The Role of Technological Relatedness in Shaping Industrial Diversification in Brazil

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Abstract

This study analyses the influence of technological knowledge on industrial diversification in 133 Brazilian intermediate regions from 2006 to 2021. The analysis shows that industrial knowledge has a stronger impact on the sectoral specialisation of regions than technological knowledge. Technological relatedness seems to be more relevant for radical innovations, which have a greater potential to change technological trajectories and industrial dynamics, than for incremental innovations. Firms' patents have a stronger effect on regional specialisation than university patents. In low-income regions, technological knowledge has a limited impact, highlighting the need for policies that promote the creation and diffusion of technological knowledge to foster industrial diversification.

Keywords: Industrial diversification; Brazilian regions; Technological Relatedness; Industrial Relatedness.

Área temática: 1. Economia

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1. Introduction

The process of regional diversification and changes in the productive structures of regions has been an important research agenda. It is known that when firms expand, they move into industries related to their current activities (Penrose, 1959; Teece et al. 1994; Breschi et al., 2003). More recent studies on diversification have found that the building of productive capacity depends on the pre-existing knowledge and industrial skills in the region (Neffke et al., 2011; Boschma et al., 2013; Freitas et al., 2024).

However, other types of capabilities play an important role in industrial dynamics, such as technological knowledge (Lall, 2000). Several studies show that knowledge accumulation and technological change play an important role in industrial dynamics and consequently in economic growth (Schumpeter, 1939; Freeman; Soete, 1977; Rosenberg, 1982; Dosi, 1984; Soete, 1985; Freeman and Louça, 2001). According to Dosi and Nelson (2010), industrial dynamism and economic growth are interrelated processes driven by technological and organizational innovations. Innovations are therefore capable of shaping firms' productivity as well as their growth rates and survival behavior (Dosi 1988; Klepper and Thompson 2006; Audretsch, 1991; Quatraro, 2010).

Schumpeter (1939) pointed out that the generation of innovations fuels a process of "creative destruction". New knowledge and technologies not only create new products and industries, but also disrupt existing ones, potentially leading to the disappearance of firms and even entire industries that fail to adapt or innovate (Schumpeter, 1939; Gort and Klepper, 1982; Nelson and Winter, 1982).

In this sense, the industrial structures of regions tend to be cohesive, not only in terms of industrial knowledge, but also in terms of technological knowledge. Studies of industries show that many firms exploit regional competencies that they have previously acquired in technologically related industries (Klepper, 2007; Boschma and Wenting, 2007; Buenstorf and Klepper, 2009). Therefore, the development of technological capabilities is essential for the further development of the industrial structure.

Drawing upon the regional innovation systems approach, the regional innovation process is the result of the interaction of a number of different but complementary institutions involved in innovation activities, such as firms, universities, R&D laboratories and the like (Cooke et al., 1997, Antonelli, 2008). Therefore, each organization has its own importance and role in the innovative development of regions and, consequently, in industrial diversification. However, while universities are important sources of scientific knowledge, their patent research is less focused on commercial results and they face challenges in transferring this knowledge to industry (Cohen et al., 2000; Fabrizio, 2007).

Moreover, the impact of technologies on industry growth and diversification depends on the characteristics of the innovations, which can be classified as radical (high-level innovation) or incremental (low-level innovation). Radical innovations introduce new technological paths and change the status quo, while incremental innovations improve the efficiency of existing technologies without overturning current ones (Schumpeter, 1939; Dosi, 1982; Fagerberg et al., 2010).

However, the relationship between technological and industrial capabilities depends on the level of development of the country or region in which they are located. Many countries and regions with a low level of development face difficulties in improving their technological capabilities. This is due to the difficulty of acquiring knowledge, as well as the complexity of breaking with the existing industrial structure and moving towards new advanced industries (Martin, 2010).

Therefore, it is important to analyze the influence of technological knowledge on industrial diversification in the regions. In addition, it is important to differentiate technological knowledge based on the institutions that apply for patents, as well as different types of patents and income levels in the regions. No other studies were found that perform this type of analysis for Brazilian regions. Eum and Lee (2022), on the other hand, conducted a study to analyze how countries diversify in terms of technologies and products based on the relationship with the productive and technological knowledge of these places. The authors found that in the early stages of development, production experience based on factor endowments influences the accumulation of technological knowledge, while in the later stages, technological knowledge acts as a source of productive knowledge.

Nesse sentido, este artigo tem como objetivo avaliar se a diversificação em novos setores é mais provável em regiões cujo portfólio regional inclui tecnologias relacionadas a esses sectors. In addition, they differentiated the estimates between the filing institutions, the types of patents and the per capita income of the regions. The density of relationships 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). Technological classes were linked to industry sectors using the algorithmic link with probabilities (ALP) proposed by Lybbert and Zolas (2014). Employment and patent data from 133 Brazilian intermediate regions were used to measure the density of industrial and technological linkages for each sector in the region, covering the period from 2006 to 2021.

The rest of the document is structured as follows: Section 2 offers a summary of pertinent literature, emphasizing noteworthy and comparable contributions. Section 3 outlines the metrics utilized, the dataset, and the econometric models employed. Section 4 delivers the results of the econometric tests, with section 5 offering concluding remarks.

2. Literature Review

2.1 Path-dependence, related diversification and technological dynamics

When planning their diversification strategies, firms generally tend to expand into products or markets related to their competencies. According to Nelson & Winter (1982), this tendency is explained by the complex nature of diversification within the firm, which involves many uncertainties and costs. When entering new markets and technologies, firms face significant uncertainties that lead them to seek a less risky path. This strategy is also observed by Penrose (1959). According to this view, firms expand into products that are technologically related to their current products, thereby minimizing risk and exploiting knowledge already acquired. Teece et al. (1994) reinforce this idea by examining the coherence of knowledge within firms. The authors show that technological diversification is closely related to the firm's existing knowledge base, suggesting that expansion tends to follow a natural path, taking advantage of the skills already developed.

In short, when firms diversify their activities, they generally choose to explore adjacent areas where they can apply their previous knowledge and experience, thereby minimizing risks and increasing the chances of success. This strategy is supported by several authors, such as Nelson and Winter (1982), Penrose (1959), and Teece et al. (1994), who demonstrate the importance of the firm's existing knowledge base in the diversification process.

Recently, several studies have tried to understand how regions and countries diversify their industries. They have found that, in general, regions diversify into sectors that are related to the region's portfolio of industrial capabilities (Frenken et al., 2007; Neffke et al., 2011; Essletzbichler, 2015; Françoso et al., 2022; Queiroz et al., 2024).

Neffke et al. (2011) analyzed the entry, retention, and exit of firms based on the proximity of regions' production structures to sectors. The estimates were made for 70 Swedish regions and covered the period from 1969 to 1994. To calculate the relatedness density, he uses the occurrence of products from different industries in portfolios of manufacturing plants. The results indicate that industries that are technologically related to existing industries are more likely to enter and persist in the regional portfolio, while those on the technological periphery are more likely to leave.

Essletzbichler (2015) examined the evolution of industries in 360 U.S. metropolitan areas between 1977 and 1997. A new measure of relatedness was developed, measured by the intensity of input and product linkages across industries and also weighted by employment. The authors find that technological relatedness is positively associated with entry into a metropolitan area's industrial portfolio, and negatively associated with exit from an industry.

For Brazil, Françoso et al. (2023), Freitas et al. (2024), and Queiroz et al. (2024) have developed work in this direction. Françoso et al. (2023) found that sectors and technologies that require capabilities similar to those in the regional portfolio are more likely to enter the region. These analyses were conducted for the Brazilian mesoregions between 2006 and 2019. Freitas et al. (2024) analyzed the evolution of sector entry, exit, and retention in the mesoregions between 2006 and 2016. However, they include other variables in the calculation of industrial relatedness, using proximity in terms of the same occupations, location, and firm operating industrial plants in two different sectors. Queiroz et al. (2024) also analyze the evolution of the entry, exit and maintenance of sectors in micro-regions between 2009 and 2019, but with a focus on examining the differences between more and less complex regions.

However, Freitas et al. (2024) and Queiroz et al. (2024) present studies in which the perspectives for analyzing the relationship are focused only on sectors and not on the proximity of technological knowledge in the region. Françoso et al. (2023) analyze the influence of technological relationships on the entry of new technologies, not on the entry of new sectors, which is the focus of this study.

Neffke et al. (2011) come closer to the perspective of technological relatedness by examining the occurrence of products from different industries in manufacturing plant portfolios. However, the approach in terms of patents and technological knowledge itself is still lacking.

Therefore, one of the advances of this work is to include the relationship with the technological knowledge of the region as an important factor for the specialization in sectors in the regions. Nelson and Winter (1982), Penrose (1959) and Teece et al. (1994) have already identified the importance of technological knowledge in the diversification of firms. Several studies point out that there is a significant difference between production capacity and technological capacity and that it is necessary to distinguish between the two different types of knowledge (Lall, 2000; Lundvall and Johnson, 1994; Bell and Pavitt, 1993).

This is also important for the path-dependency process. Just as the industrial portfolio is important for the future industrial specialization of the region, the technological knowledge of the location is also an influencing factor.

> One of the most exciting ideas in contemporary economic geography is that industrial history is literally embodied in the present. That is, choices made in the past—technologies embodied in machinery and product design, firm assets gained as patents or specific competencies, or labour skills acquired through learning — influence subsequent choices of method, designs, and practices. This is usually called ‘path dependence’. […] It does not mean a rigid sequence determined by technology and the past, but a road map in which an established direction leads more easily one way than another—and wholesale reversals are difficult. (WALKER, 2000, p. 126).

In this sense, past choices, such as patents obtained, skills developed, or technologies adopted, have a direct impact on the options available to firms and the choices they make. If a firm has developed a particular technology, it is likely to shape and influence the productive growth of that firm and the region in which it is located (WALKER, 2000). According to Bell and Pavitt (1993), diversification paths in earlier industrialization often depended heavily on prior experience, which included both the creation and use of technology.

The relationship between technological change and the dynamics of industrial evolution is an old and central issue in industrial and innovation economics (Malerba et al., 2016). Schumpeter (1939) was the first to treat technological change as a disturbance of equilibrium. For the author, innovation was the lifeblood of capitalism, but his "storms of creative destruction" were also seen as bringing down existing firms and even entire industries as new entrepreneurial visions took root. This is because technological change generates greater economic competitiveness by increasing productivity and changing the mix of products, industries, firms, and jobs that make up an economy. In this sense, it promotes structural change in the economy (Malecki, 1997). According to Bell and Pavitt (1993), many factors must be considered in any explanation of differences in the dynamic performance of firms and countries. However, somehow these explanations are always associated with considerable differences in the underlying patterns of technological accumulation (Bell, Pavitt, 1993).

Innovation and technology play a key role in the evolution of industries and are essential for successful industrial transformation. Thus, technological change is the driving force behind this transformation, as shown by various works that have analyzed the evolution and transformation of industries over time (Freeman; Soete, 1977; Rosenberg, 1982; Dosi, 1984; Soete, 1985; Freeman and Louça, 2001).

However, not all patent efforts are the same. An important differentiating factor is whether patent applications are filed by public or private institutions. From the perspective of regional innovation systems, the innovation process in a region results from the interaction of different institutions engaged in innovation activities, such as firms, universities, research and development laboratories, among others (Cooke et al., 1997; Antonelli, 2008). Thus, each organization plays a crucial role in the innovative progress of regions and, by extension, in industrial diversification. However, each institution has different results in the way new knowledge is generated and disseminated in regions (Asheim et al., 2019). With regard to universities, they have always been an essential source of knowledge and scientific and technological progress, developing tools and methodologies that are adopted by researchers in industry (Cohen et al., 2000). Nevertheless, patent research at universities and public research centers is less dependent on the guarantee of a commercial outcome, allowing researchers more cognitive freedom and leading to more basic types of research. In addition, they may find it more difficult to transfer this knowledge to industry due to restrictions on use, inhibition of disclosure, and time-consuming negotiations (Fabrizio, 2007).

Furthermore, the impact of technologies on promoting growth and diversification is linked to the characteristics of innovations. Historically, many studies have been devoted to classifying and distinguishing radical technologies from incremental innovations (Sahal, 1981; Dosi, 1982; Nelson & Winter, 1982). Radical or high level innovations, often recognized for their high degree of novelty and originality, are characterized by profound impacts on future development by introducing new fields of study, making dominant technologies obsolete, and changing the status quo. These innovations can establish new technological trajectories through the creation of new artifacts or technological approaches. On the other hand, incremental or lower-level innovations, which are less novel and unique, are seen as adaptations or refinements of existing innovations. They improve the efficiency and capabilities of current technologies without necessarily displacing competitors or inspiring new areas of research, thus maintaining the established technological landscape (Schumpeter, 1939; Dosi, 1982; Fagerberg et al., 2010). Mascarini et al. (2023) also use these two distinctions of patents with the Brazilian patent database.

The process of linking industrial and technological knowledge in regions is also influenced by the level of development of the place. Regions with lower income levels seem to have greater difficulties in improving their technological capabilities, which affects the way in which regions diversify into industrial sectors. For Eum and Lee (2022), developing countries have limited technological capabilities and are unable to influence the industrial development of these places.

Thus, we have the hypotheses of the paper:

Hypothesis 1. Regions are more likely to develop specialization in sectors related to their technological knowledge base.

Hypothesis 2: Regions are more likely to develop specializations in complex sectors when related to their technological knowledge base.

Hypothesis 3: The relationship with technological knowledge of disruptive patents has a greater influence on industrial diversification than incremental patents.

Hypothesis 4: Both types of patents are important for regional industrial diversification, but firm patents have a stronger effect on the likelihood of diversification into new sectors.

Hypothesis 5: Regions with low per capita income are more likely to develop specialization in sectors related to their industrial knowledge base.

3. Methodology

3.1 Data base

To conduct the empirical research presented in this paper, we collected employment data from RAIS (Annual Social Information Report), patent data from INPI (National Institute of Industrial Property), GDP per capita and population data from IBGE (Brazilian Institute of Geography and Statistics), covering the period 2006-2021.

To calculate the density of industrial relations and the competitiveness of sectors in the regions, we used the RAIS employment database. Several studies have chosen to use this information because of its wide geographical coverage and its coverage over several years (Freitas et al., 2024; Françoso et al., 2024). However, international trade data, as used by Hidalgo et al. (2007) and Hidalgo and Hausmann (2009), are less suitable for regional analysis in the Brazilian context. This is because many cities do not actively participate in import and export activities, and trade data often do not reflect the origin of production. In addition, it is important to note that domestic trade plays a significant role in the country's economy.

Patents serve as a widely used proxy for innovative activity and have been extensively employed in regional innovation analysis (Griliches, 1979; Jaffe, 1989; Feldman, 1994; Feldman & Florida, 1994; Acs et al., 2002). We know that there are disadvantages to using patent data, such as: not all the knowledge generated is codifiable; not every invention is patentable due to legal restrictions, other appropriation mechanisms, etc.; sectoral differences in the propensity to patent (Griliches, 1979; Albuquerque, 2004). Thus, we know that invention does not represent all forms of knowledge production within the economy and that patents do not capture all knowledge produced (Kogler et al., 2013). However, there are several advantages, such as the large amount of data available, accessibility, industrial applicability, and objective and stable criteria (Griliches, 1998; Andersson e Lööf, 2012). For this reason, we chose to use patent databases to measure technological knowledge, in line with Françoso et al. (2024) and Mascarini et al. (2023).

The INPI database contains information on both the inventor and the applicant. For general analyses, those segmented by type of invention patent (IP) and utility model (UM), and by per capita income level of the regions, we used the inventor database, as it is more evenly distributed among the different regions of the country. However, for analyses aimed at capturing disparities between institutional applicants - firms and universities/research institutes - we chose to use the applicants database. As for counting patents by region and by technological classification (IPC), we adopted the following criterion: if a patent is assigned to two inventors from the same region and is classified in two technological categories, it is counted four times in the database. This method was chosen because the knowledge generated by the patent is indivisible and is produced for each location or technological category to which it belongs.

With regard to the different classifications of patents, IP was considered to be a higher level of innovation and MU was considered to be a lower level of innovation. Invention patents (IP) are those types of products or processes that have the characteristics of inventive activity, are innovative and have industrial application, such as a new car engine or a new way of producing medicines. It is valid for 20 years from the date of filing. The Utility Model (UM) patent represents new forms of an object of practical use, such as utensils and tools, which represent improvements in their use or manufacture. It is valid for 15 years (FADEPE, 2021; INPI, 2021). It can thus be seen that an IP patent has the characteristics of more disruptive innovations, as characterized by Schumpeter. On the other hand, the UM patent seems to be more indicative of patents considered incremental.

For the purposes of this study, it was necessary to relate RAIS employment data to INPI patents, which use classification systems that are not directly related. The employment data use the CNAE (National Classification of Economic Activities) sectoral classification, while the patents use the IPC (International Patent Classification). Therefore, we need to relate the two data by translating technology classes to sectoral employment. Several studies have used the Algorithmic Link with Probabilities (ALP), which is a concordance table between production and patents created by text mining (Dosi et al., 2021; Eum & Lee, 2019). This table translates data from SITC, ISIC, and NAICS classifications to/from IPC (Lybbert & Zolas, 2014). The first step was to translate the patents from technological classes (IPC) to 2-digit ISIC Rev. 4 using ALP. Then, the information on the number of patents was transformed into 2-digit CNAE 2.0. CNAE is a classification derived from ISIC, so the 2-digit matches are almost exact, except for some product groups[1].

Our panel includes data from 133 Brazilian intermediate regions and 39 industry classes at the 2-digit CNAE level, covering the period 2006-2021. We aggregated the data into non-overlapping 4-year periods (2006-2009, 2010-2013, 2014-2017, 2018-2021), except for the patent data, where the number of patents per technology class was summed for each 4-year period and region due to the prevalence of zero values and significant fluctuations over the years, a common occurrence in the context of an underdeveloped economy (Mascarini et al. (2023).

3.2 Measuring Technological and Industrial Relatedness

Several studies (Teece et al., 1994; Hidalgo et al., 2007; Bryce & Winter, 2009; Freitas, 2024) have used co-occurrence measures to understand the relatedness between two industries.

[1] The ISIC Rev. 4 codes that had some discrepancies as to which divisions they belonged to were 1629 - Manufacture of other wood products, which may be equivalent to CNAE 2.0 codes 15.40-8 and 15.40-8; 1910 - Manufacture of coke oven products in 19.10-1 and 20.29-1. 2011 - manufacture of basic chemicals in 19.31-4, 19.32-2, 20.11-8, 20.14-2, 20.19-3, 20.21-5 and 20.29-1; 2219 - manufacture of other rubber products in 15.40-8 and 22.19-6; and 2220 - manufacture of plastic products in 15.40-8, 22.21-8, 22.22-6, 22.23-4 and 22.29-3. In order to check whether these incompatibilities would alter the results obtained by the regressions, several estimations were made in which the correspondences varied. For example, two models were estimated in which 1629 corresponded to divisions 15 and 19. This was done for product 1910, which corresponds to both divisions 19 and 20. This was done for all products that differed in their compatibility. In this way, there were no significant changes in the estimated models.

The calculation used in this paper was developed by Hidalgo et al. (2007) to analyze the path of productive diversification of countries by comparing the co-occurrence of industries with international trade data. This measure has since been used for industries (Freitas et al., 2024; 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 activities that use similar knowledge and skills (Hidalgo et al., 2007). Therefore, the relationship between two sectors/classes is revealed by the probability of their co-occurrence in a country or region. This type of calculation was used in this study to calculate the industrial and technological relatedness density of Brazilian regions. In terms of industrial proximity, employment data were used to identify the specialization of sectors in each region, as in Freitas et al. (2024). Sectors corresponding to non-tradable goods, such as education, services, etc., were removed from the data. For technological proximity, patent data were used, which had to be transformed into CNAE 2.0 divisions as explained in the previous section. Thus, Revealed Comparative Advantage (RCA) and Revealed Technological Advantage (RTA) were calculated at the level of intermediate regions and 2-digit CNAE divisions. These calculations are explained below:

$$RCA_{r,s} = \frac{\frac{emp_{r,s}}{emp_r}}{\frac{emp_s}{emp}} \tag{1}$$

where: $emp_{r,s}$ is employment in the intermediate region r in the industrial sector s; emp_r is total employment in the intermediate region *r*; emp_s is total employment in the industrial sector *c*; and emp is total employment in the country.

For patent data, the quotient is calculated as follows:

$$RTA_{r,s} = \frac{\frac{pat_{r,s}}{pat_r}}{\frac{pat_s}{pat}} \tag{2}$$

where $pat_{r,s}$ is the number of patents in the industrial sector *s* in region *r*; pat_r is the total number of patents in region *r*; pat_c is the number of patents in the industrial sector *s*; and pat is the total number of patents.

These calculations compare the share of employment or patents in each industrial sector in the intermediate regions with the share of the same technology in the country. An RCA or RTA greater than 1 means that the region has a higher concentration in the sector compared to other regions. Formal:

$$RCA_{r,s} = \begin{cases} 1, & if\ RCA_{r,s} \geq 1 \\ 0, & otherwise \end{cases} \tag{3}$$

$$RTA_{r,s} = \begin{cases} 1, & if\ RTA_{r,s} \geq 1 \\ 0, & otherwise \end{cases} \tag{4}$$

The RCA and RTA calculations are used to calculate the relationship between each pair of sectors in the region. This is done using the conditional minimum probability that each region is specializing in one sector and co-specializing in another, as in equations (5) and (6). A minimum probability is used to mitigate any bias arising from the prevalence of jobs or patents in certain sectors in certain regions, as discussed in Hausmann and Klinger (2007) and Hidalgo et al. (2007). The following equations quantify the co-location between two sectors, s and v, using employment and patent data, respectively:

$$\theta_{s,v} = \min\{P\left(RCA_{r,s} = 1 \mid RCA_{r,v} = 1\right), P(RCA_{r,s} = 1 \mid RCA_{r,v} = 1)\}, \forall\ s \neq v \tag{5}$$

$$\varphi_{s,v} = \min\{P\left(RTA_{r,s} = 1 \mid RTA_{r,v} = 1\right), P(RTA_{r,s} = 1 \mid RTA_{r,v} = 1)\}, \forall\ s \neq v \tag{6}$$

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

Next, we linked the relatedness of each pair of sectors to the specialization structure of the region to calculate the Industrial RD (Relatedness Density) and the Technological RD. This calculation, developed by Hausmann and Klinger (2007), assesses the closeness between an activity and the productive and technological structure of a given region. In our analysis, the relatedness density is calculated by adding the relatedness of a sector s to all other sectors in which the region is competitive (with an RCA or RTA index equal to 1). For example, if the majority of sectors related to sector *s* in the region have an RCA or RTA index equal to 1, the relatedness density is high, approaching 100. On the other hand, if only a small proportion of sectors related to technology *s* have an RCA or RTA index equal to one, the relatedness density will be low, approaching 0. Thus, the industrial relatedness density of sector *s* in region *r* is calculated as follows:

$$Technological\ RD_{r,s} = \frac{\sum_{s \in r, s \neq v} \varphi_{s,v}}{\sum_{s \neq v} \varphi_{s,v}}\ X\ 100 \qquad (7)$$

where $\varphi_{s,v}$ is the industrial relatedness of sector *s* with sector *v* calculated with employment data. Moreover, the Industrial Relatedness Density (RD) of the *c* technology in a *r* region is calculated as:

$$Industrial\ RD_{r,s} = \frac{\sum_{s \in r, s \neq v} \theta_{s,v}}{\sum_{s \neq v} \theta_{s,v}}\ X\ 100 \qquad (8)$$

where $\theta_{s,v}$ is the technological relatedness of sector *s* with sector *v* calculated with employment data.

3.3 Empirical model

To verify the impact of technological RD on sectoral specialization in Brazil's intermediate regions between 2006 and 2021, we used the following equation:

$$\begin{aligned} RCA_{r,s,t} = {} & \beta_0 + \beta_1 Industrial\ RD_{r,s,t-1} + \beta_2 Technological\ RD_{r,s,t-1} + \beta_3 PCI_{s,t-1} \\ & + \beta_4 (Technological\ RD_{r,s,t-1} * PCI_{s,t-1}) + \beta_5 GDP_{pc_{r,t-1}} \\ & + \beta_6 Pop_{r,t} + \tau_r + \gamma_s + \pi_t + \epsilon_{r,\,s,\,t} \end{aligned} \qquad (9)$$

Em que: $RCA_{r,s,t}$ é is the degree of specialization in a given sector s in region *r* at time *t*. Equals 1 if the region is specialised, otherwise equals 0.

Industrial $RD_{r,s,t-1}$ is the Industrial Relatedness Density variable calculated in equation (8). It is based on the work of Freitas et al. (2024) and Queiroz et al. (2024); $Technological\ RD_{r,s,t-1}$ is the main variable of interest, which was calculated in equation (7). The main objective is to demonstrate that regions diversify into sectors related to the technological knowledge of the location, according to Eum and Lee (2022).

$PCI_{c,t-1}$ is the complexity of each sector *s* at time *t-1*. The starting point for the calculation is the diversification of an economy (the number of sectors in which a region is specialized in) and the ubiquity of sectors (the number of regions specialized in that sector). More diversified regions generally tend to specialize in less ubiquitous sectors, which tend to require a greater variety of resources. These are more complex sectors that tend to be developed in a few economies and that facilitate diversification in the long run[2].

$GDP_{pc_{r,t-1}}$ is the per capita gross domestic product (in constant reais) of the intermediate

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

region r in the year t-1. According to Freitas et al. (2024), the level of economic development influences the sector 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 the process of industrial concentration (Duranton e 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; $\tau_r + \gamma_s + \pi_t$ are the fixed effects of region, sector and time, respectively.

Finally, the data were organized into a panel of 119 technological classifications (IPC) in the 39 Brazilian intermediate regions for the years 2006 and 2021, covering 4 periods (2006-2009, 2010-2013, 2014-2017 and 2018-2021), resulting in a panel of 20,748 observations. Estimates in this study were made using OLS, Probit, and Logit models. Estimates were divided into income groups based on 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 a similar number of regions: high-income, with 45 regions; middle-income; and low-income, with 44 regions for each group.

4. Results

4.1 Main results

This section contains the estimations of the equation (9) models using OLS, Probit and Logit. All the estimations have robust errors to correct the problem of heteroscedasticity, and physical effects of region, sector and period have been used to control for other characteristics that can influence the specialisation of sectors in regions.

For the estimations, we cannot compare the coefficients directly because estimations IV and V were carried out using the Probit and Logit models. However, we can compare the signs obtained in the coefficients. Table 1 shows that, for all the models, the Industrial RD has a positive influence on new specialisations in sectors in the Brazilian regions. This means that sectors are more likely to become specialised in regions where they have some kind of industrial proximity, as obtained by Neffke et al. (2011) and Freitas et al., (2024). This result confirms a literature that has already identified the dependence of industrial knowledge on sectoral specialisations in regions in different contexts.

With regard to technological RD, the positive sign of the coefficients confirms the influence of the proximity of sectors to the technological knowledge of the region. This is an important result as it identifies the influence of technological knowledge on the growth and development of sectors in regions. The neo-Schumpeterian literature already emphasises the importance of technological knowledge for the productive sector in the works of Freeman and Soete (1977), Rosenberg (1982), Dosi (1984), Soete (1985) and Freeman and Louça (2001). This result was found for countries around the world in the work of Eum and Lee (2022), with the exception of groups of developing countries. However, we have yet to find such an analysis focusing on regions, especially in a developing country.

Comparing the coefficient values in each model, we see that industrial RD has a greater influence on the probability of specialisation than technological RD. This was to be expected, given that industrial RD is the same type of capability as the sectors in the specialisations of the dependent variable. Moreover, firms appear to be much more diversified in terms of products than technologies, with their main products more related to the exploitation of their innovative knowledge (Dosi et al., 2017).

We also found that the complexity of sectors has a negative impact on the likelihood of specialisation in regions. In fact, if a sector is considered complex, it is more difficult to make it competitive in the regions because it requires more skills. This result was also found by Freitas et al. (2024). This is a dilemma for the diversification process in the regions, because the more complex sectors are difficult to develop and generally have technological and industrial capacities that are less related to the region's portfolio. However, even if they are complex, the results indicate that if the sectors are close to the technological knowledge of the region, the probability of specialisation in the region becomes positive. Finally, the GDPpc and population coefficients were not significant in any of the estimations.

Table 1: Determinants of sector diversification in Brazilian intermediate regions

	Dependent variable: RTA_t				
		OLS		*Probit*	*Logit*
	(I)	(II)	(III)	(IV)	(V)
Industrial RD_{t-1}	0.021***	0.021***	0.019***	0.069***	0.120***
	(0.000632)	(0.0006)	(0.0007)	(0.0026)	(0.0046)
Technological RD_{t-1}		0.001***	0.001**	0.005***	0.009***
		(0.000494)	(0.0005)	(0.0020)	(0.0035)
TCI_{t-1}			-0.050***	-0.360***	-0.682***
			(0.017)	(0.084)	(0.151)
Techn. RD_{t-1} * TCI_{t-1}			0.002***	0.012***	0.021***
			(0.0002)	(0.0010)	(0.0018)
$GDPpc_{t-1}$ (log)			0.033	0.126	0.298
			(0.0386)	(0.157)	(0.275)
$Population_{t-1}$ (log)			-0.054	-0.271	-0.455
			(0.144)	(0.604)	(1.072)
Constant	-0.0139	-0.0403	0.444	0.455	-0.359
	(0.0492)	(0.0500)	(2.108)	(8.873)	(15.73)
Region F.E.	Yes	Yes	Yes	Yes	Yes
Period F.E.	Yes	Yes	Yes	Yes	Yes
Sector F.E.	Yes	Yes	Yes	Yes	Yes
Observations	15,561	15,561	15,561	15,561	15,561
R^2	0.20	0.20	0.201		
Wald chi^2				2855.43***	2595.51***
Pseudo R^2				0.20	0.20

Source: Authors' elaboration.

Note: Robust standard errors in parentheses. $*p < 0.1$; $**p < 0.05$; $***p < 0.01$.

4.2 Differences between patents classifications

Table 2 shows the results for the determinants of sectoral diversification in Brazilian regions, broken down by two types of patent: low level innovation and high level innovation. We find that, regardless of the type of patent, if the sectors are related to regional technological knowledge, this increases the probability of being specialised in the region. However, the results suggest that the likelihood is higher when the sectors are related to high-level innovation than when the patents are related to low-level innovation. The literature suggests that radical innovations (upper-level innovation) have a greater capacity to establish new technological trajectories and therefore have a more profound influence on industrial dynamics. Incremental innovations (lower-level innovations), on the other hand, have less capacity to change the industrial dynamics of the region because they are increments of technologies already in use (Schumpeter, 1939; Dosi, 1982; Fagerberg et al., 2010).

Table 2: Determinants of sector diversification in Brazilian regions divided by distinct patent classifications

	Dependent variable: RTA_t			
	IP (high-level innovation)		UM (low-level innovation)	
Industrial RD_{t-1}	0.136***	0.121***	0.136***	0.121***
	(0.0043)	(0.0046)	(0.0044)	(0.00461)
Technological RD_{t-1}	0.013***	0.015***	0.003	0.010***
	(0.0032)	(0.0033)	(0.0036)	(0.0037)
TCI_{t-1}		-0.624***		-0.556***
		(0.150)		(0.150)
Techn. RD_{t-1} * TCI_{t-1}		0.020***		0.021***
		(0.0017)		(0.0019)
$GDPpc_{t-1}$ (log)		0.278		0.263
		(0.276)		(0.275)
$Population_{t-1}$ (log)		-0.355		-0.544
		(1.071)		(1.078)
Constant	-4.166***	-1.653	-4.030***	1.147
	(0.395)	(15.73)	(0.432)	(15.81)
Region F.E.	Yes	Yes	Yes	Yes
Period F.E.	Yes	Yes	Yes	Yes
Sector F.E.	Yes	Yes	Yes	Yes
Observations	15,561	15,561	15,561	15,561
Wald chi^2	2622.27***	2619.44***	2604.08***	2603.72***
Pseudo R^2	0.19	0.20	0.19	0.20

Source: Authors' elaboration.

Note: Robust standard errors in parentheses. $*p < 0.1$; $**p < 0.05$; $***p < 0.01$.

4.3 Differences between applicants

Patenting efforts vary in nature. For this reason, it is crucial to analyse the origin of patent applications, i.e. whether they come from public or private institutions. In Table 3, we calculate technological RD by differentiating patents according to the type of applicant: universities/public research institutes or enterprises. We find that the likelihood of sectors being specialised in the region is higher in terms of technological knowledge for patents coming from enterprises than from universities/public research institutes.

One explanation for this is that in universities and public research institutes, patent research is generally less tied to ensuring a commercial return, which gives researchers more cognitive freedom and leads to the exploration of basic scientific knowledge. However, there are also challenges in transferring this knowledge to industry, as noted by Fabrizio (2007). Póvoa and Rapini (2010) highlighted the challenge of interaction between firms and universities and research institutes. They noted that, in Brazil, these institutions develop technologies primarily for application in goods production, rather than providing market-ready products.

Table 3: Determinants of sector diversification in Brazilian regions divided by distinct patent applicants

	Dependent variable: RTA_t			
	Universities		*Firms*	
Industrial RD_{t-1}	0.137***	0.135***	0.137***	0.120***
	(0.0044)	(0.0045)	(0.0044)	(0.0047)
Technological RD_{t-1}	0.007*	0.009**	0.018***	0.022***
	(0.00373)	(0.0038)	(0.0037)	(0.0037)
TCI_{t-1}		-0.186		-0.595***
		(0.147)		(0.150)
Techn. RD_{t-1} * TCI_{t-1}		0.008***		0.023***
		(0.0013)		(0.0018)
$GDPpc_{t-1}$ (log)		0.333		0.183
		(0.287)		(0.284)
$Population_{t-1}$ (log)		-0.772		-0.400
		(1.076)		(1.080)
Constant	-4.015***	3.313	-4.346***	-0.202
	(0.416)	(15.78)	(0.410)	(15.86)
Region F.E.	Yes	Yes	Yes	Yes
Period F.E.	Yes	Yes	Yes	Yes
Sector F.E.	Yes	Yes	Yes	Yes
Observations	15,065	15,065	15,327	15,327
Wald chi²	2517.81***	2536.77***	2576.91***	2573.31***
Pseudo R^2	0.20	0.19	0.19	0.20

Source: Authors' elaboration.

Note: Robust standard errors in parentheses. $*p < 0.1$; $**p < 0.05$; $***p < 0.01$.

4.4 Differences between regions

Table 4 shows the determinants of sectoral specialisation by dividing regions into high, medium and low income groups. We can see that technological RD has no impact on sectoral specialisation in low-income regions. On the other hand, the industrial RD variable has an impact in all regions, regardless of income level. This may be due to the lack of technological knowledge in low-income regions. Many countries and regions with a low level of development face obstacles in improving their technological capabilities. The main reason for this is the difficulty in acquiring the knowledge needed to break through the current industrial structure and move into new advanced industries (Martin, 2010).

Table 4: Determinants of sector diversification in Brazilian intermediate regions divided by income

	Dependent variable: RTA_t					
	Logit					
	High income		*Medium income*		*Low income*	
	(I)	(II)	(III)	(IV)	(V)	(VI)
Industrial RD_{t-1}	0.162***	0.163***	0.111***	0.101***	0.0424***	0.0359***
	(0.0074)	(0.0077)	(0.0090)	(0.0093)	(0.0098)	(0.0101)
Technological RD_{t-1}	0.013**	0.014**	0.004	0.015**	-0.004	0.003
	(0.0054)	(0.0054)	(0.0061)	(0.00655)	(0.0075)	(0.0077)
TCI_{t-1}		-0.410		-0.930***		-0.743***
		(0.281)		(0.273)		(0.267)
Tech. RD_{t-1} * TCI_{t-1}		0.005*		0.031***		0.023***
		(0.0032)		(0.0044)		(0.0050)
$GDPpc_{t-1}$ (log)		0.694*		0.0709		0.399
		(0.380)		(0.631)		(0.692)
$Population_{t-1}$ (log)		-4.030*		-2.638		2.839
		(2.188)		(1.725)		(2.567)
Constant	-6.694***	45.67	-2.661***	32.84	-0.891**	-39.63
	(0.453)	(32.67)	(0.530)	(26.71)	(0.409)	(34.04)
Region F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Period F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Sector F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,265	5,265	4,884	4,884	5,016	5,016
Wald chi²	1012.60***	1008.05***	807.60***	778.85***	935.05***	931.49***
Pseudo R²	0.21	0.21	0.19	0.20	0.22	0.23

Source: Authors' elaboration.

Note: Robust standard errors in parentheses. $*p < 0.1$; $**p < 0.05$; $***p < 0.01$.

5. Conclusion

This study examines the influence of technological knowledge on industrial diversification in Brazil's 133 intermediate regions from 2006 to 2021, controlling for different types of patents, applying institutions and income levels. The analysis showed that both industrial and technological knowledge play a significant role in the sectoral specialisation of regions, with industrial knowledge having a stronger influence.

The results indicate that regions with industrial and technological proximity are more likely to specialise in new sectors, confirming the importance of industrial and technological cohesion for regional development. Technological proximity proved to be more relevant for radical innovations (high-level innovations), which have a greater potential to change technological trajectories and industrial dynamics, than for incremental innovations (low-level innovations).

In addition, business patents were found to have a greater impact on regional specialisation than those from universities and public research institutes. This finding can be attributed to the commercial focus of business patents, as opposed to the cognitive freedom and knowledge transfer challenges of academic institutions.

The analysis also showed that in low-income regions the influence of technological knowledge on sectoral specialisation is limited, while industrial proximity remains relevant. This finding suggests that the development of technological capabilities in less developed regions is crucial for overcoming barriers to diversification and industrial progress.

Policies that promote the creation and diffusion of technological knowledge, especially in low-income regions, are therefore fundamental to fostering industrial diversification. Integration between universities, firms and research institutions can be improved to facilitate technology transfer and increase the impact of technological knowledge on economic growth and industrial dynamism.

These conclusions contribute to the literature on regional diversification and point to avenues for future research and policy formulation aimed at improving the technological and industrial capacity of regions, thus promoting economic development that is consistent with the regions' capacities but focused on more complex industries and technologies.

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