | (0.321) | (16.55) | (0.445) | (0.459) | (25.65) |
| Observations | 39,624 | 39,624 | 39,624 | 7,844 | 7,844 | 7,844 |
| Wald chi² | 5581.54 | 5598.46 | 5558.94 | 1791.65 | 1807.94 | 1809.92 |
| Pseudo R² | 0.26 | 0.26 | 0.26 | 0.23 | 0.24 | 0.24 |

Source: Authors' elaboration.

Note: Robust standard errors in parentheses. $*p < 0.1$; $**p < 0.05$; $***p < 0.01$. All regressions include region, period and technological class fixed effects. The values in square brackets [ ] represent the average marginal effects.

### 4.3 Differences between regions

Table 3 shows the regression results for technological specialization by dividing the regions into low, medium, and high per capita income groups. As we move from high-income regions towards lower-income regions, the coefficient of Technological RD loses strength in the diversification dynamics of technology classes. Technological RD is no longer significant in regions with low per capita income. This result indicates that in low-income regions, the skills, knowledge, and technological capabilities are so weak that they have very limited relevance for entering new technology classes.

Most importantly, the results presented in Table 3 indicate that Industrial RD presents similar relevance for technological diversification across all income groups. In addition, as Technological RD loses relevance in lower-income regions, Industrial RD becomes relatively more important for technological diversification in these regions. In low-income areas, Industrial RD is the only significant variable in the model, indicating the importance of industrial diversification at early stages of development for initiating technological development. According to Bell and Pavitt (1993), in the early stages of the industrialization process, a region's technological diversification is strongly influenced by local market incentive mechanisms related to the production system, such as scarce (or abundant) factors of production and local investment opportunities. At a higher level of development, the local accumulation of specific technological capabilities itself becomes a driver of technological change.

Finally, a negative association between technology complexity and technological specialization is found in high-income regions, as observed in the previous analyses. According to Balland et al. (2018), these two variables have a nonlinear relationship and may be region-specific. At the same time, the likelihood of specialization is higher when the technologies, although complex, maintain links with the local industrial structure, as indicated by the positive and significant coefficient of the interaction term. Nonetheless, this effect is very small. Contrary to what was expected, however, these variables are not significant for low-income regions, while only the interaction is significant in the middle-income areas.

**Table 3: Determinants of technological diversification in Brazilian regions divided by income**

| | Dependent variable: $RTA_t$ | | | | | |
|---|---|---|---|---|---|---|
| | Logit | | | | | |
| | | *High income* | | *Medium income* | | *Low income* |
| | (I) | (II) | (III) | (IV) | (V) | (VI) |
| Technological $RD_{t-1}$ | 0.068*** | 0.071*** | 0.049*** | 0.051*** | -0.002 | 0.002 |
| | (0.0044) | (0.0045) | (0.0068) | (0.0069) | (0.0120) | (0.0120) |
| Industrial $RD_{t-1}$ | 0.024*** | 0.025*** | 0.021*** | 0.022*** | 0.016* | 0.019** |
| | (0.0029) | (0.0029) | (0.0042) | (0.0043) | (0.0088) | (0.0092) |
| $TCI_{t-1}$ | | -0.122* | | 0.030 | | 0.102 |
| | | (0.0630) | | (0.0890) | | (0.1520) |
| Industrial $RD_{t-1}$ * $TCI_{t-1}$ | | 0.003** | | 0.004* | | 0.005 |
| | | (0.00117) | | (0.0025) | | (0.0049) |
| $GDPpc_{t-1}$ (log) | | 1.184*** | | 0.163 | | -0.040 |
| | | (0.2230) | | (0.4480) | | (0.8670) |
| $Population_{t-1}$ (log) | | -0.786 | | 1.613 | | -1.084 |
| | | (1.1830) | | (1.3510) | | (2.4110) |
| Constant | -2.741*** | -3.176 | -1.149*** | -24.67 | -2.432*** | 11.56 |
| | (0.2910) | (18.01) | (0.3150) | (20.84) | (0.5340) | (32.75) |
| Observations | 16,065 | 16,065 | 14,994 | 14,994 | 13,608 | 13,608 |
| Wald chi² | 1883.19 | 1882.73 | 1858.82 | 1881.97 | 1398.10 | 1423.02 |
| Pseudo R² | 0.12 | 0.12 | 0.18 | 0.18 | 0.25 | 0.25 |

Source: Authors' elaboration.

Note: Robust standard errors in parentheses. $*p < 0.1$; $**p < 0.05$; $***p < 0.01$. All regressions include region, period and technological class fixed effects.

### 4.4 Differences between applicants

Table 4 examines the determinants of technological diversification for patents held by legal entities, distinguishing between universities/public research institutes (PRIs) and firms. In Brazil, academic institutions account for a large share of domestic patents, yet the coefficients for Industrial

RD and Technological RD are higher for firms than for universities and PRIs. Although universities play a central role as "antennas" for science and technology, there is often a mismatch between new developments and industrial capabilities (Suzigan; Rapini; Albuquerque, 2011; Kruss et al., 2015).

This disconnection between scientific institutions and the productive sector is a structural challenge in many developing economies, compounded by limited coordination and low industrial demand for innovation (Crane, 1977). Firms frequently opt to acquire foreign technology instead of investing in local R&D, which discourages tailored domestic solutions (Chaves et al., 2016). As a result, academic knowledge often fails to transform into practical applications, reinforcing dependence on imported technologies and weakening the potential for self-sustaining technological progress.

Further, Póvoa and Rapini (2010) show that patents remain underutilized by Brazilian universities and PRIs, which rely more on publications, consulting, and informal knowledge exchanges to transfer technology. Bekkers and Freitas (2008) note that collaborations, researcher mobility, and joint R&D projects typically matter more than patents in disseminating university-generated knowledge. Similarly, Lee (2000) finds that, in the United States, industry-university partnerships depend more on shared expertise and collaborative research than on direct patent-driven innovation.

Brazil has created "islands of excellence" in sectors such as health (Fiocruz), agriculture (Embrapa), energy (CENPES), and aerospace (Embraer), yet these institutions remain largely disconnected from other economic segments (Mazzucato; Penna, 2016; Cassiolato, 2015). Suzigan et al. (2006) emphasize how the country's productive structure has both influenced and constrained technological development in specific industries. These findings underscore the need for more systemic innovation policies that integrate university research with industrial demands, strengthen technology transfer offices, and foster a stronger culture of innovation for long-term economic development.

**Table 4: Determinants of technological diversification in Brazilian regions divided by distinct patent applicants**

| | *Dependent variable:* $RTA_t$ | | | |
|---|---|---|---|---|
| | *Firms* | | *Universities* | |
| Technological $RD_{t-1}$ | 0.0693*** | 0.0659*** | 0.0312*** | 0.0309*** |
| | (0.00424) | (0.00433) | (0.00344) | (0.00346) |
| Industrial $RD_{t-1}$ | 0.0283*** | 0.0289*** | 0.0103*** | 0.0115*** |
| | (0.00258) | (0.00258) | (0.00370) | (0.00373) |
| $TCI_{t-1}$ | | -0.310*** | | -0.203*** |
| | | (0.0523) | | (0.0757) |
| Industrial $RD_{t-1}$ * $TCI_{t-1}$ | | 0.0109*** | | 0.00613*** |
| | | (0.00108) | | (0.00161) |
| $GDPpc_{t-1}$ (log) | | 0.708*** | | 1.357*** |
| | | (0.274) | | (0.383) |
| $Population_{t-1}$ (log) | | -0.754 | | -0.250 |
| | | (1.150) | | (1.609) |
| Constant | -2.731*** | 1.870 | -3.205*** | -12.78 |
| | (0.299) | (18.55) | (0.477) | (25.45) |
| Observations | 42,600 | 42,600 | 22,365 | 22,365 |
| Wald chi² | 5328.89*** | 5182.26*** | 2941.02*** | 2974.52*** |
| Pseudo R² | 0.26 | 0.27 | 0.28 | 0.28 |

Source: Authors' elaboration.

Note: Robust standard errors in parentheses. $*p < 0.1$; $**p < 0.05$; $***p < 0.01$. All regressions include region, period and technological class fixed effects.

### 4.5 Discussion

Figure 3 illustrates the trajectory of technological cohesion associated with the productive and technological structures of Brazilian intermediate regions between 2006 and 2021. Technological classes in the portfolio are those in which the region has specialization (RTA>1). Likewise, the entry and exit classes are those in which the region gains or loses specialization from one period to the next. A regional structure is considered cohesive if its average density is higher than that of the technologies that are not part of it, as defined by Neffke et al. (2011) and Freitas et al. (2024).

As Figure 3 shows, regions maintain their cohesion regarding the connection between technological classes and the productive and technological structures over the period analyzed. However, there are disparities in the entry and exit of technological classes in terms of average industrial and technological density, as well as according to the region's per capita income level. As shown in Figure 3, a few processes are taking place in the regions, most of which are characterized by the strengthening of technological and industrial cohesion. Firstly, classes entering the regions always have a higher density than the non-portfolio classes, indicating a greater cohesion between the new technologies and the existing structure in the region.

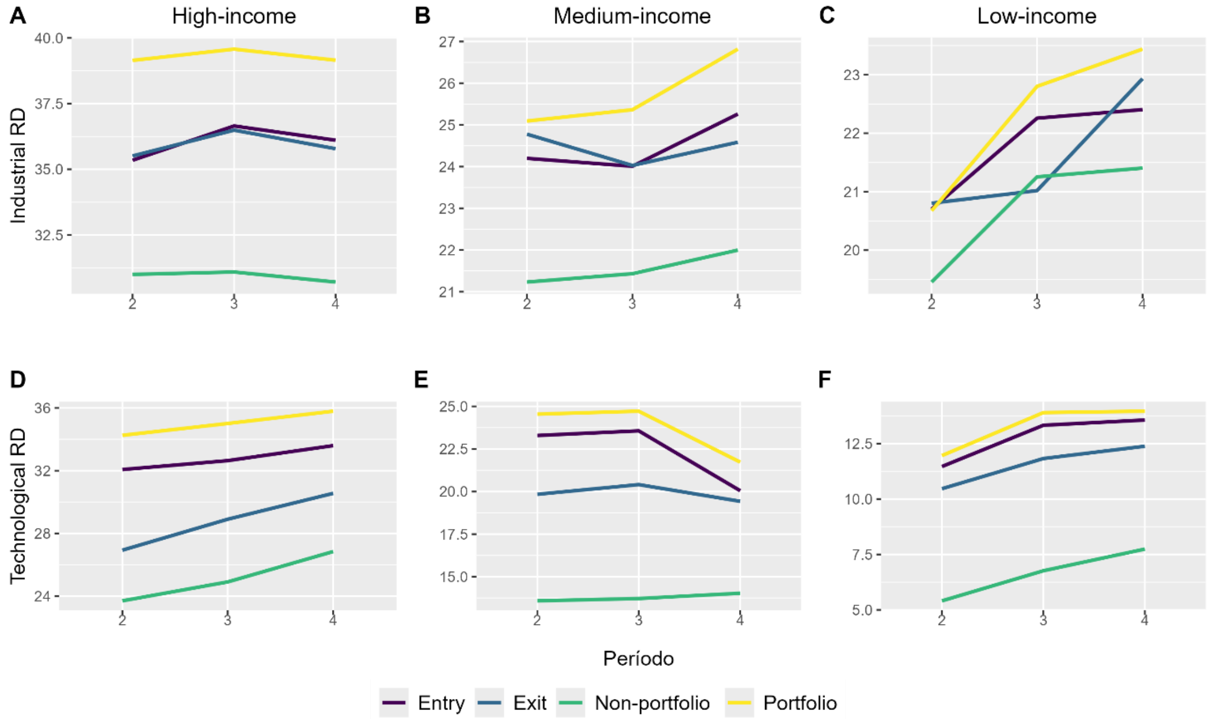
However, the average density of the classes entering the regions remains lower than the portfolio average, which reduces the cohesion of the regional structure, all else equal. Secondly, the average density of the classes leaving the region is higher than the average of the non-portfolio classes, indicating that the classes previously integrated into the industrial and technological structure of the regions were not completely dissociated from other local activities. Yet, the average density of the exiting classes remains consistently below the average density of the region's portfolio classes. This indicates that although these exiting classes were not completely unrelated to other local activities, their average position within the region's industrial and technological structure was less cohesive. These processes are observed in both industrial and technological density.

One relevant difference between industrial and technological densities deserves attention. In terms of technological density (Figures 3.D, 3.E and 3.F), the average density of the technological classes that entered the regions remains consistently higher than the line representing the classes that left the portfolio, which strengthens the region's technological cohesion. This is observed in regions with high, medium and low per capita income. Nonetheless, in terms of industrial density (Figures 3.A, 3.B, and 3.C), in some periods, the technological classes that leave the region have a higher density than those that enter, which can negatively affect industrial cohesion in terms of technological classes. In addition, for regions with low per capita income (Figure 3.C), there are sharp oscillations in the average industrial density for the non-portfolio classes. At one point, the non-portfolio classes reached an average industrial density higher than the average of the existing classes. This result suggests that the evolution of technological classes in low-income regions may face challenges in maintaining industrial cohesion through technological diversification.

To illustrate the results found in this paper, it is interesting to look at some examples of alternative development trajectories. Two interesting cases are the regions of Teresina, a low-income region in the state of Piauí, in the northeast of Brazil, and Sorocaba, a high-income region in the southeast.

Teresina has stood out in the period analyzed, with an increase in patents in the technological classifications of Human Needs (A), Processing Operations and Transportation (B), Chemistry and Metallurgy (C). The region has developed economically in the food industry sector, with an increase in patents specialized in this field in technological classes A21 (Oven baking; equipment for preparing or processing pasta; pasta for oven baking) and A23 (Food or food products; treatment thereof, not covered by other classes). The Chemistry and Metallurgy section also stands out due to the importance of metallurgy in the region. In addition, since 2015, some patents have been filed in technological class C10 (Oil, gas or coke industry; technical gases containing carbon monoxide; fuels; lubricants; peat), due to the prospects of investments in the oil and natural gas exploration segment in the state of Piauí (Filho, 2018).

**Figure 3. Industrial and Technological structural change in Brazilian regions between 2006 and 2021**




Source: Authors' elaboration.

The economy of the Sorocaba is mainly focused on manufacturing, agriculture and construction and appears to be well diversified. Among the main sectors employing people are: agriculture, animal husbandry and related services; food production; manufacture of motor vehicles, trailers and bodies; and manufacture of clothing and accessories. The metallurgy sector has been growing in recent years and is also one of the largest employers in the region.

As in the case of employment, the patent fields in which the region was competitive throughout the period under study are very diverse, covering different technological classifications in the areas of human needs (A), processing and transport operations (B) and physics (G). However, the region began to diversify and acquire competitiveness in chemistry and metallurgy (C), more specifically in the classes of organic macromolecular compounds; sugar industry; skins, hides, pelts or leather; metallurgy of iron; and electrolytic or electrophoretic processes. Therefore, we can see that most of the new technological classes are related to areas in which the region is already competitive, such as the clothing industry, agriculture and food products, and metallurgy.

## 5. Concluding remarks

The process of knowledge absorption and spillover was seen as a spatial phenomenon. For this reason, regional economies were viewed as components of an evolutionary dynamic that changed according to their trajectory and evolved through the slow recombination of their local resources. Cities and locations with a diverse range of industries and viewpoints are crucial, according to Jacobs (1969), because higher levels of knowledge heterogeneity in an area can foster learning and technological externalities between agents. Due to the knowledge base that promotes idea exchange and cross-fertilization and the creation of new knowledge in various industries that complement one another in some way, a place's industrial diversification creates an environment conducive to innovation.

Numerous studies demonstrate the existence of various regional capabilities that are crucial to the process of diversification. Studies like these show how technological capabilities affect technological diversification, whereas other studies stress how industrial capabilities affect regional industrial diversification. However, there is a notable gap in the literature in investigating the impact of industrial relatedness density on technological diversification at the level of technological classes.

In order to examine the relationship between the density of industrial relations and the diversification, entry, or exit of technological classes in 133 intermediate regions between 2006 and 2021, MQO, Probit, and Logit models were estimated. The study's conclusion highlights the significance of the connection between the industrial relatedness density in Brazilian regions and technology diversification. Furthermore, we find that a region's chances of entry and diversification are reduced by technological complexity. However, the probability of diversification increases when technologies are related to the local industrial system despite their complexity. We also find that technological relatedness does not affect technology diversification in areas with lower per capita income, but industrial relatedness has a positive relationship. In addition, the density of industrial relationships is more important for technological diversification with patents from company applicants than from university applicants.

In this sense, there are important implications for public policy. Path dependency suggests that regions will keep diversifying into technologies associated with production and technological knowledge. Still, diversification into increasingly sophisticated technologies is a complex process that must be consistent with the region's industrial structure, particularly about real-world implementation. This is especially crucial for less developed areas, where there is no minimum technological knowledge to influence technological diversification.

Therefore, it is important to understand the dynamics of the local production system by identifying dynamic sectors and existing linkages. This research emphasizes the link between technological diversification and the functioning of the regional production system. Nonetheless, funding must go toward innovations that not only address the demands of the productive sector but also further a broader and more profound advancement in the field of technology, thereby fostering a notable transformation of the region's industrial and productive environment.

Finally, we believe it is critical to continue discussing the diversification of Brazilian regions and their relationship with the productive and technological systems. The compatibility of industrial sectors and technological classes is a limitation of this research, but given the data sources available in Brazil, we believe this approach is the most appropriate. For future research, we recommend investigating the impact of specialization in specific sectors in certain regions and its effects on technological class diversification.

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