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The Roles of Industrial and Technological Relatedness in Shaping Brazilian Regional Diversification

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DANIELLE EVELYN DE CARVALHO

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Resumo

Compreender a diversificação regional é essencial para o desenvolvimento econômico, pois envolve o acúmulo de capacidades e o aumento da competitividade. Esta tese investiga os fatores que influenciam a diversificação tecnológica e industrial nas regiões brasileiras, explorando o relacionamento entre classes tecnológicas e setores industriais com os conhecimentos produtivos e tecnológicos, bem como a influência das regiões vizinhas nesse processo. Embora a influência desses conhecimentos no desenvolvimento regional já seja reconhecida, a importância do relacionamento conjunto dessas capacidades para a diversificação regional não havia sido explorada até agora, sendo este um aspecto desenvolvido nesta tese. Além disso, as capacidades locais oferecem oportunidades, mas também impõem limites à diversificação. Nesse contexto, a influência das regiões vizinhas torna-se crucial, especialmente para regiões de baixa renda. Portanto, esta tese é composta por quatro capítulos. O primeiro constrói uma base teórica ampla, abordando desenvolvimento regional, dependência de trajetória, relatedness, aglomeração e coevolução das capacidades produtivas e tecnológicas. O segundo capítulo examina empiricamente como a relação entre as classes tecnológicas e a estrutura produtiva regional afeta a diversificação em novas tecnologias. Os resultados mostram que há um aumento na probabilidade de diversificação tecnológica quando estas estão relacionadas ao portfólio de conhecimento produtivo da região. Em áreas de menor desenvolvimento econômico, a conexão dessas classes com a estrutura produtiva torna-se ainda mais relevante, visto que o relacionamento delas com o conhecimento tecnológico não se mostrou significativo para a diversificação. Isso sugere que o desenvolvimento industrial é essencial para iniciar processos de diversificação em regiões com restrições de recursos. O terceiro capítulo explora a importância do relacionamento dos setores com o conhecimento tecnológico regional para a diversificação industrial. Observou-se que há uma probabilidade maior de especialização industrial quando os setores são relacionados ao conhecimento tecnológico de patentes provenientes de empresas do que aquelas oriundas de universidades e institutos de pesquisa, refletindo a dificuldade de transferência do conhecimento acadêmico para o mercado.Em regiões menos desenvolvidas, a conexão industrial com novos setores continua sendo um fator crucial para a especialização industrial, enquanto a influência do conhecimento tecnológico permanece limitada. Isso indica que o conhecimento industrial é necessário em regiões com restrições de capacidades e que, posteriormente, pode-se avançar para o domínio do conhecimento tecnológico. O quarto capítulo analisa a influência da competitividade de regiões próximas no processo de diversificação regional, mostrando que a competitividade e a densidade de capacidades adjacentes aumentam a probabilidade de novas especializações setoriais e o crescimento do VCR, além de reduzirem a probabilidade de saída dessas especializações. Esse comportamento indica uma tendência de compartilhamento de recursos e capacidades entre áreas geograficamente próximas, favorecendo especializações em setores semelhantes ou inter-relacionados. Em regiões de menor renda, observa-se uma maior importância da influência competitiva das áreas vizinhas, sugerindo que essas localidades não podem depender exclusivamente de suas próprias capacidades para alcançar novas especializações. As implicações para políticas públicas ressaltam a importância do fortalecimento das capacidades produtivas locais como etapa inicial em regiões menos desenvolvidas. Nessas regiões, é recomendável adotar políticas que promovam a colaboração inter-regional, permitindo o compartilhamento de recursos e capacidades com áreas vizinhas. Além disso, incentivar a integração entre universidades e o setor produtivo por meio de parcerias público-privadas e clusters de inovação é essencial para aumentar o relacionamento entre o conhecimento das universidades e o mercado.

Palavras-chaves: Proximidade, Diversificação, Indústrias, Tecnologias, Competitividade regional.

Abstract

Understanding regional diversification is essential for economic development, as it involves the accumulation of capabilities and increased competitiveness. This thesis investigates the factors that influence technological and industrial diversification in Brazilian regions, exploring the relationship between technological classes and industrial sectors with productive and technological knowledge, as well as the influence of neighboring regions on this process. Although the influence of this knowledge on regional development is already recognized, the importance of the joint relationship of these capabilities for regional diversification has not been explored until now, and this is an aspect developed in this thesis. In addition, local capacities offer opportunities but also impose limits on diversification. In this context, the influence of neighboring regions becomes crucial, especially for low-income regions. This thesis, therefore, consists of four chapters. The first builds a broad theoretical basis, addressing regional development, path dependence, relatedness, agglomeration, and the coevolution of productive and technological capabilities. The second chapter empirically examines how the relationship between technological classes and the regional productive structure affects diversification into new technologies. The results show that there is an increase in the likelihood of technological diversification when these are related to the region's portfolio of productive knowledge. In areas of lower economic development, the connection of these classes with the productive structure becomes even more relevant since their relationship with technological knowledge was not significant for diversification. This suggests that industrial development is essential for diversifying resource-constrained regions. The third chapter explores the importance of the relationship between sectors and regional technological knowledge for industrial diversification. It was observed that there is a higher probability of industrial specialization when sectors are related to technological knowledge from patents originating from companies than those originating from universities and research institutes, reflecting the difficulty of transferring academic knowledge to the market. In less developed regions, industrial connection with new sectors remains a crucial factor for industrial specialization, while the influence of technological knowledge remains limited. This indicates that industrial knowledge is necessary in regions with capacity constraints and that progress can be made toward achieving technological knowledge. The fourth chapter analyses the influence of the competitiveness of nearby regions on the process of regional diversification, showing that the competitiveness and density of adjacent capacities increase the likelihood of new sectoral specializations and the growth of the RCA, as well as reducing the likelihood of exiting from these specializations. This behavior indicates a tendency for resources and capabilities to be shared between geographically close areas, favoring specializations in similar or interrelated sectors. In lower-income regions, the competitive influence of neighboring areas is more important, suggesting that these localities cannot rely exclusively on their capabilities to achieve new specializations. The implications for public policies highlight the importance of strengthening local productive capacities as an initial step in less developed regions. In these regions, it is advisable to adopt policies that promote inter-regional collaboration, allowing the sharing of resources and capacities with neighboring areas. In addition, encouraging integration between universities and the productive sector through public-private partnerships and innovation clusters is essential to increase the connection between university knowledge and the market.

Keywords: Relatedness, Diversification, Industries, Technologies, Regional competitiveness.

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Introduction

Regional diversification is widely recognized as an essential economic phenomenon for fostering the development of regions, promoting the expansion of the local knowledge and skills base through the incorporation of new activities. However, diversification must be directed towards with higher complexity sectors to achieve more solid and sustainable economic growth. This expansion into complex areas not only stimulates economic growth, but can also contributes significantly to reducing regional inequalities by generating more skilled jobs and strengthening the innovative environment. However, advancing into more complex sectors, technologies or products requires a robust accumulation of knowledge and capabilities, which represents an obstacle in the development paths of many countries and regions.

This diversification process is intrinsically linked to the pre-existing knowledge and capabilities of a region or country, since there is a greater likelihood in entering activities that are related to the local knowledge portfolio (Neffke, 2009; Freitas; Britto; Amaral, 2024). This perspective aligns with the concept of path-dependency, which is widely explored in evolutionary economics. Although path-dependency does not imply a rigid sequence determined by the past, it does suggest a propensity for historical trajectories to influence the direction of future development, where certain paths are more likely than others, and radical changes are difficult (Walker, 2000). This concept implies that regions with a history of diversification and knowledge accumulation tend to diversify more efficiently, following paths that reinforce their existing capabilities.

The research of Jacobs (1961), and later Glaeser et al. (1992), showed that regions with greater diversification are more likely to generate knowledge externalities that favor innovation and economic growth. Diversity of sectors offers a wider range of knowledge and skills, strengthening a region's ability to diversify further. Frenken, Oort and Verburg (2007) argue that a greater diversity of related industries expands learning opportunities and facilitates the diffusion of knowledge, promoting faster and more sustainable growth. Thus, diversification into complex activities requires in-depth knowledge of the regional environment, which can be an obstacle to the development process. In this context, diversification is not merely a random process; on the contrary, the development of new activities is profoundly influenced by the local knowledge base, which shapes the possibilities and limits of regional innovation and growth paths.

The Principle of Relatedness has been widely applied in studies investigating diversification across industries, products, patents, and publications (Hausmann; Klinger, 2007; Freitas; Britto; Amaral, 2024; Boschma; Balland; Kogler, 2015). However, these studies typically examine diversification dynamics within the same type of knowledge, often overlooking interactions between different knowledge domains. The literature suggests that a broader knowledge base is necessary for regions to diversify into more complex sectors, incorporating complementary knowledge beyond specific industry or technology domains.

Technological and productive knowledge interaction generates a feedback loop that strengthens regions' industrial and economic structure. Technological knowledge enables continuous innovation that redefines production systems and expands industrial frontiers. For Freeman and Louçã (2001), technological innovations arise as a response to production needs, increasing efficiency and competitiveness. Schumpeter's theory of "creative destruction" (1939) also points out that these innovations transform products and processes, forcing industries to adapt, which results in new economic structures and profound changes in the market (Malecki, 1997).

Technological capabilities are fundamental to industrial growth and diversification, facilitating the development of subsequent innovations (Bell; Pavitt, 1993). According to Dosi and Nelson (2010), the accumulation of technological skills allows companies and regions to remain competitive, directly influencing firms' productivity and sustainability. The strength of technological capabilities in a region or country facilitates economic expansion and is a central factor in industrial growth and diversification (Lall, 2000; Eum; Lee, 2022b).

In addition, productive knowledge is essential in generating new technologies, especially in the early stages of industrial development. Learning by doing, which comes from productive experience, facilitates innovation through the continuous adaptation and improvement of processes (Arrow, 1962; Kaldor, 1966). Historical cases such as the Industrial Revolution in the British textile sector and the development of the chemical industry in Germany illustrate how productive practice can stimulate incremental innovations and ensure competitiveness over time (Freeman; Louçã, 2001; Murmann, 2003).

The interdependence between technological and productive capacities shows that the development of one strengthens the other, establishing a continuous cycle of industrial evolution. Bell and Pavitt (1993) state that diversification paths in emerging economies benefit from robust production bases, which create a favorable environment for developing new technologies and strengthening the production system. This virtuous cycle allows economies to advance sustainably, overcoming initial limitations and generating new opportunities for innovation and competitiveness on the global stage (Eum; Lee, 2022a).

Nonetheless, it is crucial to recognize that regional diversification does not occur in isolation. Regions are interconnected and can benefit from the knowledge and resources available in neighboring areas. For regions with limited internal capacities, diversification can rely on the advantages and knowledge offered by nearby regions. Geographical proximity plays a significant role in the transmission of knowledge, especially tacit knowledge, which is more easily shared between adjacent regions. Polanyi (1967) and Arrow (1962) point out that physical distance limits the transmission of knowledge, especially regarding more complex and specific information. In this way, proximity between regions facilitates the dissemination of knowledge and promotes a more collaborative and innovative.

The influence of neighboring regions can either encourage or hinder regional development. According to Myrdal (1957), "propagation effects" occur when economic growth in one region stimulates development in adjacent areas through increased demand and the diffusion of innovations. However, "backward effects" can also arise when growth in one region attracts resources, such as capital and labor, from neighboring regions, accentuating regional disparities. This delicate balance between propagation and backlash effects reinforces the importance of an in-depth analysis of regional interactions, especially in a context such as Brazil's, marked by significant economic disparities.

In Brazil, regional inequalities make the relevance of interactions between regions for economic development even more evident. Less diversified regions often face difficulties in accessing new knowledge and resources internally, leading them, in some cases, to a state of lock-in, in which they remain restricted to limited development paths (Hassink; Lagendijk, 2001). In these cases, dependence on established trajectories makes extra-regional interaction a vital component for diversification, especially in areas with lower technological capacity. Regions that share borders with more developed areas can benefit from the flow of knowledge and innovation from these neighbors, overcoming barriers to economic diversification.

This thesis aims to explore how diversification in technologies and industries occurs, influenced by the pre-existing technological and industrial structures of regions and their connections with other competitive areas. To accomplish this, the thesis is structured into four chapters: the first chapter serves as a theoretical framework, discussing relevant literature, while the following three chapters present original empirical contributions. The primary objective of Chapter 1 is to review the literature on regional development and economic diversification, with a focus on the interaction between productive structures, technological capacities, and the mechanisms driving regional economic transformation. The concept of relatedness is examined as a crucial factor for regional diversification. Additionally, the chapter highlights the interdependence between productive and technological systems, illustrating how both types of knowledge can influence regional diversification. Through this review, the chapter establishes the essential theoretical foundations for the subsequent empirical analyses, identifying gaps in the existing literature, particularly concerning the interaction between different forms of knowledge and the role of regional proximity in economic diversification.

Chapter 2 aims to assess whether a region is more likely to diversify into new technological classes when they are related to its productive structure. The analysis used patent and employment data from Brazil's intermediate regions between 2006 and 2021. Industrial sectors were associated with technology classes through the Algorithmic Link with Probabilities (ALP), as proposed by Lybbert and Zolas (2014). Additionally, regions were categorized into groups based on income levels, while patents were analyzed according to the origin of their applicants. Beyond confirming widely accepted hypotheses about the relevance of local technological knowledge for diversification, this chapter makes three key contributions:

- The probability of diversification into a technological class increases when it is related to the region's productive knowledge.
- In low-income regions, the relatedness with local industrial knowledge is more significant for technological diversification than technological knowledge alone.
- The connection with productive knowledge is more relevant for the diversification of technologies from companies than from universities.

Chapter 3 investigates whether diversification into new sectors is more likely in regions with a technological portfolio related to these sectors, considering different types of patents, institutions, and income levels. Employment and patent data for Brazil's intermediate regions between 2006 and 2021 were utilized, with patent information linked to employment data using the Algorithmic Link with Probabilities (ALP) proposed by Lybbert and Zolas (2014). Beyond the common hypothesis affirming the importance of regional industrial knowledge for sectoral diversification, this chapter presents four main contributions:

- The likelihood of industrial diversification increases when a sector is related to the region's technological knowledge.
- Regions with low per capita income tend to develop industrial specializations in sectors aligned with their industrial knowledge base. In contrast, the influence of technological knowledge in these regions is relatively limited.
- Connection with high-innovation patents is more relevant for industrial diversification than knowledge associated with low-innovation patents.
- Industrial diversification is more likely when sectors are connected to technological knowledge from company patents than from universities and research centers.

Chapter 4 investigates the influence of neighboring regions' competitiveness on the entry and exit of specializations, as well as on the growth of regional competitiveness. Additionally, sectoral analyses were conducted to examine whether this influence varies and to identify the presence of competitiveness clusters in sectors within neighboring Brazilian regions. For this analysis, employment data from 2006 to 2021 were utilized. The main contributions of this chapter include:

- The competitiveness and density of neighboring regions influence the likelihood of new specializations entering and the growth of the RCA in the same sectors while also reducing the likelihood of specializations exiting.
- Being close to the industrial knowledge of neighboring regions is even more important for new specializations than proximity to the region's knowledge portfolio, demonstrating the relevance of diversifying into sectors related to the knowledge of surrounding regions.
- Regions with low economic complexity and income rely heavily on the skills and knowledge accumulated in neighboring regions to promote new specializations. In these regions, the limitations of local resources and capabilities restrict the possibility of diversification, reinforcing the need for external support and targeted public policies.
- Having a neighbor with a higher economic complexity intensifies the effects of neighbors' competitiveness and density on the likelihood of specialization in the regions.

The final section of this thesis offers a comprehensive overview of the main results obtained, contextualizing them within the field of study of regional economic diversification. The discussion focuses on the repercussions of these findings for formulating public policies, highlighting how they can influence practice and theory. Additionally, this section includes the limitations of the research and suggestions for future studies.

1 Technological and Productive Co-evolution: A Regional Perspective

1.1 Introduction

Regional development and economic diversification are central economic themes, especially regarding regions' productive and technological capacities. This theoretical chapter explores the main theories underpinning the relationship between productive structure, technological knowledge and regional diversification, emphasizing how these elements interact and influence each other. Examining different theoretical approaches seeks to understand the underlying mechanisms that drive the diversification of regions and types of knowledge in economic development, providing a solid basis for subsequent empirical analysis.

Section 1.2, "Theories of Regional Development and Economic Geography", discusses the contributions of classic authors such as Perroux (1955), Myrdal (1957), and Hirschman (1961). Perroux introduces the concept of 'growth poles,' arguing that economic growth is uneven across regions due to differences in productive structure and resource endowment. Myrdal presents the theory of 'circular and cumulative causation,' emphasizing the inherent instability of economic systems, where positive feedback processes tend to exacerbate regional disparities. Hirschman, in turn, proposes 'backward and forward linkage effects,' underscoring how growth in specific sectors can either stimulate or inhibit development in other sectors and regions. This section also examines theories of agglomeration and regional specialization, drawing on the contributions of Marshall (1890), Jacobs (1969), and Porter (1990). Marshall focuses on external economies of scale resulting from industrial specialization and proximity, such as access to skilled labor, specialized suppliers, and technological spillovers. Jacobs argues that urban economic diversity fosters innovation through cross-sectoral interactions, while Porter emphasizes the role of clusters and local competition in driving innovation and productivity. Finally, the evolutionary approach in economic geography incorporates concepts like path dependence, increasing returns, and selection. Drawing on the work of Nelson and Winter (1982), Boschma and Frenken (2006), and Boschma and Martin (2010), this perspective highlights that economic development and diversification are dynamic, non-linear processes shaped by historical trajectories and interactions among diverse agents, with historical evolution and technological innovation playing essential roles in regional economic dynamics.

Section 1.3, "Relatedness as a Driver of Regional Diversification", explores the concept of relatedness and its relevance to economic diversification. Drawing on the theories of Penrose (1959), Teece (1982), and Boschma (2005), it examines how cognitive proximity between economic activities facilitates knowledge exchange and innovation. Methods for measuring relatedness are discussed, including analyses of co-occurrence and similarities in the resources used. The empirical literature on the subject is reviewed, highlighting studies such as Hidalgo et al. (2007), Neffke, Henning and Boschma (2011) and Balland et al. (2018), which demonstrate the importance of relatedness in regional and technological diversification.

Finally, in section 1.4, "Coevolution and Dependence between Productive and Technological Systems", the interdependence between productive and technological capacities is analyzed. Drawing on the work of Bell and Pavitt (1993), Lall (2000), and Eum and Lee (2022a), it discusses how productive capacity drives technological development, while technological advancements, in turn, support productive growth. It explores the distinction between know-how and know-why Lundvall and Johnson (1994) and examines how this difference influences a country or region's capacity for innovation and diversification. Historical examples illustrate this coevolution, emphasizing the importance of policies that simultaneously foster productive and technological development.

This chapter, therefore, establishes a theoretical framework that integrates different perspectives on regional development, agglomeration, diversification, and relatedness. Understanding how productive and technological capacities interact and influence each other makes it possible to understand better the mechanisms that drive diversification and regional growth. This understanding is fundamental to analyzing the empirical chapters developed in this thesis, allowing for a more consistent and grounded approach to the evidence presented.

1.2 Theories of Regional Development, Agglomeration and Economic Geography

Marshall (1890) recognized the benefits of the concentration of producers at the end of the 19th century. However, it was only in the 1950s that agglomeration began to be used consistently to analyze regional growth and development (Monasterio; Cavalcante, 2011). This concept played a significant role in Perroux's theory of growth poles (1955), Myrdal's "circular and cumulative causation" (1957), and Hirschman's "forward and backward linkages" (1961). Interestingly, according to Monasterio and Cavalcante (2011), Marshall (1890) did not directly influence these thinkers in any formal way. The most notable influences on their work came from Keynes and Schumpeter, especially in the case of Perroux (1955).

Perroux's theory of growth poles (1955) emphasizes that economic growth occurs unevenly between regions due to variations in the productive structure and the internal endowment of resources. The internal factors differentiating each region include the availability of natural and human resources, the local market, and the productive configuration. Thus, for Perroux, growth does not manifest uniformly across the territory but is concentrated in certain poles with varying intensities. This growth spreads through various channels, generating different effects throughout the economy. Over time, this concept, initially rooted in sectoral dynamics, was expanded to incorporate regional and geographical dimensions. Boudeville (1968) played a crucial role in this adaptation by linking the idea of growth poles to specific territorial contexts, highlighting how economic activities are organized spatially and how regions interact through flows of goods, capital, and labor. Boudeville's work underscored the importance of regional characteristics in shaping the diffusion of growth, thereby providing a framework for understanding uneven development at the geographical level.

Perroux (1955) argues that economic growth brings about structural changes, which are expressed in three main aspects: i) the emergence and disappearance of industries, ii) the variation in the participation of different sectors in industrial production and territorial distribution, and iii) the diversity in growth rates between sectors and regions. Therefore, the theory of polarized growth seeks to understand why specific industries and regions grow faster than the average, causing imbalances that the neoclassical model does not predict. As a result, there is a tendency for regional inequalities to widen since growth is not only unbalanced between regions but also between sectors, with different knock-on effects on the economic development of each location.

A central concept in understanding the disparity in growth among industries and regions is that of the 'driving industry.' Building on Schumpeter's (1985) ideas about the role of innovation in capitalist dynamics, Perroux examines the interaction between 'driving' industries, which stimulate demand for services in other sectors, and 'driven' industries, whose sales directly benefit from the growth of these driving industries. In this way, driving industries not only promote overall economic growth but also foster development by boosting the activity of the industries connected to them. This dynamic enables the most vibrant industrial centers to reshape both the geographic landscape and the national economic structure through the interconnected demands they generate.

In addition, economic spaces, conceived as force fields, are made up of centers (or poles) from which the central forces emanate and towards which they disperse. Each center acts simultaneously as a point of attraction and repulsion. The company, seen as one of these centers, emits centrifugal and centripetal forces. It attracts people and resources (human and material aggregations around the company) to its common space or pushes them away (diverting activities, areas reserved for future expansion, etc.). Thus, according to the nature of its activities and inputs, the company attracts or expels economic elements, such as supplies and demands, generating a dual effect of attraction and repulsion according to the force field (Perroux, 1955)

In dialogue with Perroux's growth poles (1955), Myrdal (1957) presented a theory of regional economic dynamics - both between and within countries - based on circular and cumulative causation, according to which the economic system is inherently unstable and unbalanced. Myrdal explains the concept of circular and cumulative causation through the idea of a vicious circle, in which one negative factor acts simultaneously as a cause and consequence of other negative factors. He illustrates this with the example of poverty in developing countries: *"the concept implies, of course, a circular constellation of forces tending to act and react upon one another in such a way as to keep a poor country in a state of poverty"* (Myrdal, 1957, p. 11). This process can occur in both positive and negative directions and, if left unregulated, tends to widen regional disparities. Myrdal argues that the circular and cumulative causation process reflects social changes more accurately than the classical hypothesis of stable equilibrium because there is no automatic tendency for economic forces to converge toward a point of equilibrium within the social system.

Various social dynamics, such as the loss of an industry in a given region, exemplify the process of circular causation. The immediate effects of this loss include rising unemployment, coupled with a decline in local income and demand. These initial impacts, in turn, precipitate a further reduction in income and demand across other regional sectors, thus reinforcing a vicious cycle of cumulative circular causation. In the absence of external interventions, the region progressively loses attractiveness, prompting the outmigration of key factors of production, such as capital and labor, in search of better opportunities. This outflow further intensifies the reduction in local income and demand (Lima; Simões, 2010).

In this context, it is essential to distinguish between the effects generated by regional dynamics: spread effects and backwash effects. According to Myrdal (1957), economic development in one region can generate positive effects for other less developed areas, the so-called "spread effects", which include gains such as the supply of consumer goods and raw materials, as well as technological spillovers that encourage economic progress in stagnant regions. However, the "backwash effects" tend to predominate without a sufficiently strong expansion force, reinforcing the cumulative cycle that exacerbates inequalities. These adverse effects, described by Myrdal as "polarization effects", occur when the growth of a region selectively attracts labor and capital, generating a vacuum of resources in the peripheral regions, which is intensified by migration and the leakage of savings. Factors such as the lack of an efficient transportation system and the insufficient quality of public services, such as education and health, also deepen these disparities. Thus, while spread effects can mitigate the concentration of wealth, backwash effects often act in the opposite direction, resulting in different rates of progress between regions, with less developed areas remaining relatively stagnant compared to more dynamic economic centers.

Another vital author on regional development is Hirschman (1961), with his theory of backward and forward effects. Hirschman (1961), like Perroux (1955) and Myrdal (1957), criticized theories of balanced growth, arguing that economic development does not occur homogeneously or simultaneously in all regions. For him, growth occurs unevenly, concentrated in specific points, which later influence other areas. This initial concentration is fundamental to creating incentives for investment and generating subsequent innovations, in an unbalanced process which, paradoxically, can be essential for driving economic progress.

Hirschman (1961) introduced the concepts of backward and forward linkages, which describe how economic sectors are interconnected so that the growth of one industry can stimulate the development of others. Backward linkages arise when an industry demands inputs from previous sectors in the production chain, promoting new investments to meet this demand. Forward linkages occur when the production of one industry provides inputs for other activities, expanding the impact of development. These chain effects are central to understanding how growth at a specific point can trigger a domino effect, promoting economic development in other areas and sectors.

Hirschman (1961) describes two main effects of concentrated growth: trickling-down and polarization effects. Trickling-down effects refer to the positive impacts of growth in one region on others, such as increased demand for goods and services, direct investment, and even higher productivity in less developed regions. These effects, when predominant, can benefit underdeveloped regions through increased trade and investment from wealthy areas. However, alongside these positive effects, Hirschman (1961) also recognizes the existence of polarization effects, which represent concentration forces, in which developed regions attract resources such as capital and labor from poorer regions, exacerbating regional inequalities.

Despite the possible adverse effects of polarization, Hirschman (1961) has a more optimistic view of the development process than Myrdal (1957). For him, trickling-down effects can potentially overcome the effects of polarization, primarily if appropriate public policies are implemented to facilitate this positive transmission of growth. He argues that policymakers should concentrate investments in areas of potential growth and simultaneously implement measures that can neutralize the adverse effects of polarization, such as subsidies and incentives aimed at less favored regions. In this way, Hirschman (1961) sees development as an interconnected process, where initial growth in economic hubs can benefit the entire regional structure with the proper intervention, creating more balanced long-term development.

Theories of unbalanced regional growth share the view that regions, even within the same country, have different growth rates. According to Diniz (2009), these theories have been fundamental in guiding and supporting the formulation of public policies for regional development in various countries, stimulating strategies to reduce territorial disparities. In addition, these theories suggest that some more developed regions can positively influence neighboring areas through spillover effects, promoting the development of less favored regions through increased demand, technology transfer, and new economic opportunities.

However, these positive effects are not guaranteed, as uneven growth can produce adverse outcomes for neighboring regions, exacerbating existing inequalities. This phenomenon is described by Myrdal (1957) and Hirschman (1961), who highlight that concentrated development in one region may lead to negative consequences, such as the outflow of resources and the migration of skilled labor to more prosperous areas, further disadvantaging underdeveloped regions. Consequently, the literature on unbalanced growth acknowledges both the potential positive and negative effects between regions, reflecting the complexity of interregional development.

Although Perroux (1955), Myrdal (1957), and Hirschman (1961) were not formally influenced by Marshall (1890), the principles of the positive externalities of agglomeration played a crucial role in the development of these theories Monasterio and Cavalcante (2011). Marshall argued that the spatial concentration of economic activities within the same region favors sharing knowledge and resources, generating positive externalities that boost local growth. On the other hand, the unbalanced regional growth literature focuses on the relationships between different regions and the possible spillover effects, which can be positive or negative. Thus, while Marshallian agglomeration theory explores the internal advantages of a concentrated space, the theories of Perroux, Myrdal, and Hirschman explore how the development of one region can affect others—for better or worse. It is therefore important to explore these theories to understand the dynamics of regional development.

The economic geography literature has a long-standing tradition of studying agglomeration externalities, which are the benefits derived from the proximity of firms and institutions and their impact on regional economic growth. A central issue in this literature is the importance of location: depending on the regional context, firms and institutions can gain significant advantages by locating in specific areas. Broadly speaking, three main theories explain the externalities arising from agglomerative advantages: the works of Marshall (1890), Arrow (1962), Romer (1986), Jacobs (1961) Jacobs (1969), and Porter (1990).

According to Glaeser et al. (1992), the Marshall-Arrow-Romer (MAR) externality refers to knowledge spillovers between firms in the same industry due to local specialization. The concept, originally introduced by Marshall (1890), was later developed by Arrow (1962) and Romer (1986). Marshall (1890) identified that the geographic concentration of firms in the same industry can generate a range of benefits that would not be available if these firms were dispersed. These advantages arise from physical proximity and frequent interactions among firms and workers within the same sector. The author summarizes his argument in the following excerpt:

> Many of those economies in the use of specialized skill and machinery which are commonly regarded as within the reach of very large establishments, do not depend on the size of individual factories. Some depend on the aggregate volume of production of the kind in the neighbourhood; while others again, especially those connected with the growth of knowledge and the progress of the arts, depend chiefly on the aggregate volume of production in the whole civilized world (Marshall, 1890, p. 87).

Marshall (1890) explained the concentration of economic activities in specific locations through external economies of scale. According to Marshall, the benefits of agglomeration result in two pecuniary externalities and one technological externality: i) the advantage of an abundant supply of labor and ii) the possibility provided by a prominent local market that enables the existence of input suppliers with scale efficiency; and iii) the exchange of information that occurs when companies in the same sector are located close to each other.

The first externality refers to the advantages derived from the large supply of specialized and highly qualified labor. Employers tend to settle in areas that find workers with the specific skills they need, while individuals look for job opportunities in places that demand these skills, where they are more likely to find good opportunities. This facilitates the replacement and mobility of the workforce, allowing employers and employees to break contracts more quickly when necessary.

The second externality pertains to the advantages of proximity to input suppliers. When firms within the same sector are geographically clustered, they can more effectively benefit from specialized suppliers and the availability of sector-specific inputs. This concentration fosters a more robust market for these inputs, reducing costs and increasing supply chain efficiency. Additionally, the proximity to other market participants enhances access to new resources and streamlines logistics, generating economies of scale and enabling greater agility in meeting business demands.

Finally, the third externality concerns technological spillovers. The accumulation of knowledge in a given location facilitates the dissemination of relevant information about production processes to other companies. This dynamic environment fosters the constant exchange of ideas and innovations, creating a fertile context for new developments. As Marshall (1890, p. 225) observes, *"if one man starts a new idea, it is taken up by others and combined with suggestions of their own; thus it becomes the source of further new ideas"*. In this sense, when an industry chooses a location, it will likely stay there for a long time, as the benefits arising from agglomeration tend to increase.

Contrary to the specialization-driven externalities described by Marshall, Jacobs (1961; 1969) highlights the importance of sectoral diversity and urbanization economies. In her analysis, Jacobs (1969) compares the English cities of Manchester and Birmingham in the mid-19th century to demonstrate the advantages of diversification. She observes that, at the time, Manchester was viewed as the city of the future due to its dominant textile industry. In contrast, Birmingham, characterized by small businesses in various sectors, was not seen as having significant potential. However, as other cities began to compete more effectively in the textile industry, Manchester experienced substantial market losses. Birmingham, on the other hand, did not face obsolescence; its fragmented and initially inefficient small industries continued to create new jobs and expand, with some eventually achieving substantial growth.

Jacobs (1969) argues that cities must maintain diversity to thrive. As she asserts, "big cities are natural generators of diversity and prolific incubators of new enterprises and ideas of all kinds" Jacobs (1969, p. 145) Urban diversification—which encompasses a variety of production activities, facilities, skills, preferences, needs, and cultures—facilitates the exchange of ideas and innovations across different economic sectors within the same region. Jacobs (1969) cautions that if a city lacks sufficient diversity and becomes dominated by a single industry, it may face long-term difficulties. A lack of diversification can hinder a city's ability to adapt to economic shifts and reduce its resilience to external challenges, making it more susceptible to sector-specific crises.

> [...] a very successful growth industry poses a crisis for a city. Everything – all other development work, all other processes of city growth, the fertile and creative inefficiency of the growth industry's suppliers, the opportunities of able workers to break away, the inefficient but creative use of capital – can be sacrificed to the exigencies of the growth industry, which turns the city into a company town (Jacobs, 1969, p. 124-125).

Jacobs' theory emphasizes that sectoral diversity within a geographical region fosters the creation of knowledge externalities, thereby enhancing innovation and economic growth. A varied industrial environment encourages the imitation, sharing, and recombination of ideas and practices across different sectors. The presence of a robust scientific base facilitates the exchange and cross-fertilization of ideas, establishing a solid foundation for interaction and the development of new solutions. Furthermore, urban diversity supports the division of labor, allowing distinct skills and specializations to complement and integrate with one another. This dynamic creates new opportunities for innovation, as different sectors collaborate and generate synergies that drive the emergence of new fields of activity. The exchange of knowledge among firms and various economic agents stimulates experimentation and the pursuit of innovative solutions, rendering a more diversified economy fertile ground for growth and development (Jacobs, 1969).

In addition, Jacobs argues that competition is a crucial factor for the growth of cities and companies, as it acts as a strong incentive for innovation and accelerates the adoption of new technologies. Cities play a key role in the social learning process, promoting and encouraging various ideas through intense competition. This competition propagates and enriches the economic environment, generating the most significant externalities due to the diversity of economic activities (Jacobs, 1969).

The third type of externality is addressed by Porter (1990), and is also associated with Jacobs' ideas, and refers to the positive impact of competition on economic growth. Porter highlights the crucial role of clusters in the economy, describing them as geographical concentrations of interconnected companies, which include specialized suppliers, service providers, companies from related sectors, and associated institutions, such as universities, standards agencies, and trade associations. These clusters foster an environment where companies compete and collaborate, creating a dynamism that favors growth and innovation.

These connections among companies and sectors are essential for fostering competition, enhancing productivity, and shaping the direction and pace of new business formation and innovation. According to Porter (1990), firms encounter many shared needs, opportunities, constraints, and challenges regarding productivity. Clusters create a constructive and efficient environment for dialogue among related companies, suppliers, government entities, and other institutions, facilitating collaboration and knowledge exchange. Beyond their direct benefits to current productivity, clusters are critical in driving innovation and productivity growth. The proximity resulting from the co-location of firms, customers, suppliers, and other institutions intensifies the pressures to innovate and adapt. Consequently, cluster participants can often identify and respond more swiftly to the evolving needs of new buyers. Companies within a cluster benefit from the concentration of specialized knowledge, related firms' proximity, and buyers' sophistication. This advantageous environment enables them to acquire new components, services, machinery, and other necessary elements more rapidly to implement innovations, such as new product lines, processes, or logistical models (Porter, 1990).

Porter (1990) also points out intense competition within geographically concentrated clusters creates constant pressure. The similarity of primary conditions, such as labor costs and public services, combined with multiple rivals, stimulates companies to look for creative ways to stand out, encouraging innovation. While individual companies may struggle to stay ahead for long, a cluster of companies can progress much more quickly. In addition, participation in a cluster provides advantages in identifying new technological, operational, or delivery possibilities. Companies exposed to more advanced insights into technological evolution, component availability, and service concepts benefit from ongoing relationships with other entities within the cluster, including universities, and the ease of direct interaction, which is more difficult for isolated companies (Porter, 1990).

The three theories of agglomeration externalities focus on knowledge spillovers, although each interprets the origin and nature of these externalities differently. Although the theories are not necessarily mutually exclusive, they differ mainly in two respects. Firstly, there is disagreement over whether knowledge spillovers come mainly from interactions within the same industry or between different industries. Secondly, predictions about how local competition affects these knowledge spillovers also vary between the theories.

Marshall, Jacobs, and Porter agree on the effects of geographical agglomeration on companies, but their views differ on the nature of these externalities. For Jacobs, they are related to urban diversity, where the variety of technologies fosters creativity and facilitates the exchange of ideas between different sectors, creating a more favorable environment for innovation. On the other hand, Marshallian externalities derive from a specialized urban structure characterized by the concentration of companies in the same sector. This specialization reduces costs by allowing a better combination of skilled labor and inputs and promoting more effective learning through knowledge spillovers between companies in the same industry located in the same space. On the other hand, Porter aligned himself with Marshall's perspective by recognizing the externalities generated by the concentration of firms in the same sectors. However, he saw competitiveness between companies, rather than the sharing of resources, as the primary driver of innovation. Furthermore, Porter stated that specialization in clusters of related industries, rather than isolated industries, is particularly beneficial for regional development, as it favors strengthening production chains and exchanging knowledge between complementary sectors.

Glaeser et al. (1992) explore urban diversification and its economic influence in addition to agglomeration economies (location and urbanization effects). The research reveals that intra-industry knowledge spillovers are less significant for growth for cities in the United States than intersectoral spillovers, especially in more developed cities. However, the authors warn that these results should be interpreted cautiously, as they were obtained in large, mature cities that were not growing rapidly. Knowledge spillovers within the same industry may be more relevant in the early stages of development, while the cross-fertilization of ideas between sectors, as discussed by Jacobs, accelerates growth.

Henderson, Kuncoro and Turner (1995) investigate Jacobs' externalities by differentiating between new and old industries. They find that employment growth in established industries is best explained by the location economies associated with more specialized cities, which aligns with the theories of Marshall and Porter. In contrast, emerging and high-tech industries benefit more from environments with high information exchange and industrial diversity, reflecting the externalities described by Jacobs. Building on the studies by Glaeser et al. (1992) and Henderson, Kuncoro and Turner (1995), the empirical literature on MAR, Jacobs, and Porter externalities has expanded, revealing evidence for

MAR externalities in regional innovation, especially in specialized regions (Panne, 2004).

Paci and Usai (1999) found that specialization externalities - MAR - and diversification externalities - Jacobs - positively impact regional innovative activity, being more intense in high-tech industries and metropolitan regions. Antonelli et al. (2017) corroborate this view, showing that a more significant portfolio of technologies at the regional level contributes positively to generating knowledge, evidencing Jacobs' externalities. However, the differences in the evidence highlight the importance of considering the context and methodology used in the analysis. Combes and Overman (2004) point out that discrepancies in results can be attributed to factors such as the choice of dependent variables, differences in samples, and study periods.

Paci and Usai (1999) found that specialization externalities—MAR—and diversification externalities—Jacobs—positively impact regional innovative activity, with effects more intense in high-tech industries and metropolitan regions. Antonelli et al. (2017) corroborates this view, showing that a more diverse portfolio of technologies at the regional level positively contributes to knowledge generation, highlighting Jacobs' externalities. However, differences in evidence underscore the importance of considering context and methodology in analysis, as Combes and Overman (2004) note that discrepancies in results can arise from factors such as choice of dependent variables, sample differences, and study periods. These nuances point to the need for a deeper understanding of how spatial factors and economic dynamics interact over time, a perspective further enriched by the Evolutionary Economic Geography approach.

Economic geography studies since the 1990s, with the work of Krugman et al. (1991) and Porter (1990), have emphasized the importance of geography in understanding the dynamics and competitiveness of the economy, highlighting the role of spatial agglomeration of economic activities as a source of increasing returns. This new theoretical current is called the New Economic Geography (NGE), which incorporates a mathematical approach to research into spatial location, the distribution of economic activities, and interaction between regions. However, NGE does not address historical evolution and how the economic landscape of regions changes over time. On the other hand, the evolutionary perspective incorporates these aspects into its analysis of technological progress, competitive advantage, restructuring, and economic growth (Boschma; Martin, 2010).

The seminal work by Nelson and Winter (1982) laid the theoretical foundations for the development of Evolutionary Economics. In evolutionary models, the economy and economic development are understood as dynamic processes driven by innovation, learning, and interaction between heterogeneous agents, which evolve in a context of uncertainty, competitive selection, and historical dependence, shaped by institutions and continuous change Dosi (1982), Nelson and Winter (1982). According to Witt (2003), the main objective of evolutionary economics is to understand the internal mechanisms that drive economic transformation over time. To this end, evolutionary theories must meet three criteria: they must be dynamic, deal with irreversible processes, and include the generation of innovations as an engine of transformation.

While the New Economic Geography abstractly treats history, Evolutionary Economics attributes central importance to the historical process in shaping the present and modeling prospects Boschma and Martin (2010). In this sense, evolutionary economics has traditionally focused on technological innovation and structural change, focusing on the behavior of companies and the performance of national economies (Dosi, 1984; Nelson, 1995). However, this approach initially did not give due importance to the geographical dimensions of development. In recent years, several theoretical or empirical studies have explored the synergies between Evolutionary Economics and Economic Geography, revealing that both disciplines can complement each other in a significant way (Boschma; Lambooy, 1999; Boschma; Frenken, 2006; Boschma; Martin, 2010; Kogler; Rigby; Tucker, 2015; Martin; Sunley, 2023).

Thus, Boschma and Lambooy (1999) argue that the evolutionary approach has fundamental concepts to explain central phenomena in economic geography, such as path-dependence, increasing returns, and selection. The central argument of path dependency holds that the development of companies, regions, and industries is shaped by historical processes specific to each location (Boschma; Frenken, 2006; David, 1985; Martin; Sunley, 2010). This concept is so widespread in economic geography that Walker (2000) explains that:

> 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. This logic applies to industrial locations as well (Walker, 2000, p. 126).

The diversification path is understood not as a predetermined process but with probabilistic outcomes. Thus, since there is no predetermined result, the future results are from individual agents' or groups' actions (intentional or accidental) in specific locations Grillitsch and Sotarauta (2020). An important application of this idea is the development of work, which shows that diversification into new activities is related to their existing activities and knowledge base Boschma and Frenken (2011). Most empirical research shows that regional diversification tends to occur in a more related than unrelated way (Content; Frenken, 2016).

Increasing returns is another essential concept in the evolutionary approach connected to economic geography studies (Boschma; Lambooy, 1999). In one of his models, Arthur (1994) shows how increasing returns is essential in determining the spatial pattern of an industry. As soon as one of the companies in a region takes the lead in the industry and has locational advantages - better infrastructure, specialized services, greater demand for inputs, skilled labor, among others - other companies are attracted to the region. This process of agglomeration economies generates the positive externalities that make these companies earn increasing returns (Arthur, 1994).

Finally, the concepts of chance and selection are incorporated into economic geography to explain the location decisions of new companies. Companies do not make perfectly rational and conscious decisions when choosing their locations, as neoclassical economics suggests. On the contrary, they often do not have complete information, and the success of a new location is determined by chance or arbitrary factors, such as the entrepreneur's hometown. Regions with better access to information, usually established production centers, increase companies' chances of survival and success. However, uncertainty and sub-optimal results are expected, as the spatial margin of profitability can be vast and unpredictable (Boschma; Lambooy, 1999).

Based on these concepts, the authors believe that evolutionary thinking can help describe and explain: i. the process of localized "collective" learning promoted by spatial proximity in innovative environments; ii. Negative lock-in refers to regions facing difficulties adapting to a world of increasing variation, which occurs when a region becomes excessively dependent on a specific sector or technology; iii. spatial lock-in is the process of new industries emerging in a spatial context and taking advantage of increasing returns. Thus, using these concepts makes it possible to interpret economic geography from an evolutionary perspective.

In this sense, Boschma and Martin (2010, p. 6) define Evolutionary Economic Geography (EEG) as: *"the processes by which the economic landscape - the spatial organization of economic production, circulation, exchange, distribution, and consumption - is transformed from within over time."*. However, it is crucial to recognize that, as this spatial organization evolves, it also feeds into and alters the processes that drive this transformation. Change in the economic landscape can occur gradually and cumulatively or abruptly and disruptively and is often the result of the interaction between these two processes.

As Boschma and Martin (2010) argue, evolutionary economic geography focuses on the spatialities of economic novelty, encompassing innovations, new firms, new industries, and new networks. This field examines how the spatial structures of the economy emerge from the micro-behaviors of economic agents, including individuals, firms, and organizations. Specifically, it investigates how the economic landscape exhibits self-organization without central coordination or direction. Furthermore, it explores how path creation and path dependence interact to shape the geographies of economic development and transformation and the reasons and mechanisms by which such processes can be place-dependent.

Therefore, evolutionary economic geography incorporates concepts such as path dependence, increasing returns, and selection to explain the spatial dynamics and transformation of economic activities. By focusing on historical processes and the micro-level behaviors of agents, EEG provides a robust framework for understanding regional economic development and change. Recent literature has utilized these concepts, particularly path dependence, to comprehend the entry and exit of sectors and technologies in different regions. Additionally, the concept of relatedness has emerged as a crucial force driving regional diversification processes. The next section examines this concept in detail, exploring its theoretical foundations and reviewing the pertinent literature on the topic.

1.3 Relatedness as a Driver of Regional Diversification

1.3.1 Theoretical Foundations of the Relatedness Concept

The current literature on diversification widely discusses the concept of relatedness, drawing from established research on firm growth, particularly the works of Penrose (1959), Chandler (1962) and Teece (1982). Penrose (1959) emphasized the intrinsic relationship between a firm's growth, diversification, and the efficient and coherent use of its internal resources. She argued that diversification arises when companies leverage their underutilized capabilities to engage in new activities, provided these align with their core competencies. This alignment is essential for channeling surplus resources into areas that enhance the firm's technological strengths. Additionally, Penrose (1959) highlighted the limitations of diversifying into multiple fields, emphasizing the importance of maintaining a strategic balance between diversification and resource allocation. While companies can expand into various sectors, Penrose noted that the effectiveness of such expansion depends heavily on their ability to invest sustainably in each new area. As firms move further from their original areas of specialization, the effort required to achieve and sustain adequate competence increases substantially.

Chandler (1962) also contributed to this discussion by emphasizing the role of organizational structure in diversification. He noted that successful expansion into new markets or products depended heavily on the company's ability to integrate new activities with its existing operations. For Chandler, internal coherence and managerial capacity were crucial to successful diversification, highlighting the need for an appropriate structure to enable this integration to occur efficiently.

Teece (1982) broadened this perspective by introducing the concept of economies of scope, which refers to a company's ability to use its resources in multiple activities, reducing costs and promoting more efficient diversification. Teece pointed out that, as companies diversify, coherence between activities is essential to capture these economies of scope, ensuring that resources, especially human capital, and knowledge, are used to generate value in different areas of activity. However, he also warned of the limits of this diversification. At some point, this generalization compromises efficiency and reduces the profitability of diversification since specialized human capital becomes less effective when allocated to multiple fronts. In addition, Teece points out that the economies of scope achieved by sharing indivisible physical assets also have limits. Once fully utilized, these assets cease to offer additional gains when they are applied to activities that are increasingly distant from the company's original specialization.

The most recent literature is in line with the theories of Penrose (1959), Chandler (1962) and Teece (1982), but the focus has evolved from the level of the firm to that of the region. In this context, cognitive proximity between agents plays a fundamental role in exchanging and recombining knowledge. However, this proximity must be carefully balanced. Nooteboom (2000) introduced the concept of optimal cognitive proximity, arguing that cognitive distance should be neither too great to guarantee effective communication nor too small to avoid lock-in since both extremes would damage the interactive learning process. Similarly, Boschma (2005) argues that a moderate cognitive distance is essential to avoid lock-in and promote innovation, especially in regions where access to a diversity of knowledge is crucial for economic and technological development.

Neffke (2009) suggest that cities with varied sectors facilitate a greater diffusion of ideas between different economic activities, becoming knowledge repositories. Diversity, however, is only advantageous when there is a common basis for effective communication between agents. Thus, neither extreme specialization nor unconnected diversity is ideal. The balance lies in combining ideas from different but related sectors. Therefore, the "ideal region" would have a high concentration of diverse industries and technologies, but with internal coherence, promoting interconnected activities that stimulate innovation.

Therefore, it is essential to recognize the importance of proximity between agents for knowledge exchange. However, it is necessary to specify which types of proximity are relevant and how they can be measured. Boschma (2005) identified five dimensions of proximity: i) geographical proximity, the most traditional, which refers to the physical proximity between agents; ii) cognitive proximity, related to the common knowledge base between them; iii) organizational proximity, which involves the shared organizational structure, such as participation in the same company or network; iv) social proximity, which encompasses relationships of trust and social interactions; and v) institutional proximity, associated with interaction through norms and rules.

1.3.2 Measuring Relatedness: Methods and Approaches

To analyze related variety and diversification, it is crucial to evaluate the interconnections among various economic activities, including industries, products, and technologies. Three predominant methods are employed for this analysis. The first method utilizes standard industrial classification systems to identify relatedness between industries. Industries sharing the same two-digit codes are typically regarded as related. However, this approach has faced criticism for lacking a robust theoretical foundation to substantiate that these classifications accurately measure the degree of relatedness between industries Neffke, Henning and Boschma (2011).

The second approach focuses on economies of scope, analyzing the similarities between the resources used in different industries, such as skills, technologies, and materials. Some researchers use links derived from input-output tables to assess these similarities (Fan; Lang, 2000), while others examine similarities in occupational profiles or workforce mobility between sectors (Eriksson; Hane-Weijman; Henning, 2018; Neffke; Henning, 2013). Neffke and Henning (2013) note that these approaches face a theoretical limitation: the strategic relevance of resources can vary widely between industries. For example, material-based measures are more suitable for the production of goods than for services.

The third approach is co-occurrence analysis, which assesses the frequency with which two products, industries or technologies occur simultaneously in a given location, be it a country, a region, a firm or a plant (Bryce; Winter, 2009; Hidalgo et al., 2007; Teece et al., 1994). The main limitation of this approach is that it is based on observational results and assumes that a region's portfolio of products or industries is coherent. Based on this assumption, it is inferred that co-occurrence reflects the relationship between sectors (Neffke; Henning, 2013). Thus, while resource-based indicators examine the possible origins of economies of scope, co-occurrence indicators measure their consequences. This approach captures the complexity of the relationships and takes into account the multidimensionality of the phenomenon, as it is not possible to evaluate these relationships from a single perspective, such as skills (Neffke; Henning, 2013).

The different methodologies for measuring the relatedness or proximity between economic activities have both advantages and limitations. However, the co-occurrence approach has been widely used in diversification analyses, both in Brazil and in other countries (Hidalgo et al., 2007; Neffke; Henning; Boschma, 2011; Rigby, 2015; Freitas; Britto; Amaral, 2024). The following section will explore these studies and discuss their main results.

1.3.3 Literature Review on Relatedness

Research in economic complexity has introduced innovative methodologies for comprehending the productive structure and diversification based on a region or country's capabilities. Significant contributions by Hausmann and Klinger (2007), Hidalgo et al. (2007), and Hidalgo and Hausmann (2009) have introduced variables such as economic complexity, product complexity, and relatedness. These studies use export data to characterize countries and products based on attributes such as diversity and ubiquity. Diversity refers to the number of products a country can competitively produce, while ubiquity indicates the number of countries that can competitively produce a specific product. Leveraging this information, the authors calculate the complexity of both countries and products. The core premise is that developed countries typically produce highly complex goods that are not widely produced across many countries. In contrast, developing countries concentrate on manufacturing less complex goods, which demand lower productive capacity and are consequently produced in a larger number of countries.

Since productive capacities cannot be observed directly, the authors developed a measure that infers the similarity between the capacities required by different goods by observing the probability that these products are exported simultaneously by the same country. This calculation is based on the Revealed Comparative Advantage (RCA), where $VCR \geq 1$ indicates that the country has a comparative advantage in exporting a given good. At the same time, $VCR < 1$ suggests that the country is not competitive in that product, as shown in the following equation:

$$RCA_{p,c} = \frac{\frac{X_{p,c}}{X_p}}{\frac{X_c}{X}} \tag{1.1}$$

where: $X_{p,c}$ is the export of country c for product P; X_p is the global export of product P; X_c is the total export of country c; and X is the world's total export.

Using this indicator, Hidalgo et al. (2007) and Hausmann and Klinger (2007) calculate the relatedness between products. To do this, they use the conditional probability that a country that exports product p also exports product p, determining the strength of the connection between them. As the conditional probabilities are not symmetrical, the minimum probability of exporting product p and the inverse for p' are captured, making the measure symmetrical, as shown in equation 1.2:

$$\varphi_{p,p'} = \min\left\{P\left(\frac{RCA_p}{RCA_{p'}}\right), P\left(\frac{RCA_{p'}}{RCA_p}\right)\right\} \tag{1.2}$$

where for the whole country c:

$$rca_{p,c} = \begin{cases} 1, & \text{se } RCA_{p,c} \geq 1 \\ 0, & \text{caso contrário} \end{cases} \tag{1.3}$$

Utilizing this indicator, the authors developed the concept of the Product Space, which establishes relatedness between products based on their co-occurrence within countries' export portfolios. The Product Space formalizes the intuitive notion that a nation exporting apples is more likely to export mangoes than jet engines, as the production of different goods necessitates specific sets of capabilities, which may be either similar or distinct. Products requiring analogous capabilities are positioned closer to one another within the Product Space, whereas those demanding significantly divergent capabilities are located further apart.

The accumulation of capabilities over time shapes the set of products a country can produce competitively. A nation's ability to diversify into new industries is contingent upon the similarity between the capabilities needed for these new products and those the country already possesses. Consequently, it is more feasible for a country to expand its production into goods closely related to those it already manufactures, as this allows it to leverage existing capabilities rather than develop entirely new competencies.

The Product Space is not homogeneous; on the contrary, it has densely connected areas, where many products are close regarding the required capacities, and sparse areas, where products are more isolated. Developed countries tend to produce goods competitively in sectors located in the core of the Product Space, represented by industries such as chemicals, machinery, and equipment. These dense areas facilitate diversification, as transitioning to new products requires acquiring a few additional capabilities. In contrast, developing countries are positioned on the periphery of the Product Space, characterized by less dense connections and dominated by sectors with low technological content. In these cases, diversification is more challenging, as it requires the development of capabilities beyond those already existing in the country. The related diversification process shows that the path to the more complex parts of the Product Space is considerably more difficult for peripheral regions due to the lower connectivity between sectors in these areas.

Advances in measuring concepts such as proximity between sectors have significantly improved our empirical understanding of diversification across various domains, including products, industries, technologies, and academic publications. Numerous studies have applied these new concepts to demonstrate a strong relationship between the likelihood of developing a competitive activity in a region and its proximity to other activities within the local knowledge portfolio. Hidalgo et al. (2018) consolidated these contributions under the Principle of Relatedness. Although researchers did not initially refer to it by this name and have faced challenges formalizing it, scholars have studied this phenomenon for many years (Penrose, 1959; Chandler, 1962; Teece, 1982). Researchers have tested the

Principle of Relatedness at different spatial levels—national and regional—using various methodologies and research approaches.

Hausmann and Klinger (2007)'s study focused on analyzing the Product Space using international trade data. By calculating a density indicator to measure the proximity between products and the existing knowledge and capabilities within countries, the authors demonstrated that density is a crucial determinant of structural change in countries. In other words, when shifts in specialization patterns occur, countries tend to move primarily toward closely related products in terms of required capabilities. Later, Hidalgo and Hausmann (2009) expanded this analysis by including new elements that refined previous approaches, highlighting the critical role of capabilities in economic development. They demonstrated that economic complexity correlates with a country's income level and predicts future economic growth.

Building on these initial findings, numerous other studies have been conducted, covering different geographic and temporal contexts. Boschma, Minondo and Navarro (2013) investigated the exports of 50 Spanish regions at the NUTS 3 level between 1988 and 2008. The results confirm earlier conclusions, showing that regions diversify into sectors that leverage already-developed capabilities. However, the study makes a significant contribution by highlighting that the dissemination of these capabilities is strongly influenced by regional factors, indicating that the regional structure plays a more significant role than the national structure in the diversification process. These findings reinforce the importance of the regional context in building and developing new capabilities.

In a similar study, Donoso and Martin (2016) analyzed U.S. state-level export data from 2002 to 2012 and reaffirmed the importance of regional capabilities for productive diversification. However, their results differ regarding the influence of the national structure. Unlike in the Spanish regions, the effect of the national industrial structure in the U.S. was negative, suggesting that competition between states plays a more significant role, with the transfer of capabilities occurring primarily at the regional level.

Studies in other countries also support these trends. Alonso and Martín (2019), applying the same methodology to Brazil and Mexico, reaffirmed the importance of established economic activities for product diversification. Additionally, they identified spillovers from neighboring regions, suggesting that both regional and national governments can leverage local and foreign capabilities to promote productive diversification by absorbing external knowledge and technology.

On the other hand, Poncet and Waldemar (2015) analyzed firm-level data from China between 2000 and 2006. They found that regional connections primarily benefited domestic firms and traditional trade activities regarding exports. Foreign firms, in contrast, integrated less with the local environment, which limited the regional spillover process.

They also highlighted that more productive firms could better absorb these externalities, emphasizing the critical role of absorptive capacity in the local learning process.

Researchers have also applied the Principle of Relatedness to examine how regions within a country develop new industries. Neffke, Henning and Boschma (2011) led the way in studying regional diversification into new industries. They examined the economic evolution of 70 Swedish regions between 1969 and 2002, using the framework of Teece, Pisano and Shuen (1997) and factory-level data to measure the relatedness between manufacturing industries. By analyzing the co-occurrence of products from different factory sectors, they demonstrated that an industry was more likely to emerge in a region if it was technologically related to its existing industries. In contrast, unrelated industries tended to leave the region.

Following this line of research, Freitas, Britto and Amaral (2024) proposed a measure of similarity between economic sectors based on three dimensions, using Brazilian employment microdata from 2006 to 2016. The first dimension, co-location, examines the frequency with which two sectors coexist in the same region, similar to the approach of Hidalgo et al. (2007). The second dimension, co-occupation, evaluates the number of common occupations between sectors, while the third dimension, co-corporation, looks at how often related industries appear within the same corporation. The final relatedness indicator combines these three dimensions, showing that the productive specialization of Brazil's microregions follows a process heavily dependent on previous trajectories. Thus, the emergence of new economic activities remains conditioned by the pre-existing productive structure.

Essletzbichler (2015) introduced an alternative approach to measuring technological relatedness using input-output linkages between 362 manufacturing industries across 360 U.S. metropolitan regions in 1977, 1982, 1988, and 1992. Despite methodological and contextual differences, the author essentially confirmed the findings of Neffke, Henning and Boschma (2011) regarding the Swedish manufacturing sector, reinforcing the idea that regional diversification heavily relies on pre-existing trajectories.

He, Yan and Rigby (2015) applied the methodology of Hidalgo et al. (2007) and Hausmann and Klinger (2007) to Chinese manufacturing industry data from 1998 to 2008 to examine industrial evolution in Chinese cities. They found that the entry and exit of industries correlate with the existing capabilities in these regions. However, the authors emphasize that external factors, such as globalization and institutions, also play a crucial role in shaping China's regional industrial evolution, significantly impacting the establishment and extinction of industries.

In a complementary approach, Zhu, He and Zhou (2017) explored how Chinese regions can disrupt their established technological trajectories and achieve a 'leap' in their industrial space. Using export data, the authors demonstrated that path-dependent technological development could be interrupted through investments in extra-regional connections and internal innovation. Various studies investigating the industrial structure of regions highlight that the entry and exit of industries depend on their relationship with regional productive knowledge. For instance, Neffke, Henning and Boschma (2011) utilized the hierarchical structure of the Standard Industrial Classification (SIC) system to capture this relationship, positing that industries closer in the system share greater relatedness. Freitas, Britto and Amaral (2024) employed three dimensions to measure this technological proximity, based on employment microdata from RAIS. However, these studies did not consider the impact of patent production on calculating relatedness density.

Enhancing the measure of density through patent information offers a promising avenue. Patents provide more detailed technological classifications, allowing for more precise identification of regional technological relatedness. Rigby (2015) pioneered the study of technological diversification using a co-occurrence method for calculating relatedness, similar to the approach by Hidalgo et al. (2007) and Hausmann and Klinger (2007). The study focused on U.S. cities from 1975 to 2005, using Logit and Probit estimations with fixed effects. Rigby (2015) was also the first to analyze the Knowledge Space, measuring the proximity between different technology classes through citation analysis and examining how these relate to cities' technological trajectories. The findings revealed that technologies aligned with a region's existing knowledge space were more likely to be adopted than unrelated technologies. This indicates that cities tend to develop competencies around related technologies over time, shaping the knowledge paths they follow. Technological diversification in cities depends on current practices and the proximity of new technological opportunities to existing specializations.

Following an approach similar to Rigby (2015), Boschma, Balland and Kogler (2015) investigated the entry and exit of technological knowledge conditioned by the pre-existing technological knowledge base in U.S. cities from 1981 to 2010, utilizing data on patented technology classes and a fixed effects probit model. Their results align with the findings of Balland et al. (2018), who focused on European Union regions from 1985 to 2009. Balland et al. (2018) sought to analyze how regions diversified technologically based on their pre-existing knowledge. The results indicate that diversifying into complex technologies poses challenges for many regions, although achieving this becomes easier when such technologies relate closely to the existing knowledge core. Furthermore, regions tend to experience more significant growth when they specialize in complex technologies related to their existing technological capabilities. These studies on technological relatedness gain relevance for public policy in Europe, as numerous initiatives have emerged to develop innovative specialization strategies to diversify the technological landscape of European regions (Barca, 2009; Foray; David; Hall, 2009; McCann; Ortega-Argilés, 2015).

To understand how a country's technological and scientific diversification influences its trajectory of technological diversification, Catalán, Navarrete and Figueroa (2020) introduced the concept of scientific and technological cross-density through a two-stage methodology applied to a sample of 182 countries between 1988 and 2014. They defined density as the average proximity of a potential new technology to a country's scientific and technological portfolio. The findings reveal that the closer a country's technological portfolio is to a new technology, the greater the likelihood that the country will achieve global relevance in producing that technology. Conversely, when a technology bears little relation to a country's technological portfolio, the probability of that technology exiting the country increases.

Françoso, Boschma and Vonortas (2024) examined sectoral and technological diversification in Brazilian regions between 2006 and 2019. Their results indicate that regions diversify into sectors and technologies that require capabilities similar to locally available ones. Generally, as the complexity of the sector or technology increases, the likelihood of diversification decreases.

Rigby (2015) employs the methodology established by Leten, Belderbos and Looy (2007), utilizing patent citations and the leading technology classes associated with the cited patents to measure the distance between them. In contrast, Boschma, Balland and Kogler (2015) follow the methodology of Hidalgo et al. (2007) through technology co-occurrence in cities. Catalán, Navarrete and Figueroa (2020) also adopt this latter methodology, adding several steps to define scientific and technological cross-density. Meanwhile, Balland et al. (2018) and Françoso, Boschma and Vonortas (2024) calculate technological relatedness based on the co-occurrence of technology classes within each patent document.

Consequently, the concept of relatedness expands and finds application across various themes, consistently linking the concepts of specialization and diversification in regions or countries. Beyond the dimensions of relatedness concerning products, industries, and technologies, other studies integrate this concept into different areas. One such area relates to the relatedness of skills, which can be understood as a continuation of related industries, as the mobility of related human capital drives the diversification process. Neffke and Henning (2013) argue that through employment mobility, skilled individuals migrate to sectors where their current skill set aligns, as skills acquired in one industry can find utility in others. Their analysis, conducted in Sweden between 2004 and 2007, reveals that firms are approximately 100 times more likely to diversify into sectors related to the qualifications of their primary sector than into sectors weakly related to those qualifications.

Muneepeerakul et al. (2013) analyzed the diversification of occupations in U.S. metropolitan regions, using a measure of relatedness based on the frequency of co-location of occupational specializations. The authors argue that some occupations within the same classification group relate closely to each other. Thus, when a region specializes in one occupation, it will likely specialize in another, demonstrating the path dependence of regions concerning their occupational levels. Boschma, Balland and Kogler (2015) investigated the impact of scientific relatedness on knowledge dynamics in biotechnology at the city level between 1989 and 2008. Their findings show that new scientific topics in biotechnology often emerge in cities that host related themes. Furthermore, existing scientific topics are more likely to disappear from a city when they do not strongly relate to that city's scientific knowledge portfolio.

Understanding the phenomenon of diversification, regardless of the dimensions analyzed—such as product, knowledge, industry, technology, scientific publications, and occupations—reveals a convergence in the results. This convergence suggests that the tendency toward diversification depends on the available capabilities within a region or country. While this situation may pose challenges, indicating that regions or countries lacking diversification policies face significant obstacles to altering their existing structures, it also presents an opportunity to develop diversification strategies based on related capacities, steering towards more complex structures. The current literature follows a similar logic: it analyzes diversification by examining the proximity between specializations and existing knowledge in the region, focusing on the same area of knowledge. In this sense, researchers assess new product specializations by their proximity to the productive knowledge of the region or country. The same applies to other areas of analysis, such as industry, technology, scientific publications, and occupations. This thesis advances toward research that connects specializations with proximity to regional knowledge from other areas. Specifically, it examines how industrial specializations are influenced by regional technological knowledge and how technological specializations are shaped by regional productive knowledge. These analyses hold significance because the literature indicates a mutual influence between technological and industrial or sectoral knowledge, as discussed in the following subsection.

1.4 Co-evolution and Dependency Between Productive and Technological Systems

Several studies point out a significant difference between production capacity and technological capacity, and it is necessary to distinguish between these two types of knowledge (Lall, 2000; Lundvall; Johnson, 1994; Bell; Pavitt, 1993). Production capacity involves the tangible resources and processes used to manufacture goods with a specific efficiency level. This includes equipment (including capital technology), work skills (encompassing operational and managerial expertise), product specifications, and organizational methods. Production capacity reflects the company's or country's ability to use existing technologies efficiently within the prevailing production structures. In contrast, technological capabilities refer to the resources needed to generate, manage, and integrate technical changes. These capabilities encompass the skills, knowledge, institutional structures, and linkages essential for technological innovation and adaptation (Bell; Pavitt, 1993). They include the know-how to operate production systems and the expertise to modify, improve, or create new technologies. This distinction is crucial because technological capabilities form the basis for technological accumulation - the process by which these capabilities are developed and expanded.

The development of production systems is closely linked to technological capabilities, and their coevolution shapes the industrial landscape. Nelson and Winter (1978) pioneered the idea that technological change and market structures evolve together. Their evolutionary theory posits that companies adapt and innovate based on routines shaped by past experiences, leading to industry-wide transformations. Historically, the development of countries in the 18th and 19th centuries, as in the case of textile machinery, demonstrated a significant overlap between these domains. The knowledge needed to operate and improve the machines was accessible to those involved in production, allowing the experience gained in production to contribute directly to technological learning (Bell; Pavitt, 1993). The existence of the cotton industry in England catalyzed the development of fundamental technological innovations, such as ring spinning and the automatic loom, which in turn extended and strengthened the industry's growth throughout the 19th century. These innovations increased productivity and efficiency and allowed the cotton industry to dominate industrial energy consumption, accounting for 30% of this total in 1870. This process illustrates the coevolution of technologies and industries, in which technological advances emerge as a response to production demands and simultaneously transform the sector, shaping its structures and expanding its market capacities. This interdependent dynamic shows how innovation and production drive each other, leading to economic strengthening and diversification (Freeman; Louçã, 2001).

Technological innovations and knowledge play a fundamental role in the evolution of industries and are essential for a successful industrial transformation. Technological change is the driving force behind this transformation, as demonstrated by various studies analyzing the evolution and transformation of industries over time (Soete; Freeman, 1977; Rosenberg, 1982; Dosi, 1984; Soete, 1985; Freeman; Louçã, 2001). Schumpeter (1939) was the first to treat technological change as a disturbance of equilibrium. For the author, innovation was the essence of capitalism, but his "storms of creative destruction" were also seen as factors that brought down companies and even entire industries as new entrepreneurial visions emerged. Technological change generates greater economic competitiveness by increasing productivity and altering the composition of products, industries, companies, and jobs that make up the economy. In this sense, it promotes economic structural change (Malecki, 1997). According to Bell and Pavitt (1993), many factors must be considered in explaining the differences in the dynamic performance of companies and countries. However, somehow, these explanations are always associated with significant differences in the underlying patterns of technological accumulation (Bell; Pavitt, 1993).

Chandler (1962), Penrose (1959), and Teece et al. (1994) have already identified the importance of technological knowledge in company diversification. Furthermore, Dosi and Nelson (2010) reinforce that industrial dynamism and economic growth are interrelated processes driven by technological and organizational innovations. These innovations directly affect companies' productivity, growth, and survival behavior (Klepper; Thompson, 2006; Audretsch, 1991; Quatraro, 2010). In this context, Lall (2000) points out that technological capabilities play a critical role in industrial dynamics, directly influencing these variables. Thus, technological knowledge is a central element for companies' diversification and industrial expansion in regions. It is a crucial aspect of economic transformation.

Dosi and Nelson (2010) reinforce that industrial dynamism and economic growth are interrelated processes driven by technological innovations. These innovations directly affect companies' productivity, growth, and survival behavior (Klepper; Thompson, 2006; Audretsch, 1991; Quatraro, 2010). Similarly, Lall (2000) emphasizes that technological capabilities are essential for industrial dynamics. Eum and Lee (2022a) support this perspective, but the relationship between technology and productive structure depends on the country's level of development. In the early stages of development, resource-based productive experience contributes to accumulating technological knowledge, which evolves into new productive know-how in more advanced stages, creating a continuous cycle of innovation and industrial growth.

Walker (2000) discusses the impact of past technological choices on the future trajectory of industries, emphasizing the concept of path dependence. Decisions made in the past - such as technologies incorporated into machinery and patents acquired - shape the options available to companies and influence their future choices. This reinforces the idea that, once a direction has been established, it is easier for companies to continue on that path than to change course completely, highlighting the complexity and rigidity of technological and productive trajectories. According to Bell and Pavitt (1993), diversification paths in earlier stages of industrialization often depended significantly on previous experience, which included both the creation and use of technology.

Recent studies highlight that considering technological capabilities only as a factor of production can underestimate the possibility of technology-based diversification (Dosi; Grazzi; Moschella, 2017; Kim et al., 2017). Countries often find new export opportunities based on what they already know and develop technological advantages through years of productive experience, even if these opportunities seem unrelated to what they were doing before (Eum; Lee, 2022a). Therefore, these advances in unrelated industries are not necessarily disconnected but can be interpreted as path-dependent advances based on technological capacity.

On the other hand, a place or company's productive and industrial structure can influence the technologies and innovations generated. For example, the emergence of the organic chemicals industry in Germany resulted from the German industry's pressure on the government to create institutions responsible for technological development in partnership with the production system. German universities advanced scientific and technological knowledge in chemistry, resulting in the development of synthetic dyes. Companies, in turn, set up laboratories within their industries so that scientists could work on discovering and developing new products with the support of funding from the German government (Chandler, 1990; Murmann, 2003; Nelson, 2008). Another example of this process is the British textile industry during the Industrial Revolution. The importance of the textile industry in Britain meant that it had productive knowledge which, with incentives for research, was responsible for several incremental innovations throughout the 19th century. This resulted in the maintenance of Britain's competitive advantage in foreign trade through continuous improvements and economies of scale in the production process (Freeman; Louçã, 2001). While it is more evident that technological knowledge generates externalities and fosters innovation, productive knowledge also plays a critical role, especially in the early stages of development (Eum; Lee, 2022a). This foundational knowledge supports technological advancement by providing complementary insights and practical experience, which gradually enhance production efficiency through continuous observation and improvement—a process often described as learning by doing (Arrow, 1962).

Despite this relevance, few studies have explored the relationship between technological diversification and proximity to productive knowledge. Aarstad, Kvitastein and Jakobsen (2016) and Tavassoli and Carbonara (2014) point out that regions with more related industries are associated with more innovative companies. In the same vein, Feldman (1993) and Audretsch and Feldman (1996) showed the importance of the relationship between the production of innovations and the geographical concentration of manufacturing sectors, noting that related industries are the most relevant for innovative activities. Other works suggest that effective learning from production experience can lead to innovation (Berger, 2013; Locke; Wellhausen, 2014; Eum; Lee, 2019; Eum; Lee, 2022a).

This gap in the literature is particularly pronounced when it comes to developing countries. In the context of Brazil, a notable exception is the study conducted by Mascarini, Garcia and Quatraro (2023), which investigated the impact of the diversity of related and unrelated industries on regional innovation. However, this analysis was carried out at a regional level, focusing on the influence of various industries on the number of patents. Pavitt (1984) and Malerba (2002) have previously highlighted that the propensity to patent differs significantly between industries. It is, therefore, crucial to incorporate sectoral dynamics into the technological diversification of regions, which is one of the contributions of this study.

In this sense, Eum and Lee (2022a) explain the relationship between productive and technological knowledge and their interactions in a country's development process. For the authors, in the early stages of development, productive experience based on natural resources and intensive labor influences the accumulation of technological knowledge. Countries and firms combine their available and unused resources to exploit new productive opportunities, which are generally related to the firms' existing technological knowledge (Penrose, 1959; Teece, 1982; Chatterjee; Wernerfelt, 1991; Montgomery; Wernerfelt, 1988). During the transition phase, exporters depend on external sources of knowledge to innovate their products. Until they accumulate enough production experience to meet diversified demands, it becomes feasible and sometimes necessary to turn to foreign buyers for product design technology (Westphal et al., 1981). As the country continues to produce, it observes and learns from production processes to increase efficiency - a phenomenon often described as learning by doing (Arrow, 1962). At this stage, the country does not yet have the total capacity to understand the technology underlying production, but the continuity of production activities allows it to acquire the know-how, even without fully understanding the know-why (Lall, 2000; Lundvall; Johnson, 1994).

In order to gain technological knowledge, it is vital to comprehend know-why, which involves understanding the fundamental principles behind products—such as their design and operational mechanisms—as opposed to know-how, which encompasses practical skills that are more confined to efficient production (Lundvall; Johnson, 1994). Although production can help internalize tacit knowledge, it does not always lead to in-depth knowledge or innovation.

More recent studies have revisited the intimate relationship between production and technological knowledge, suggesting that the role of production in stimulating innovation needs greater emphasis (Berger, 2013; Locke; Wellhausen, 2014; Pisano; Shih, 2012). These works emphasize the inseparable nature of production and knowledge throughout the production stages, from prototype development to commercialization.

Countries can identify new business opportunities with the knowledge acquired through production experience (Kim et al., 2017). Diversification is characterized by the incremental accumulation of capabilities (Dosi; Grazzi; Moschella, 2017), where the ability to design new products is based on accumulated know-how. This type of diversification, based on knowledge, allows a country to achieve international competitiveness in products that are less related to its current portfolio. To do this, it is essential that the country thoroughly analyzes its innovation capacity and technological system, distinguishing its competencies to explore new fields.

Distinguishing between technological and productive capacity is fundamental to understanding industrial development (Bell; Pavitt, 1993; Lall, 1992). If a country only has an advantage in production, it can act as a subcontractor without comprehensive technological capacity. For example, a country specializing in car assembly may have a high export volume but limits itself to assembling imported parts without developing its knowledge (Lee; Baek; Yeon, 2019). This situation can hinder progress towards related products and obscure the diversification process based on comparative advantages. In this sense, industrial diversification depends not only on productive capacity but also on technological capacity and may not occur linearly following current comparative advantages. As a result, unrelated diversifications based on technological capacity can emerge, along with possible slowdowns or failures during the coevolution between production and technological capacities.

Therefore, transformations in industrial structures inevitably require the accumulation of various capacities, especially in terms of knowledge (Cimoli; Dosi; Stiglitz, 2008). Countries seek to secure the necessary technological capacity to support product diversification processes - distinct from the productive capacity (Bell; Pavitt, 1993). However, these paths towards industrial sophistication and diversification are neither linear nor automatic. For this reason, nations develop policies aimed at updating knowledge and diversifying their products (Amsden, 2001; Mazzucato, 2013) to advance through complex and challenging knowledge (Hidalgo et al., 2007), the results of which are not guaranteed.

1.5 Concluding remarks

This chapter analyzes the main theories explaining regional development and economic diversification, emphasizing the interaction between productive structures, technological capacities, and the mechanisms driving regional economic transformation.

Initially, the theories of regional development by Perroux (1955), Myrdal (1957), and Hirschman (1961) emphasized that economic growth is intrinsically unequal between regions due to variations in productive structure, resource endowments, and chain effects. These authors emphasized that growth tends to be concentrated in specific poles or regions, generating positive and negative effects in the surrounding areas. While Perroux introduced the concept of growth poles and motor industries that drive development, Myrdal highlighted the circular and cumulative causation process, where feedback forces can widen regional disparities. Hirschman, in turn, presented the backward and forward linkage effects, demonstrating how growth in specific sectors can stimulate or inhibit development in other sectors and regions. These theories highlight the complexity of regional development, where internal and external factors interact to shape different growth trajectories.

Next, the agglomeration and regional specialization theories of Marshall (1890), Jacobs (1969), and Porter (1990) were explored. Marshall emphasized the external economies of scale derived from industrial specialization and geographical proximity, highlighting advantages such as the availability of skilled labor, specialized suppliers, and technological spillovers. Jacobs countered this view, arguing that urban economic diversity promotes innovation through interaction between different sectors, and warned of the risks of over-reliance on a single industry. Porter combined elements of both perspectives, emphasizing the role of clusters and local competition in promoting innovation and productivity. Although with different approaches, these theories converge on the importance of the positive externalities derived from spatial proximity and the interaction between economic agents for regional development.

The evolutionary perspective in economic geography was introduced as an approach incorporating concepts such as path dependence, increasing returns, and selection, offering a dynamic and historical understanding of regional development. The concept of path dependence suggests that past choices significantly influence the future options of companies and regions, shaping their development trajectories. Increasing returns, as discussed by Arthur (1994), explain how initial advantages can lead to spatial patterns of industrial concentration. In addition, the role of chance and selection highlights that companies' location decisions are not always perfectly rational and are influenced by contingent factors. This evolutionary perspective emphasizes that economic development is a non-linear process shaped by complex interactions between heterogeneous agents over time.

The concept of relatedness has emerged as a critical driver of regional diversification. Based on Penrose's (1959) and Teece's (1982) work and later extended to the regional context, relatedness reflects the importance of cognitive proximity between economic activities in facilitating knowledge exchange and innovation. Empirical studies, such as those by Hidalgo et al. (2007) and Neffke, Henning and Boschma (2011), have shown that regions tend to diversify into activities related to their existing capabilities, following a principle of path dependence. Different methodologies for measuring relatedness have been discussed, including co-occurrence analyses and similarities in the resources used. The literature shows that the set of accumulated capacities guides economic diversification and that proximity between productive and technological sectors significantly influences this process.

In addition, it was pointed out that the application of the relatedness concept has expanded to various areas, such as products, industries, technologies, and skills, always highlighting the tendency for regions or countries to diversify into activities related to their existing capabilities. This finding points to the importance of diversification strategies considering already established competencies, directing efforts towards related areas that boost economic development.

Finally, the coevolution and dependence between productive and technological systems were analyzed, highlighting the interdependence between productive and technological capacities in economic development. The distinction between productive capacity (know-how) and technological capacity (know-why), as discussed by Lundvall and Johnson (1994), is crucial to understanding how innovation and diversification occur in regions. Studies have shown that productive experience can lead to the development of technological capabilities and that technological advances can, in turn, influence the productive structure. Historical examples, such as the British textile industry and the German chemical industry, illustrate how the interaction between production and technology drives innovation and economic growth.

It has also been shown that accumulating technological capabilities is essential, especially in developing countries, to overcome path dependencies and promote knowledge-based diversification. The distinction between productive and technological capacity is fundamental to understanding why some countries or regions manage to diversify their economies and move towards more complex sectors. In contrast, others remain stuck in less sophisticated productive structures.

Therefore, this chapter laid the fundamental foundations for the analyses discussed throughout this thesis. The relationship between technological and productive knowledge, agglomeration externalities, the diversification process, and relatedness were considered crucial elements in this context. Despite significant advances in the literature, essential gaps that require further research have been identified. Notably, most studies on economic diversification analyze the influence of relatedness on diversification about a single type of knowledge, whether productive or technological, without considering the interaction between different types of knowledge. This approach limits understanding of how productive and technological capacities can complement each other and drive regional diversification.

In addition, current literature often treats diversification as a process influenced only by existing capabilities within the same sphere of knowledge. There is a lack of studies examining how regional technological knowledge can influence diversification into new industrial sectors. This gap is particularly relevant for developing countries, where resources are scarce. Therefore, using resources available in neighboring regions can be a way to favor regional diversification.

In short, this chapter has established a solid theoretical framework for the subsequent empirical analyses and identified fundamental issues that still need to be explored in the literature. This thesis seeks to advance the understanding of the mechanisms that drive regional development by addressing the interactions between different types of knowledge (productive and technological) and the influence of regional proximity on diversification.

2 The effect of industry relatedness on regional technological diversification

2.1 Introduction

Diversification is crucial for regional economic development. Jacobs' pioneering work emphasized the importance of cities with greater productive diversification for knowledge externalities and economic growth (Jacobs, 1961). 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; Oort; Verburg, 2007; Neffke; Henning; Boschma, 2011; Freitas; Britto; Amaral, 2024), several works have also explored the importance of related technological diversification for technological competitiveness (Rigby, 2015; Boschma; Balland; Kogler, 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 have explored the interplay between industrial and technological relatedness for technological upgrading in regions. According to the evidence found by Aarstad, Kvitastein and Jakobsen (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, 2022a). 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, Garcia and Quatraro (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 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 and 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.

2.2 Literature Review

2.2.1 Determinants of Regional Technological Diversification

Innovation processes are strongly influenced by geographically localized knowledge and the proximity of agents and institutions (Audretsch; Feldman, 1996; Feldman, 1993; Jaffe, 1989; Asheim; Gertler, 2005; Doloreux, 2002). Regions with a diversified knowledge base are, therefore, more likely to foster innovation due to the greater potential for idea generation and exchange. Cities that host a wide range of industries facilitate the diffusion of ideas across sectors, serving as repositories of knowledge through the diversity of economic activities in which individuals are engaged. This dynamic environment enables the recombination of ideas, creating new opportunities for innovation. By recombining existing resources or knowledge components, new knowledge and innovations can emerge. A broader variety of knowledge fosters this process, as it increases the chances of generating novel ideas (Schumpeter, 1985; Jacobs, 1969; Neffke; Henning; Boschma, 2011). This aligns with Jacobs (1969)'s argument that cities with diverse industries are more likely to experience innovation, as the exchange of knowledge across sectors drives the development of 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; Henning; Boschma, 2011; Essletzbichler, 2015; Freitas; Britto; Amaral, 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; Henning; Boschma, 2011; Essletzbichler, 2015; Rigby, 2015; Boschma; Balland; Kogler, 2015; Balland et al., 2018; Freitas; Britto; Amaral, 2024).

Regarding regional technological capabilities, the pioneering work of Rigby (2015) 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, Balland and Kogler (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 relatedness between technologies in a variety of forms. Rigby (2015) used the co-occurrence between citations of pairs of technology classes, while Boschma, Balland and Kogler (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, despite the different calculation methods of the relatedness between technological classes, the results are convergent. Rigby (2015), Boschma, Balland and Kogler (2015) and 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 firm 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, Garcia and Quatraro (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; Garcia; Quatraro, 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 relatedness density 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 and less likely to lose existing specializations in technological classes related to their industrial knowledge base.
- *Hypothesis 2:* Regions with low per capita income are more likely to develop specializations in technological classes related to their industrial knowledge base.
- *Hypothesis 3:* Regions are more likely to develop new specializations in complex technology classes when related to their industrial knowledge base.
- *Hypothesis 4:* The proximity of patent technological classes to the region's industrial knowledge is more important for generating patent specializations from firms than from universities.

2.3 Methodology

2.3.1 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; Anselin; Varga, 2002). However, there are limitations to using this indicator to measure innovation. As Griliches (1998, 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 et al. (2005) 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, 1998; Andersson; Lööf, 2012). For this reason, patent databases are chosen to measure technological knowledge, in line with Françoso, Boschma and Vonortas (2024) and Mascarini, Garcia and Quatraro (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; Britto; Amaral, 2024; Françoso; Boschma; Vonortas, 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 connection between production and knowledge (Dosi; Riccio; Virgillito, 2021; Eum; Lee, 2022b) 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 [1]. Finally, a translation of the 2-digit CNAE 2.0 was obtained for the technological classes (IPC) of patents at the 3-digit level using ALP. An explanation of the application of the ALP concordance table can be found in Appendix A.

Our panel consists of data for 133 Brazilian intermediate regions and 119 patent technology classes at the three-digit level from 2006-2021. The data is averaged 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, 2015; Boschma; Balland; Kogler, 2015).

2.3.2 Measuring Technological and Industrial Relatedness

Several recent studies have used co-occurrence measures to understand industry relatedness (Bryce; Winter, 2009; Freitas; Britto; Amaral, 2024; Hidalgo et al., 2007; Teece

[1] 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, 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.

et al., 1994). Co-occurrence measures the relatedness 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; Klinger, 2007), industries (Neffke; Henning; Boschma, 2011; He; Yan; Rigby, 2015; Freitas; Britto; Amaral, 2024) and technologies (Boschma; Balland; Kogler, 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 given location. Only tradable industries were considered, excluding services. [2] 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:

$$RCA_{r,c} = \frac{\frac{emp_{r,c}}{emp_r}}{\frac{emp_c}{emp}} \tag{2.1}$$

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:

[2] The main reason for this is that patents are primarily applicable to tangible production sectors, making their relevance to service industries limited. 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).

$$RTA_{r,c} = \frac{\frac{pat_{r,c}}{pat_r}}{\frac{pat_c}{pat}} \tag{2.2}$$

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:

$$RCA_{r,c} = \begin{cases} 1, & \text{se } RCA_{r,c} \geq 1 \\ 0, & \text{caso contrário} \end{cases} \tag{2.3}$$

$$RTA_{r,c} = \begin{cases} 1, & \text{se } RTA_{r,c} \geq 1 \\ 0, & \text{caso contrário} \end{cases} \tag{2.4}$$

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 2.5 and 2.6. 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:

$$\theta_{c,d} = \min\left\{P\left(RCA_{r,c} = 1 \middle| RCA_{r,d} = 1\right), P\left(RCA_{r,c} = 1 \middle| RCA_{r,d} = 1\right)\right\}, \forall \quad c \neq d \tag{2.5}$$

$$\varphi_{c,d} = \min\left\{P\left(RTA_{r,c} = 1 \middle| RTA_{r,d} = 1\right), P\left(RTA_{r,c,} = 1 \middle| RTA_{r,d} = 1\right)\right\}, \forall \quad c \neq d \tag{2.6}$$

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:

$$Industrial\ RD_{r,c} = \frac{\sum_{c \in r, c \neq d} \theta_{c,d}}{\sum_{c \neq d} \theta_{c,d}} \times 100 \tag{2.7}$$

where $\theta_{c,d}$ is the industrial relatedness of technological class c with respect to technology d, calculated with employment data. Moreover, the Technological Relatedness Density (RD) of the technology c in a r region is calculated as:

$$Technological\ RD_{r,c} = \frac{\sum_{c \in r, c \neq d} \varphi_{c,d}}{\sum_{c \neq d} \varphi_{c,d}} \times 100 \tag{2.8}$$

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

2.3.3 Empirical model

$$\begin{aligned}\mathrm{Y}_{r,c,t} = \beta_0 &+ \beta_1 \text{Technological RD}_{r,c,t} + \beta_2 \text{Industrial RD}_{r,c,t} + \beta_3 \text{TCI}_{r,c,t} \\ &+ \beta_4 (\text{Industrial RD}_{r,c,t} * \text{TCI}_{\text{r,c,t}}) + \beta_5 \text{PIB}_{\text{pc}_{r,t}} + \beta_6 \text{Pop}_{r,t} \\ &+ \tau_r + \gamma_c + \mu_t + \epsilon_{r,c,t}\end{aligned} \tag{2.9}$$

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 $Entry_{r,c,t}$ is set to 1 if a region r was not specialized in technology class c at time $t-1$ ($RTA_{r,c,t-1} < 1$) but becomes specialized in c at time t ($RTA_{r,c,t} \geq 1$). 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 ($RTA_{r,c,t-1} < 1$). On the other hand, the variable $Exit_{r,c,t}$ follows the opposite logic. It takes the value 1 if region r was specialized in a technological class c at time $t-1$ ($RTA_{r,c,t-1} \geq 1$) but has ceased to be so at time t ($RTA_{r,c,t} < 1$). The value 0 is assigned if the region r was specialized at $t-1$ and remains specialized at t. Therefore, for the variable $Exit_{r,c,t}$, the observations are limited to cases where the region is specialized in the technological class c ($RTA_{r,c,t-1} \geq 1$) at time $t-1$. Formally the definitions are as follows:

$$\text{Entry}_{r,c,t} = I(c \notin \text{PF}(r,t) \cap i \in \text{PF}(r,t+1)) \tag{2.10}$$

$$\text{Exit}_{r,c,t} = I(c \in \text{PF}(r,t) \cap i \notin \text{PF}(r,t+1)) \tag{2.11}$$

where PF stands for Probability Function.

Rigby (2015), Kogler, Rigby and Tucker (2015), Boschma, Balland and Kogler (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 $\text{RD}_{r,c,t-1}$, 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 $\text{RD}_{r,c,t-1}$ 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 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 regional knowledge spillovers.

$\text{TCI}_{r,c,t-1}$ 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 specialize in less ubiquitous technologies, which tend to require a greater variety of resources. These more complex technologies tend to be developed in a few economies and facilitate diversification in the long run (Hausmann; Klinger, 2007).

$\text{PIB}_{\text{pc}_{r,t-1}}$ is the per capita gross domestic product (in constant reais) of the intermediate region r in the year $t-1$. According to Petralia, Balland and Morrison (2017), the level of economic development influences the technological diversification of a place. $\text{Pop}_{\text{r,t}-1}$ is the population of the intermediate region r in the period $t-1$. Urban characteristics are relevant to knowledge generation and industrial concentration (Duranton; Puga, 2004). The advantages of urban agglomeration include greater diversity in production, facilities, skills, tastes, needs, and cultures, which fosters the transfer of ideas across different economic activities within the same urban area. According to Jacobs (1961), large cities are natural incubators for new businesses and ideas. 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. τ_r, γ_s and μ_t are the fixed effects of region, sector, and time, respectively. $\epsilon_{r,s,t}$ is the regression residual.

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 < 1 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 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. The average per capita income for the entire period was considered, and the sample was divided into three groups with similar regions: high-income, with 45 regions; middle-income; and low-income, with 44 regions in each group.

One of the limitations of this study concerns the possible endogeneity of the relationship between regional production structure and technological diversification. The model used assumes that the interdependence of industrial relatedness density influences the technological specialization of Brazilian regions, suggesting that proximity to established industrial sectors favors the emergence of new technological specializations. However, this relationship may not be strictly unidirectional. It is plausible that technological diversification itself, by promoting innovation and expanding the knowledge base of the regions, also affects the productive structure, making the relationship between the variables bidirectional.

This interaction suggests that the results presented should be interpreted as associations rather than causal relationships. The observed positive effect of industrial relatedness on technological diversification may partly reflect a process of co-evolution between industry and technology rather than direct causality. For a more precise analysis of the direction of this effect, it would be necessary to resort to methods that address endogeneity, such as instrumental variables or simultaneous equation models. However, this analysis focuses on exploring the patterns of association between the variables, confirming the importance of the local productive structure in the technological diversification of Brazilian regions.

2.4 Results

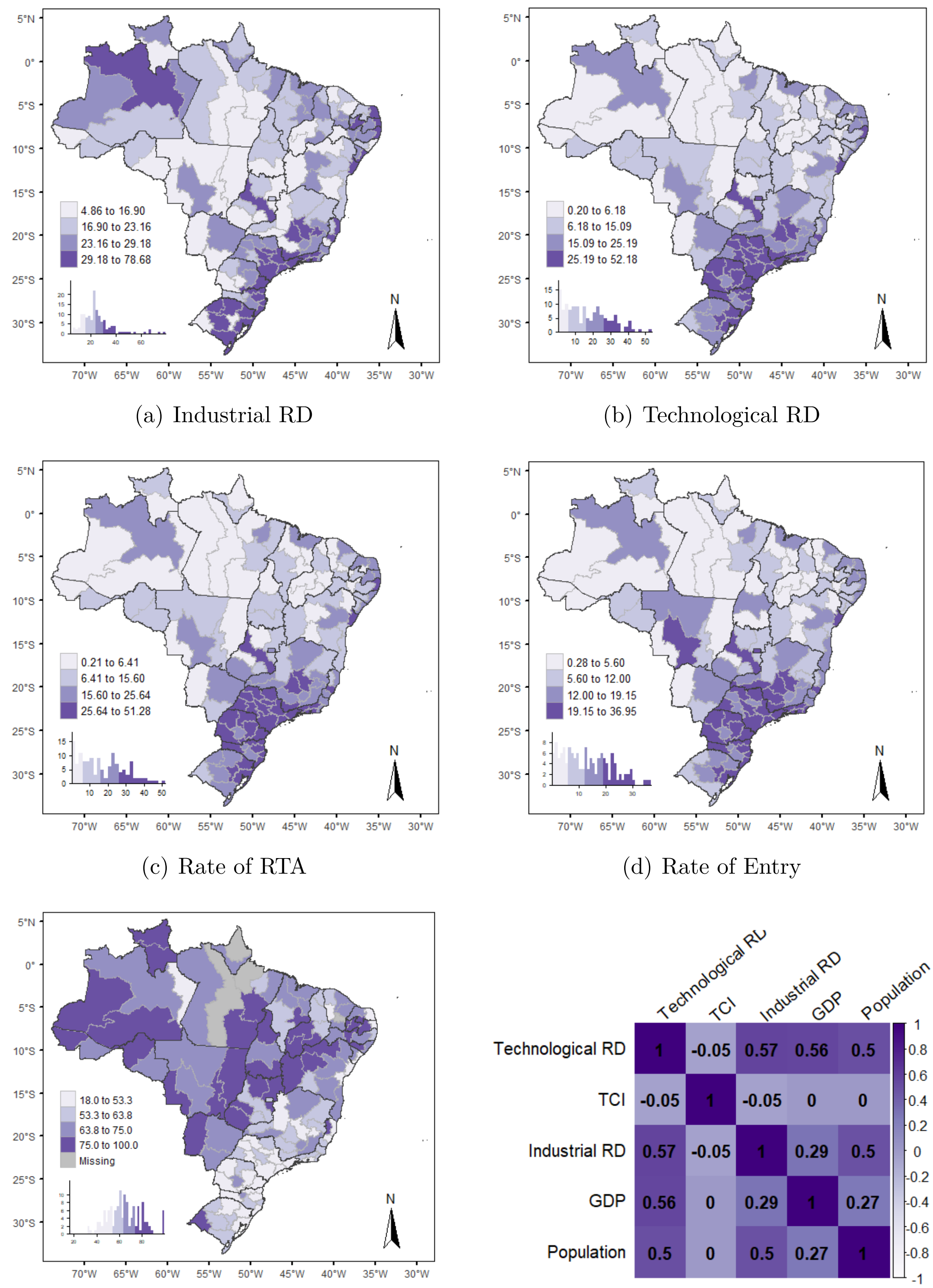
2.4.1 Descriptive analysis

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.

The differences in diversification potential between the different Brazilian regions are also apparent. 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



(a) Industrial RD

(b) Technological RD

(c) Rate of RTA

(d) Rate of Entry

(e) Rate of Exit

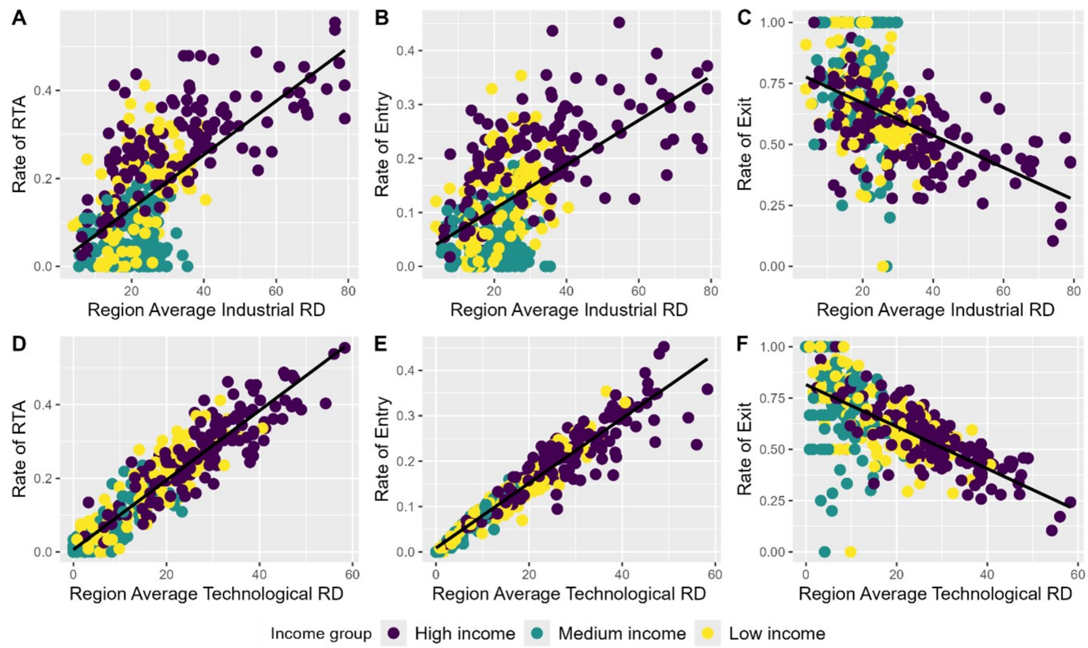
(f) Correlogram

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, Balland and Kogler (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.

2.4.2 Main results

This section presents the results of the estimations described in equation 2.9. The models were estimated using OLS, Probit, and Logit as in Boschma, Balland and Kogler (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 $RTA_{r,c,t}$ and $Entry_{r,c,t}$ models (hypothesis 1); (ii) a negative coefficient for Industrial RD in the $Exit_{r,c,t}$ 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, Balland and Kogler (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 1 indicate that Industrial RD is positively associated with technological diversification in Brazilian regions. As found by Aarstad, Kvitastein and Jakobsen (2016), Tavassoli and Carbonara (2014) and Mascarini, Garcia and Quatraro (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, it was found that technological classes related to the region's industrial portfolio are more likely to specialize in that technology within 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)
Constante	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	0,17		
Wald chi^2				6.988,14	6.403,68
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 and Boschma (2021) found.

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

	Dependent variable:					
	Entry$_t$			*Exit$_t$*		
	(I)	*(II)*	*(III)*	*(IV)*	*(V)*	*(VI)*
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)	
			[-0.027]		[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 chi^2	5581.54	5598.46	5558.94	1791.65	1807.94	1809.92
Pseudo R^2	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.

2.4.3 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 the analysis progresses from high-income to lower-income regions, the influence of Technological RD on the diversification of technological classes diminishes. In regions with low per capita income, Technological RD becomes insignificant. 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 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					
	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 R^2	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.

2.4.4 Differences between applicants

Table 4 presents the determinants of technological diversification, considering only patents held by legal entities, which are further classified into universities/public research institutes and enterprises. This distinction is particularly relevant, as the mechanisms underlying technology generation and development differ significantly across patenting institutions. In Brazil, universities and public research institutes account for the majority of patents filed by domestic applicants. However, the results indicate that the coefficients for both Industrial RD and Technological RD are higher for patents registered by firms than those filed by universities and research institutes. While universities and research institutes play a central role in the Brazilian innovation system, the proximity between productive and technological knowledge appears to be more significant for firms' patent specialization than for that of academic institutions. Universities and research institutes primarily function as “antennas” for the absorption and dissemination of science and technology, playing a pivotal role in the technological upgrading of peripheral economies. However, this specific function often leads to research activities that are "ahead of demand," resulting in a mismatch between new technological developments and existing industrial capabilities (Suzigan; Rapini; Albuquerque, 2011; Kruss et al., 2015).

The disconnection between scientific institutions and the productive sector is a well-documented structural challenge in many developing economies. This gap inhibits the full absorption and application of technological innovations generated in universities and research institutes by the industrial sector. In Brazil, this issue is further exacerbated by the absence of effective coordination mechanisms among key actors within the national innovation system. As a consequence, the knowledge produced in academic institutions frequently fails to translate into practical applications, thereby widening the gap between research advancements and the technological needs of industry. This structural fragmentation not only limits the real-world impact of academic research but also reinforces the perception that innovation efforts are not sufficiently aligned with the productive demands of the economy (Crane, 1977).

Furthermore, the limited demand for innovation within the Brazilian industrial sector mirrors a common trend observed in developing countries, as highlighted by (Crane, 1977). Many firms opt to acquire foreign technologies rather than invest in domestic research and development, a preference driven by macroeconomic constraints, inadequate public policies, and a general undervaluation of innovation as a competitive advantage (Chaves et al., 2016). This reliance on external technological solutions further discourages universities and research institutes from tailoring their innovations to meet the specific needs of the domestic market, perpetuating a cycle of weak integration between academia and industry. Consequently, the lack of an established innovation culture and the absence of effective incentives for local technological development reinforce Brazil's dependence on imported technologies, posing significant challenges to the establishment of a self-sustaining and robust national innovation system (Crane, 1977).

The findings of Póvoa and Rapini (2010) further substantiate this discussion, indicating that patents remain one of the least-utilized channels of technology transfer by Brazilian universities and public research institutes. The authors argue that while patents may serve as a critical mechanism for firms, academic institutions predominantly rely on publications, consulting activities, and informal knowledge exchanges as their primary means of technology transfer. These findings align with those of (Bekkers; Freitas, 2008), who emphasize that university patents are generally not the primary channel for technology transfer; rather, collaboration, student mobility, and joint research projects play a more substantial role.

Similarly, Lee (2000) highlights that in the United States, firms that engage with universities benefit more from knowledge spillovers and access to cutting-edge research rather than direct patent acquisition. The study suggests that industry-university collaborations are sustained primarily due to expertise-sharing and long-term partnerships, rather than immediate patent-driven innovation.

Additionally, Bekkers and Freitas (2008) conducted a survey among Dutch industrial and academic researchers regarding knowledge transfer channels. Their results indicate that patents are assigned relatively low importance as a transfer mechanism, whereas formal collaborations, joint R&D projects, and researcher mobility are regarded as far more significant. This evidence supports the broader argument that while patents contribute to technology transfer, direct academic-industry interactions are often the most effective means of fostering innovation.

According to Cassiolato (2015), Brazil has built a strong science and technology infrastructure and developed expertise in cutting-edge research fields such as health (led by Fiocruz and other university-based research centers), agriculture and food production (led by Embrapa), energy (led by CENPES, Petrobras' research center), and aerospace (led by Embraer). Nevertheless, these "islands of excellence" remain largely disconnected from other economic sectors, as noted by Mazzucato and Penna (2016). The work of Suzigan et al. (2006) further illustrates how Brazil's productive structure has influenced and, in some cases, shaped technological development in specific industries. This underscores the need for innovation policies that adopt a more integrated and systemic perspective, recognizing the interconnected nature of technological advancement, rather than relying solely on sector-specific approaches.

These findings highlight the urgency of establishing stronger mechanisms to integrate university research into industrial innovation. Policies should aim to enhance collaboration between academic institutions and enterprises, encourage the development of technology transfer offices, and foster a culture of innovation that aligns with industry demands. Without such measures, the persistent gap between university research and industrial application will continue to hinder Brazil's ability to achieve sustainable technological progress and long-term economic development.

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

	Dependent variable: RTA_t			
	Firms		*Universities*	
	(I)	*(II)*	*(III)*	*(IV)*
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 R^2	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.

2.4.5 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, Henning and Boschma (2011) and Freitas, Britto and Amaral (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.

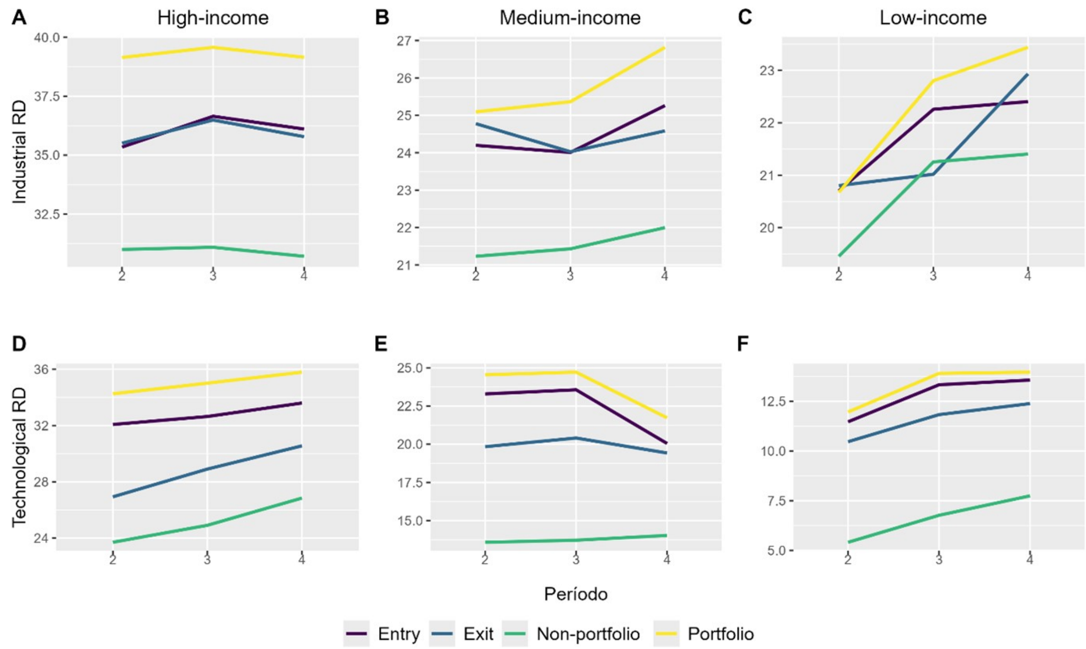
One relevant difference between industrial and technological densities deserves attention. In terms of technological density (Figures 3.D, 3.E and 3.F), the average density of the technological classes that entered the regions remains consistently higher than the line representing the classes that left 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, it can be observed 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.

2.5 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 industrial relatedness density 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, 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. It is also found that technological relatedness density does not affect technology diversification in areas with lower per capita income, while industrial relatedness has a positive relationship. In addition, the industrial relatedness density 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, It is critical to continue discussing the diversification of Brazilian regions and their relationship with productive and technological systems. The compatibility of industrial sectors and technological classes is a limitation of this research, but given the available data sources in Brazil, this approach is considered the most appropriate. Future research should investigate the impact of specialization in specific sectors in certain regions and its effects on technological class diversification.

3 The Role of Technological Relatedness in Shaping Industrial Diversification

3.1 Introduction

The process of regional diversification and changes in regional productive structures 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; Lissoni; Malerba, 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; Henning; Boschma, 2011; Boschma; Minondo; Navarro, 2013; Freitas; Britto; Amaral, 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; Soete; Freeman, 1977; Rosenberg, 1982; Dosi, 1984; Soete, 1985; Freeman; Louçã, 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; 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; Klepper, 1982; Nelson; 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; Wenting, 2007; Buenstorf; 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; Uranga; Etxebarría, 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; Nelson; Walsh, 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; Srholec; Verspagen, 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; Sunley, 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 (2022b), 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.

In this sense, this article aims to assess whether diversification into new sectors is more likely in regions whose regional portfolio includes technologies related to these sectors. In addition, they differentiated the estimates between the filing institutions, the types of patents and the per capita income of the regions. The industrial and technological relatedness density 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.

3.2 Literature Review

3.2.1 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 and 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), 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; Oort; Verburg, 2007; Neffke; Henning; Boschma, 2011; Essletzbichler, 2015; Françoso; Boschma; Vonortas, 2024; Queiroz; Romero; Freitas, 2024).

Neffke, Henning and Boschma (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, Boschma and Vonortas (2024), Freitas, Britto and Amaral (2024), and (Queiroz; Romero; Freitas, 2024) have developed work in this direction. Françoso, Boschma and Vonortas (2024) 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, Britto and Amaral (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, Romero and Freitas (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, Britto and Amaral (2024) and Queiroz, Romero and Freitas (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, Boschma and Vonortas (2024) analyze the influence of technological relatedness density on the entry of new technologies, not on the entry of new sectors, which is the focus of this study. Neffke, Henning and Boschma (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; Johnson, 1994; Bell; 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, 1997; Rosenberg, 1982; Dosi, 1984; Soete, 1985; Freeman; Louçã, 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; Uranga; Etxebarría, 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; Grillitsch; Trippl, 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; Nelson; Walsh, 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 by creating 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 research areas, thus maintaining the established technological landscape (Schumpeter, 1939; Dosi, 1982; Fagerberg; Srholec; Verspagen, 2010). Mascarini, Garcia and Quatraro (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 place's level of development. Regions with lower income levels seem to have greater difficulties improving their technological capabilities, which affects the way in which regions diversify into industrial sectors. For Eum and Lee (2022a), developing regions have limited technological capabilities and cannot influence the industrial development of these places.

Thus, the hypotheses of the paper are as follows:

- *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 relatedness 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.

3.3 Methodology

3.3.1 Data base

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

This research used the RAIS employment database to calculate the industrial relatedness density and the competitiveness of sectors in the regions. Several studies have chosen to use this information because of its wide geographical coverage and its coverage over several years (Freitas; Britto; Amaral, 2024; Françoso; Boschma; Vonortas, 2024). However, international trade data, as used by Hidalgo et al. (2007) and (Hidalgo; 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 are 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; Anselin; Varga, 2002). It is known that there are disadvantages to using patent data, such as: not all 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, invention does not represent all forms of knowledge production within the economy and patents do not capture all knowledge produced (Kogler; Rigby; Tucker, 2015). However, there are several advantages, such as the large amount of data available, accessibility, industrial applicability, and objective and stable criteria (Griliches, 1998; Andersson; Lööf, 2012). For this reason, patent databases were chosen to measure technological knowledge, in line with Françoso, Boschma and Vonortas (2024) and Mascarini, Garcia and Quatraro (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, the inventor database was used, 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 -, the applicant's database was chosen for this analysis. For counting patents by region and technological classification (IPC), the following criterion was adopted: 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 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 applications, 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, it is necessary to relate the two datasets by translating technology classes into 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; Riccio; Virgillito, 2021; Eum; Lee, 2022b). This table translates data from SITC, ISIC, and NAICS classifications to/from IPC (Lybbert; Zolas, 2014). The first step involved converting the number of patents from 3-digit technological classes (IPC) to 2-digit ISIC Rev. 4 using the ALP concordance table. Next, the patent data classified under ISIC at the 2-digit level were translated into 2-digit CNAE 2.0. Since CNAE is derived from ISIC, the classifications at the 2-digit level are nearly identical, with only a few exceptions related to specific product groups [1]. A detailed discussion on the use of the ALP concordance

[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,

table is provided in Appendix A.

Our panel includes data from 133 Brazilian intermediate regions and 39 industry classes at the 2-digit CNAE level, covering the period 2006-2021. The data were aggregated 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; Garcia; Quatraro, 2023).

3.3.2 Measuring Technological and Industrial Relatedness

Several studies (Teece et al., 1994; Hidalgo et al., 2007; Bryce; Winter, 2009; Freitas; Britto; Amaral, 2024) have used co-occurrence measures to understand the relatedness between two industries. 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; Britto; Amaral, 2024; Hausmann; Klinger, 2007; He; Yan; Rigby, 2015; Neffke; Henning; Boschma, 2011) and technologies (Boschma; Balland; Kogler, 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 relatedness 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, Britto and Amaral (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:

$$RCA_{r,s} = \frac{\frac{emp_{r,s}}{emp_r}}{\frac{emp_s}{emp}} \tag{3.1}$$

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.

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 s; and emp is total employment in the country.

For patent data, the quotient is calculated as follows:

$$RTA_{r,s} = \frac{\frac{pat_{r,s}}{pat_r}}{\frac{pat_s}{pat}} \tag{3.2}$$

where: $pat_{r,s}$ is the number of patents in the intermediate region r in industrial sector s; pat_r is the total number of patents in region r; pat_s is the number of patents in 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:

$$RCA_{r,s} = \begin{cases} 1, & \text{se } RCA_{r,s} \geq 1 \\ 0, & \text{caso contrário} \end{cases} \tag{3.3}$$

$$RTA_{r,s} = \begin{cases} 1, & \text{se } RTA_{r,s} \geq 1 \\ 0, & \text{caso contrário} \end{cases} \tag{3.4}$$

The RCA and RTA calculations are used to calculate the relatedness 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 4.5 and 4.6. 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:

$$\theta_{s,v} = \min\left\{P\left(RCA_{r,s} = 1 |\, RCA_{r,v} = 1\right), P\left(RCA_{r,v} = 1 |\, RCA_{r,s} = 1\right)\right\}, \forall \quad s \neq v \tag{3.5}$$

$$\varphi_{s,v} = \min\left\{P\left(RTA_{r,s} = 1 |\, RTA_{r,v} = 1\right), P\left(RTA_{r,v} = 1 |\, RTA_{r,s} = 1\right)\right\}, \forall \quad s \neq v \tag{3.6}$$

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, the relatedness of each pair of sectors was linked 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 sector 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:

$$Industrial\ RD_{r,s} = \frac{\sum_{s \in r, s \neq v} \theta_{s,v}}{\sum_{s \neq v} \theta_{s,v}} \times 100 \tag{3.7}$$

where $\theta_{c,d}$ is the industrial relatedness of technological class c with respect to technology d, calculated with employment data. Moreover, the Technological Relatedness Density (RD) of the technology c in a r region is calculated as:

$$Technological\ RD_{r,s} = \frac{\sum_{s \in r, s \neq v} \varphi_{s,v}}{\sum_{s \neq v} \varphi_{s,v}} \times 100 \tag{3.8}$$

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

3.3.3 Empirical model

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

$$\begin{aligned} \text{RCA}_{r,s,t} = \beta_0 &+ \beta_1 \text{RD Industrial}_{r,s,t-1} + \beta_2 \text{RD Technological}_{r,s,t-1} + \beta_3 \text{PCI}_{r,s,t-1} \\ &+ \beta_4 (\text{RD}_{r,s,t-1} * \text{PCI}_{\text{r,s,t}-1}) + \beta_5 \text{GDP}_{\text{pc}_{r,t-1}} + \beta_6 \text{Pop}_{r,t-1} \\ &+ \tau_r + \gamma_s + \mu_t + \epsilon_{r,s,t} \end{aligned} \tag{3.9}$$

Em que: $\text{RCA}_{r,s,t-1}$ is the degree of specialization in a given sector s in region r at time $t-1$. Equals 1 if the region is specialized, otherwise equals 0. Industrial $\text{RD}_{r,s,t-1}$ is the Industrial Relatedness Density variable calculated in equation 4.7. It is based on the work of Freitas, Britto and Amaral (2024) and Queiroz, Romero and Freitas (2024); Technological $\text{RD}_{r,s,t-1}$ is the main variable of interest, which was calculated in equation 4.8. The main objective is to demonstrate that regions diversify into sectors related to the technological knowledge of the location, according to Eum and Lee (2022b).

$\text{PCI}_{r,t-1}$ 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] .

$\text{GDP}_{r,t-1}$ is the per capita gross domestic product (in constant reais) of the intermediate region r in the year $t-1$. According to Freitas, Britto and Amaral (2024), the level of economic development influences the sector diversification of a place. $\text{Pop}_{r,t-1}$ 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; 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. τ_r, γ_s and μ_t are the fixed effects of region, sector, and time, respectively. $\epsilon_{r,s,t}$ is the regression residual.

The base is organized into 39 CNAE divisions for 133 intermediate regions of Brazil between 2006 and 2021 (Divided into 4 periods of 4 years - 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. The average per capita income for the entire period was considered, and the sample was divided into three groups with a similar number of regions: high-income, with 45 regions; middle-income; and low-income, with 44 regions in each group.

As in the previous chapter, this study faces a potential endogeneity problem, since the relationship between the density of technological relatedness and industrial diversification may not be strictly exogenous. The model assumes that technological proximity, measured by the technological relatedness density, influences the probability of new industrial specialization. However, this relationship may be bidirectional, i.e. industrial diversification also contributes to the consolidation of the regional technological base. The expansion of industrial sectors can stimulate investment in innovation and research, generating new technologies which in turn strengthen the competitiveness of these sectors.

The results presented should therefore be interpreted as evidence of correlation rather than proof of causation. Although the analysis suggests that industrial specialization benefits from proximity to regionally developed technologies, this effect cannot be said to be exogenous and independent of the evolution of the industrial sector itself. Overcoming

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

this limitation would require econometric strategies that control for endogeneity, such as instrumental variables or natural experiments. However, the results underscore the importance of the interdependence between the technological and industrial capacities of Brazilian regions and highlight the role of technology in shaping development.

3.4 Results

3.4.1 Main results

This section contains the estimations of the 4.9 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 specialization of sectors in regions.

For the estimations, the coefficients cannot be directly compared because estimations IV and V were carried out using the Probit and Logit models. However, the signs obtained in the coefficients can be compared. Table 5 shows that, for all the models, the Industrial RD has a positive influence on new specializations in sectors in the Brazilian regions. This means that sectors are more likely to become specialized in regions where they have some kind of industrial proximity, as obtained by Neffke, Henning and Boschma (2011) and Freitas, Britto and Amaral (2024). This result confirms a literature that has already identified the dependence of industrial knowledge on sectoral specializations 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 technological knowledge on the likelihood of specializing in these sectors in the regions. 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 emphasizes the importance of technological knowledge for the productive sector in the works of Freeman and Soete (1997), Rosenberg (1982), Dosi (1984), Soete (1985), and Freeman and Louçã (2001). This result was found for countries worldwide in the work of Eum and Lee (2022b), except for groups of developing countries. However, such an analysis focusing on regions, especially in a developing country, has yet to be conducted.

Comparing the coefficient values in each model reveals that industrial RD has a greater influence on the probability of specialization than technological RD. This is expected, as industrial RD reflects the same type of capability as the sectors in the specializations 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 exploiting their innovative knowledge (Dosi; Grazzi; Moschella, 2017).

It was also found that the complexity of sectors negatively impacts the likelihood of specialization in regions. Specifically, when a sector is considered complex, it becomes more challenging to make it competitive in the regions due to the greater skills required. This result was also found by Freitas, Britto and Amaral (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 specialization in the region becomes positive. Finally, the GDPpc and population coefficients were not significant in any of the estimations.

Table 5 – Determinants of sector diversification in Brazilian intermediate regions

	Dependent variable: RCA_t				
	OLS			*Probit*	*Logit*
	(I)	*(II)*	*(III)*	*(IV)*	*(V)*
Industrial RD_{t-1}	0.021***	0.021***	0.019***	0.069***	0.120***
	(0.0006)	(0.0006)	(0.0007)	(0.0026)	(0.0046)
Technological RD_{t-1}		0.001***	0.001**	0.005***	0.009***
		(0.0005)	(0.0005)	(0.0020)	(0.0035)
PCI_{t-1}			-0.050***	-0.360***	-0.682***
			(0.017)	(0.084)	(0.151)
Technological RD_{t-1} * PCI_{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)
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. $*p < 0.1$; $**p < 0.05$; $***p < 0.01$. All regressions include region, period and sector fixed effects.

3.4.2 Differences between patents classifications

Table 6 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. It was found that, regardless of the type of patent, if the sectors are related to regional technological knowledge, the probability of specialization in the region increases. 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; Srholec; Verspagen, 2010).

Table 6 – Determinants of sector diversification in Brazilian regions divided by distinct patent classifications

	Dependent variable: RCA_t			
	IP (high-level innovation)		*UM (low-level innovation)*	
	(I)	*(II)*	*(III)*	*(IV)*
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)
PCI_{t-1}		-0.624***		-0.556***
		(0.150)		(0.150)
Technological RD_{t-1} * PCI_{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)
Observations	15,561		15,561	
Wald chi^2	2622.27***		2604.08***	
Pseudo R^2	0.19		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 sector fixed effects.

3.4.3 Differences between applicants

Patenting efforts vary widely in their objectives and applications. It is, therefore, essential to examine the origin of patent applications, differentiating between those that come from public institutions, such as universities and research institutes, and those that arise from private companies. In Table 7, Technological RD is calculated in two ways: considering the number of patents from universities/public research institutes and the number of patents originating from companies. Although the volume of patents from universities is significantly higher than that from companies, the data shows that the region's sectoral diversification probability is higher when associated with technological knowledge originating from patents from companies compared to patents from universities or public research institutions.

This result reflects the different orientations and motivations that drive patent development in each context. In universities and research institutes, the development of technologies often does not require direct application in the market. Universities also conduct basic research to expand scientific knowledge, allowing greater cognitive freedom for fundamental research. Although some companies also carry out basic research, this type of long-term, high-risk research is usually restricted to a few multinationals with significant market power. Even so, in companies, basic research tends to have a long-term commercial focus (Rosenberg, 1982). Thus, companies' patenting efforts often align more with commercial objectives, maintaining a direct connection with the market. This may explain their greater contribution to regional sectoral specialization when there is proximity between the sector and the technological knowledge originating from company patents.

In addition, even when patents from universities and public institutions have the potential to be applied in the market, there is a well-known difficulty in integrating and transferring this knowledge to the productive sector. This challenge arises both on the side of the university, which often operates with rigid structures for the commercialization of technologies, and on the side of companies, which may face cultural or logistical barriers to the adoption of this knowledge. Fabrizio (2007) highlights the complexity of transferring academic knowledge to industry. In contrast, Póvoa and Rapini (2010) observes that, in Brazil, universities and public research institutes tend to develop technologies aimed at production processes rather than products directly ready for the market.

Universities play an essential role in the Brazilian innovation system, as highlighted by (Suzigan; Albuquerque, 2011), and are fundamental to developing a competitive, knowledge-oriented environment. These findings highlight the need for public policies that encourage interaction between the academic and business sectors, facilitating the transfer of innovations to commercial applications. To this end, it is crucial to strengthen relational social capital and implement tax incentives that motivate industry to seek innovation through academic partnerships and strategically distributed public funding, supporting industrial development and increasing competitiveness, with increasingly structured cooperation between academia and industry (Rossoni; Vasconcellos; Rossoni, 2024).

However, collaboration between universities and companies encounters specific barriers, such as lack of trust, fear of knowledge leakage, and reluctance to share information in the initial phases (O'Dwyer; Filieri; O'Malley, 2023). These difficulties can be overcome gradually, starting with smaller-scale projects and increasing complexity as trust based on integrity and intellectual property agreements are consolidated in the engagement phase (Rossoni; Vasconcellos; Rossoni, 2024). The partners' previous experience is fundamental in the initial stages, while cohesion and complementarity of knowledge become vital as the collaboration progresses (O'Dwyer; Filieri; O'Malley, 2023).

Table 7 – Determinants of sector diversification in Brazilian regions divided by distinct patent applicants

	Dependent variable: RCA_t			
	Universities		*Firms*	
	(I)	*(II)*	*(III)*	*(IV)*
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)
PCI_{t-1}		-0.186		-0.595***
		(0.147)		(0.150)
Technological RD_{t-1} * PCI_{t-1}		0.008***		0.023***
		(0.0013)		(0.0018)
GDPpc_{t-1} (log)		0.333		0.183
		(0.287)		(0.284)
$\mathrm{Population}_{t-1}$ (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)
Observations	15,065		15,327	
Wald chi²	2517.81***		2576.91***	
Pseudo R²	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 sector fixed effects.

3.4.4 Differences between regions

Table 8 shows the determinants of sectoral specialization by dividing regions into high, medium, and low-income groups. Technological RD has no impact on sectoral specialization in low-income regions. In contrast, the industrial RD variable affects all regions, regardless of income level. This may be attributed 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; Sunley, 2010).

Table 8 – Determinants of sector diversification in Brazilian intermediate regions divided by income

	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)
PCI_{t-1}		-0.410		-0.930***		-0.743***
		(0.281)		(0.273)		(0.267)
Technological RD_{t-1} * PCI_{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)
Observations	5,265	5,265	4,884	4,884	5,016	5,016
Wald chi^2	1012.60***	1008.05***	807.60***	778.85***	935.05***	931.49***
Pseudo R^2	0.21	0.21	0.19	0.20	0.22	0.23

Source: Authors' elaboration.

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

3.5 Concluding remarks

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 industrial and technological knowledge play a significant role in the sectoral specialization of regions, with industrial knowledge having a stronger influence.

The results indicate that regions with industrial and technological proximity are more likely to specialize in new sectors, confirming the importance of industrial and technological cohesion for regional development. Technological proximity proved 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 specialization than those from universities and public research institutes. This finding can be attributed to the commercial focus of business patents, as opposed to academic institutions' cognitive freedom and knowledge transfer challenges. The analysis also showed that in low-income regions the influence of technological knowledge on sectoral specialization is limited, while industrial proximity remains relevant. This finding suggests that developing technological capabilities in less-developed regions is crucial for overcoming diversification and industrial progress barriers.

Policies that promote the creation and diffusion of technological knowledge, especially in low-income regions, are therefore fundamental to fostering industrial diversification. Improving integration between universities, firms, and research institutions can 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 regions' technological and industrial capacity. Thus, they promote economic development that is consistent with the regions' capacities but focused on more complex industries and technologies.

4 The Role of Neighboring Regions in Industrial Diversification in Brazil

4.1 Introduction

It is now a consensus that economic diversification of regions is a heavily path-dependent process. Several studies have found that the development of new capabilities in a region is profoundly influenced by its pre-existing knowledge and skills (Neffke; Henning; Boschma, 2011; Boschma; Minondo; Navarro, 2013; Freitas; Britto; Amaral, 2024). However, most studies neglect the importance of extra-regional links and interactions for developing new capabilities. These connections are crucial, as regions do not operate in isolation but interact and connect, fostering mutual exchanges and enabling the introduction of new knowledge. Therefore, factors external to regions can influence and contribute to new specialization paths.

The transmission of knowledge between regions is significantly influenced by geographical distance, due to the difficulty of transmitting tacit knowledge and local capabilities to more distant places (Polanyi, 1967; Arrow, 1962; Jaffe; Trajtenberg; Henderson, 1993; Markusen, 1996; Feldman, 1994; Audretsch; Feldman, 1996; Boschma, 2005). Physical proximity between regions facilitates the diffusion of knowledge, which is essential for economic development, particularly in industries that act as growth poles and generate multiplier effects (Perroux, 1955). The literature on agglomeration externalities explains why knowledge and other advantages spread more easily in nearby areas, where companies seek to grow within their local networks. Advantages include access to a specialized workforce, efficient input supply through economies of scale, and the exchange of information (Marshall, 1890). Consequently, knowledge interactions are more commonly observed between neighboring regions than between those that are more distant (Boschma, 2017).

However, Myrdal (1957) highlighted that the influence of neighboring regions can have both positive and negative effects on regional development. Positive "spread effects" occur when economic growth in one region stimulates growth in neighboring areas through increased demand and the diffusion of innovation. Conversely, negative "backwash effects" arise when the growth of a dominant region draws resources, such as labor and capital, away from neighboring regions, potentially exacerbating regional disparities. Therefore, while proximity can facilitate beneficial exchanges, it can also lead to regressive outcomes for less competitive regions.

Although knowledge transmission has a regional component, many studies focus primarily on internal capabilities in the diversification process, neglecting interactions with other regions (Neffke; Henning; Boschma, 2011; Boschma; Minondo; Navarro, 2013; Freitas; Britto; Amaral, 2024). Local capabilities provide opportunities but also impose limits on regional diversification. Especially for regions that are not very diversified, the difficulty in transitioning to new specializations can generate a lock-in if these places rely solely on internal capabilities (Hassink; Lagendijk, 2001; Hassink, 2005). Hence, for less developed regions it is particularly relevant to rely on external connections to help in developing new capabilities, as their local resources and networks are often insufficient to independently foster diversification (Fitjar; Rodríguez-Pose, 2011; Grillitsch; Nilsson, 2015; Dawley, 2014; Isaksen; Trippl, 2016). Some capabilities can be leveraged from neighboring regions, such as labor, transport infrastructure, input supply, trade, among others (Cohen; Paul, 2005; Lundquist; Trippl, 2013; Jara-Figueroa et al., 2018; Gao et al., 2021).

Given the geographically biased nature of capability diffusion and the interactions and exchanges between regions, it is reasonable to expect regions to develop in industrial sectors where their neighbors are already competitive. This phenomenon not only boosts regional specialization but can also strengthen interregional collaboration to stimulate economic growth. Geographically close countries tend to exhibit significant similarities in their export portfolios, a convergence that decreases with distance, explained by the dissipation of the effect of distance on the diffusion of tacit knowledge (Bahar; Hausmann; Hidalgo, 2014). Boschma (2017) and He et al. (2019) reinforce this idea, showing that subnational regions in the US and China, driven by network connections between neighbors, are more likely to develop new industries in which their neighbors already specialize.

Therefore, this article aims to verify the influence of the competitiveness of neighboring regions on entry/exit specializations, as well as growth in regional competitiveness. The study advances the literature by addressing several limitations in previous research. Unlike Bahar, Hausmann and Hidalgo (2014) and Boschma (2017), the approach incorporates the density of neighboring regions to capture the intensity of regional interactions more precisely. While He et al. (2019) includes density weighted by distance, this method is avoided due to spatial complexities within regions, opting not to weigh by distance. The analysis is conducted at a finer regional level than the more aggregated country and state levels used in prior studies, allowing for a detailed examination of regional specialization and competitiveness.

Furthermore, instead of relying on export data like previous studies, employment data is used to capture better internal economic activities, which is particularly important in a large country like Brazil, where internal trade plays a significant role. Additionally, none of the previous authors analyze the sectoral influence of neighboring regions; this gap is addressed by dividing the research into sectors to understand whether sectoral differences lead to varying results in the links between neighboring regions. This discussion concerns intra-industry knowledge spillovers from neighboring regions and the dissemination of knowledge from related industries in those regions. The study fills a gap in Brazilian regional literature by investigating how neighboring regions affect the diversification of Brazilian regions. It offers a novel perspective on regional development, focusing on the diffusion of skills and knowledge. In addition, the regions were divided based on economic complexity and income to analyze whether the level of development influences the spillover effects between neighboring regions. An analysis was also carried out by the neighboring RCA group, considering the presence of more complex neighboring regions.

The chapter is organized into five sections. The first section is the introduction, followed by a review of literature related to the research area. The third section outlines the adopted methodology. The fourth section analyzes the findings, and the fifth section presents the main conclusions.

4.2 Literature Review

4.2.1 Industrial Diversification and Neighborhood Regions

Regions' economic structures are shaped by its existing industrial structure. The literature on diversification suggests that local capabilities determine which new activities are most likely to develop (Hidalgo et al., 2007; Hausmann; Klinger, 2007). If a region already has most of the skills that a particular new industry requires, acquiring competitiveness and specializing in that new industry becomes less costly. If not, there is a barrier of skills that are required and which may be too high for the region to overcome (Boschma; Minondo; Navarro, 2013). Hence, industries that use similar capabilities make diversification easier. Nonetheless, this also impose limits on diversification, particularly in regions with few capabilities. This limitation can create a cycle of low growth, which external factors can contribute to break (Myrdal, 1957).

In addition to their internal capabilities, regions exist within a context of external interactions. Regions do not develop industrially in isolation but through constant exchanges with other regions. Therefore, rather than considering each region individually, it is important to analyze its interrelationships and connections with the appropriate surroundings (Storper, 1997; Storper, 2013). Physical proximity between regions facilitates the diffusion of knowledge, especially tacit knowledge, which is difficult to codify and transmit over long distances. Therefore, the exchange and diffusion of this type of knowledge are especially dense and efficient with economic actors having frequent face-to-face interactions (Polanyi, 1967; Arrow, 1962; Jaffe; Trajtenberg; Henderson, 1993; Markusen, 1996; Feldman, 1994; Audretsch; Feldman, 1996; Boschma, 2005). For this reason, neighboring regions can generate different spillovers and knowledge flows between them.

Agglomeration externalities, discussed in economic geography literature, explain why knowledge spillovers and other positive externalities occur in close physical proximity. Marshall (1920) argues that the concentration of activities in specific locations facilitates the reduction of transportation costs, the availability of skilled labor, and the efficient transmission of knowledge. Through mobility between workers, related industries can transfer knowledge and skills to each other (Feldman, 1999; Lundquist; Trippl, 2013; Jara-Figueroa et al., 2018). Because labor market regions mainly limit this mobility (Eriksson 2011), neighboring regions benefit most from labor flows and can influence the generation of capabilities for new regional specializations. Other empirical studies have also found other types of positive externalities arising from the concentration of economic activities and spillovers between nearby regions (Lundquist; Trippl, 2013), for example, through migration (Jara-Figueroa et al., 2018), transportation infrastructure (Gao et al., 2021), supply of inputs (Cohen; Paul, 2005)).

Furthermore, Myrdal (1957) emphasized that interactions between regions can produce both positive and negative outcomes, introducing the concepts of "spread effects" and "backwash effects." Spread effects refer to positive impacts where economic growth in one region stimulates development in neighboring areas through increased trade, innovation diffusion, and investment flows. Conversely, backwash effects are negative impacts that occur when the growth of a dominant region attracts resources like labor and capital away from neighboring regions, potentially leading to regional disparities and underdevelopment. Thus, neighboring regions can positively and negatively affect each other, and understanding this dynamic is crucial for regional development strategies. Building on this concept, Perroux (1955) theory of growth poles suggests that specific industries or regions act as 'growth poles,' driving economic development and generating multiplier effects that can benefit neighboring areas. However, as Myrdal highlighted, these positive spillovers are not automatic. Without proper mechanisms and supportive policies, the dominant region's growth may result in backwash effects, drawing resources away from less developed neighboring regions.

Marshall (1890) further emphasized the importance of supplementary industries in neighboring regions for generating externalities in other sectors. Access to knowledge is often limited by companies' ability to absorb external information (Nelson; Winter, 1982). Therefore, firms frequently seek new knowledge within their networks and local environments. The presence of related industries in neighboring regions can facilitate knowledge spillovers and positive externalities, enhancing spread effects while mitigating backwash effects. This interconnectedness underscores the need to consider both the potential benefits and drawbacks of regional interactions when formulating economic diversification and development strategies.

Therefore, for positive externalities between regions, a relatedness is needed between new specializations and the portfolio of capabilities from adjacent areas. Nooteboom (2000) argues that there is an optimum cognitive proximity between economic agents, stressing that the cognitive distance should neither be too great to allow effective communication nor too small to avoid lock-in, as both extremes hinder the interactive learning process. Porter (2003) was one of the first to recognize the importance of spatial externalities in related industries, incorporating this idea into his cluster concept, in which specialization in clusters of related industries benefits regional development. Consequently, an "ideal region" would have a high concentration of industries in different sectors and possessing different types of capabilities, but with some coherence and relationship between this knowledge (Neffke, 2009). Frenken, Oort and Verburg (2007) was one of the first studies to implement the idea of related variety and show its influence on regional growth. However, Hidalgo et al. (2007) introduced methodological advances to related diversification based on its co-occurrence in the context of countries' export portfolios, and these advances were applied in this work.

Despite the advancements discussed above, the diversification literature still needs to pay more attention to the role of external sources and capabilities in regional development, mainly because extra-regional connections are crucial to avoid lock-in (Hassink; Lagendijk, 2001; Hassink, 2005). Less developed regions often face limitations in their local resources and networks, making it challenging to drive industrial diversification independently. To overcome these challenges, underdeveloped regions must rely on external connections and well-designed public policies that specifically aim to build new capabilities within these regions. Such targeted interventions enable these areas to expand their industrial base and achieve economic growth (Fitjar; Rodríguez-Pose, 2011; Grillitsch; Nilsson, 2015; Vale; Carvalho, 2013).

Recent studies confirm that the capabilities of neighboring regions or countries are important for diversification. Bahar, Hausmann and Hidalgo (2014) analyzed a wide range of countries worldwide and showed that geographically close countries exhibit significant similarities in their export portfolios. The authors state that a neighboring country being a competitive exporter of the same product increases the probability of a product being added to a country's export basket by, on average, 65%. Although they believe other common factors between the countries may exist, they attribute this tendency to the localized nature of knowledge diffusion. Boschma (2017) reinforce this idea by analyzing the specializations of US states between 2000 and 2012. They found that a state is more likely to develop a comparative advantage in a new industry if a neighboring state specializes in that industry, confirming that neighboring states in the US have more similar export structures. This export similarity seems to be explained by the greater social connectivity between neighboring states, as embodied in their bilateral migration patterns. He et al. (2019) also found similar results of firms' exports to regions in China between 2002 and 2011, confirming that knowledge spillovers from neighboring regions play a crucial role in regional industrial diversification. In addition to analyzing spillovers between neighboring regions with competitiveness in the same industries, the authors also find that the industrial proximity of new sectors with knowledge from neighboring regions influences regional diversification.

In short, while some studies confirm the importance of regional capabilities for diversification, there is a significant gap in the literature regarding the effect of interregional links on regional diversification, especially in the context of developing countries like Brazil. In addition, studies with similar objectives use export data, which differs from the employment information used in this research. Therefore, the aim is to investigate the influence of neighboring regions' competitiveness on the entry/exit of specializations and the growth of competitiveness.

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

- *Hypothesis 1:* The competitiveness and density of neighboring regions increase the likelihood of new specializations entering and of RCA growth, as well as reducing the outflow of specializations.
- *Hypothesis 2:* Proximity to the local knowledge portfolio is more relevant for new specializations than proximity to the industrial knowledge of neighboring regions.
- *Hypothesis 3:* Regions with low economic complexity and income depend even more on neighboring regions than on their own capabilities to promote new specializations.
- *Hypothesis 4:* The presence of neighbors with greater economic complexity intensifies the effects of the competitiveness and density of neighboring regions on specialization.

4.3 Methodology

4.3.1 Database

This chapter uses a class-level (five-digit) aggregation from CNAE, focusing on Brazil's immediate geographic regions and covering the years 2011, 2016, and 2021. RAIS employment data was employed to calculate key metrics such as Revealed Comparative Advantage (RCA), Relatedness Density, and Economic Complexity. The 2020 IBGE data was used to determine neighboring regions, defining neighbors as those regions sharing a border with the region under analysis. Additional data, including GDP per capita and population, were also gathered from IBGE.

4.3.2 Specialization, Relatedness Density, and Economic Complexity

The literature on economic development has been significantly shaped by the methodological innovations proposed by Hidalgo et al. (2007) and Hidalgo and Hausmann (2009). These scholars contend that disparities in development across nations stem from distinct sets of capabilities and their interactions. Such capabilities are embedded in a country's production processes and are not easily transferable between nations. Countries with a more diverse range of capabilities are better positioned to manufacture complex goods of high economic value, which are only within the reach of a few nations.

Hidalgo et al. (2007) utilized international trade data as the foundation for their methodological framework, drawing upon the concept of Revealed Comparative Advantage (RCA). The RCA index measures the specialization of economic activity by comparing its share in a local economy with its share in the global economy. If the local share surpasses the global share, the country or region possesses a competitive advantage in that sector. Depending on the data analyzed, this advantage can manifest in various forms, such as exports, production, or employment. Conceptually, the RCA index parallels the Location Quotient (LQ) commonly employed in regional studies. The RCA index is computed using the following equation:

$$RCA_{r,s} = \frac{\frac{emp_{r,s}}{emp_r}}{\frac{emp_s}{emp}} \tag{4.1}$$

Where: $emp_{r,s}$ is employment in the immediate region r in the sector s; item emp_r is total employment in the immediate region r; emp_s is total employment in the sector s; emp is total employment in the country.

Building on this foundation, (Hidalgo; Hausmann, 2009) developed a methodology to assess the productive capabilities of economies. This approach relies on two key indicators: the sophistication of products and the diversification of countries, each quantifying the complexity and breadth of economic activities. Formally:

$$D_r = k_{r,0} = \sum_s M_{r,s} \tag{4.2}$$

$$U_s = k_{s,0} = \sum_r M_{r,s} \tag{4.3}$$

Where:

$$M_{r,s} = \begin{cases} 1, & \text{if } RCA_{r,s} \geq 1 \\ 0, & \text{otherwise} \end{cases} \tag{4.4}$$

In this analysis, D_r represents diversity, quantified by counting the sectors where a region r has an RCA ≥ 1, and U_s as ubiquity, measured by the number of regions with an RCA ≥ 1 in a sector s. Complexity is assessed based on diversification, which indicates a region's capacity to produce a wide array of sectors, and ubiquity, which reflects the extent to which sectors requiring specialized knowledge are concentrated in a few regions with the necessary skills. As a result, a complex region or product is characterized by high diversification and low ubiquity. In addition, Hidalgo and Hausmann (2009) used iterated combinations of the two indicators. The ubiquity measure weighted the diversity index, while the diversity measure weighted the ubiquity index. The iterated combinations are formally presented below:

$$k_{r,N} = \left(\frac{1}{k_{r,0}}\right) \sum_{s} M_{r,s} k_{s,N-1} \tag{4.5}$$

$$k_{s,N} = \left(\frac{1}{k_{s,0}}\right) \sum_{r} M_{r,s} k_{r,N-1} \tag{4.6}$$

Where N refers to the number of iterations. After that, Equation (4.5) is substituted into Equation (4.6), resulting in the following equation:

$$k_{r,N} = \sum_{r'} \widetilde{M}_{rr'} k_{r',N-2} \tag{4.7}$$

Where:

$$\widetilde{M}_{rr'} = \sum_{s} \frac{M_{r,s} M_{r',s}}{k_{r,0} k_{s,0}} \tag{4.8}$$

Equation (4.7) is solved when $k_{r,N} = k_{r,N-2} = 1$. The eigenvector of $\widetilde{M}_{rr'}$ associated with its largest eigenvalue satisfies this condition. However, the first eigenvector, which forms a unit vector with all values equal to 1, is not useful. Consequently, the complexity measure relies on the eigenvector of $\widetilde{M}_{rr'}$ that corresponds to the second largest eigenvalue, as it captures most of the variation in the original data. Therefore, Economic Complexity Index (ECI) is defined as follows:

$$ECI = \frac{\vec{K} - \langle \vec{K} \rangle}{\text{stdev}(\vec{K})} \tag{4.9}$$

Where K is the eigenvector corresponding to the second largest eigenvalue of $\widetilde{M}_{rr'}$, with the operator $\langle\rangle$ representing the mean and stdev denoting the standard deviation. The Product Complexity Index (PCI) is measured using a similar method, substituting Equation (4.6) into Equation (4.5). The PCI is derived from the eigenvector (Q) associated with the second largest eigenvalue of the $M_{ss'}$ matrix. Formally, it is expressed as follows:

$$PCI = \frac{\vec{Q} - \langle \vec{Q} \rangle}{\text{stdev}(\vec{Q})} \tag{4.10}$$

Relatedness Density is computed using the $M_{r,s}$ matrix. The relatedness between sectors is determined based on the probability that one sector is co-located with another within the same region. To assess the relatedness between each pair of sectors in a region, the conditional minimum probability that a region exhibits specialization in one sector and co-specialization in another is utilized. This minimum probability is employed to mitigate bias arising from the concentration of employment in specific sectors within certain regions, following the methodologies of Hausmann and Klinger (2007) and Hidalgo et al. (2007). The following equation quantifies the co-location of two sectors, s and u, using employment data:

$$\theta_{s,u} = \min \left\{ P(M_{r,s} = 1 | M_{r,u} = 1), P(M_{r,u} = 1 | M_{r,s} = 1) \right\}, \forall s \neq u \tag{4.11}$$

Where θ is the industrial relatedness in each pair of sectors. In this way, two proximity index matrices are obtained based on analyzing the co-occurrence of sectors s and an intermediate region r.

Following this calculation, the regional specialization structure across sectors was analyzed using the Relatedness Density indicator. Developed by Hausmann and Klinger (2007), the concept of Relatedness evaluates the proximity between an economic activity and the region's industrial structure. In this framework, relatedness density is defined as the sum of the linkages between a sector s and all other sectors in which the region has a Revealed Comparative Advantage (RCA) equal to or greater than 1. If the region exhibits an RCA equal to or greater than 1 in most sectors with a high relatedness index with sector s, the relatedness density approaches 100, indicating a high value. Conversely, if only a small proportion of the sectors where region r is competitive have high relatedness values with sector s, the relatedness density will be low, nearing 0. Thus, the Industrial Relatedness Density of sector s in region r is calculated as:

$$\text{Density}_{r,s} = \left(\frac{\sum_{s \in r, s \neq u} \theta_{s,u}}{\sum_{s \neq u} \theta_{s,u}} \right) \times 100 \tag{4.12}$$

To quantify the competitiveness of neighboring regions in sectors s in region r, the following calculation was performed:

$$\text{Mean RCA Nb}_{r,s,t} = \frac{\sum_{r' \in \text{Nb}(r)} \text{RCA}_{r',s,t}}{|\text{Nb}(r)|} \tag{4.13}$$

Where Mean RCA $\text{Nb}_{r,s,t}$ is the average RCA of the neighboring regions of region r in sector s at time t; $\text{Nb}(r)$ represents the set of neighboring regions of region r; $\text{RCA}_{r',s,t}$ is the RCA value for the neighboring region r' in sector s at time t; $|\text{Nb}(r)|$ is the total number of neighboring regions of r. This variable represents the competitiveness of neighboring regions to a location in certain sectors.

To quantify the proximity of the knowledge portfolio of neighboring regions in sectors s in regions r, the following calculation is used:

$$\text{Mean Density Nb}_{r,s,t} = \frac{\sum_{r' \in \text{Nb}(r)} \text{Density}_{r',s,t}}{|\text{Nb}(r)|} \tag{4.14}$$

Where Mean Density $\text{Nb}_{r,s,t}$ is the average density of the neighboring regions of region r in sector s at time t; $\text{Nb}(r)$ represents the set of neighboring regions of region r; $\text{Density}_{r',s,t}$ is the density value for the neighboring region r' in sector s at time t; $|\text{Nb}(r)|$ is the total number of neighboring regions of r. This variable represents the proximity of the knowledge of neighboring regions to a locality for certain sectors.

4.3.3 Empirical model

The following model was used to assess how the competitiveness of neighboring regions impacts the local specialization:

$$\begin{aligned} Y_{r,s,t} = \beta_0 &+ \beta_1 \text{Mean RCA Nb}_{r,s,t-5} + \beta_2 \text{Mean Density Nb}_{r,s,t-5} \\ &+ \beta_3 \text{RCA}_{r,s,t-5} + \beta_4 \text{Density}_{r,s,t-5} + \beta_5 \text{ECI}_{r,s,t-5} + \beta_6 \text{PCI}_{r,s,t-5} \\ &+ \beta_7 \log(\text{GDP pc}_{r,t-5}) + \beta_8 \log(\text{Pop}_{r,t-5}) + \tau_r + \gamma_s + \pi_t + \epsilon_{r,s,t} \end{aligned} \tag{4.15}$$

Where $Y_{r,s,t}$ represents the three dependent variables used in the estimated models: $\text{Entry}_{r,s,t}$, $\text{Exit}_{r,s,t}$, and RCA $\text{Growth}_{r,s,t}$. RCA $\text{Growth}_{r,s,t}$ is the growth rate of the RCA value between t and $t-5$. The variable Entry is set to 1 if a region r was not specialized in sector s at time $t-5$ (RCA < 1) but becomes specialized in s at time t (RCA ≥ 1). It takes the value 0 if the region r was not specialized at $t-5$ and remains unspecialized at t. Thus, this variable only considers the subset of sectors in which the region was not competitive at time $t-5$ (RCA < 1). On the other hand, the variable Exit follows the opposite logic. It takes the value 1 if region r was specialized in a sector s at time $t-5$ (RCA ≥ 1) but ceases to be so at time t (RCA < 1). The value 0 is assigned if the region r was specialized at time $t-5$ and remains specialized at time t. Formally, the definitions are as follows:

$$\text{Entry}_{r,s,t} = I(s \notin \text{PF}(r,t) \cap s \in \text{PF}(r,t+5)) \tag{4.16}$$

$$\text{Exit}_{r,s,t} = I(s \in \text{PF}(r,t) \cap s \notin \text{PF}(r,t+5)) \tag{4.17}$$

Where PF stands for Probability Function.

Our variable of interest, Mean RCA $\text{Nb}_{r,s,t-5}$, represents the average RCA of all regions neighboring region r for sector s at time $t-5$. A positive β_1 coefficient is expected. As shown by Boschma (2017) and Bahar, Hausmann and Hidalgo (2014), the competitiveness of neighboring regions can foster the development of new specializations and enhance regional competitiveness while reducing the likelihood of industries exiting the regions. The main argument is that neighboring regions can positively influence a region's economy by leveraging shared infrastructure, specialized labor, and other resources through spillover effects. However, competition may also inhibit the development of industries in neighboring regions where specialization occurs.

The second variable of interest, Mean Density $\text{Nb}_{r,s,t-5}$, represents the average density of all neighboring regions r in sector s at time $t-5$. (Boschma, 2017) and Bahar, Hausmann and Hidalgo (2014) focus exclusively on the impact of the competitiveness of neighboring regions within the same sector. In contrast, our analysis of the average density of neighboring regions enables us to assess how closely a sector aligns with the capability portfolios of these neighboring regions. This approach allows us to capture an element of complementarity in our study. He et al. (2019) conducted a similar investigation for China's provinces and observed a positive relatedness, which aligns with our expectation for the β_2 sign.

$\text{RCA}_{r,s,t-5}$ and $\text{Density}_{r,s,t-5}$ represent the values of the Revealed Comparative Advantage (RCA) and density for region r in sector s at time $t-5$. These variables capture the regional capabilities related to the entry and exit of specializations, and the growth of RCA. Numerous analyses for Brazil and developed countries (Neffke, 2009; Essletzbichler, 2015; Freitas; Britto; Amaral, 2024) have demonstrated that regional capabilities influence diversification within the region.

$\text{ECI}_{r,s,t-5}$ and $\text{PCI}_{r,s,t-5}$ denote the complexity variables for region r and sector s at year $t-5$, respectively. GDP $\text{pc}_{r,t-5}$ and $\text{Pop}_{r,t-5}$ are control variables intended to capture the level of development and agglomeration within the regions.

Finally, the dataset is organized into 344 class sectors across 510 immediate regions for 2011, 2016, and 2021, resulting in a panel of 526,320 observations. Estimations were performed using OLS, Probit, and Logit models. Additionally, estimations were conducted to distinguish between the regions' different income levels and various sector classifications. To measure the spatial association of CNAE sections in Brazil's immediate regions, the Local Moran Index is used, which identifies whether regions (spatial units) have RCA values similar to those of their neighbors. This approach helps to capture spatial clusters and identify regions with significantly high or low RCA values relative to their surroundings.

4.4 Results

4.4.1 Descriptive statistics

Table 9 presents the descriptive statistics of the variables used in the econometric models. The dataset covers the dimensions of sector, region, and year in a panel format. The Entry variable has a mean of 0.04, with a standard deviation of 0.2. The Exit variable shows a mean of 0.3 and a standard deviation of 0.4. Both variables are binary and therefore vary between 0 and 1. Thus, their averages indicate the percentage of observations with a value of 1. The average of 0.04 for the Entry variable suggests that, among the possible entries (sectors that were not competitive in the regions), 4% became competitive. For the Exit variable, among the possible exits (sectors that were competitive in the regions), 30% lost competitiveness.

The Growth RCA variable has an average of 1,356.8, with values ranging from -1.0 to 15,878,000. This variable measures the variation in RCA over time, and the wide range of variation suggests significant disparities in RCA growth between regions, with some extreme values influencing the mean and standard deviation.

The average of the Mean RCA variable for neighboring regions is 0.9, while the average of the Max RCA variable for neighboring regions is 3.7. Both variables have minimum values of 0 and maximum values of 793.9 and 2,999.4, respectively. The high dispersion and extreme values in these variables justify the use of logarithmic transformation in the estimates. The Mean Density variable for neighboring regions has an average of 10.6, with values ranging from 0.2 to 46.1. The Max Density for neighboring regions shows an average of 17.8, with a range from 0.3 to 83. These statistics highlight the wide dispersion and extreme values present in the density and RCA variables of neighboring regions.

Furthermore, the general RCA variable, which measures the revealed comparative advantage of the region itself, has an average of 0.9 and a standard deviation of 11.1, with values ranging from 0 to 2,999.4, indicating significant dispersion. The general density variable, reflecting the proximity of sectors within the region's production structure, has an average of 10.1, with a standard deviation of 7.0 and ranges from 0 to 83. This pattern is similar to that of neighboring regions, reflecting both the concentration and diversity of production in the regions.

The Economic Complexity Index (ECI) ranges from -2.3 to 3.1, while the Product Complexity Index (PCI) varies between -2.2 and 2.5. According to the calculation methodology, both indices have a mean of 0 and a standard deviation of 1. As for GDP per capita (GDPpc), the average is 16,050.5, with a range varying from 1,889.0 to 102,065.8. This wide variation indicates marked economic inequalities between regions, with some regions having significantly higher GDP per capita compared to others. Lastly, the population variable has an average of 382,504.1, with values ranging from 24,657 to 21,242,939, demonstrating the large disparity in the populations of the regions analyzed.

Table 9 – Descriptive Statistics of Variables in the Econometric Models

Statistic	N	Mean	St. Dev.	Min	Max
Entry	470,623	0.04	0.2	0	1
Exit	55,697	0.3	0.4	0	1
RCA growth	526,320	1,356.8	47,596.6	-1.0	15,878,000.0
Mean RCA Nb	526,320	0.9	5.1	0.000	793.9
Max RCA Nb	526,320	3.7	23.9	0.000	2,999.4
Mean Density Nb	526,320	10.6	5.2	0.2	46.1
Max Density Nb	526,320	17.8	9.4	0.3	83.0
RCA	526,320	0.9	11.1	0.000	2,999.4
Density	526,320	10.1	7.0	0.0	83.0
ECI	526,320	0.0	1.0	-2.3	3.1
PCI	526,320	-0.003	1.0	-2.2	2.5
GDPpc	526,320	16,050.5	12,296.1	1,889.0	102,065.8
Population	526,320	382,504.1	1,143,084.0	24,657	21,242,939

Source: Authors' elaboration.

4.4.2 General analysis

Table 10 provides the results of the various estimations for the OLS, Logit, and Probit models. In all columns, the dependent variable is the acquisition of competitiveness in the immediate regions of a new industry between years t and t+5. As expected, the coefficient of the average RCA index of neighboring regions is positive and statistically significant. This result indicates that the competitiveness of the same sector in neighboring regions is positively correlated with the probability of developing a new industry in an immediate region in Brazil. Similar findings were observed by Boschma (2017) for states in the United States, and by He et al. (2018) for regions in China. Bahar, Hausmann and Hidalgo (2014) also identified the same pattern across countries.

In model (4), estimated using the Logit approach, an increase of 1 in the average RCA of neighboring regions is associated with an average increase of around 0.03% in the probability of industry diversification. In contrast, an increase of 1 in the region's CAR is associated with an increase of around 9.27% in the probability of diversification. This result suggests that the skills present in the region at time t have a much greater impact on the probability of diversification at time t+5, compared to the influence of the skills of neighboring regions.

Additionally, the density coefficient is positive and statistically significant, indicating that specialization in related industries facilitates the development of new industries. Similar results have been found for Brazilian regions in the works of Freitas, Britto and Amaral (2024), Queiroz, Romero and Freitas (2024), and Françoso, Boschma and Vonortas (2024). A new finding, however, is the influence of the average density of neighboring regions on specializations. The density of related knowledge in neighboring regions is fundamental to the emergence of new specializations. When a region's sectors share a portfolio of knowledge close to that of sectors in neighboring regions, there is a greater likelihood that this region will develop specializations in these related sectors, highlighting the influence of regional knowledge on the emergence of new specializations.

In model (4), based on the average effect values, an increase of 10 units in the average density of neighboring regions corresponds to an increase of approximately 5.26% in the probability of specialization in new sectors within the region. In comparison, a 10-unit increase in the density of the region itself results in a 2.96% increase in the same probability. Therefore, the density of neighboring regions has a greater effect on the probability of diversification than the density of the region itself.

Based on these results, it is possible to make some important observations. When analyzing a region's specialization in specific sectors, the internal capacities of that region tend to have a greater influence than the capacities of neighboring regions. In other words, the region's own RCA has a greater impact than the average RCA of neighboring regions. However, when considering the knowledge portfolios of related sectors, the region's local capabilities become even more decisive in driving new sectoral diversifications than its internal capabilities. In other words, the density of knowledge in the region is less relevant than the average density of neighboring regions. This phenomenon indicates that the presence of sectors with related knowledge in neighboring regions can be a crucial factor for a region to expand its specializations.

Table 10 – The influence of the RCA and the density of neighboring regions on the entry of sectors into the immediate regions in Brazil

	Dependent variable: Entry$_t$					
	OLS		*Logit*		*Probit*	
	(1)	(2)	(3)	(4)	(5)	(6)
Mean RCA Nb$_{t-5}$	0.001***	0.001***	0.010***	0.009***	0.005***	0.005***
	(0.0001)	(0.0001)	(0.002)	(0.001)	(0.001)	(0.001)
				[0.0003]		
Mean Density Nb$_{t-5}$	0.008***	0.004***	0.275***	0.168***	0.124***	0.077***
	(0.0002)	(0.0002)	(0.006)	(0.007)	(0.003)	(0.003)
				[0.0053]		
RCA$_{t-5}$		0.267***		2.956***		1.537***
		(0.004)		(0.032)		(0.017)
				[0.0927]		
Density$_{t-5}$		0.003***		0.094***		0.046***
		(0.0002)		(0.005)		(0.002)
				[0.003]		
ECI$_{t-5}$		−0.009***		−0.265***		−0.144***
		(0.001)		(0.049)		(0.022)
				[-0.0083]		
PCI$_{t-5}$		0.015***		0.446***		0.221***
		(0.001)		(0.052)		(0.023)
				[0.0014]		
Population (log)$_{t-5}$		0.004*		0.049		0.034
		(0.002)		(0.078)		(0.036)
				[0.0015]		
GDPpc (log)$_{t-5}$		0.009		0.179		0.056
		(0.006)		(0.225)		(0.102)
				[0.0056]		
Constant	0.088***	−0.141	−3.874***	−7.641**	−1.967***	−3.504**
	(0.014)	(0.086)	(0.175)	(3.203)	(0.088)	(1.462)
Pseudo R^2			0.13	0.2	0.14	0.2
Observations	470,623	470,623	470,623	470,623	470,623	470,623
R^2	0.046	0.096				
Adjusted R^2	0.044	0.095				
Log Likelihood			−64,272.010	−59,482.520	−64,166.790	−59,166.720
Akaike Inf. Crit.			130,258.000	120,691.000	130,047.600	120,059.400
Residual Std. Error	0.184	0.179				
F Statistic	26.391***	58.154***				

Source: Authors' elaboration. Note: Robust standard errors in parentheses. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$. All regressions include region, period, and sector fixed effects.

For the robustness check (presented in Appendix A), the dependent variable of entry is estimated as the permanence of competitiveness, defined as when a region acquires competitiveness between $t-5$ and t in certain sectors and remains competitive at $t+5$. The results indicate an increase in the probability of remaining competitive with an increase in the average RCA of neighboring regions. This finding highlights that the competitiveness of neighboring regions is important not only for the entry of specialization into regions but also for regions to maintain their competitiveness. Additionally, the highest RCA value from neighboring regions is used in the entry estimations, as applied by (Boschma, 2017). The coefficient remains significant but is lower than that of the average RCA value. This outcome suggests that an increase in the average RCA of neighboring regions has a greater influence on the probability of new specializations entering compared to considering only the region with the highest RCA value.

Table 11 presents additional estimations using RCA exit and growth as the dependent variables. The results show that the average RCA and the density of neighboring regions decrease the probability of the focus region losing competitiveness and promote an increase in the RCA growth rate. However, for RCA growth, the variables related to the region's RCA display a negative and significant sign, which diverges from expectations. It would be expected that a higher RCA at $t-5$ would indicate higher RCA growth at t. However, if the RCA is already high in the region at $t-5$, growth opportunities may be limited at t. Growth may still occur, but not at a constant rate. Additionally, the coefficient for the region's density is not significant, suggesting that proximity to local productive knowledge does not directly influence RCA growth. Therefore, for RCA growth, it is essential to consider both the RCA and the average density of neighboring regions.

Table 11 – The influence of RCA and the density of neighboring regions on the output and growth of sectors in the immediate regions in Brazil

	Dependent variable: Entry$_t$			
	Exit		RCA growth	
	Logit		*OLS*	
	(1)	(2)	(3)	(4)
Mean RCA Nb$_{t-5}$	−0.029***	−0.021***	72.908**	76.248**
	(0.004)	(0.004)	(35.086)	(35.326)
Mean Density Nb$_{t-5}$	−0.129***	−0.087***	200.730***	296.854***
	(0.008)	(0.009)	(64.228)	(65.830)
RCA$_{t-5}$		−0.022***		−24.991***
		(0.005)		(4.985)
Density$_{t-5}$		−0.057***		−47.272
		(0.005)		(44.389)
ECI$_{t-5}$		0.202***		−227.821
		(0.063)		(337.392)
PCI$_{t-5}$		−0.191***		2,187.771**
		(0.074)		(849.480)
Population (log)$_{t-5}$		0.009		−685.646
		(0.096)		(485.507)
GDPpc (log)$_{t-5}$		−0.614**		−464.005
		(0.293)		(2,822.197)
Constant	1.099***	9.448**	−1,734.678**	14,150.590
	(0.233)	(4.148)	(763.012)	(39,059.900)
Pseudo R2	0.1	0.11		
Observations	55,697	55,697	526,320	526,320
R^2			0.005	0.005
Adjusted R^2			0.003	0.003
Log Likelihood	−29,820.600	−29,357.720		
Akaike Inf. Crit.	61,355.200	60,441.450		
Residual Std. Error			47,526.720	47,523.980
F Statistic			2.810***	2.868***

Source: Authors' elaboration. Note: Robust standard errors in parentheses. *p < 0.1; **p < 0.05; ***p < 0.01. All regressions include region, period, and sector fixed effects.

Table 12 shows the estimates of the influence of the RCA and the average density of neighboring regions on the entry of specializations, differentiating by the region's income level. For all income levels, the average RCA of neighboring regions positively and significantly influences the probability of new specializations in regions. However, there are variations in the value of the coefficient, indicating that the higher the income level, the greater the influence of the competitiveness of neighboring regions on the probability of specialization in the regions. Although positive and significant for all income levels, the neighborhood density coefficient is lower for high-income regions. This indicates that for regions with lower levels of development, the influence of proximity to the knowledge portfolio of neighboring regions on new specializations is greater.

In addition, the results indicate that the region's RCA in $t-5$ influences new specializations in t and that this influence increases more when moving towards higher-income regions. However, the coefficient on the density of regions was only significant for middle- and high-income regions. This suggests that, for low-income regions, the need for internal capacities in related sectors may hinder the development of new specializations. Consequently, this result emphasizes that neighboring regions' capabilities and productive structure are particularly relevant for the diversification of low-income regions. Thus, less developed regions are more dependent on external connections and targeted public policies designed to promote the development of new productive capacities. Due to their limited resources and insufficient local networks, these regions cannot drive economic diversification autonomously. Previous studies Fitjar and Rodríguez-Pose (2011), Grillitsch and Nilsson (2015), Isaksen and Trippl (2016) confirm that these regions need external support to expand their economic activities. In this context, policies that encourage interregional partnerships and consider spillovers between neighboring regions are essential to promote investments in innovation and diversification of the productive structure.

Table 12 – The influence of RCA and density of neighboring regions on the entry of sectors differentiated by the income of the immediate regions of Brazil

	Dependent variable: Entry$_t$					
	Low-income		Medium-income		High-income	
	(1)	(2)	(3)	(4)	(5)	(6)
Mean RCA Nb$_{t-5}$	0.009***	0.008***	0.014**	0.010*	0.018***	0.017***
	(0.002)	(0.002)	(0.006)	(0.006)	(0.004)	(0.003)
Mean Density Nb$_{t-5}$	0.212***	0.178***	0.260***	0.178***	0.240***	0.118***
	(0.018)	(0.018)	(0.012)	(0.013)	(0.008)	(0.009)
RCA$_{t-5}$		2.337***		3.054***		3.282***
		(0.302)		(0.056)		(0.049)
Density$_{t-5}$		0.030		0.089***		0.090***
		(0.358)		(0.010)		(0.007)
ECI$_{t-5}$		−0.045		−0.468***		−0.170*
		(0.381)		(0.084)		(0.090)
PCI$_{t-5}$		0.443		0.693***		0.201***
		(0.313)		(0.095)		(0.078)
Population (log)$_{t-5}$		0.144		0.307**		−0.034
		(0.350)		(0.142)		(0.102)
GDPpc (log)$_{t-5}$		1.327***		0.406		−0.430
		(0.357)		(0.384)		(0.334)
Constant	−3.822***	−19.020***	−4.999***	−13.176**	−4.366***	0.550
	(0.319)	(0.319)	(0.300)	(5.140)	(0.285)	(4.642)
Pseudo R2	0.19	0.22	0.14	0.21	0.13	0.22
Observations	161,438	161,438	155,967	155,967	153,218	153,218
Log Likelihood	−17,375.760	−16,790.000	−20,874.170	−19,199.060	−24,715.540	−22,140.850
Akaike Inf. Crit.	35,781.520	34,622.000	42,778.330	39,440.120	50,473.080	45,335.700

Source: Authors' elaboration. Note: Robust standard errors in parentheses. *p $<$ 0.1; **p $<$ 0.05; ***p $<$ 0.01. All regressions include region, period, and sector fixed effects.

Table 13 presents the entry estimates, distinguishing between the levels of economic complexity in Brazil's immediate regions. Similar to income disparities between regions, as the economic complexity of regions increases, the competitiveness of neighboring regions exerts a more pronounced influence on the probability of entering new sectors. Additionally, the average density of neighboring regions has a positive and significant effect on the likelihood of new specializations. However, as a region's level of complexity rises, the impact of the average density of neighboring regions on new specializations diminishes.

The region's RCA coefficient proved significant and positive in all the estimation groups. On the other hand, the density coefficient was not significant in low-complexity regions. This suggests that, as with income differentiation, the portfolio of industrial capacities is more restricted in less complex regions. Consequently, these regions depend more on the industrial capacities of neighboring regions to develop the skills needed to create new local specializations.

Table 13 – The influence of RCA and density of neighboring regions on the entry of sectors differentiated by the economic complexity of the immediate regions of Brazil

	Dependent variable: Entry$_t$			
	Low	Medium-Low	Medium-High	High
	(1)	(2)	(3)	(4)
Mean RCA Nb$_{t-5}$	0.009***	0.008***	0.017***	0.019**
	(0.003)	(0.001)	(0.005)	(0.008)
Mean Density Nb$_{t-5}$	0.180***	0.175***	0.088***	0.037**
	(0.026)	(0.011)	(0.014)	(0.017)
RCA$_{t-5}$	2.431***	2.752***	3.402***	3.512***
	(0.101)	(0.046)	(0.061)	(0.104)
Density$_{t-5}$	0.033	0.040***	0.095***	0.083***
	(0.023)	(0.008)	(0.010)	(0.013)
ECI$_{t-5}$	−0.286*	−0.295***	−0.265*	−0.167
	(0.153)	(0.085)	(0.136)	(0.286)
PCI$_{t-5}$	0.792***	0.602***	0.234**	−0.576***
	(0.172)	(0.075)	(0.102)	(0.150)
Population (log)$_{t-5}$	0.307	−0.211**	0.232	0.630
	(0.324)	(0.103)	(0.203)	(0.521)
GDPpc (log)$_{t-5}$	0.686	−0.173	0.913	−2.908**
	(0.475)	(0.359)	(0.672)	(1.174)
Constant	−14.296**	0.697	−18.862**	29.847
	(7.164)	(4.963)	(8.905)	(19.043)
Pseudo R2	0.249	0.199	0.211	0.247
Observations	93,041	253,683	97,450	26,449
Log Likelihood	−7,973.098	−30,840.660	−14,264.230	−4,860.612
Akaike Inf. Crit.	16,926.200	63,069.320	29,534.460	10,507.220

Source: Authors' elaboration. Note: Robust standard errors in parentheses. *p < 0.1; **p < 0.05; ***p < 0.01. All regressions include region, period, and sector fixed effects.

Table 14 presents the estimates for the entry of new specializations in the regions by dividing them into groups based on the average RCA value of the neighboring regions (RCA between 0-1, 1-2, 2-3, 4+) and more complex neighbors. The results indicate that, for values of RCA above 2, there is no significant influence on the probability of new specializations appearing. Furthermore, it was observed that the relationship between the RCA of neighboring regions and the probability of new specializations is stronger in RCA intervals between 0 and 1 than between 1 and 2, suggesting that regions with lower RCA have greater potential to generate new specializations. In other words, although an increase in the RCA of neighboring regions generally contributes positively to sectoral diversification, increases in the RCA have a more significant impact on regions with a lower RCA.

On the other hand, concerning the average density of the neighboring regions, all the coefficients were significant and positive, but the intensity of this influence varied according to the different RCA ranges of the neighboring regions. It was observed that, in the groups with the lowest CAR, the density coefficient was more positive, indicating that, in these cases, the proximity of the sector to the knowledge portfolio of neighboring regions has an even stronger impact on the likelihood of new specializations. This suggests that proximity in terms of resources and capabilities becomes an even more relevant factor for new specializations, especially when the RCA of neighboring regions is lower.

In addition, considering the group of regions with at least one neighbor with a complexity of more than one standard deviation, there is a greater influence on the probability of specialization of the average RCA and density of neighboring regions. On the other hand, compared to the general model, there is a decrease in the region's RCA and density coefficients. When regions have more complex neighboring regions, the influence of the competitiveness and density of neighboring regions on the probability of diversification intensifies. At the same time, there is a loss of influence from the competitiveness and density of the region itself. Regions with greater complexity, therefore, have greater resource and capacity-sharing effects with neighboring regions.

Table 14 – The influence of RCA and the density of neighboring regions on the entry of sectors, differentiated by the RCA value group and more complex neighbors

	Dependent Variable: $Entry_t$					
	General Model	0-1	1-2	2-4	4+	At least one neighbor 1 s.d. more complex
	(1)	(2)	(3)	(4)	(5)	(6)
Mean RCA Nb_{t-5}	0.009***	0.457***	0.174**	0.026	0.00004	0.011***
	(0.001)	(0.046)	(0.083)	(0.061)	(0.002)	(0.002)
Mean Density Nb_{t-5}	0.168***	0.125***	0.100***	0.079***	0.080***	0.214***
	(0.007)	(0.009)	(0.020)	(0.029)	(0.030)	(0.009)
RCA_{t-5}	2.956***	3.024***	2.873***	2.839***	2.804***	2.851***
	(0.032)	(0.040)	(0.085)	(0.126)	(0.154)	(0.046)
$Density_{t-5}$	0.094***	0.094***	0.089***	0.099***	0.092***	0.056***
	(0.005)	(0.006)	(0.014)	(0.020)	(0.021)	(0.009)
ECI_{t-5}	−0.265***	−0.395***	0.026	0.056	−0.220	−0.214***
	(0.049)	(0.059)	(0.127)	(0.188)	(0.202)	(0.062)
PCI_{t-5}	0.446***	0.439***	0.321*	0.392	0.789***	0.516***
	(0.052)	(0.059)	(0.176)	(0.264)	(0.239)	(0.076)
Population $(\log)_{t-5}$	0.049	0.104	−0.004	−0.170	−0.421	−0.059
	(0.078)	(0.094)	(0.209)	(0.309)	(0.316)	(0.103)
GDPpc $(\log)_{t-5}$	0.179	0.064	1.170*	0.465	−1.778*	0.876***
	(0.225)	(0.268)	(0.651)	(0.938)	(0.911)	(0.315)
Constant	−7.641**	−6.663*	−19.044**	−7.270	24.602*	−15.299***
	(3.203)	(3.812)	(9.220)	(13.461)	(12.958)	(4.011)
Pseudo R^2	0.199	0.196	0.207	0.254	0.264	0.204
Observations	470,623	409,345	30,966	16,556	13,756	275,120
Log Likelihood	−59,482.520	−43,394.290	−7,385.597	−3,643.056	−3,017.850	−30,877.980
Akaike Inf. Crit.	120,691.000	88,514.580	16,495.190	9,010.111	7,745.699	63,045.960

Source: Authors' elaboration. Note: Robust standard errors in parentheses. *p < 0.1; **p < 0.05; ***p < 0.01. All regressions include region, period, and sector fixed effects.

4.4.3 Sectoral analysis

Table 15 shows the estimates of the influence of the average RCA and the density of neighboring regions on the entry of new regional specializations. The estimates are divided according to CNAE divisions but using observations at: 1. Agriculture, Livestock, Forestry, Fishing and Aquaculture; 2. Mining and Quarrying; 3. Manufacturing; 4. Electricity, Gas, Steam, and Air Conditioning Supply; 5. Water, Sewage, and Waste Management; and 6. Construction.

The mean competitiveness (RCA) of neighboring regions in the sector has a significant and positive effect for the sectors of Agriculture, Manufacturing, and Water Supply; Sewerage, and Waste Management. In the sectors of Mining, Electricity Supply, and Construction, the coefficient is not significant, indicating that the competitiveness of neighboring regions does not influence the entry of these sectors in the region. Especially in the case of Mining and Quarrying, the result can be explained by the fact that it is an industry that depends directly on natural resources, requiring them to locate where these resources are available, regardless of production in adjacent regions.

The mean density of neighboring regions, measuring how close the sector is to the knowledge portfolio of neighboring regions, shows a significant and positive coefficient across all sectors, including Agriculture, Mining, Manufacturing, Electricity Supply, Water Supply, and Construction. This result indicates that in all the sectors analyzed, the closer the sector is to the knowledge base of nearby regions, the higher the probability of its entry into the target region. This positive effect shows the importance of proximity to knowledge in neighboring regions for the regions' new specializations.

The sector's competitiveness in the region, measured by the RCA five years prior, has positive and significant coefficients across all sectors analyzed: Agriculture, Mining, Manufacturing, Electricity Supply, Water Supply, and Construction. This indicates that the existing competitiveness in a region is a consistent factor for the subsequent development of the sector, regardless of the type of activity.

The density in the region, measuring the proximity of the sector to the local knowledge portfolio, yields varied results across sectors. It is significant and positive for the sectors of Mining, Manufacturing, and Construction, suggesting that in these sectors, higher local density contributes to the sector's entry into the region. However, for Agriculture, Electricity Supply, and Water Supply, the coefficient is not significant, indicating that in these sectors, proximity to local knowledge does not significantly impact sector entry. This variation reflects that while compatibility with the local knowledge portfolio is crucial in some sectors, it does not hold the same influence across all industries.

Table 15 – The influence of RCA and the density of neighboring regions on the entry of sectors dividing between CNAE sections in the immediate regions of Brazil

	Agriculture, Livestock, Forestry, Fishing and Aquaculture	**Mining and Quarrying**	**Manufacturing**	**Electricity, Gas, Steam, and Air Conditioning Supply**	**Water Supply; Sewerage, and Waste Management**	**Construction**
Mean RCA Nb_{t-5}	0.0107^{***}	0.00149	0.0205^{***}	0.00920	0.0422^{*}	0.00827
	(0.00229)	(0.00166)	(0.00272)	(0.00727)	(0.0244)	(0.00704)
Mean Density Nb_{t-5}	0.251^{***}	0.209^{***}	0.158^{***}	0.258^{***}	0.173^{***}	0.171^{***}
	(0.0212)	(0.0340)	(0.00918)	(0.0504)	(0.0443)	(0.0282)
RCA_{t-5}	2.700^{***}	2.392^{***}	3.253^{***}	1.600^{***}	2.456^{***}	1.944^{***}
	(0.0845)	(0.256)	(0.0406)	(0.271)	(0.171)	(0.102)
$Density_{t-5}$	0.00118	0.102^{***}	0.0829^{***}	-0.00798	0.0294	0.0366^{**}
	(0.0147)	(0.0268)	(0.00650)	(0.0350)	(0.0264)	(0.0178)
ECI_{t-5}	0.0739	0.161	-0.480^{***}	0.203	0.149	0.0288
	(0.120)	(0.257)	(0.0638)	(0.289)	(0.226)	(0.145)
PCI_{t-5}	0.520^{***}	0.841^{***}	0.434^{***}	-0.467	0.145	0.317^{*}
	(0.201)	(0.197)	(0.0660)	(0.391)	(0.180)	(0.163)
GDPpc $(\log)_{t-5}$	-0.270	0.195	0.0628	0.227	0.806^{**}	-0.0780
	(0.217)	(0.370)	(0.104)	(0.427)	(0.367)	(0.206)
Population $(\log)_{t-5}$	-0.374	-1.192	0.259	0.856	2.941^{**}	-0.674
	(0.538)	(1.112)	(0.306)	(1.464)	(1.183)	(0.597)
Constant	4.008	8.549	-9.148^{**}	-17.19	-50.24^{***}	5.548
	(7.680)	(15.72)	(4.361)	(20.67)	(17.10)	(8.469)
Pseudo R^2	0.22	0.29	0.21	0.17	0.15	0.16
Observations	14,355	40,652	355,319	4,493	9,924	26,546
Log Likelihood	−7764.63	−1760.48	−37668.55	−1205.11	−2465.4581	
Akaike Inf. Crit.	120,691.000	88,514.580	16,495.190	9,010.111	7,745.699	63,045.960

Source: Authors' elaboration. Note: Robust standard errors in parentheses. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$. All regressions include region, period, and sector fixed effects.

To measure the spatial association of CNAE sections in Brazil's immediate regions, the Local Moran Index is used, which identifies whether regions (spatial units) have RCA values similar to those of their neighbors. It is important to note that the estimates account for the influence of the average RCA in neighboring regions on the probability of new regional specializations emerging. In Figure 4, clusters are presented to identify groupings of sectors with similar RCA values. Although both analyses are complementary, their objectives and approaches differ. This geospatial factor is critical for understanding patterns of regional specialization and sectoral distribution in Brazil. Figure 1 illustrates the LISA (Local Indicator of Spatial Association) clusters based on data from the CNAE Section for 2021, showing how these clusters are spatially distributed and emphasizing the concentration of activities in specific sectors and regions.

For Agriculture, Livestock, Forestry, Fishing and Aquaculture, clusters are especially prominent in the states of the Central-West region, as well as in significant areas of Piauí, Maranhão, Bahia, Tocantins, Pará, and Minas Gerais. Compared to other sectors, this one shows clusters with the largest immediate regions, reflecting Brazil's extensive productive knowledge portfolio, historically specialized in agricultural and farming products. In Minas Gerais, the cluster covers nearly all the immediate regions of the intermediate regions of Patos de Minas, Montes Claros, and Teófilo Otoni, demonstrating the strong specialization of these areas in agricultural and related activities.

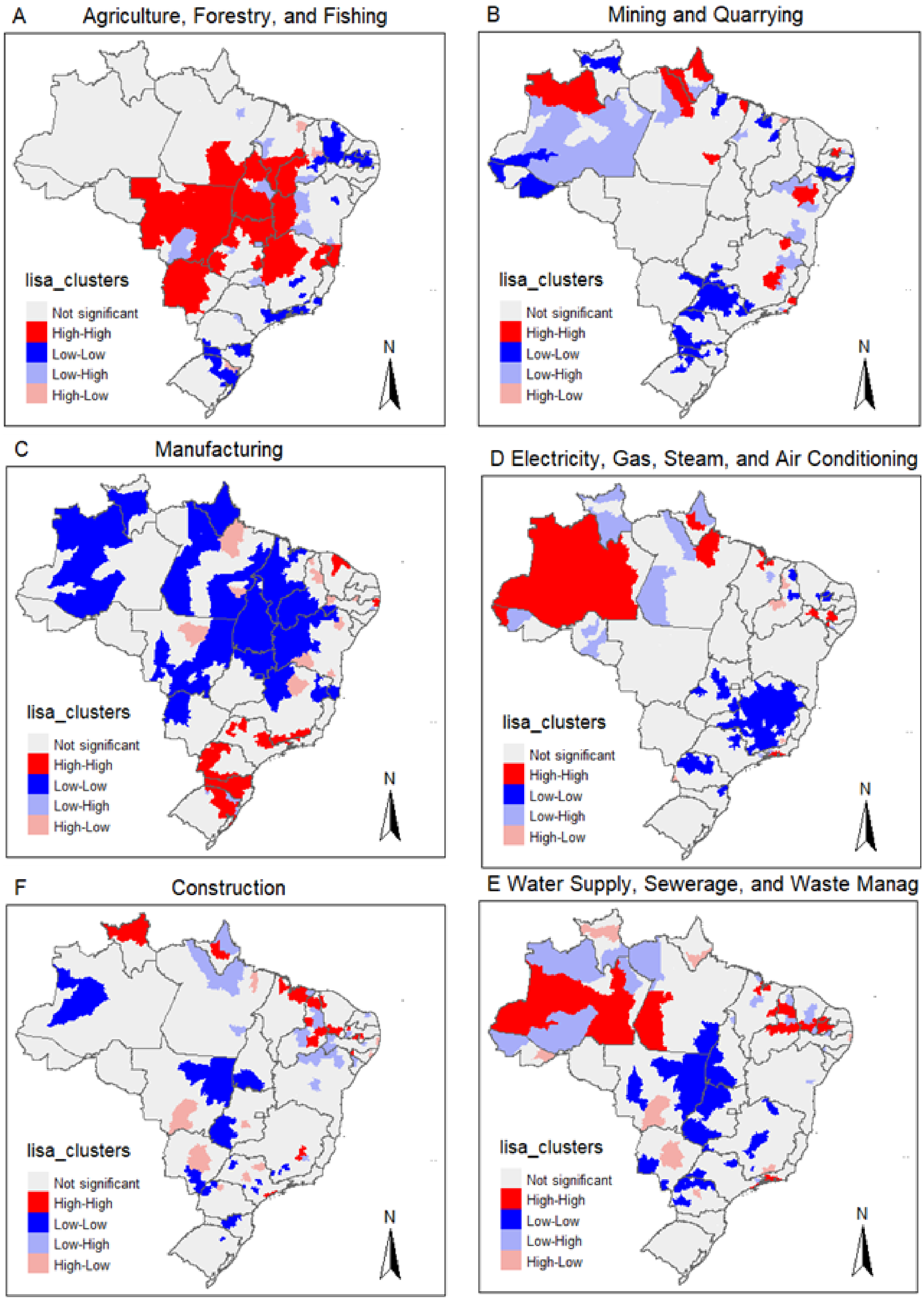
For Mining and Quarrying, clusters appear in the immediate regions of Amazonas, Pará, Amapá, Rio Grande do Norte, Bahia, Minas Gerais, and Rio de Janeiro. The concentration of mining activities reflects the wealth of natural resources in these areas and the development incentives for these activities, particularly in Pará and Minas Gerais, traditional mining hubs in Brazil. However, this is the only sector that does not show a significant positive relationship with the average RCA of neighboring regions, suggesting that adjacent regions are not a relevant factor for specialization development.

Regarding Manufacturing, the analysis reveals a clear concentration of clusters in the immediate southern regions of Minas Gerais, São Paulo, Paraná, Santa Catarina, and Rio Grande do Sul. These regions form Brazil's industrial belt, showcasing a diverse and competitive manufacturing industry. The clusters highlight how geographical proximity stimulates growth and innovation within the industrial sector, with neighboring regions simultaneously collaborating and competing. However, several low-specialization clusters are also identified, primarily in the Midwest, Northeast, and North immediate regions.

The last three sectors present less relevant patterns. For Electricity, Gas, Steam, and Air Conditioning Supply, clusters appear in the immediate regions of Amazonas, Pará, Amapá, Rio Grande do Norte, Bahia, Minas Gerais, and Rio de Janeiro. For Construction, clusters are observed in the immediate regions of Roraima, Amapá, Maranhão, Piauí, Ceará, Pernambuco, Alagoas, Minas Gerais, and São Paulo. Lastly, for Water Supply;

Sewerage, and Waste Management, high-high clusters are observed in the immediate regions of Amazonas, Pará, Maranhão, Piauí, Ceará, Paraíba, Rio de Janeiro, and São Paulo.

Figure 4 – Clusters Lisa do valor do RCA por Seção da CNAE no Brasil em 2021



Source: Authors' elaboration.

Overall, the analysis shows that geographical factors heavily influence sectoral specialization in Brazilian regions. Neighboring regions play a pivotal role in developing new specializations, emphasizing the need to understand the spatial dynamics of regional competitiveness. This suggests that specialization clusters emerge in different regions of Brazil depending on the sector analyzed, indicating that regional policies should consider geographical proximity and spillover effects to foster industrial diversification and specialization across regions.

4.5 Concluding remarks

Diversification in complex sectors is important for regions to develop capacities and increase income and employment. However, some regions need more resources and knowledge, which can restrict the development of new specializations. Furthermore, regions are not isolated; they connect, exchange resources, and generate spillovers. It is, therefore, important to identify how competitiveness and proximity to the knowledge portfolio of neighboring regions influence the diversification of regions. Therefore, this study aims to analyze the influence of competitiveness and proximity to the industrial knowledge of neighboring regions on the probability of entry and exit of specializations and on the growth in competitiveness of regions. Analyzing data from 344 sectors across 510 Brazilian regions for the years 2011, 2016, and 2021, the results indicate that the competitiveness (RCA) and capability density of neighboring regions positively impact the probability of new specializations and RCA growth within a region, while also reducing the likelihood of specialization exit. These findings highlight the importance of both internal capacities within regions and those of neighboring regions for sectoral diversification. Although the competitiveness of neighboring regions is important, the results showed that the region's past competitiveness matters even more for new specializations. However, when considering proximity to the knowledge portfolio in all sectors, the influence of neighboring regions is more significant for the likelihood of diversification than the region's portfolio. This highlights the strategic importance of diversifying into sectors related to the knowledge base of neighboring regions, probably due to the sharing of resources and capabilities facilitated by geographical proximity.

The analysis suggests that regions with well-established productive capacities can sustain and expand their industries more autonomously. However, regions with lesser economic complexity and lower income levels rely heavily on the skills and knowledge accumulated in neighboring regions to foster new specializations. In these regions, limitations in local resources and productive networks restrict the capacity for independent innovation, reinforcing the need for external support and targeted public policies. An important policy implication of the results found in this paper is that regional policies should consider creating interregional collaboration networks and promoting infrastructure that facilitates the mobility of resources and the transmission of knowledge between neighboring regions.

For values of neighbors' RCA above 2, the influence on the entry of new specializations is insignificant. The relationship between neighbors' CAR and diversification is stronger when the RCA is between 0 and 1, suggesting greater potential for diversification in regions with lower RCAs. In groups with lower RCA, density has a stronger impact, indicating that the proximity of knowledge and capabilities of neighbors becomes even more relevant for the emergence of new specializations. Furthermore, in regions with at least one high-complexity neighbor (above one standard deviation), the RCA and density of the neighbors exert an even greater influence on the probability of new specializations. In contrast, the influence of the RCA and the region's density decreases compared to the general model. This indicates that when neighbors are more complex, the effects of sharing resources and capacities with nearby regions intensify.

Regarding the sectoral analyses, competitiveness clusters in the Brazilian regions depend on the analyzed sectors. The main finding of the analysis is that the mean density of neighboring regions is significant for all sectors, highlighting the importance of proximity to the knowledge base of neighboring regions for new specializations. The influence of the other variables, such as the competitiveness of neighboring regions and the region's competitiveness and density, varies depending on the sector.

In regions of low economic complexity and income, where the scarcity of resources and knowledge limits the possibilities for diversification, policies that encourage collaboration between regions are essential. Such policies should prioritize forming cooperation networks between nearby regions and facilitating the sharing of resources, capacities, and infrastructure. Public policy can boost economic development, especially in areas with low RCA and industrial density, by incentivizing joint development projects and knowledge transfer between neighboring regions, strengthening local economies, and reducing regional inequalities.

This study has some limitations that could be addressed in future research. Firstly, employment information was used to calculate the RCA, which is widely available for regional analysis. However, analyzing production data from the regions and their neighboring regions would be valuable. Competitiveness was inferred from employment information, but it serves as a proxy for capturing the productive structure. Additionally, examining other variables that influence the competitiveness of neighboring regions, such as infrastructure and job flows, would be interesting.

Conclusions

The central aim of this thesis was to investigate the technological and industrial diversification of Brazilian regions from the perspective of the influence of productive and technological capacities and their connection with neighboring regions. Understanding regional diversification is essential for economic development, as it implies strengthening and diversifying the local knowledge and skills base, making the regional economy competitive and with a higher income, also depending on the sectors that have been developed. In this context, economic diversification assumes great importance in the theory of regional development and public policies since a region's ability to advance into more complex sectors depends directly on the accumulation of knowledge and the interaction between different types of knowledge.

This diversification process is intrinsically linked to the pre-existing knowledge and capabilities of a region or country, since there is a greater likelihood of entry into activities related to the local knowledge portfolio. This perspective aligns with the concept of path-dependency, widely explored in evolutionary economics, and the Principle of Relatedness, a concept explored in the most current diversification literature. Although these concepts do not imply a rigid sequence determined by the past, they do suggest a propensity for historical trajectories to influence the direction of future development, where specific paths are more likely than others, and radical changes are challenging. This concept implies that regions with a history of diversification and knowledge accumulation tend to diversify more efficiently, following paths that reinforce their existing capacities (Walker, 2000).

The thesis was structured in four chapters. The first chapter develops a comprehensive theoretical basis that explores the factors influencing regional development and economic diversification, emphasizing the interaction between productive and technological knowledge, agglomeration externalities, diversification processes, and cognitive proximity. Concepts such as path dependency, agglomeration, and the coevolution of productive and technological capacities illustrate that regions tend to diversify based on already established competencies. However, the review showed that the literature often treats diversification as a process influenced in isolation by productive or technological knowledge without adequately exploring how this knowledge interacts to drive regional diversification, especially in resource-constrained environments characteristic of developing regions.

The empirical chapters looked at regional diversification from two perspectives of knowledge, industrial and technological, focusing on Brazilian regions. Chapter 2 examined the influence of proximity between technological classes and the regional productive structure on the likelihood of a region diversifying into new technological classes. The results showed that, in addition to the technological relatedness density, greater proximity between a technological class and the local productive structure significantly increases the likelihood of that class being incorporated by the region. This finding highlights the importance of productive knowledge in technological diversification, especially in low-income regions. In contexts of low economic development, the impact of the density of technological knowledge is limited, while the industrial relatedness density has a positive effect. In this way, industrial development, rather than technological development, emerges as a preponderant factor in the diversification of these regions, revealing that knowledge applied to productive practice plays a fundamental role in boosting the technological capacity of regions.

Furthermore, Chapter 2 identified that the industrial relatedness density is more relevant to technological diversification when associated with patents from private companies than those from universities and research institutions. This result suggests that the private sector's contribution is more directly linked to expanding regional technological capabilities. At the same time, academic knowledge faces significant barriers to being transferred to the market despite its importance. This finding highlights the need for public policies that strengthen the interaction between academia and the productive sector, promoting convergence between the production of academic knowledge and industry's demands for innovation. It is worth noting, however, that not all knowledge generated by universities and research centers needs to be directly applied to the market. However, this alignment with the productive sector is essential for knowledge of a more applied nature to maximize its economic and social impact.

In Chapter 3, the thesis investigated the relevance of technological proximity to industrial diversification in Brazilian regions. The study showed that in addition to the influence exerted by proximity to industrial knowledge, proximity to technological knowledge also plays a crucial role in regional industrial diversification. It was also observed that the probability of the emergence of new specializations increases when sectors are closer to knowledge associated with radical innovations (high-level innovation) compared to incremental innovations (low-level innovation). In addition, there is a greater likelihood of sectoral diversification when industries are closer to technological knowledge from business patents rather than from universities and public institutions. The commercial focus of business patents in academic institutions can explain this phenomenon. However, they have greater research freedom and sometimes face challenges in converting their knowledge into commercially applicable innovations. In low-income regions, the influence of technological knowledge on sectoral specialization is limited, while industrial proximity plays an important role. This result highlights the importance of public policies aimed at strengthening productive knowledge in low-income regions, encouraging the development of a solid industrial base that can gradually sustain technological diversification.

Chapter 4 explored the influence of the competitiveness of neighboring regions on the process of regional diversification. The results indicate that the competitiveness and density of capacities of neighboring regions positively influence the probability of entry of new sectoral specializations and the growth of the regions' RCA. At the same time, it was observed that competitiveness and density reduce the probability of sectoral specializations leaving. This result reinforces the idea that the capabilities of neighboring regions have a positive influence on the diversification of regions through the sharing of resources. Proximity to the industrial knowledge of neighboring regions is even more important for new specializations than proximity to the region's knowledge portfolio, highlighting the importance of diversifying into sectors related to the expertise of surrounding regions. In regions with low economic complexity and income, the reliance on the accumulated capacities and knowledge of neighboring areas becomes even more pronounced, as these regions depend heavily on external resources to foster new specializations. However, the limitations of local resources and capacities restrict the potential for diversification, underscoring the need for external support and targeted public policies. Furthermore, the presence of neighboring regions with greater economic complexity amplifies the effects of competitiveness and capacity density in shaping the likelihood of specialization, emphasizing the role of more developed neighbors in driving regional specialization.

These findings have important implications both in the literature and in terms of public policy. This is one of the first studies to analyze the interaction between productive and technological knowledge in regions' industrial and technological diversification. It was already clear how productive and technological knowledge had a multiple influence on the development of regions and countries (Freeman; Louçã, 2001; Soete; Freeman, 1977; Eum; Lee, 2022b). Studies have shown the importance of proximity to industrial and technological capacities for regional diversification, but in isolation (Neffke, 2009; Freitas; Britto; Amaral, 2024; Boschma; Balland; Kogler, 2015). However, they had not yet explored the importance of proximity to the capabilities of these two types of knowledge together for regional diversification.

Another important implication for the literature is the influence of neighboring regions on regional diversification, especially for low-income regions. Local capabilities provide opportunities but also impose limits on regional diversification. Especially for regions that are not very diversified, the difficulty transitioning to new specializations can generate a lock-in if these places rely solely on internal capabilities (Hassink, 2005). Therefore, it may be relevant for these regions to take advantage of the capabilities and knowledge of neighboring regions to build their diversification process.

In terms of public policies, the thesis highlights the importance of policies promoting local productive capacities, especially in less economically developed regions. For these areas, it is essential to create programs that encourage strengthening productive knowledge through apprenticeship practices, promoting the know-how needed to advance to more complex technologies in subsequent phases. Gradually building this base will allow less developed regions to start diversification processes and keep up with the advances of more industrialized regions.

Another crucial point for public policies is encouraging integration between universities and the productive sector. As the results show, although public research institutions generate the majority of patents, there is sometimes a disconnect between the knowledge they generate and its application in the market. Policies that encourage the creation of public-private partnerships and innovation clusters could reduce this gap, promoting the conversion of academic knowledge into commercial innovations that directly benefit the regional economy. In addition, encouraging the creation of technology centers that integrate companies and higher education institutions can promote greater harmony between the knowledge generated and local innovation needs.

Policies promoting interregional collaboration are necessary in low economic complexity and income regions, where limited resources and knowledge restrict diversification possibilities. These policies should prioritize the creation of cooperation networks between nearby regions, enabling the sharing of resources, capacities, and infrastructure. Public policy can catalyze economic development, especially in regions with low RCA and industrial density, by incentivizing joint development projects and knowledge transfer between neighboring regions, strengthening local economies, and reducing regional inequalities.

This study has some limitations that could be addressed in future research. Employment information was used to calculate the RCA, which is widely available for regional analysis; however, incorporating production data from both regions and their neighbors could enrich the analysis. Competitiveness was inferred based on employment data, serving as an approximation of the productive structure. Still, it would also be relevant to include additional variables that influence the competitiveness of neighboring regions, such as infrastructure and job flows. Additionally, the compatibility between industrial sectors and technological classes limits this research; however, given the data sources available in Brazil, this approach is the most appropriate. Future studies could investigate the impact of specialization in specific sectors within certain regions and its effects on diversifying technological classes.

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Appendix

APPENDIX A – Summary of the ALP Industry-Level to Patent/Technology-Level Crosswalk

The *Algorithmic Links with Probabilities (ALP)* concordance table is a methodology used to relate industrial classifications (such as ISIC, SITC, and NAICS) to patent classifications (such as IPC and CPC). Since these classification systems are not directly related, the ALP crosswalk provides a probabilistic approach to linking production sectors with technological knowledge.

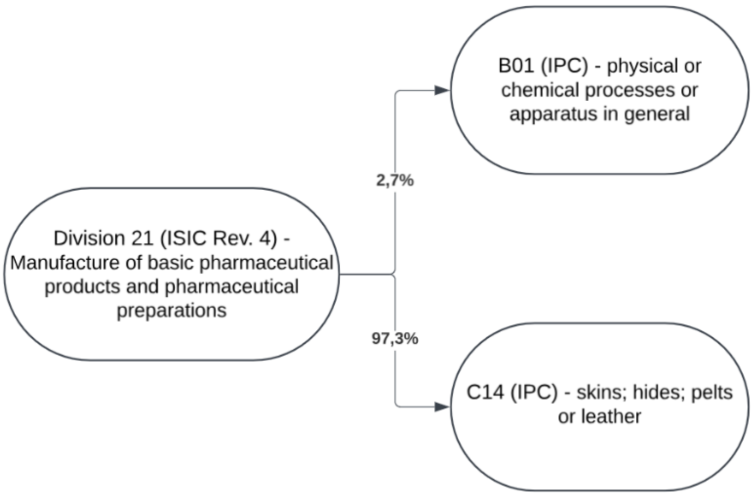
- **Available Versions** Two versions of the concordance table exist—one including service industries and one excluding them. Since mapping services to patents is more uncertain, researchers are advised to rely primarily on the version without services.
- **Data Structure** Each file contains three variables: the original classification, the new classification, and a probability weight (ranging from 0 to 1). The weights sum to 1 within each industry or technology class.
- **Weighting Methodology** The weights are based on the *hybrid probability weighting structure* described by Lybbert and Zolas (2014). A 2% cutoff threshold was applied, meaning that weights below 2% were removed, and the remaining weights were renormalized.
- **Directional Mapping** The crosswalk is designed to translate data in one direction only (e.g., ISIC $\rightarrow$ IPC). Reverse translation (IPC $\rightarrow$ ISIC) is not possible using the same weights, as the relationships between industries and technologies are asymmetrical. Because of this, two separate documents are provided: one specifically for converting ISIC to IPC, and another for converting IPC to ISIC. Each document contains probability weights that reflect the best approximation for mapping between these classifications in a consistent and meaningful way.
- **Levels of Aggregation** The crosswalk is available at multiple levels of detail (from 1-digit to 6-digit classifications). Since both industrial and patent classifications follow hierarchical structures, separate crosswalks are necessary for different levels of aggregation.

To illustrate the process, Figure 5 presents an example of how ISIC classifications are converted into IPC technological classes, while Figure 6 demonstrates the inverse conversion from IPC back to ISIC. When required, translations between ISIC and CNAE, or vice versa, were also performed. The methodology relies on ISIC Rev. 4 at the 2-digit level and IPC at the 3-digit level, providing a structured and systematic approach to linking sectoral employment data with patent classifications.

The percentages shown in the figures represent the probability weights assigned in the ALP concordance table. When translating from patents to industries, these weights are multiplied by the number of patents in each IPC category to estimate their corresponding industrial classification. Conversely, when translating from industries to patents, the weights are applied to employment data (or production data in other studies) to estimate their technological distribution.

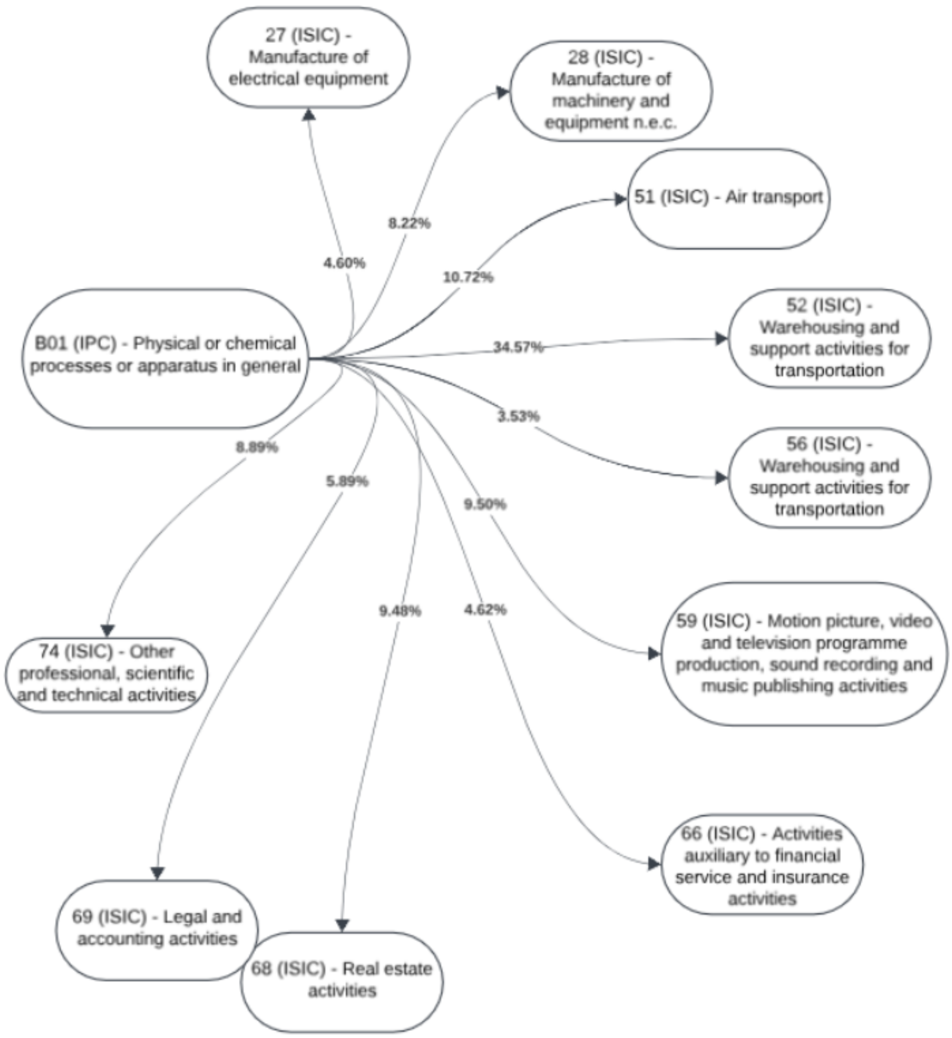
The ALP concordance table is a valuable tool for economic and innovation studies, enabling researchers to analyze the relationships between industrial and technological activity.

Figure 5 – Example of ISIC to IPC conversion



Source: Authors' elaboration.

Figure 6 – Example of IPC to ISIC conversion



Source: Authors' elaboration.

APPENDIX B – Chapter 4

Table 16 – The Influence of Maximum RCA and Maximum Density of Neighboring Regions on Sector Entry in Brazil's Intermediate Regions

	Dependent variable: Entry					
	OLS		*Logit*		*Probit*	
	(1)	(2)	(3)	(4)	(5)	(6)
Max RCA Nb	0.0001***	0.0001***	0.002***	0.002***	0.001***	0.001***
	(0.00002)	(0.00002)	(0.0003)	(0.0002)	(0.0002)	(0.0001)
Max Density Nb	0.003***	0.002***	0.098***	0.062***	0.044***	0.028***
	(0.0001)	(0.0001)	(0.002)	(0.003)	(0.001)	(0.001)
RCA		0.268***		2.987***		1.551***
		(0.004)		(0.032)		(0.017)
Density		0.004***		0.114***		0.055***
		(0.0002)		(0.005)		(0.002)
ECI		−0.009***		−0.289***		−0.156***
		(0.001)		(0.049)		(0.022)
PCI		0.012***		0.315***		0.163***
		(0.001)		(0.052)		(0.023)
Population (log)		0.004*		0.040		0.032
		(0.002)		(0.078)		(0.036)
GDPpc (log)		0.010*		0.204		0.065
		(0.006)		(0.225)		(0.102)
Constant	0.131***	−0.146*	−2.491***	−7.626**	−1.340***	−3.485**
	(0.014)	(0.086)	(0.168)	(3.200)	(0.085)	(1.461)
Observations	93,951	93,951	93,951	93,951	93,951	93,951
R^2	0.047	0.086				
Adjusted R^2	0.038	0.077				
Log Likelihood			-29,159.970	-26,610.510	-29,153.620	-26,664.390
Akaike Inf. Crit.			60,021.950	54,935.010	60,009.230	55,042.790
Residual Std. Error	0.299	0.293				
F Statistic	5.348***	10.182***				

Source: Authors' elaboration. Note: Robust standard errors in parentheses. *p < 0.1; **p < 0.05; ***p < 0.01. All regressions include region, period, and sector fixed effects.

Table 17 – The influence of RCA and density max of neighboring regions on the entry of sectors differentiated by the income of the immediate regions of Brazil

	Dependent variable: Entry					
	Low-income		Medium-income		High-income	
	(1)	(2)	(3)	(4)	(5)	(6)
Max RCA Nb	0.001***	0.001***	0.003***	0.002***	0.005***	0.004***
	(0.0003)	(0.0003)	(0.001)	(0.001)	(0.001)	(0.001)
Max Density Nb	0.054***	0.044***	0.078***	0.058***	0.086***	0.043***
	(0.007)	(0.007)	(0.005)	(0.005)	(0.003)	(0.004)
RCA		2.365***		3.088***		3.303***
		(0.069)		(0.055)		(0.049)
Density		0.049***		0.115***		0.103***
		(0.012)		(0.009)		(0.006)
ECI		−0.084		−0.468***		−0.211**
		(0.082)		(0.083)		(0.089)
PCI		0.267**		0.542***		0.110
		(0.110)		(0.094)		(0.078)
Population (log)		0.251		0.288**		−0.064
		(0.236)		(0.142)		(0.102)
GDPpc (log)		1.402***		0.425		−0.411
		(0.505)		(0.383)		(0.334)
Constant	−2.890***	−20.347***	−2.780***	−12.492**	−3.177***	0.810
	(0.305)	(6.355)	(0.252)	(5.127)	(0.277)	(4.641)
Pseudo R2	0.19	0.21	0.14	0.21	0.12	0.22
Observations	161,438	161,438	155,967	155,967	153,218	153,218
Log Likelihood	−17,430.580	−16,823.630	−21,017.050	−19,236.100	−24,897.530	−22,164.290
Akaike Inf. Crit.	35,891.170	34,689.260	43,064.110	39,514.190	50,837.050	45,382.580

Table 18 – The influence of RCA and density max of neighboring regions on the entry of sectors differentiated by the economic complexity of the immediate regions of Brazil

	Dependent variable: Entry$_t$			
	Low	Medium-Low	Medium-High	High
	(1)	(2)	(3)	(4)
Max RCA Nb	0.002***	0.001***	0.003***	0.004**
	(0.001)	(0.0003)	(0.001)	(0.001)
Max Density Nb	0.054***	0.058***	0.031***	0.009
	(0.011)	(0.004)	(0.005)	(0.007)
RCA	2.458***	2.780***	3.419***	3.518***
	(0.101)	(0.046)	(0.061)	(0.104)
Density	0.079***	0.064***	0.105***	0.089***
	(0.021)	(0.008)	(0.010)	(0.012)
ECI	−0.330**	−0.327***	−0.308**	−0.173
	(0.153)	(0.085)	(0.137)	(0.286)
PCI	0.637***	0.459***	0.166*	−0.591***
	(0.168)	(0.074)	(0.101)	(0.151)
Population (log)	0.426	−0.179*	0.144	0.650
	(0.323)	(0.102)	(0.202)	(0.520)
GDPpc (log)	0.897*	−0.179	0.954	−3.142***
	(0.476)	(0.358)	(0.673)	(1.165)
Constant	−17.158**	0.782	−18.451**	33.048*
	(7.171)	(4.946)	(8.922)	(18.930)
Pseudo R^2	0.248	0.198	0.211	0.247
Observations	93,041	253,683	97,450	26,449
Log Likelihood	−7,988.749	−30,896.090	−14,273.010	−4,863.093
Akaike Inf. Crit.	16,957.500	63,180.170	29,552.020	10,512.190

Source: Authors' elaboration. Note: Robust standard errors in parentheses. *p < 0.1; **p < 0.05; ***p < 0.01. All regressions include region, period, and sector fixed effects.