KNOWLEDGE PROXIMITY AND TECHNOLOGICAL DIVERSIFICATION
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The role of stability and the alternatives.

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Abstract

This paper examines the processes of generating new technical knowledge, aiming to contribute to an understanding of how less developed economies can diversify their knowledge base to support economic development. We study the structure of relatedness of required knowledge between technologies at a global level, conceived as a network where technologies are connected according to the intensity with which they co-occur in the inventors' portfolios. Based on this, topological characteristics of the network are studied using node-level metrics to propose diversification strategies that alleviate the lock-in effects suffered by less developed economies. The paper contributes to the literature by proposing two indicators that can be used to analyse relevant dimensions of the innovation system of cities in less developed regions. One of the indicators enables us to compare the levels of stability of the technologies that comprise the knowledge base of the cities. The second provides a measure of the level of alternatives available to the city for each diversification decision. The results, based on the analysis of Latin American cities, show that the stability of the technologies present in a city, as well as the alternatives available to choose its diversification path, are relevant to designing diversification strategies that could contribute to overcoming the constraints generated by the characteristics of the knowledge base of those cities.

Keywords: relatedness; innovation systems; patents; cities; Latin America; Evolutionary Economic Geography

JEL: B52, D85, O31, O32, O34

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1 Introduction

Innovation is the basis of structural change, which is key to economic development (Schumpeter, 1934, 1943). In turn, innovation is largely based on the generation of new technical, scientific, and practical knowledge (Nelson & Winter, 1977, 1982). Knowledge can be described in different ways, but in any case it is the human capacity to transform its environment. In turn, new knowledge can be seen as the recombination of previously available knowledge (Arthur, 2009; Fleming & Sorenson, 2001, 2004; Sorenson, Rivkin, & Fleming, 2006; Youn, Strumsky, Bettencourt, & Lobo, 2015). Therefore, the knowledge base of a society affects its ability to generate new knowledge and, through this, its innovation capability. Hence, we can say that the diversification of a society's knowledge base is a central element for its economic development. This paper examines the processes of new knowledge generation, aiming to contribute to an understanding of how less developed economies can diversify their knowledge base to support economic development.

The diversification of the knowledge base is a central concept within the evolutionary economics framework, in which it is understood that the firm cannot be described by a production function to be optimised, as it operates with bounded rationality[1]. This is why the firm generates routines to carry out its production, which it adjusts over time based on its economic results and the learning it generates in interaction with its environment. The updating of the firm's routines occurs through an adaptive learning process that makes it dependent on its trajectory. This adaptive process leads to recombinations of its knowledge base, which can result in innovations that modify its routines (Antonelli, 2011; Nelson & Winter, 1982).

In recent decades, evolutionary economic geography (EEG) has contributed to the understanding that the processes to which firms are subject not only depend on their history but also on the territory in which they conduct their activities (Boschma & Frenken, 2006; Boschma & Lambooy, 1999; Martin, 1999). Within this conceptual framework, it is possible to study territories as economic units competing for the development of new activities that allow them to foster local development. This poses a conceptual difficulty, as the evolutionary approach considers firms' entry and exit market as a central element of its framework. However, territories are entities that do not enter or exit the system. Even so, it is possible to analyse territories as units that compete for the establishment of economic activities, where the loss or gain of these activities affects their economic development (Boschma, 2004). These activities are seen as materialisations of the knowledge base of the territory; therefore, their diversification and complexity show the development of the underlying knowledge base available (Balland & Rigby, 2017; Frenken, Van Oort, & Verburg, 2007).

To understand the processes of diversification of the knowledge base in territories, the EEG considers different dimensions of proximity between activities (Balland, Boschma, & Frenken,

[1]This idea can be generalised to other types of economic agents and the objective functions with which they are described.

2015; Boschma, 2005). This aims to contribute to the understanding of the factors that affect the entry and exit of activities in the territories. Research along these lines has shown that an activity is more likely to enter a territory if there are other related activities present. Similarly, activities developed in a territory are less likely to exit the territory, the greater the number of related activities within it (Boschma, Balland, & Kogler, 2015; Hidalgo et al., 2018; Neffke & Henning, 2013; Neffke, Henning, & Boschma, 2011).

For less developed economies, diversification of their knowledge base is a key element. From an EEG perspective, path and territory dependence can lead to lock-in situations that make it particularly difficult for less developed regions to improve their situation. A significant number of applied works study this phenomenon for different regions and from various perspectives (Hartmann, Guevara, Jara-Figueroa, Aristarán, & Hidalgo, 2017; Hartmann, Zagato, Gala, & Pinheiro, 2021; Isaksen, 2015), with particular emphasis on the variety of capabilities needed to develop an activity, as well as on the ubiquity of the activity at the regional or global level.

To address these two dimensions, these works use complexity indicators following different adaptations of the one initially proposed by Hidalgo and Hausmann (2009). The applied studies show that territories can be trapped in a productive structure, understood as the set of activities that take place in them, which limits their economic development. These territories, being specialised in low-complexity activities, do not have the capabilities that would allow them to develop more complex activities (i.e. they are distanced from them), which leaves them trapped. The search for strategies to overcome this lock-in is key to the design of public policies. In particular, for decisions concerning the development of technical knowledge, which has been shown to have a high predictive power on the future export basket of countries (Pugliese et al., 2019).

Although the literature on technological diversification from this perspective is extensive, certain elements have not been studied and could contribute to a better understanding. Firstly, this literature has made use of relatedness networks that establish a link between two activities if both show a higher volume of co-occurrences than expected according to different statistical criteria[2]. From these, it is possible to analyse, in the case of technologies, the relevance of this relatedness links to the probability that a territory starts (or stops) developing a technology. However, this is only part of the information offered by these networks of relatedness. Further study of their topology can help us understand other dimensions of relatedness between technologies, thereby improving our understanding of the knowledge necessary for a technology to enter a territory.

In this way, the relatedness network can be seen as a map of knowledge flowing between activities, which recombine with one another. This flowing knowledge is a product of social

[2]The type of co-occurrences analysed is broad but, as an example, we can mention goods that co-occur in the export basket of countries (Hidalgo, Klinger, Barabási, & Hausmann, 2007), technologies that co-occur in the technological portfolio of cities (Rigby, 2015), industries that are repeated in the labour trajectory of workers (Neffke & Henning, 2013).

structures, and therefore, we can expect that the evolution of relatedness between activities does not follow a purely random behaviour (Fleming & Sorenson, 2001; Sorenson et al., 2006). In this sense, following Polanyi and his idea of "emergence" (Polanyi, 1966b), new knowledge cannot be explained only by an evolutionary theory in which random recombination generates species and these last according to their capacity to adapt. In the generation of knowledge, the recombination of ideas is central, but the product obtained is greater than the sum of its parts in the sense that something else is involved and cannot be described by that recombination alone. This central element, which modifies the process, is tacit knowledge and can lead to a small-world topological structure (Watts & Strogatz, 1998), as observed in many social networks.

Secondly, for the analysis of technological diversification processes, mainly the co-occurrence of technology codes in patents has been used, since a patent can be classified under more than one code. However, patent records also allow us to identify the inventors involved. This information enables the analysis of the portfolio of technologies developed by the inventors, similar to what has been done for other types of activities (Neffke & Henning, 2013). Using the inventors' portfolio brings us closer to the tacit dimension of knowledge, as individuals are the carriers of this tacit knowledge.

Tacit knowledge is that which individuals can use but not explain or teach in a codified way. Taking this dimension of knowledge into consideration allows us to recognise that the product of what we create is not only the recombination of codifiable knowledge (Polanyi, 1966a, 1966b). The relevance of tacit knowledge can manifest itself as know-how that is the individual's own or as collective knowledge that individuals in a community possess but cannot necessarily pass on. This type of knowledge is not only expressed in the ability to do things but also in the ability to identify problems (Collins, 2010; Cowan, David, & Foray, 2000). This is central to the generation of new knowledge, as problem identification is the source that drives its development in many fields. These characteristics make it particularly relevant to understand the relatedness of activities from this perspective, as it is knowledge that cannot be easily transferred or communicated. While there is tacit knowledge that is firm-specific, and this is central to the evolutionary approach, the production of frontier know-how is embedded in global value chains that can decouple the place where the knowledge is developed from the place that holds the property rights over it. This is especially relevant in relatively less developed regions.

Third, most empirical research in this literature has focused on developed economies, although there has been a recent growing focus on the consequences of public policies derived from this approach on less developed regions (Foray, 2019; Hassink, 2010; Hassink & Gong, 2019). The tendency towards temporal and spatial dependence in diversification can be reinforced by policies that promote the development of activities closely aligned with the knowledge base of the territories. These policies are based on the fact that pursuing distant activities is more risky and may lead to undesirable outcomes. However, in regions where low-dynamic activities are prevalent, this may mean that their opportunities for diversification will lead them to remain in this situation (Balland, Boschma, Crespo, & Rigby, 2019; Boschma, 2022).

This lock-in makes it relevant to have more information on the relatedness structure in order to identify strategies to direct diversification towards dynamic activities. Policies of this type can be particularly useful in regions like Latin America, where considerable heterogeneity exists within countries and, generally, there are difficulties in developing complex activities. However, this literature has studied Latin America comparatively less.

To contribute to filling the identified gaps, we study the structure of relatedness of required knowledge between technologies at a global level, conceived as a network where technologies are connected according to the intensity with which they co-occur in the inventors' portfolios. Based on this, some topological characteristics of the network are studied using node-level metrics to propose diversification strategies that alleviate the lock-in effects suffered by less developed economies. In this sense, the paper contributes to the literature by proposing two indicators that can be used to analyse relevant dimensions of the innovation system of Latin American cities. One of the indicators enables us to compare the levels of stability of the technologies that comprise the knowledge base of the cities. The second provides a measure of the level of alternatives available to the city for each diversification decision.

The results show that it is possible to identify characteristics of the topological structure of the relatedness network that are associated with a higher probability of a city developing comparative advantages in a given technology. In particular, it is observed that the stability of the technologies present in a city, as well as the alternatives available to choose its diversification path, are relevant to designing diversification strategies that contribute to overcoming the constraints generated by the knowledge base in Latin American cities.

The rest of the paper, beginning in Section 2, presents the relevant literature, defines the main concepts, and proposes the hypotheses. The empirical strategy for the operationalisation of the concepts and hypotheses testing is presented in section 3. The results obtained are presented in section 4, where their support for the hypotheses is also discussed. Finally, the paper's conclusions are summarised in section 5.

2 Theoretical framework

2.1 The structure of knowledge relatedness as a network of technologies

In recent years, a body of literature has developed, arising from Hidalgo et al. (2007) and Hidalgo and Hausmann (2009), which uses information on the co-occurrence of activities to study the relatedness between them, their complexity, and the complexity of the territories in which they are carried out[3]. Within this literature, the 'Principle of Relatedness' is particularly

[3]This literature has been reviewed in recent works (Balland et al., 2022; Boschma, 2017; Hidalgo, 2021; Hidalgo et al., 2018) that seek to show its development, robustness, and scope, with an emphasis on different aspects of this approach.

relevant (Hidalgo et al., 2018). The intuition behind this principle is that, by observing the co-occurrence of activities in different types of analytical units, it is possible to infer the relatedness between these activities through the use of network analysis. This enables the identification of diversification trajectories that consider local capabilities, thereby reducing the inherent risk associated with diversification processes.

This approach has been applied to understand the relatedness, for example, between exportable goods (Hausmann et al., 2013; Hidalgo et al., 2007), areas of scientific knowledge (Guevara, Hartmann, Aristarán, Mendoza, & Hidalgo, 2016; Lyu, Zhou, & Leydesdorff, 2020), brands (Drivas, 2022), occupations (Farinha, Balland, Morrison, & Boschma, 2019; Muneepeerakul, Lobo, Shutters, Goméz-Liévano, & Qubbaj, 2013), industrial sectors (Breschi, Lissoni, & Malerba, 2003; De Raco & Semeshenko, 2019; Essletzbichler, 2015; Neffke et al., 2011), or technologies (Alstott, Triulzi, Yan, & Luo, 2017; Kogler, Rigby, & Tucker, 2013). In particular, technologies in this framework are considered areas of technical knowledge, and these works utilise patented inventions as materialisations of advances in this type of knowledge.

Particularly relevant to this research are the works of Neffke and Henning (2013); Neffke et al. (2011); Neffke, Otto, and Weyh (2017), which use the flow of workers between industries as input to estimate the relatedness of the skills required in them. With this information, the authors seek to infer whether worker transitions between two industries occur more frequently than would be expected in a random process. If this is the case, the authors argue that both industries have skills relatedness.

This application of the principle of relatedness is appropriate for inferring the relatedness of knowledge between technologies by analysing the portfolio of technologies produced by inventors. We will say that if the number of inventors who have technology X and technology Y in their portfolio (they register patents classified in technology X and also patents classified in technology Y) is above what we would expect in a probability distribution conditioned on the relative sizes of the production of both, then technologies X and Y have a relatedness of knowledge between them. This result would indicate that the experience gained in developing one technology provides useful knowledge to develop the other.

Knowledge relatedness provides a framework for considering whether two technologies are related in terms of the knowledge required to develop them. In this way, we can analyse the set of technologies as a network, in which each technology is a node and a pair of nodes is connected if there is a link of relatedness between the technologies they represent. On the other hand, using information about the place of residence of inventors, we can learn about the technologies that are patented in each city. By combining these two elements, we can propose a method to measure the relatedness of a city's knowledge base to each technology.

Although there are precedents that use this approach for developing countries (Alonso & Martín, 2019; Dosi, Mathew, & Pugliese, 2020; Petralia, Balland, & Morrison, 2017), this literature has focused on developed countries (Boschma et al., 2015; Guevara et al., 2016; Kogler et al., 2013; Muneepeerakul et al., 2013; Neffke et al., 2011; Zhu, He, & Zhou, 2017). On the other hand, studies that examine the relatedness between technologies do so by considering co-citation between technologies (Alstott et al., 2017; Kogler et al., 2013). However, there are no studies that examine the relatedness of knowledge between technologies, as expressed by the portfolios of inventors.

2.2 Related and unrelated diversification

Economic diversification can be achieved by developing activities related to those already present in the territory (related diversification), by attempting to develop activities that are distant from the available knowledge base (unrelated diversification), or by combining both strategies in line with the characteristics of the region under study (Boschma, 2022). Based on the concepts of related variety and unrelated variety (Frenken et al., 2007), the implications of adopting either of these strategies have been studied.

From a theoretical perspective, it is proposed that both have potential benefits that are naturally associated with different risks. Related diversification takes advantage of the externalities of agglomeration (Jacobs, 1969) and is associated with increases in productivity in each activity and the generation of incremental innovations where the new activities are related to the old ones. For its part, unrelated diversification can contribute to diversifying risk from a portfolio perspective (Montgomery, 1994), as well as generating disruptive innovations where the activities that emerge are distant from the original ones.

Related diversification has been proposed as the basis for smart specialisation policies, widely promoted in Europe (Balland et al., 2019; Boschma, 2022; Foray, 2014). However, unrelated diversification has also received considerable attention as it is associated with potentially more disruptive, but also riskier, transformation processes (Alshamsi, Pinheiro, & Hidalgo, 2018; Castaldi, Frenken, & Los, 2015; Grillitsch, Asheim, & Trippl, 2018; Janssen & Frenken, 2019; Pinheiro, Hartmann, Boschma, & Hidalgo, 2021; Zhu et al., 2017). This has led to advances in the literature in understanding the characteristics and relationship between these two concepts (Asheim, Boschma, & Cooke, 2011; Content & Frenken, 2016; Juhász, Broekel, & Boschma, 2021; Whittle & Kogler, 2020). The debate on the advisability of promoting strategies based on related or unrelated diversification remains open (Foray, 2019; Hassink & Gong, 2019), among other things, because it is understood that the former can reinforce the lock-in of less developed economies in low-complexity structures. This aspect has been studied recently from this perspective, observing that this lock-in exists and is difficult to overcome for countries in this situation (Hartmann et al., 2021; Pinheiro, Balland, Boschma, & Hartmann, 2022).

In a context like that of Latin America, where there is a relative lag in the development of cutting-edge technical knowledge, it is particularly relevant to analyse alternatives for achieving more complex and dynamic technologies. In this sense, fully exploiting the information contained in knowledge-relatedness networks can facilitate the identification of unrelated diversification opportunities, thereby reducing the risk associated with this strategy.

2.3 Knowledge production and cities in Latin America

Cities have been highlighted as objects of study due to the role they play in today's societies (Jacobs, 1969; Neal, 2012). Economic geography has emphasised their relevance, both from a neoclassical perspective (Krugman, 1991, 2011) and from that of regional studies (Glaeser, Kallal, Scheinkman, & Shleifer, 1992). The evolutionary economic geography approach pays special attention to urban agglomerations as units of analysis, given their ability to bring together different dimensions of proximity that this approach considers central to innovation processes (Balland et al., 2015; Boschma, 2005; Boschma & Frenken, 2006; Boschma & Lambooy, 1999; Martin & Sunley, 2006).

Globally, cities play a central role in knowledge production (Maisonobe, Grossetti, Milard, Eckert, & Jégou, 2016). The literature on technical knowledge development, based on the use of patent data, has emphasised the regional effects of collaboration networks between cities (Boschma, 2005; Cantner & Graf, 2006; Strumsky & Thill, 2013), and the relevance of large cities for concentrating the most complex activities (Balland et al., 2020).

In Latin America, more than 81% of the population lived in urban areas in 2018, and this number is projected to reach 89% by 2050. In addition, megacities with more than 10 million inhabitants are home to more than 14% of the population[4]. Urban agglomerations account for most economic activity, representing nearly 60% of Latin America's GDP and concentrating nearly 30% in about 40 cities (Montero & García, 2017). This importance is reflected in the concentration of knowledge production, which has been widely studied (Arond, Rodríguez, Arza, Herrera, & Sánchez, 2011; Bianchi, Galaso, & Palomeque, 2020; Cabello, 2022; Fischer, Queiroz, & Vonortas, 2018).

Although Latin American countries play a peripheral role in the global knowledge production system (Chaves, Leonardo Costa Ribeiro, Ulisses Pereira, dos Santos, & Albuquerque, 2020), the region's characteristics lead to highly heterogeneous development, resulting in different trajectories of capacity accumulation (Bianchi, Galaso, & Palomeque, 2021, 2023). This is reinforced by a process of regionalisation of higher education and research centres, which has led to cities occupying a central place in this regard (Rama & Cevallos, 2016). These aspects prompt academic reflection on the need for specific approaches to public policy for the region that take this territorial structure into account (Duque Franco, 2021; Marchetti, Oliveira, & Figueira, 2019).

The region has traditionally been led by megacities that are now facing the exhaustion of the benefits provided by urban density and concentration, partly due to a lack of infrastructure and persistent inequality (Fischer et al., 2018). At the same time, recent evidence shows that the advantages associated with city size are limited (Fritsch & Wyrwich, 2021). On the other hand, new cities are beginning to emerge, characterised by the relevance of their middle class and with the potential to contribute to the growth of countries (Montero & García, 2017). Based

[4] https://population.un.org/wup/DataQuery/

on this, the diversity of characteristics between cities appears to be relevant to understanding innovation processes in Latin America. This diversity cannot be fully observed in studies that use countries as units of analysis.

2.4 Knowledge flows and network structure

Relatedness networks have been used to study processes of related diversification between technologies (Boschma et al., 2015). To do this, these studies use an indicator of the relatedness density of the territory (region, city, etc.) to each existing technology. The procedure for calculating this indicator[5] for each territory consists of taking a technology (which we will call the target) and listing all the technologies with which the target technology is linked in the relatedness network (first-degree neighbourhood of the target technology). The proportion of these technologies linked to the target that are present in the territory is then calculated. To define which technologies are present in the territory, revealed comparative advantage indicators are used, in the style of Balassa (1986), which compares the share of the technology in the territory's portfolio with its share in the total portfolio of the reference region. Previous work shows that relatedness density is positively associated with the probability that technology will begin to be developed in the city and negatively associated with it leaving (Balland et al., 2019; Balland & Rigby, 2017; Boschma et al., 2015; Hidalgo et al., 2018).

On the other hand, in recent decades, several studies have examined the topological characteristics of knowledge flow networks. They find that many of these networks are characterised by small-world structures (Breschi & Lenzi, 2016; Burt, 2004; Fleming, King, & Juda, 2007; Uzzi & Spiro, 2005; Watts & Strogatz, 1998), in which characteristics of random networks (links between nodes follow a random distribution) are combined with others present in social networks (links depend on node characteristics). This leads to structures with a marked tendency towards triad closure, which makes them highly clustered but with links between clusters that allow for the traversal of the network in a small number of steps.

In the context of the study of relatedness networks, it is possible to consider these characteristics of knowledge flow networks by analysing not only the density of the city towards the target technology but also towards the technologies with which the target technology shows relatedness (its first-degree neighbourhood). This involves analysing the relatedness of the city to technologies that are close to the target but may or may not be present in the city. Taking Figure 1 as an example, if we want to achieve technology i, we cannot only consider that x is the only technology present in the city that is linked to i. We can also consider the city's density to x, p, and q (first-degree neighbourhood of i).

[5] The formal definition of the indicators discussed in this section will be presented in section 3.

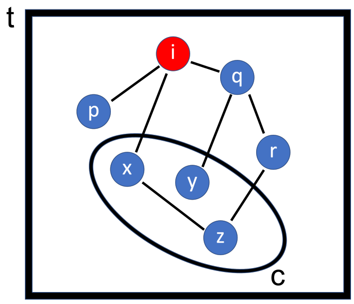

Figure 1: An illustrative example where the nodes in the network are technologies. The black oval represents the city (C), in which three technologies (x, y, z) are present. Technology i is the target, and the links between technologies indicate knowledge relatedness.

In the example above, the relatedness density of city C to technology i is $1/3$, since only one of the three technologies related to i is present in city C. On the other hand, it is important to note that cities can have a low relatedness density to the technologies that are present in them. For example, even though x is present in the city, the relatedness density of C to x is $1/2$. We can even have cases such as y, whose relatedness density to the city C is 0 (the only technology related to y is q, which is not present in C). Therefore, the relatedness density of the city to the technologies present does not necessarily have to be high. Similarly, we can have cases such as p, where the relatedness density of C to it is 0, but the relatedness density to the neighbourhood of p, which is given by i, is $1/3$.

This analysis of the network topology allows us to propose two density measures different from those used in the previous literature, which capture the city's relatedness to the technologies linked to the objective. First, the "stability density" will be constructed from the relatedness density of the city to the technologies, linked to the target technology, that are present in the city. In the example in Figure 1, x is the only technology that we must take into account when calculating the stability density to i. The second is called 'alternative density' and involves the same reasoning but to technologies that are not present in the city (p and q in Figure 1).

These measures contribute to the literature, as they allow us to use more information contained in the knowledge relatedness network. The stability density provides an idea of the environment of the technologies that serve as a basis for the diversification decision, considering the possibility that the technologies present in the city are poorly rooted. This makes their development heavily dependent on external knowledge, increasing the possibility that they will cease to be developed in the territory. On the other hand, the density of alternatives indicates the proximity of the city to the as-yet undeveloped environment of technologies that are close to those it wishes to achieve. In the context of scarce resources, diversification decisions may be affected by these alternatives.

2.5 Hypothesis

The relatedness density of a city to existing technologies has been shown to be a key factor for studying the likelihood of a region diversifying towards a specific technology (Boschma et al., 2015; Kogler et al., 2013; Rigby, 2015). These studies also found that higher relatedness density is associated with a lower likelihood of technology ceasing to be produced in the city.

In this sense, the stability density proposed in the previous section can be seen as a way of approximating the stability of technologies related to the objective. A low stability density implies, ceteris paribus, that the technology to be achieved is linked to technologies present in the city that may have a high probability of disappearing, and this may hinder the consolidation of the new technology in the territory.

The presence of technologies with low stability density in a city may be associated with public policies that have promoted their development without considering the city's capacity to sustain them. Their presence may also be due to the existence of isolated agents who participate in global knowledge production flows but whose location is not associated with the availability of specialised knowledge in the territory. In less developed regions with immature and fragmented innovation systems, it is particularly important to consider these conditions. In these territories, the development of technology may be due to the presence of natural resources or institutional conditions that favour the establishment of isolated activities. Access to global knowledge flows through actors linked to the rest of the world can be fundamental for the development of these territories. However, their capacity to absorb and distribute knowledge may be limited.

In turn, a high density of stability provides evidence of a high level of rooting of the technologies linked to the target. This condition is associated with a lower probability that these technologies will cease to be produced in the territory, providing more secure support for the technology towards which diversification is desired. Furthermore, the fact that the technologies contributing to the relatedness density are also sustained in the territory indicates that they can rely on local knowledge for their development.

On the other hand, a high density of alternatives shows us, ceteris paribus, that the city has the capacity to attract technologies related to the target technology that are not yet present in the city. These alternatives can divert resources, in this case inventors, towards technologies other than the target technology, reducing the probability of its emergence in the city. Similarly, if the city has few alternatives within the set of technologies related to the target technology, its resources will be focused, and the probability of developing the target technology will increase.

The two proposed densities provide information about the conditions for a given technology to be developed in a city, and we can expect them to be complemented by the relatedness density, which has already been studied in previous work (Boschma et al., 2015). When considering the relatedness between technologies as a network of knowledge flows, it is essential to take this complementarity into account. In this sense, stability density and alternatives density could increase the probability of a city developing a technology for which it has below-average relatedness density.

In turn, for technologies for which the city has a high relatedness density, high levels of stability density and alternatives density would imply that the incorporation of the new technology may be redundant for the city's knowledge base. The proximity approach used in this theoretical framework highlights the importance of proximity for the development of new activities, but also recognises that too much proximity can have negative effects (Balland et al., 2015; Boschma, 2005). Therefore, it is relevant to analyse the association of the proposed densities to the probability of the emergence of a new technology, taking into account their interaction with relatedness density. Based on the above, the following hypotheses are proposed:

Hypothesis 1a: *The stability density to a technology has a positive association with the probability that this technology will begin to be developed in the city.*

Hypothesis 1b: *The alternatives density to a technology has a negative association with the probability that this technology will begin to be developed in the city.*

Hypothesis 2a: *Stability density and alternatives density compensate for the lack of proximity, manifested in low levels of relatedness density, in which case they are positively associated with the probability of developing the new technology in the city.*

Hypothesis 2b: *Stability density and alternative density generate an excess of proximity in the presence of high levels of relatedness density, in which case they are negatively associated with the probability of developing the new technology in the city.*

Finally, in line with the above, if we consider that stability density and alternative density provide us with information about the knowledge base available in the territory, and that a high density of alternatives implies that the city has a wide range of options for diversifying its technology portfolio, we can expect it to do so towards those with the greatest potential to offer economic returns. The ability to generate future economic returns is not observable by the agents who must make diversification decisions. However, recent literature has shown that complexity can be considered a measure of an activity's ability to generate this type of return (Balland & Rigby, 2017; Rigby, Roesler, Kogler, Boschma, & Balland, 2022). Therefore, the following hypothesis is proposed:

Hypothesis 3: *The interaction of alternative density with high levels of complexity has a positive effect on the probability of developing new technology.*

3 Data and methods

This research uses data from the United States Patent and Trademark Office (USPTO)[6], obtained through the PatentsView project[7], which provides disambiguated information (Monath, Jones, & Madhavan, 2021; Monath & McCallum, 2015) on the inventors and owners of the patents, as well as the technologies in which they are classified. The process of disambiguating inventors is particularly relevant in this case, as it allows for the analysis of their patent portfolio, as well as their place of residence at the time of registration. These elements are key to calculating the indicators and assigning patents to cities in Latin America. USPTO patent records are widely used in this literature (Balland & Rigby, 2017; Boschma et al., 2015; Kogler et al., 2013; Perruchas, Consoli, & Barbieri, 2020; Petralia et al., 2017), not only because of their wide availability and coverage, but also because they avoid the comparability problems faced when using data from national offices, due to the different legal frameworks to which they respond.

In terms of technological classification, the database allows the use of the International Patent Classification (IPC)[8], from the World Intellectual Property Organization (WIPO). This technological classification is disaggregated at section, class and subclass levels. Although patents may be classified in more than one technology, the USPTO database identifies the order of appearance of each technological field in the patent. This is important because it represents an order of relevance, in which the first field is the one that best describes the technology to which the patent contributes. This is the criterion followed by the USPTO to determine the technicians who will be assigned to analyse each patent.

The database used contains 7,217,426 patents accepted by the USPTO, which were filed between 1972 and 2019. It also includes 3,659,986 inventors, 54.4% of whom are involved in more than one patent. For the purposes of this study, it is particularly relevant to have a considerable number of inventors who patent more than one technology. In this regard, the available data show that 31.7% of inventors register patents in more than one section, the most aggregated level of the IPC classification. Obviously, this proportion increases if we look at less aggregated levels, rising to 37.7% at the class level and 41.7% at the subclass level. Given that nearly half of inventors have only one registration, if we consider only inventors with more than one patent, these percentages almost double (58.2% at the section level, 69.3% at the class level and 76.6% at the subclass level).

In terms of the magnitude of registrations with inventors from Latin America, the proportion of inventors from the region in the total, as well as the proportion of patents in which they participate, has grown in recent years. Although inventors from Latin America represent a maximum of 0.51% of the total annually, and patents associated with them represent 0.45%, this growth has occurred simultaneously with the growth in the total number of patents globally.

[6] https://www.uspto.gov/
[7] https://patentsview.org/
[8] https://www.wipo.int/classifications/ipc/en/

Therefore, patents at the USPTO involving Latin America have grown in relative and absolute terms.

Considering the entire period covered by our database, inventors from Latin America represent 0.98% of the total number of inventors worldwide and account for 0.29% of patents. 30% of inventors from Latin America are involved in more than one patent, of which 38.8% have registrations in more than one section of the IPC classification. As was the case when analysing the global data set, the proportion of inventors who patent in more than one class and subclass is higher (50.9% and 59.7%, respectively).

As expected, given the characteristics of the region's economies, the proportion of inventors with a portfolio of several technologies is below the global level. However, considering that 26.1% of the classes observed globally appear in the region, and only 18.1% of the subclasses, it is clear that inventors in Latin America have fewer alternatives in this regard. On the other hand, this situation shows that the region has considerable potential to diversify the technologies it patents.

Based on previous work (Bianchi et al., 2021, 2023), we know that, for Latin America, country assignment does not present problems in this database, but city identification and coordinates require some refinement. To do this, the country and city data from the database are used to determine the city to which the inventor belongs. This information allows small localities to be grouped into the cities to which they belong. The name of the city and country is used to locate it on Google Maps. Since the name of the city may contain errors, characters such as numbers, dots or symbols are removed before proceeding with this step. In this way, Google Maps returns a name and coordinates for each city-country. This name may not match exactly how it is referred to in the database, but this allows us to disambiguate records that may refer to the same city in different ways. The coordinates of each city then allow us to analyse the distance between them and define a criterion for grouping small cities (few patents) into larger cities. This is especially important because city records are not standardised in the patent database, and different countries have different administrative levels. For this reason, there may be records in which the inventor declares the town where they live, but this is located within a city.

For the analysis presented in this section, if a city with a relatively low number of patents has a larger city less than 30 kilometres away, then the patents from the smaller city are assigned to the larger one. Finally, for each country, the largest cities that together account for 95% of the country's patents are selected. This excludes small localities with few records.

This procedure identifies 20,207 patents over the period covered by the data, distributed across 126 cities in the 19 countries considered. Table 1 shows descriptive information at the country level, showing the number of cities identified in each country, as well as other relevant figures, such as the number of patents and inventors, both in absolute terms and per million inhabitants, and the number of years in which each country appears in our data.

Patents registered between 2000 and 2019 were considered for the calculation of indicators

Country	Cities	Inventors	Inventors per million	Patents	Patents per million	Years
Brazil	25	8780	41.34	7530	35.45	48
Mexico	25	6368	48.13	5814	43.95	48
Argentina	12	2086	46.25	2533	56.16	48
Chile	7	1353	73.93	1110	60.66	47
Venezuela	10	907	27.65	924	28.17	46
Colombia	7	824	16.55	669	13.43	46
Costa Rica	2	358	71.60	648	129.60	46
Peru	5	193	5.87	210	6.38	42
Uruguay	2	175	50.00	190	54.29	36
Cuba	1	709	61.65	182	15.83	39
Ecuador	5	98	5.73	122	7.13	41
Panama	3	83	19.76	116	27.62	41
Dominican Republic	6	72	6.55	92	8.36	35
Guatemala	3	56	3.18	78	4.43	39
Bolivia	3	32	2.81	51	4.47	29
Honduras	4	34	3.54	46	4.79	22
El Salvador	1	27	4.22	28	4.38	19
Paraguay	2	28	4.00	25	3.57	19
Nicaragua	3	10	1.56	12	1.88	10

Table 1: Country-level information, in descending order by number of patents. The same patent may be counted in more than one country, so the total is higher than the 20,207 considered. Population by country from the World Bank for 2018.

and econometric analysis, grouping the registrations into four-year time windows. The volume of patent registrations with Latin American inventors at the USPTO was low until the beginning of this century. For this reason, we have chosen to work with the first twenty years of this century in order to use information that reflects the current pattern of inventive development in the region. On the other hand, in order to work with approved patents, the lag period between their filing and approval must be taken into account, which is why records up to 2019 are used. Table 2 shows the distribution among countries of the 80 cities used in the econometric analysis because they appear in the five time windows studied.

Country	# Cities	Country	# Cities
Argentina	8	El Salvador	1
Brazil	24	Guatemala	1
Chile	5	Honduras	1
Colombia	5	Mexico	22
Costa Rica	1	Panama	1
Cuba	1	Peru	1
Dominican Republic	1	Uruguay	1
Ecuador	1	Venezuela	6

Table 2: Cities, by country, considered in the econometric analysis

3.1 Variables and models

Our data allow us to construct co-occurrence matrices (F) of technologies in the inventors' portfolios for each period analysed[9]. To do this, if an inventor patented a technology j and also a technology i, we would have $F_{j,i} = F_{i,j} = 1$. By adding the co-occurrences between pairs of technologies, we obtain a symmetric matrix of $N \times N$, where N is the total number of technologies. With F, we can estimate a null model that allows us to measure the deviation of the observed co-occurrences from the expected ones ($\hat{F}$). Based on this, following Neffke and Henning (2013), the knowledge relatedness indicator (kr) is calculated as follows:

$$\hat{F}_{i,j} = \frac{\sum_j F_{i,j} \sum_i F_{i,j}}{\sum_i \sum_j F_{i,j}}$$

$$kr^{**}_{i,j} = \frac{F_{i,j}}{\hat{F}_{i,j}}$$

First, the observed co-occurrences $(F_{i,j})$ are compared with the estimated ones $(\hat{F}_{i,j})$. If $0 < kr^{**}_{i,j} \leq 1$, we say that the observed co-occurrences between technology i and j are below or equal to the estimated ones. Values of $kr^{**}_{i,j} > 1$ indicate that the volume of inventors patenting in i and j exceeds expectations, which is interpreted as a knowledge relatedness between both technologies. The indicator $kr^{**}_{i,j}$ has the disadvantage of presenting a pronounced right tail, because it takes values between zero and infinity. For this reason, it is normalised, and each technology is also forced to be perfectly related to itself.

$$kr^{*}_{i,j} = \begin{cases} \dfrac{kr^{**}_{i,j} - 1}{kr^{**}_{i,j} + 1} & \forall\, i \neq j \\ 0 & \forall\, i = j \end{cases}$$

Finally, the knowledge relatedness matrix is restricted between zero and one as follows:

$$kr_{i,j} = \frac{1}{2}\left(kr^{*}_{i,j} + 1\right) \tag{1}$$

Equation 1 establishes that $kr \in [0,1]$, where pairs of technologies with values close to 0 will be considered strongly dissimilar in terms of knowledge requirements, and those close to 1 will be considered highly related in this regard.

To determine which technologies are present in each city, we use the revealed comparative advantage index proposed by Balassa (1986) and applied in several works in this literature (Boschma et al., 2015; Hidalgo et al., 2007). Thus, we say that technology i is present in city u if the following is true:

$$RCA_{u,i} = \frac{pat_{u,i} / \sum_i pat_{u,i}}{\sum_u pat_{u,i} / \sum_u \sum_i pat_{u,i}} > 1$$

[9] To simplify the notation, the subscript t is excluded, but all indicators are calculated for each period.

Where ${pat_{u,i}}/{\sum_i pat_{u,i}}$ is the proportion represented by technology i in the technology portfolio of city u, and ${\sum_u pat_{u,i}}/{\sum_u \sum_i pat_{u,i}}$ is the proportion represented by technology i in the set of cities analysed. Therefore, we will say that city u has comparative advantages in technology i ($RCA_{u,i} > 1$), if this technology represents a larger proportion in its portfolio than in the set of cities.

We then define an indicator for the relatedness density of a city with respect to each technology observed globally. To do this, we establish a threshold ($\theta = 0.5$) for kr, above which we say that the relatedness of knowledge is significant[10]. Then, we define $KR_{u,i}$ as the number of technologies present ($RCA_{u,j} > 1$) in the city u that have knowledge relatedness with technology i (i.e. $kr_{j,i} > \theta$), and A as the total number of technologies with knowledge relatedness to i. Based on this, $relatedness_{u,i} \in [0,1]$ is defined as the relatedness density of city u to technology i:

$$relatedness_{u,i} = \frac{KR_{u,i}}{A} \tag{2}$$

To analyse the proximity of cities to technology neighbourhoods, the following indicators are defined.

$$stability_{u,i} = \begin{cases} \dfrac{\sum_j^J relatedness_{u,j}}{J} & \forall\, J > 0 \\ 0 & si\ J = 0 \end{cases} \tag{3}$$

The stability density is defined in equation 3, where $j \in [1,J]$ are the technologies present in city u, which belong to the degree-one neighbourhood of technology i in the knowledge relatedness network. Therefore, as defined in section 2.4, this indicator measures the average relatedness density of city u to the technologies present in it, belonging to the degree-one neighbourhood of technology i.

$$alternatives_{u,i} = \begin{cases} \dfrac{\sum_k^K relatedness_{u,k}}{K} & \forall\, K > 0 \\ 0 & si\ K = 0 \end{cases} \tag{4}$$

For its part, equation 4 defines the alternatives density, where $k \in [1,K]$ are the technologies that are not present in city u and belong to the degree-one neighbourhood of technology i in the knowledge relatedness network. This indicator, therefore, measures the average density of city u to technologies that are not present in it and belong to the degree-one neighbourhood of technology i.

With the available information, it is also possible to calculate the complexity indicator for each technology using the 'Eigenvector Method', following Hidalgo and Hausmann (2009) and Balland and Rigby (2017). This indicator, widely used in the literature (Hidalgo, 2021), can be

[10]This document does not discuss alternatives for defining this threshold, but this is a central issue in network analysis and there is an extensive literature on the subject (Coscia & Neffke, 2017; Coscia & Rossi, 2019; Neal, 2013, 2014).

calculated using the second eigenvector of the transposed bipartite matrix of technologies and cities. In intuitive terms, this method considers the global ubiquity of the technology, as well as the diverse knowledge it requires, based on the other technologies that comprise the portfolio of the territories in which it is produced.

To test hypotheses 1 (a and b) and 2 (a and b), the following model is estimated:

$$
\begin{aligned}
new_{u,i,t} = {} & \beta_1 relatedness_{u,i,t-1} + \beta_2 stability_{u,i,t-1} + \beta_3 alternatives_{u,i,t-1} + \\
& \beta_4 relatedness_{u,i,t-1} * stability_{u,i,t-1} + \beta_5 relatedness_{u,i,t-1} * alternatives_{u,i,t-1} + \\
& \beta_6 stability_{u,i,t-1} * alternatives_{u,i,t-1} + \\
& \beta_7 complexity_{i,t-1} + \beta_8 transitivity_{i,t-1} + \\
& B_9 X_{u,t-1} + \gamma_u + \delta_i + \zeta_t + \varepsilon_{u,i,t}
\end{aligned}
\tag{5}
$$

Following previous work (Boschma et al., 2015; Kogler et al., 2013; Rigby, 2015), $new_{u,i,t}$ is used as the dependent variable, which takes the value 1 if technology i appears in city u in period t. The periods are 4-year windows that aggregate observations over time. The variable $complexity_{i,t-1}$ measures the level of complexity of the technology. For its part, the variable $transitivity_{i,t-1}$ measures the proportion of closed triangles, among the possible ones, within the neighbourhood of technology i in the knowledge relatedness network. These two variables capture characteristics of the technology that vary over time but not between cities. Controlling for these factors is relevant to this work, as levels of complexity can affect the probability of developing a technology, and transitivity is a topological feature of the network that is associated with the proposed density indicators. For its part, $X_{u,t-1}$ represents a vector of controls that vary between cities and periods, including the number of patents, inventors and technologies. Finally, γ_u, δ_i and ζ_t are fix effects for city, technology and time, respectively, and $\varepsilon_{u,i,t}$ is the error term.

To understand the association between the characteristics of a city's knowledge base and the probability of developing a given technology in the future, it is necessary to consider lagged independent variables. This, in turn, mitigates the risk of the model presenting simultaneity problems. On the other hand, fix effects help to mitigate possible endogeneity problems arising from the omission of relevant variables. Furthermore, this model allows us to test the hypotheses considering clustered errors. Given that the dependent variable is dichotomous, a Generalised Linear Model is used. Hypothesis 1a will be supported by the evidence if we find that β_2 is significant and positive, while hypothesis 1b will be supported if β_3 is significant and negative. On the other hand, hypotheses 2a and 2b will be supported by the evidence if β_4 and β_5 are significant and negative. Finally, to test hypothesis 3, the following model is proposed, where the complexity indicator interacts with the measures of *stability* and *alternatives*:

$$
\begin{aligned}
new_{u,i,t} = {} & \beta_1 relatedness_{u,i,t-1} + \beta_2 stability_{u,i,t-1} + \beta_3 alternatives_{u,i,t-1} + \\
& \beta_4 relatedness_{u,i,t-1} * stability_{u,i,t-1} + \beta_5 relatedness_{u,i,t-1} * alternatives_{u,i,t-1} + \\
& \beta_6 stability_{u,i,t-1} * alternatives_{u,i,t-1} + \beta_7 complexity_{i,t-1} + \beta_8 transitivity_{i,t-1} + \\
& \beta_9 stability_{u,i,t-1} * complexity_{i,t-1} + \beta_{10} alternatives_{u,i,t-1} * complexity_{i,t-1} + \\
& B_{11} X_{u,t-1} + \gamma_u + \delta_i + \zeta_t + \varepsilon_{u,i,t}
\end{aligned} \quad (6)
$$

We will find support for hypothesis 3 if β_{10} is significant and positive.

4 Results

This section discusses the results of the econometric analysis of the proposed hypotheses. In Table 3, model 1 represents the specification set out in equation 5 and model 2 represents that of equation 6[11].

Firstly, it can be observed that the coefficient associated with the city's relatedness density to the different technologies (*relatedness*) is statistically significant and positive, in line with the results found in previous studies (Boschma et al., 2015; Kogler et al., 2013; Rigby, 2015). This indicates a positive association between the presence of technologies close to the target and the likelihood that the technology will be developed with comparative advantages in the city.

In line with hypothesis 1a, the coefficient associated with stability density is significant and positive. Given that this variable also interacts with the city's relatedness to the target technology, the coefficient represents the estimated effect of stability density on the probability of the city developing comparative advantages in a new technology of average relatedness[12]. Therefore, under these conditions, cities have been more likely to develop a new technology when they have a higher stability density.

These technologies present in the city, which are related to the new technology, determine the relatedness density with it. Therefore, the stability density allows us to observe the extent to which the city possesses the necessary knowledge to sustain the development of technologies that, in turn, will sustain the new technology. Based on the theoretical framework developed in this paper, we can interpret that diversification based on technologies that are strongly rooted in the territory, i.e., with high stability density, favours the consolidation of the technology achieved. Conversely, when the technologies related to the objective are poorly rooted in the territory (low stability density), it becomes more challenging to develop comparative advantages in their production.

[11] The appendix of section 6 presents other specifications of these models, which show the robustness of the results.

[12] The model also considers the interaction between stability and alternatives densities, but this is not significant and is therefore not included in the analysis.

On the other hand, the negative and significant coefficient associated with the density of alternatives supports hypothesis 1b. Given the interactions present in the model, the interpretation of this coefficient is analogous to the previous one. Therefore, it can be seen as the association of this variable with the probability of the emergence of a new technology of average relatedness. Thus, the evidence suggests that under these conditions, a higher density of alternatives is associated with a lower probability of developing new technologies.

Technologies close to the target that are not present in the city make up the density of alternatives. Following the argument presented in this paper, we can interpret this result as a consequence of the fact that the actors present in the city have options, within the set of technologies close to the target, for which they possess greater average knowledge. This can lead to efforts being directed towards these other technologies, rather than the target technology, reducing the likelihood that it will be produced in the city.

To analyse the contrast with the evidence for hypotheses 2a and 2b, we need to interpret the coefficients associated with the interactions between the city's relatedness density, regarding new technologies, and the stability and alternatives densities. To do this, it is important to bear in mind that the model used transforms the variables, extracting their mean, in order to consider fix effects. Therefore, the values used are deviations from the mean, which means that observations in which the variables are below the mean will have negative values.

As can be seen in Table 3, both the coefficient associated with *proximity* $\times$ *stability* and the coefficient associated with the interaction *proximity* $\times$ *alternatives* are significant and negative. In the first case, this implies that when the relatedness density is below the mean (*relatedness* < 0), the effect of stability density on the probability of entry is more significant than when the relatedness density is at the mean (*relatedness* $= 0$) or above it (*relatedness* > 0). In the case of the interaction with the alternatives density, when the relatedness density is below the mean, the effect of the alternatives density remains negative but of lesser absolute magnitude than for a relatedness density at or above the mean[13]. Therefore, the interaction of relatedness density with stability and alternatives densities increases the probability of developing a technology for which the relatedness density is below average. This result supports hypothesis 2a and allows us to say that the analysis of stability and alternatives densities is relevant for studying the likelihood of developing technologies that are distant from the city's knowledge base.

On the other hand, when the city's relatedness density to the new technology is high (*relatedness* > 0), the *relatedness* $\times$ *stability* interaction reduces the positive effect of stability density, and the *relatedness* $\times$ *alternatives* interaction makes the negative effect of alternatives density stronger, compared to an average relatedness density (*relatedness* $= 0$). Therefore, when considering these different types of density, we see that an excess in the accumulation of proximity around a technology decreases the probability of its development, supporting hypothesis 2b.

[13] As mentioned in section 3, because the dependent variable is dichotomous, the coefficients are estimated using a Generalised Linear Model. Therefore, the magnitude of the coefficients does not correspond to the marginal effects, an estimate of which can be found in Table 4 in the appendix of the section 6.

Dependent variable:	new	
Model:	(1)	(2)
Variables		
relatedness	10.84^{***} (2.075)	11.06^{***} (1.961)
stability	110.8^{***} (24.40)	102.4^{***} (36.77)
alternatives	-11.60^{***} (2.430)	-23.65^{***} (5.010)
complexity	-0.6096 (0.6854)	-2.055^{**} (0.9812)
transitivity	-1.355 (1.217)	-1.045 (1.392)
# inventors	0.1166 (0.1311)	0.1108 (0.1840)
# patents	-0.2012 (0.1464)	-0.1633 (0.2046)
# technologies	0.1559 (0.2223)	-0.0279 (0.2398)
relatedness $\times$ stability	-210.3^{***} (54.08)	-167.6^{***} (45.95)
relatedness $\times$ alternatives	-96.34^{***} (33.75)	-109.6^{***} (32.78)
stability $\times$ alternatives	-5.896 (17.06)	57.67^{***} (17.78)
stability $\times$ complexity		-19.76 (25.60)
alternatives $\times$ complexity		28.45^{***} (6.799)
Fix effects		
city	Yes	Yes
window	Yes	Yes
technology	Yes	Yes
Fit statistics		
Observations	199,772	199,772
Pseudo R^2	0.20218	0.20576
BIC	39,971.2	39,848.8

Clustered standard-errors in parentheses (city & window & technology)
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 3: Estimation results for the models of equations 5 and 6. For simplicity, subscripts are omitted but all independent variables are lagged. The estimations are performed using a Generalised Linear Model of the logit type. Table 6 in the appendix of the section 6 presents other specifications performed as robustness exercises.

The inclusion of interactions in the model means that the marginal effect of stability density and alternative density can only be measured by fixing the value taken by the variables with which they interact. The interpretation of the coefficients for hypotheses 1 and 2 considered values relative to the mean of the variables. Figure 2 shows the evolution of the marginal effect of stability density and alternatives density for the different values of relatedness density, using the observed values of the other variables. It can be seen that the marginal effect of stability density is positive in almost all cases, and the opposite is true for the effect of alternatives density, as stated in hypotheses 1a and 1b. On the other hand, the trend lines serve to illustrate the evolution of the effects in moving averages, where it can be seen that the average marginal effect of stability density grows along with relatedness density for low values of the latter, but begins to decrease from a certain point onwards. The behaviour of alternatives density is opposite, but of a lower absolute magnitude than that of stability density.

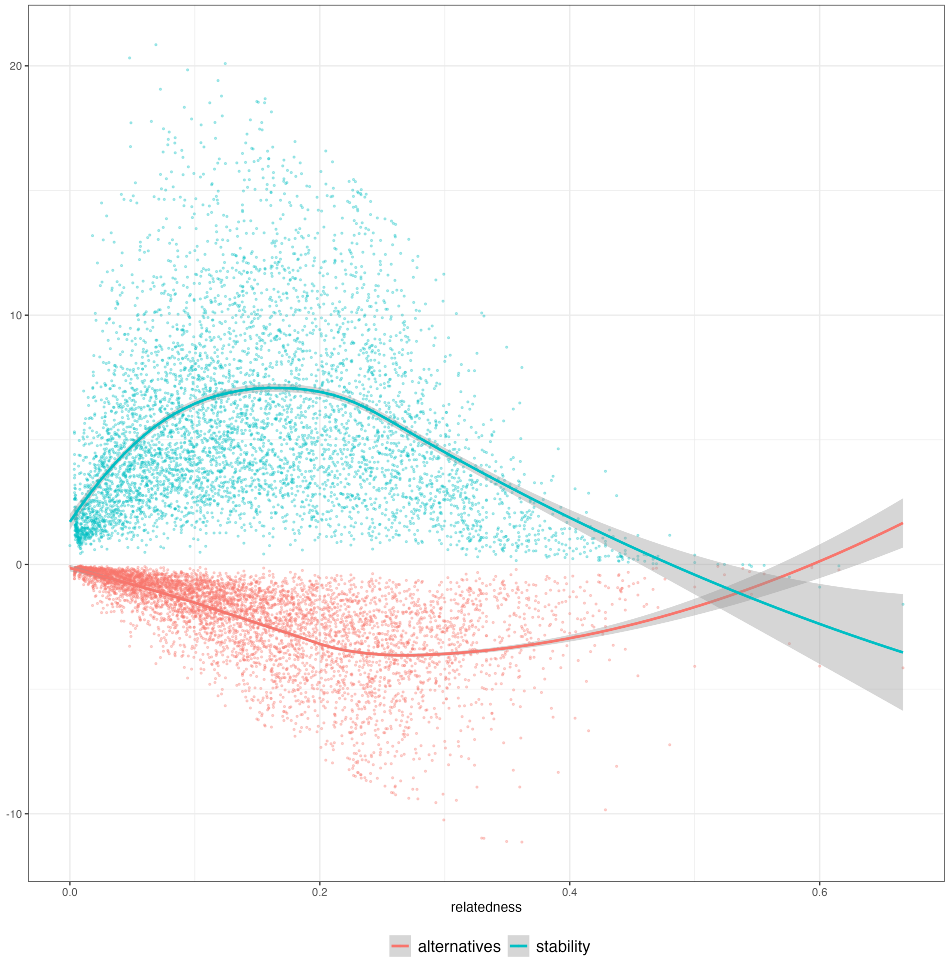

Figure 2: Marginal effects of *stability* and *alternatives* in the model of equation 5, measured in the values observed in the data and ordered by relatedness density.

To explore hypothesis 3, we have to look at model 2 in Table 3. Here, we observe that the general results remain unchanged, but the coefficient associated with technology complexity becomes significant and negative. This means that there is a negative association between the complexity of the technology and the likelihood that it will be developed with comparative advantages in the city. Given that this model interacts the complexity of technology with the city's stability and alternatives densities, the interpretation of the coefficient associated with *complexity* is that in a city with average levels of both densities, greater complexity reduces the probability that the technology will be produced with comparative advantages. This result is consistent with the existing literature in this field and is particularly relevant for Latin America, given its position as a peripheral region in global knowledge production, which is associated with significant challenges in developing complex technologies.

The inclusion of the interaction between technological complexity and stability, as well as alternatives densities, allows us to analyse how these factors affect the probability of achieving more complex technologies. What we can see is that the coefficient associated with *complexity* $\times$

$stability$ is not significant but, in line with hypothesis 3, the coefficient associated with $complexity \times alternatives$ is significant and positive. Therefore, a higher level of technological complexity attenuates the negative effect observed for the alternatives density. This supports the argument developed around this density since, to the extent that actors have different alternatives within the set of technologies close to the target, it is expected that they will direct their resources towards those technologies with greater complexity due to the economic returns that can be expected from them.

Figure 3 shows the evolution of the marginal effect of stability density and alternatives density, using the values of the other variables observed in the data and ordered by levels of technological complexity. It can be seen how the effect of the alternatives density remains negative, but its absolute magnitude decreases as complexity increases. Meanwhile, the dispersion in the marginal effects observed for the stability density explains why the interaction $complexity \times stability$ is not significant.

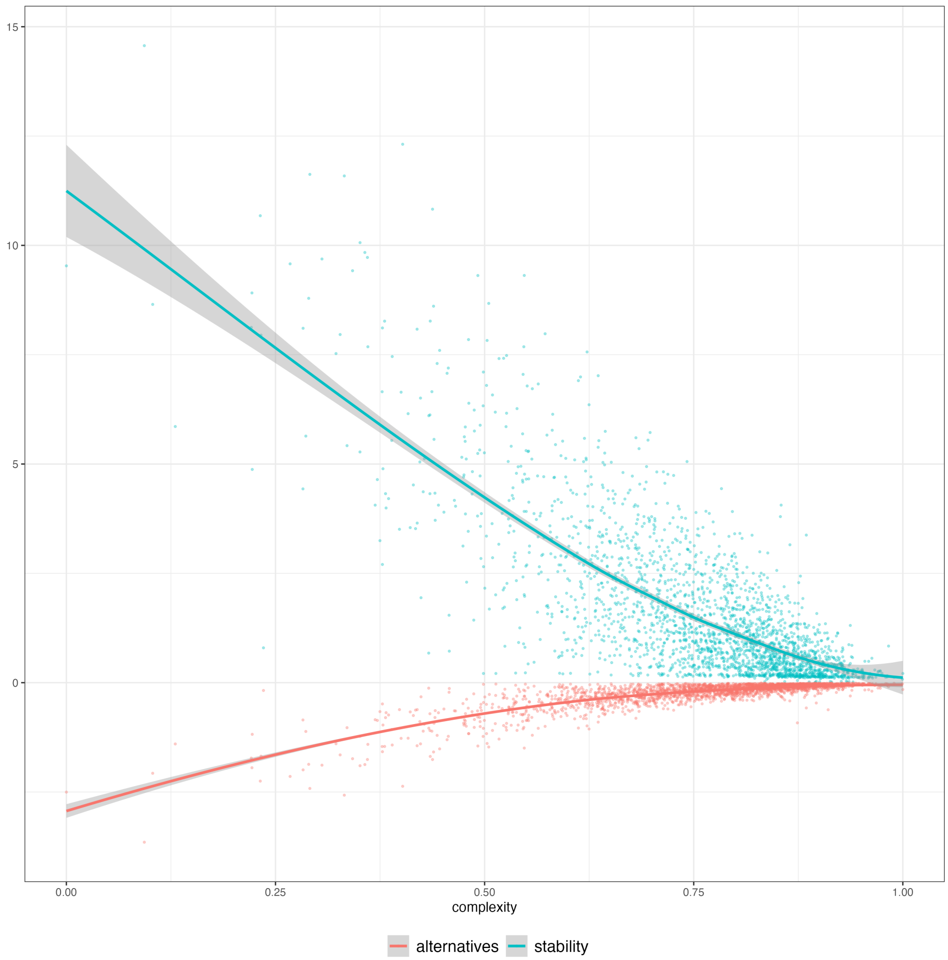

Figure 3: Marginal effects of $stability$ and $alternatives$ in the model of equation 6, measured in observed values and sorted by $complexity$.

Finally, it is interesting to note that when the interaction between technological complexity and stability or alternatives densities is included, the coefficient associated with the interaction between the two becomes significant. Although this does not affect the qualitative results of model one, since the sign and significance of the coefficients analysed in it remain unchanged, it seems interesting to briefly interpret this result even though it is not linked to any of the hypotheses of this study.

The coefficient associated with $stability \times alternatives$ shows, on the one hand, that when stability density is below average (*stability* $<$ *0*), its interaction with alternatives density is associated with a lower likelihood of the target technology appearing, as alternatives density increases. Based on the findings of this study, this can be interpreted as suggesting that the displacement of resources due to the existence of alternatives is greater when the relatedness to the focal technology is less stable (low stability density). Conversely, when stability density is above average, this displacement is lower. From another perspective, when the density of alternatives is below average (*alternatives* $<$ *0*), an increase in stability decreases the probability of the technology appearing, attenuating the positive association of stability density. In the framework of our work, this may reflect that the city already has a high level of specialisation in the set of technologies related to the focal technology, which means that incorporating it may have little impact on local capabilities. On the other hand, when the density of alternatives is above average, a higher stability density increases the probability of technology entry, mitigating the negative effects of the alternatives density analysed in model one.

5 Conclusions

The development of technical knowledge is a key factor for territories seeking to maintain and improve their position in the global innovation system. For regions on the periphery of the global knowledge production system, diversifying their technology portfolio is particularly important for their development, as it enables them to close the gap with more developed regions. A diversified knowledge base is necessary for their innovation systems to be sustained by local developments focused on solving local and global problems, while also increasing their capacity to take advantage of global knowledge flows (Cohen & Levinthal, 1989, 1990; Yoguel & Robert, 2010).

In this sense, cities play a central role as spaces for the exchange of ideas, given the concentration of actors and services that interact in them, particularly in the most dynamic technologies (Balland et al., 2020). For agents that integrate a city's innovation system, knowing the diversification paths that best suit local capabilities and seeking to develop dynamic technologies is essential to overcoming situations of stagnation in which they may find themselves.

The present work contributes to the literature by analysing how the stability of local technologies, as well as the alternatives available to the territory, affect the emergence of new technologies according to their relatedness to the local knowledge base. To this end, the structure of knowledge relatedness between technologies is studied, using the portfolio of technologies patented by inventors in cities, in order to identify local capabilities. Thus, using social network analysis tools, a set of indicators is proposed that captures dimensions proven to be relevant in this type of relatedness structure.

The proposed indicators represent a contribution in this field, as they are closely related to other measures used but extend the level of analysis of relatedness networks. This enables the exploitation of a greater volume of information contained in these networks, facilitating a better understanding of the characteristics of the knowledge base of the studied territories. The empirical results support the relevance of this work and its argument.

The first observation is that the generation of new technical knowledge, measured through the development of comparative advantages in patented technologies, requires not only knowledge related to the technologies to be achieved but also the stability of this knowledge within the territory's knowledge base. A city may perform well in the development of certain technologies, but if these are not based on the use of the local knowledge base, its capacity to support the development of new technologies will be limited. Technologies that do not draw on the local knowledge base are more likely to leave the territory, making them less stable and limiting the capacity to diversify from them.

Our work shows that technology may seem like a good option for diversification based on the technologies produced in the city. However, if these capabilities are not sustained locally, the probability of establishing the new technology in the territory will be lower. This implies taking into account a dimension that previous literature had not considered, which may be especially relevant in regions with fragmented innovation systems or those that are highly dependent on external knowledge flows for their development.

On the other hand, the paper also acknowledges that targeted technologies are components of groups of technologies that are related to each other in terms of the knowledge required to develop them. This makes it possible to analyse the role that these alternatives play in diversification processes. In this sense, the evidence suggests that these alternatives could divert resources, thereby reducing the likelihood that a technology will be produced in the city.

This perspective has not been addressed in the literature until now, and it is important to do so. If we consider the relatedness of a city's knowledge base to a technology, but do not account for its proximity with a set of related technologies, the available resources may be dispersed, and the possibility of developing the new technology may be limited. In particular, the empirical results support the argument presented in this paper, which proposes that more complex technologies will be able to attract more resources among available alternatives.

The analysis of the interaction of the proposed density measures provides particularly relevant elements for the discussion on unrelated diversification strategies. In this sense, the empirical results support the argument about the ability of stability and alternatives density to compensate for the lack of relatedness to target technologies. This is a central element in the context of lagging regions, as their knowledge base may tend to limit their ability to achieve complex technologies (Balland et al., 2019). In this way, the proposed densities can contribute to the design of diversification strategies towards technologies that appear relatively distant. The analysis of these interactions also reveals that excessive relatedness reduces the likelihood of a technology entering the territory (Balland et al., 2015; Boschma, 2005). This highlights the importance of not limiting the measurement of diversification to quantitative indicators but also analysing its qualitative dimension.

These results contribute to a vibrant and prolific academic literature that seeks to understand diversification processes embedded in complex innovation systems, where dependence on the past and territory plays an important role (Boschma & Frenken, 2006; Boschma & Lambooy, 1999; Martin & Sunley, 2007). In this sense, the concepts proposed have significant potential for dialogue with this literature while also contributing to its application in the context of less developed innovation systems. Given the widespread use of this literature in the design and implementation of public policies, this contribution may also serve to enhance their design and the outcomes achieved.

The argument elaborated in this article leaves open some lines of research for further analysis. Among them, two extensions could be particularly relevant. First, this paper does not consider the role that external knowledge flows and collaboration between cities can play. This perspective is central in a world embedded in global chains that fragment knowledge production but must also take advantage of the benefits offered by geographical relatedness in many activities. On the other hand, the discussion in this article is limited to the analysis of a particular type of knowledge; however, it seems relevant to extend it to a wide range of activities, such as scientific knowledge production or the industrial and productive diversification of territories.

6 Appendix

Dependent variable:	new	
Model:	(1)	(2)
Variables		
relatedness	0.043 (0.060)	0.037 (0.066)
stability	1.814*** (0.679)	1.547** (0.742)
alternatives	-0.360*** (0.130)	-0.236** (0.108)
complexity	-0.012 (0.011)	-0.007 (0.010)
transitivity	-0.026 (0.020)	-0.020 (0.022)
# inventors	0.002 (0.003)	0.002 (0.004)
# patents	-0.004 (0.003)	-0.003 (0.003)
# technologies	0.003 (0.004)	-0.001 (0.005)
Fix effects		
city	Yes	Yes
window	Yes	Yes
technology	Yes	Yes
Fit statistics		
Observations	199,772	199,772
Pseudo R^2	0.20218	0.20576
BIC	39,971.2	39,848.8

Clustered standard-errors in parentheses (city & window & technology)
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 4: Estimation of marginal effects, using numerical methods, for the models of equations 5 and 6. For each variable, the coefficient represents the average marginal effect, considering the remaining variables at their observed values. To simplify reading, subscripts are omitted, but all independent variable are lagged.

Dependent variable:	new				
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
relatedness	5.385***			10.84***	11.06***
	(1.082)			(2.075)	(1.961)
stability		11.07*		110.8***	102.4***
		(6.721)		(24.40)	(36.77)
alternatives			-8.793***	-11.60***	-23.65***
			(3.244)	(2.430)	(5.010)
complexity	-0.4375	-0.4125	-0.4754	-0.6096	-2.055**
	(0.6616)	(0.6448)	(0.6407)	(0.6854)	(0.9812)
transitivity	-0.8964	-0.5841	-0.8116	-1.355	-1.045
	(1.139)	(1.125)	(1.114)	(1.217)	(1.392)
# inventors	0.0511	0.0408	0.0672	0.1166	0.1108
	(0.1162)	(0.1163)	(0.1321)	(0.1311)	(0.1840)
# patents	-0.2642*	-0.2671*	-0.1789	-0.2012	-0.1633
	(0.1415)	(0.1395)	(0.1429)	(0.1464)	(0.2046)
# technologies	0.1220	0.2559	0.4198***	0.1559	-0.0279
	(0.2346)	(0.2167)	(0.1562)	(0.2223)	(0.2398)
relatedness × stability				-210.3***	-167.6***
				(54.08)	(45.95)
relatedness × alternatives				-96.34***	-109.6***
				(33.75)	(32.78)
stability × alternatives				-5.896	57.67***
				(17.06)	(17.78)
stability × complexity					-19.76
					(25.60)
alternatives × complexity					28.45***
					(6.799)
Fix effects					
city	Yes	Yes	Yes	Yes	Yes
window	Yes	Yes	Yes	Yes	Yes
technology	Yes	Yes	Yes	Yes	Yes
Fit statistics					
Observations	199,772	199,772	199,772	199,772	199,772
Pseudo R^2	0.19611	0.19393	0.19450	0.20218	0.20576
BIC	40,158.4	40,247.9	40,224.6	39,971.2	39,848.8

Clustered standard-errors in parentheses (city & window & technology)
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 5: In this table, models 4 and 5 correspond to models 1 and 2 in Table 3, which were used to test the hypotheses. Models 1 to 3 show the results of including the variables relatedness, stability, and alternatives one by one, without considering interactions.

Dependent variable:	new			
Model:	(1)	(2)	(3)	(4)
Variables				
relatedness	9.580***	10.79***	10.84***	11.06***
	(1.377)	(1.969)	(2.075)	(1.961)
stability	-19.45		110.8***	102.4***
	(14.81)		(24.40)	(36.77)
alternatives		-5.551**	-11.60***	-23.65***
		(2.648)	(2.430)	(5.010)
complexity	-0.4455	-0.5543	-0.6096	-2.055**
	(0.6665)	(0.6684)	(0.6854)	(0.9812)
transitivity	-0.9981	-1.474	-1.355	-1.045
	(1.128)	(1.377)	(1.217)	(1.392)
# inventors	0.0905	0.1025	0.1166	0.1108
	(0.1161)	(0.1208)	(0.1311)	(0.1840)
# patents	-0.1916	-0.1397	-0.2012	-0.1633
	(0.1357)	(0.1458)	(0.1464)	(0.2046)
# technologies	-0.0548	0.0655	0.1559	-0.0279
	(0.2452)	(0.2472)	(0.2223)	(0.2398)
relatedness × stability	-8.312		-210.3***	-167.6***
	(30.84)		(54.08)	(45.95)
relatedness × alternatives		-45.55***	-96.34***	-109.6***
		(17.53)	(33.75)	(32.78)
stability × alternatives			-5.896	57.67***
			(17.06)	(17.78)
stability × complexity				-19.76
				(25.60)
alternatives × complexity				28.45***
				(6.799)
Fix effects				
city	Yes	Yes	Yes	Yes
window	Yes	Yes	Yes	Yes
technology	Yes	Yes	Yes	Yes
Fit statistics				
Observations	199,772	199,772	199,772	199,772
Pseudo R^2	0.19707	0.19928	0.20218	0.20576
BIC	40,143.7	40,053.0	39,971.2	39,848.8

Clustered standard-errors in parentheses (city & window & technology)
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 6: In this table, models 3 and 4 correspond to models 1 and 2 in Table 3, which were used to test the hypotheses. Here, models 1 and 2 show the results of including the stability and alternatives density variables one by one, as well as the interactions between them and with the relatedness density.

Dependent variable:	new						
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Variables							
relatedness	-1.055	2.219^{*}	11.36^{***}	-0.7648	10.97^{***}	10.86^{***}	11.06^{***}
	(1.777)	(0.9207)	(1.347)	(1.974)	(1.898)	(1.232)	(1.961)
stability	82.13^{***}	42.48	69.00^{***}	81.25^{**}	100.3^{**}	69.53^{*}	102.4^{**}
	(22.29)	(24.55)	(17.98)	(28.10)	(30.99)	(34.44)	(36.77)
alternatives	-10.33^{***}	-12.05^{***}	-20.38^{***}	-11.39^{***}	-22.70^{***}	-21.20^{***}	-23.65^{***}
	(2.364)	(1.488)	(4.284)	(2.209)	(4.904)	(3.987)	(5.010)
complexity	-5.494^{***}	-5.618^{***}	-1.747^{***}	-5.746^{***}	-2.287^{***}	-1.948^{*}	-2.055^{*}
	(0.1381)	(0.3004)	(0.3146)	(0.2877)	(0.3705)	(0.8091)	(0.9812)
transitivity	-3.421^{***}	-3.268^{***}	-2.224^{**}	-3.241^{**}	-0.4882	-1.024	-1.045
	(0.3520)	(0.9694)	(0.7359)	(0.9983)	(0.8801)	(1.085)	(1.392)
# inventors	0.0752	-0.0381	-0.0234	0.0869	0.2894^{**}	-0.0276	0.1108
	(0.1212)	(0.0575)	(0.0476)	(0.1280)	(0.1104)	(0.0544)	(0.1840)
# patents	-0.1845	-0.1607	-0.2583^{***}	-0.2549^{*}	-0.2334	-0.1647	-0.1633
	(0.1569)	(0.1658)	(0.0699)	(0.1276)	(0.1446)	(0.1398)	(0.2046)
# technologies	-0.1533	0.8617^{***}	1.069^{***}	-0.1136	-0.0267	1.022^{***}	-0.0279
	(0.2373)	(0.1520)	(0.1044)	(0.2708)	(0.1820)	(0.0983)	(0.2398)
relatedness $\times$ stability	-88.16^{***}	-54.08	-138.0^{***}	-84.74^{*}	-168.1^{***}	-140.6^{*}	-167.6^{***}
	(18.49)	(45.99)	(22.54)	(41.40)	(31.95)	(56.40)	(45.95)
relatedness $\times$ alternatives	-1.118	-30.94	-104.1^{***}	-2.102	-112.1^{***}	-100.4^{*}	-109.6^{***}
	(21.81)	(20.34)	(19.55)	(24.78)	(25.73)	(40.76)	(32.78)
stability $\times$ alternatives	-136.6^{*}	19.06	124.2^{**}	-123.2^{*}	71.96	121.6^{*}	57.67^{**}
	(56.42)	(28.83)	(39.26)	(52.09)	(50.59)	(48.84)	(17.78)
stability $\times$ complexity	-28.95	-26.75^{*}	-4.957	-32.22	-16.18	-4.948	-19.76
	(18.79)	(10.86)	(18.43)	(18.30)	(24.97)	(19.99)	(25.60)
alternatives $\times$ complexity	29.92^{***}	25.18^{***}	25.60^{***}	29.49^{***}	28.17^{***}	25.13^{***}	28.45^{***}
	(3.744)	(2.094)	(5.878)	(3.846)	(6.671)	(5.608)	(6.799)
Fix effects							
city	Yes			Yes	Yes		Yes
window		Yes		Yes		Yes	Yes
technology			Yes		Yes	Yes	Yes
Fit statistics							
Observations	248,208	248,208	199,772	248,208	199,772	199,772	199,772
Pseudo R^2	0.17290	0.16580	0.19437	0.17593	0.20466	0.19595	0.20576
BIC	36,559.2	35,931.2	39,302.4	36,479.1	39,845.1	39,286.4	39,848.8

Clustered standard errors at the level of the fix effects of each specification

*Signif. Codes: ***: 0.001, **: 0.01, *: 0.05*

Table 7: In this table, model 7 corresponds to model 2 presented in Table 3. Models 1 to 6 consider the different possible combinations of the three fix effects.

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