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Improving Locally While Competing Globally: Network Effects on Innovation Performance in Cities

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ABSTRACT

The impact of local and global networks on innovation has been extensively studied. However, existing literature has not explored whether these effects result from territories gradually improving their networks, or competing with each other through their networks. This paper aims to address this gap by examining innovation networks in Latin American cities. Using patent data from the USPTO, we construct local networks connecting actors within cities and a global network linking different cities in different countries. We estimate the effects of networks on innovation using panel data regressions. To discern whether these effects result from cities' improvements or competition, the models follow the within-between approach. Our findings indicate that cities benefit from improvements in their local network, regardless of whether this network is worse or better than that of other territories. This is not the case in the global network, where cities compete with each other by gaining better access to resources flowing through the network. These findings hold important research and policy implications, especially for developing countries where relative backwardness, weak local networks, and limited participation in global networks may hinder territories' ability to compete with more developed counterparts.

1 | Introduction

Innovation is an essentially urban process. Cities provide a conductive environment for innovation because they have the right combination of proximity, density and diversity of innovators (Z. Cao et al. 2022). An extensive literature has reported the important advantages of agglomeration of actors in cities for various economic activities, particularly in knowledge creation (Jaffe et al. 1993; Glaeser 1999; Bettencourt et al. 2007).

In this environment, actors interact, collaborating and competing at the same time, forming networks in which ideas are contrasted and new knowledge is disseminated (Fan et al. 2020; Wang et al. 2021). The literature has distinguished two fundamental types of networks based on their geographic scope: local networks and global networks (e.g., Asheim and Isaksen 2002; Bathelt et al. 2004; Breschi and Lenzi 2013). While local networks can facilitate the rapid diffusion and contrast of ideas among nearby actors, the connection with global networks allows the introduction of novel ideas in the territory. Previous literature, in particular the so-called *local buzz—global pipelines* approach, has extensively studied how both types of networks can complement each other to drive innovation processes (Bathelt et al. 2004).

However, there are important aspects about the influence of these networks on innovation that are still understudied. In particular, we are interested in analyzing two issues: (1) how the evolution of networks impacts innovation in cities, and (2) how the competition between cities (through these networks) affects innovation. Comparing these two aspects allows to delve into a research question that has not yet been explored in the literature: *are the effects of local and global networks on innovation driven by a territory's own improvements or by its competition with other territories?*

Guided by this question, we develop a theoretical framework based on the literature on the geography of innovation. In particular, we hypothesize that cities can foster their innovation results when they improve their local networks and they compete with other cities in obtaining a better position in global networks. We empirically test this hypothesis through an analysis on patent collaboration networks in Latin American cities. We use USPTO data on inventions carried out by actors located in Latin American cities to elaborate and analyze local and global collaboration networks. Subsequently, we use panel data regressions to estimate the effects of both types of networks on innovation performance of cities. The models follow the within-between approach to differentiate whether the effects of networks occur because the city improves on itself in the past or because it ranks above other cities. Our findings reveal that cities benefit from local networks when they achieve improvements. On the other hand, regarding global networks, cities obtain better innovation results not only when they improve, but also when they outperform other cities in the connection to the network. This finding indicates that cities aiming to benefit from the flows that the global network puts into circulation must compete with each other, positioning themselves in better network positions than other cities.

With these findings, our paper aims to make a novel contribution to the literature on innovation and networks. In particular, we seek to contribute to the discussion on the role of local and global networks in innovation processes, showing the relevance of considering both evolution and competition between territories. In this regard, our work connects the literature on networks and innovation with research from the perspective of development and economic geography. For example, according to Porter's (1998) vision, territory is a source of competitive advantages for firms. Authors such as Camagni (2002) or Malecki (2007) argue that cities and regions (and not only firms) compete with each other to attract investment and skilled workers, and to define a better role in the international division of labor. More recently, Calignano (2022) emphasizes the importance of relative innovativeness (i.e., a city's innovative performance compared to the performance of other cities) over absolute innovativeness when determining the connection of cities to global innovation networks. In this line, our study points to the relevance of considering the extent to which territories compete among each other to ensure that some factors, such as networks drive their innovation and development processes. Therefore, our study aims to join the discussion by offering empirical evidence that contributes to the understanding of the processes of development and innovation in cities.

Our findings have also relevant implications regarding innovation processes in developing countries. In such territories, the relative backwardness, weak local networks and low participation in global networks may limit the ability of cities to compete with other more developed territories. Therefore, understanding how these cities can benefit from strengthening their networks is crucial to improve their innovative performance. This aspect supports the relevance of conducting an empirical study for Latin American cities, a developing region that is lagging behind in terms of innovation and relatively disconnected from global knowledge networks.

The rest of the paper is structured as follows: section two presents the theoretical framework and formulates the research hypotheses; section three explains the methodology for the empirical testing of the hypotheses. The results of the analysis are reported in section four. Finally, section five discusses the results and presents the conclusions and implications of the study.

2 | Theoretical Framework

Various strands of the literature have emphasized the relevance of collaboration networks for understanding innovation processes (see, for instance, Pippel 2013; Phelps et al. 2012, for literature reviews). Research on this topic is extensive and can broadly be grouped into three main areas: first, studies analyzing the structure and evolution of innovation networks (e.g., Tomasello et al. 2017); second, research examining the determinants of network formation and configuration (e.g., Cantner et al. 2016; Barbosa et al. 2024); and third, studies exploring the effects of such networks on innovation outcomes (e.g., Fleming et al. 2007; Schilling and Phelps 2007).

Although these studies have addressed a wide variety of specific topics, one particularly important issue is the geographical scope of networks, most notably, the distinction between local and global networks. This approach is relevant not only because it determines which actors are connected (local vs. global), but also because it conditions the type of linkages between actors (their frequency, cost, etc.) and the resources (essentially knowledge) that flow through the networks.

On the one hand, local networks, that is, networks connecting actors located in the same territory, are characterized by face-to-face links, many of which are informal, with unplanned and often recurring encounters. Local networks are a highly conducive environment for the diffusion and contrast of ideas, as well as for the transmission of knowledge (Uzzi and Spiro 2005). Interaction enabled by local networks, also known as *local buzz* (Bathelt et al. 2004), facilitate the circulation of tacit knowledge, which is highly embedded in social relations and is closely associated with the specific context of the territory (Asheim and Isaksen 2002). The stickiness of this type of knowledge can be considered as one of the few phenomena in the global economy that remain genuinely localized (Markusen 1996). Moreover, the contextual embeddedness of local networks facilitates the search for shared solutions to problems, reciprocal behaviors and the building of trust between actors (Granovetter 1985; Uzzi 1997; Bathelt et al. 2004). Thus, local networks constitute a valuable resource for the territory: they cannot be transferred from one place to another and can only be built over time (Lawson and Lorenz 1999). This helps explain why complex activities, such as research and innovation are disproportionately concentrated in cities (Balland et al. 2020).

However, local networks alone can lead to lock-in situations, resulting from the recirculation of homogeneous and redundant knowledge in the territory (Bathelt et al. 2004; Bettencourt et al. 2007). The repetition of interactions between the same co-located agents may cause the knowledge exchanged to progressively lose value as opportunities for knowledge recombination are depleted (Boschma and Frenken 2010). Therefore, an excessive local orientation of networks, without the participation of some actors outside the territory, can lead to a negative impact on innovation (Breschi and Lenzi 2013).

In order to address this problem, it is fundamental to connect the territory with global networks, since such links allow the introduction of new external knowledge (Bathelt et al. 2004; Obschonka et al. 2023). Global links, also known as *global pipelines*, connect geographically distant actors. Compared to those in local networks, links in global networks tend to have a predetermined goal or intention, they are often more selective and costly for those who maintain them. For example, collaborative links between firms in different countries require complex organizational routines or skilled personnel, so not all actors in the territory can maintain global connections (Bathelt and Li 2020). Nevertheless, connections with global networks are of great value because they provide access: (1) to codified knowledge and technologies that are novel to the territory (Bathelt et al. 2004) and are particularly relevant in formal, science-based innovation processes (Grillitsch and Trippl 2014); (2) to information on market opportunities and new demands (Bresnahan et al. 2001); and (3) to a large pool of specialized professionals in areas where the territory may not have resources (Saxenian 2006). These global networks are a key element of the so-called global innovation system, where transnational firms and leading research centers interact to generate and diffuse frontier innovations (Binz and Truffer 2017).

But links to global networks are not necessarily good per se. When local actors focus too much on global connections, then local fragmentation can occur, which would slow down the diffusion of knowledge, thus hindering innovation processes (Bathelt and Taylor 2002). Also, excessive focus on external links could lead to technological dependence on the outside and local incoherence, threatening local competitiveness (Z. Cao et al. 2022). This is where the combination of global and local networks is crucial: links with global networks will be of little use to the territory unless there is a dynamic local network that allows actors in the same historical, geographical and cultural context to be adequately connected, so that the territory can absorb and disseminate the external knowledge introduced by global connections (Bianchi et al. 2023b). In sum, both networks (local and global) appear to be valuable only in the presence of the other, and when one has certain weaknesses, then the other is negatively affected (Bathelt et al. 2004). Thus, the interaction between local and global networks can produce virtuous (or vicious) circles, which can explain the unequal evolution of innovation systems between developed and underdeveloped territories (Bianchi et al. 2023b).

The complementarity of local and global networks has been the main motivation of the literature on the subject (e.g., Bathelt et al. 2004; Asheim and Isaksen 2002; Coffano et al. 2017; Breschi and Lenzi 2013, 2016; Wen et al. 2021; X. Cao et al. 2023). Yet, some papers have documented substitutive rather than complementary effects between local and global networks (e.g., Whittington et al. 2009). Other studies suggested that the complementarity between both types of networks depends on the size and characteristics of firms (Aarstad et al. 2016).

Some studies are critical of the buzz and pipelines approach, arguing that it does not allow for an adequate understanding of the mechanisms through which actors access knowledge. For example, Moodysson (2008) claims that it is more important to differentiate connections according to the modes of knowledge creation associated with the link (analytical or synthetic). Trippl et al. (2009) suggest that the type of linkage should be considered by distinguishing between market relations, formal networks, spillovers, and informal networks.

Despite the important advances documented in previous studies, there are relevant aspects that have been scarcely analyzed. For example, as Aarstad et al. (2016) point out, the literature still needs to go much deeper in understanding the effects generated by local and global networks on innovation. Other works stress the need to delve deeper into a dynamic approach of local and global networks (Bathelt and Li 2020). Furthermore, according to Esposito and Rigby (2019), the ideas presented in the literature are still very general, so that the conditions under which different forms of interaction confer benefits to actors in a territory remain unclear.

In agreement with these arguments, in this paper we seek to delve deeper into an aspect not addressed by the literature: we inquire whether the key factor of local and global networks lies in the territory's achievement of improvements compared to its previous state, or whether what is relevant is that the territory competes with (and eventually outperforms) other territories. In other words, we aim to explore the relevance of evolution versus competition in networks, differentiating between two geographical scales: local and global. In the following sections we will delve into this aspect. To do so, we first propose a conceptualization of networks and innovation within territories, and then we outline our research hypotheses.

2.1 | A Territorial Approach to Local and Global Networks Through the Lens of Social Network Analysis

To conceptualize networks from a territorial perspective, we propose distinguishing between two geographical levels (Figure 1). First, at the local level (bottom part of Figure 1), we consider that within each territory there exists a network formed by actors or nodes (e.g., companies, research centers, or researchers) located in that territory and collaborating with each other, thus establishing the links of the local network. Some of these actors also establish connections with nodes located in other territories, that is, global connections. This leads us to the global plane of networks (top part of Figure 1), where each

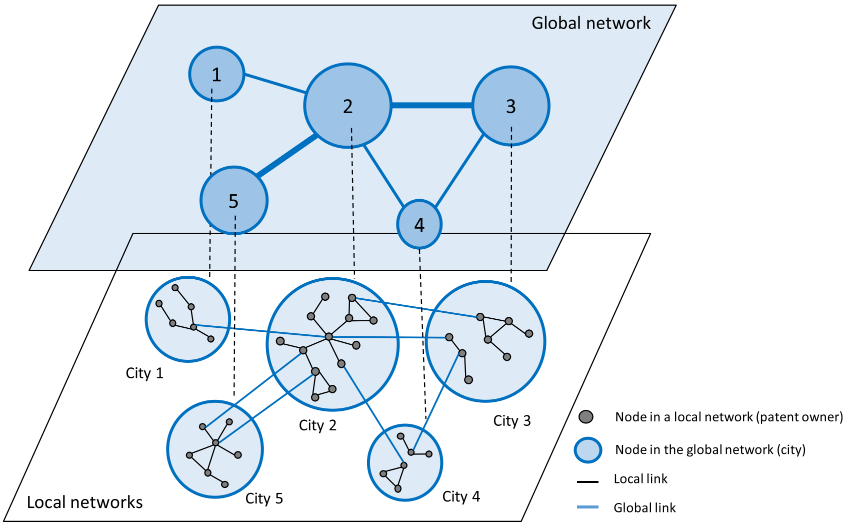

FIGURE 1 | Local and global networks. *Source:* authors.

territory can be considered as a single node and the connections between them correspond to collaborations between different territories.

According to the previous literature, networks at both levels can influence innovation processes in cities and regions. At the local level, the structure or topology of networks within territories can facilitate the circulation of knowledge as well as encourage cooperative solutions, leading to increases in innovation (Fleming et al. 2007; Whittington et al. 2009; Breschi and Lenzi 2013, 2016). As argued by Fitjar and Rodríguez-Pose (2016), the mere concentration of actors within the same territory is not sufficient to foster innovation, since knowledge does not circulate through the air—as suggested by Marshall's well-known quote (Marshall 1890)—but rather through local networks that are actively constructed by firms. In this regard, Crescenzi et al. (2016) emphasize that not all local networks are equally effective; their performance depends on how they are structured and mobilized, rather than solely on the geographical proximity of actors. Consequently, certain topologies or structural properties of local networks can be conceived as a form of collective capital for cities and regions, since they not only depend on—and are co-produced by—all the actors involved, but also can contribute to the development of innovation at the territorial level (Galaso 2018).

One of the key structural properties of local networks is closeness. This topology is observed in a network when, on average, the distance between nodes (i.e., the number of steps to connect them) is small. Previous literature has extensively documented how local networks whose nodes are close to each other allow a rapid diffusion of ideas, since information flows require fewer intermediaries and actors can access them more easily (Fleming et al. 2007; Breschi and Lenzi 2016). Clustering is another network topology that has been widely studied in the literature. This property measures the formation of subgroups (i.e., clusters) of highly interconnected nodes. Within these clusters, information flows very quickly and allows for the contrast and recombination of ideas. Moreover, this network structure is associated with strong and recurrent relationships between actors, which facilitates mutual monitoring and enhances local trust (Uzzi and Spiro 2005; Crowe 2007).

Some networks combine high levels of both closeness and clustering. These are so-called small-world networks (Watts and Strogatz 1998). The literature has documented how the small-world property can improve innovation because it amplifies the advantages of closeness and clustering (Uzzi and Spiro 2005): on the one hand, the effects of clustering are greater when clusters are not too far from each other (i.e., when closeness is high) and, vice versa, the advantages of closeness increase when there are different and well-connected clusters in the network (i.e., when clustering is high) (Uzzi and Spiro 2005; Breschi and Lenzi 2016). However, excessive levels of these network properties may also reduce innovation. Networks whose nodes are too close and/or have too high clustering, may reduce the heterogeneity of the knowledge that circulates through the network, making it more redundant and ultimately reducing innovation (Uzzi and Spiro 2005). Evidence suggests that there is an inverted u-shaped relationship between these network properties and collective outcomes (Uzzi and Spiro 2005), which implies that there are optimal levels of these network topologies associated with better innovation performance of the territories.

In the case of global networks (top part of Figure 1), we can think of each city as a node in an inter-city network that includes territories in different regions, countries or even continents (Wang et al. 2021). In line with the literature on the world-city network (Derudder and Taylor 2016), cities occupy different positions in the global network, and these positions are associated with different access to the resources flowing in the network. According to Derudder and Taylor (2020), the position a city occupies within the network is closely linked to its capacity to attract, coordinate, and benefit from transnational flows of services, knowledge, and capital, thereby reinforcing its role as a key node in global capitalism. In a similar vein, Robinson et al. (2022) analyze the global financial infrastructure network for payments, emphasizing the informational dimension of finance, the geographical concentration of financial power, and the role of digital platforms. Their findings suggest that these financial infrastructure networks may exacerbate asymmetries in the production and circulation of knowledge at the global scale. More recently, Trincado-Muñoz et al. (2023) explore how digitalization is giving rise to a new spatial and functional logic within the global city system, reshaping global innovation networks. Digitally integrated cities, particularly those with a strong service base, are increasingly leading innovation processes, mediating knowledge flows across sectors and territories, and occupying key positions within a global innovation network driven by data, platforms, and technological services.

The field of social network analysis has developed multiple analytical tools that can be used to measure the relative positioning of cities in the global inter-city network. Centrality, in particular, stands out as a widely applied indicator, which measures the prominence or relative importance of each node in the network. The literature has shown that more central nodes have better access to the resources that the network puts into circulation, such as knowledge (Borgatti 2005; Fang et al. 2015).

In addition to centrality, we can study if the city occupies brokerage positions in the global network. That is, to analyze the extent to which the city is connected to two other cities, which, in turn, are disconnected from each other. The literature has identified different forms of brokerage according to the types of nodes between which they intermediate (Gould and Fernandez 1989). Evidence has been reported on how occupying these positions allows access to diverse sources of knowledge that can foster innovation processes in cities (Guan et al. 2015; Yao et al. 2020; Bianchi et al. 2023a, 2023c). A third way of analyzing a city's connection to the global network is to study where its connections are directed to, distinguishing, for example, between links to the same region and connections linking other continents. Geographical distance may be associated with a greater diversity of knowledge provided by global networks and, therefore, the regional or extra-regional orientation of the links could influence innovation performance (Bianchi et al. 2023a, 2023c).

However, increasing centrality, brokerage or extra-regional connections may not always lead to improvements in innovation. Centrality can be costly, since maintaining links is time consuming (Giuliani 2007) and requires devoting efforts to information processing (Giuliani and Bell 2005; Laursen and Salter 2014). Similarly, increasing connections with distant (extra-regional) cities and occupying broker positions entails high costs as it requires a capacity and efforts to coordinate unconnected actors as well as to interpret diverse knowledge sources (Breschi and Lenzi 2015; Bianchi et al. 2023a). This evidence suggests that there may be optimal levels of global network indicators (i.e., centrality, extra-regional openness and brokerage) associated with positive effects on city innovation. Thus, for a city to improve its position in the global network would not imply that it increases these indicators, but rather that it approaches these optimal levels.

The following table summarizes the key elements of our theoretical framework for analyzing local and global networks (see Table 1).

2.2 | Improvements or Competition Between Territories? Hypotheses Formulation

Based on the above conceptualization, we now explore the meanings of improvement versus competition within these networks. First, at the local level, we propose that network improvement can be understood as an evolution of the structure of a city's local network toward optimal levels of closeness, clustering and/or small world. Accordingly, a city will compete with (and eventually outperform) other cities when its local network presents better levels (i.e., closer to optimal levels) of closeness, clustering and small world compared to the local networks of other cities.

In short, we analyze improvement by observing the evolution of a city's local network, while competition is analyzed by comparing the city's network configuration at a given point in time with those of other cities. This view of evolution and competition does not imply that cities take deliberate actions or decisions to improve or outperform other territories. Rather, we understand them as a result of decentralized actions of innovators (firms, organizations and individuals) interacting with each other to form links, which leads to cities achieving better or worse network configurations relative to networks in other periods or territories.

At this point, we inquire whether the relevance of local networks for innovation is associated with improvement or with competition. According to the literature, when local networks evolve appropriately, the territory achieves better innovation results. From an endogenous development perspective, we can understand that the territory is improving its local resources and capacities, thus leading to improvements in innovation (Maillat 1995). In this process, we can assume that the local network is not competing with other cities or regions. By improving its configuration, this local network achieves improvements in innovation, regardless of what the networks in other cities are like.

Based on these ideas, we propose the following hypothesis:

H1. *In local networks, it is relevant to improve and not to compete. In other words, the local network has an impact on the city's innovation when its structure evolves positively, regardless of whether this structure is better or worse than that of other cities.*

At the global level, the distinction between improving and competing in networks can be stated as follows: a city improves its position in the global network when it approaches optimal levels of centrality, brokerage and extra-regional orientation. On the other hand, for a city to compete with other territories in the global network would mean that the city occupies better positions in the global network than other cities. That is to say, that the city presents better levels of centrality, brokerage or openness than other cities in the global network.

If we ask what is relevant on a global scale, improvement or competition, we can argue as follows: the global network puts into circulation a set of resources (essentially knowledge and opportunities to develop innovations) and the cities occupying better positions will have better access to these resources, while

TABLE 1 | Conceptualization of local and global networks.

	Local networks	Global networks
Network approach	Each city contains a network where nodes represent local innovators, and links represent collaborations among them	Each city is a node in the global network, and each link represents collaboration between innovators located in two cities
Network analysis	Network-level analysis, which measures the structural properties of the network as a whole, considering all nodes and links within the city	Node-level analysis, which considers the relative positioning of the node (city) in the global network
Influence on innovation	Certain network properties (closeness, clustering, small-world) can facilitate knowledge diffusion and the emergence of new ideas within the territory	Specific positions occupied by the city in the global network (centrality, brokerage, external connections) can facilitate access to external knowledge

Source: Own elaboration.

the worst positioned cities will have worse access to the resources. Therefore, while improving the position on the global network relative to previous years may be good for innovation in a certain city, it does not necessarily mean outperforming other cities in the competition for the resources that the global network puts into circulation. Let us take, for example, the case of a city that increases its centrality by adding a new link to the global network. This new global connection can bring advantages to the city in terms of innovation. However, if the rest of the cities connected to the global network increase their centrality by adding two or more links, then the city in question will occupy a more peripheral position compared to the rest of the cities. This will allow other territories to capture a larger share of the resources that the global network puts into circulation. As a result, these other territories could benefit comparatively more in their innovation processes.

Based on these ideas, we can formulate our second hypothesis, complementary to the first one, as follows:

H2. *In the global network, it is more relevant to compete than to improve. In other words, although a city can innovate more by improving its connections to the global network, the effect of the network on innovation will be greater when the city manages to outperform other cities by occupying better positions in the global network.*

3 | Data and Methods

To test these hypotheses, we conduct an empirical study of collaboration networks associated to innovation processes in Latin American cities. We use data from the US Patent & Trademark Office (USPTO) retrieved from the PatentsVew Database. USPTO data allows for comparing inventive activities across different countries, with different property rights regimes (Bianchi et al. 2023a, 2023c; Guan et al. 2015; Innocenti et al. 2022). Furthermore, PatentsView database incorporates disambiguated identifiers for inventors and innovators, which is crucial for elaborating collaboration networks. We focus on patents involving at least one inventor located in Latin America and analyze the period between 2006 and 2017. This period is of particular interest given that, during these years, Latin America experienced an important emergence of patenting activities, with a large growth in patent collaborations, both locally and between different cities (Bianchi et al. 2020; WIPO 2018).

3.1 | Selection of Cities and Reconstruction of Networks

In patent data, some inventions are co-patented by different owners, which often reflects a collaborative innovation process. This enables the reconstruction of collaboration networks, differentiating, in addition, their territorial scope between local and global. First, in the case of local networks, we consider that the nodes are the patent owners—that is, firms or research centers, although they can also be individuals, the literature refers to them as innovators– located in the same city and the links are the co-patents registered between them. Second, for the global network, we consider that the cities are the nodes and the links are the co-patents registered between innovators located in different cities. Thus, we reconstruct one local network for each city, and a single global network of cities.

Some of the selected patents are co-owned by actors located outside Latin America. This leads us to include in the global network not only Latin American cities, but also cities from other parts of the world, as long as they are connected to Latin American cities. This allows us analyzing intra-regional versus extra-regional collaboration links.

The list of cities that we obtain following this procedure is too broad, including a large number of cities that have very limited inventive activity (with very few patent registrations). Furthermore, some co-patents do not imply actual collaboration between assignees—such as knowledge exchange or joint technological development—particularly when the assignees are located in different cities. Thus, co-patent networks often contain a large number of links that are not relevant for capturing meaningful collaborative interactions (Neal 2014; Gomes Ferreira et al. 2022). Yet, we are interested in selecting cities with relevant inventive activity and, especially, connections between these cities that reflect relatively important collaboration between their actors. To address this, we apply a backbone extraction method, which identifies statistically significant ties between patent owners based on the number of co-patents shared (Neal 2014). As the term suggests, backbone extraction techniques isolate the core structure of the network by retaining only those relationships that are statistically meaningful in light of the research question. This method has been widely used in network science and innovation studies to extract meaningful interaction patterns from complex relational data (e.g., Farinha et al. 2019; Heo and Lee 2019; Bianchi et al. 2023a, 2023c). The resulting network includes only statistically significant links, representing collaboration between Latin American cities and other cities worldwide in the patenting process. This filtered network is expected to better reflect actual knowledge flows across urban areas. As a result, we obtain a network that connects 118 Latin American cities and 645 cities in other regions of the world.

The econometric study focuses on Latin American cities, thus, we select the 31 Latin American cities that remain connected to the network during the whole period of analysis (some cities remain in the network only for some years, but not for the whole period). The remaining cities (87 Latin American and 645 extra-regional) are not included in the econometric analysis, although they are part of the network and, therefore, their links are used to calculate the global network indicators that we will explain below. The list of Latin American cities identified with this method, which are the ones analyzed in our models, along with their levels of patenting, can be found in Appendix A1. Selecting these cities entails working with a relatively small sample size, but it ensures that our unit of analysis captures only those territories where patenting and collaboration dynamics are at least minimally relevant. Moreover, as detailed in the following section, we implement a series of econometric strategies that allow us to address the challenges associated with this reduced sample. Figure 2 shows, for illustrative purposes, a cutout of our networks that includes the global and local links of four of the best-connected cities in the region: Buenos Aires (AR), Mexico City (MX), Santiago (CL) and Sao Paulo (BR).

3.2 | Econometric Analysis

In order to analyze the evolution of networks, we build 4-year windows and elaborate networks for each time window. Previous literature on co-patenting networks has widely used time windows of similar sizes, assuming that collaboration links among actors that jointly patent exist both before and after the patent application date (e.g., Bianchi et al. 2023a; Breschi and Lenzi 2015; Fleming et al. 2007). We then calculate different network statistics that measure the structure of each city local network and its connection to global networks.

We use panel data regression models in order to estimate how local and global networks may influence the innovative performance of cities. The dependent variable is the number of patents registered by actors located in each city in each subperiod. The use of patents as an indicator of innovation has been widely discussed in the literature (Archibugi 1992) and has been used by similar studies (e.g., de Araujo et al. 2019; Coffano et al. 2017; Whittington et al. 2009; Breschi and Lenzi 2013, 2016). The main limitations of these data are that they reflect only part of the innovative activity (Archibugi 1992) and that they are often sectorally biased (Griliches 1990). These limitations notwithstanding, we consider that patent data present an important advantage: they provide comparable information at the subnational level on innovation activities in different countries of the region.

The independent variables used in our models measure, on the one hand, local networks configuration and, on the other hand, the connection of the city to global networks (Appendix A2 provides the formal definitions of these network variables). Regarding the local network variables, we use indicators that measure the topology or structure of the patent owners' network in each city. In particular, we calculate three statistics widely used in the literature: average reach, average clustering and small world. First, the *average reach* measures the average proximity of the nodes in the network, that is, its closeness. Strictly speaking, the reach is the inverse distance between two nodes in the network. This variable reflects how close, on average, the nodes (i.e., patent owners) in each city are to each other. Second, the *average clustering* measures the degree to which the local network is made of groups or clusters of densely

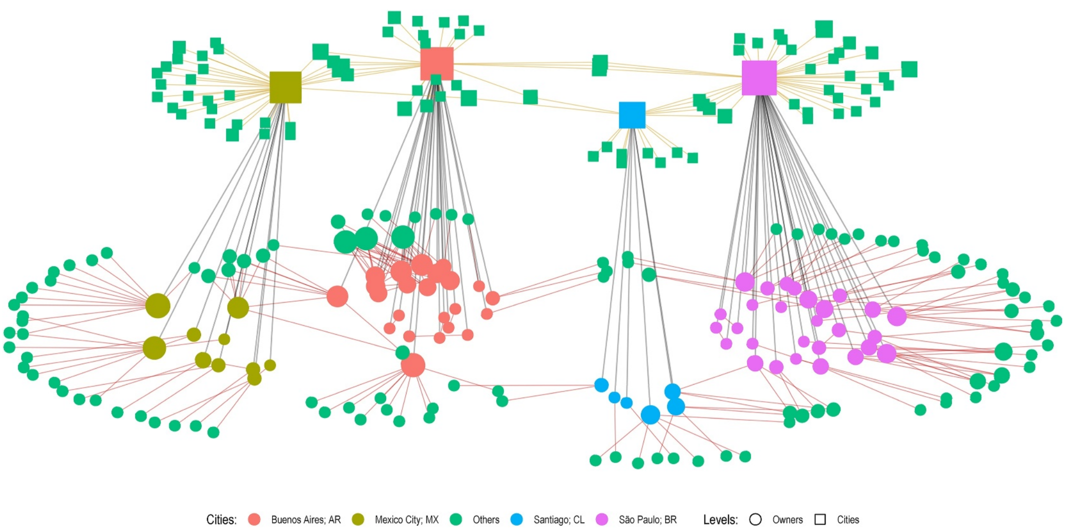

FIGURE 2 | Global inter-city network and local intra-city networks for the cases of Buenos Aires (AR), Mexico City (MX), Santiago (CL) and Sao Paulo (BR). The top level shows the global network formed by inter-city connections where the nodes (squares) are the cities of Buenos Aires (green), Mexico City (pink), Santiago (blue), Sao Paulo (purple) and those other cities with which they collaborate (rest of squares). The bottom level presents the local networks, where the nodes (circles) are patent owners located in the above cities as well as owners in other territories. *Source:* authors based on PatentsView data.

connected actors. The clustering coefficient of a node is the proportion of its neighbors that are connected to each other, and the average clustering coefficient is this value averaged over all the nodes in the network. The third indicator for studying local networks measures the *small-world* property, that is, the combination of high levels of clustering and strong closeness between nodes (Watts and Strogatz 1998). For this purpose, the product of average reach and average clustering is calculated. As explained in the theoretical framework, reach, clustering and small world can have positive effects on innovation processes of cities, but excessive levels of these network properties can generate negative effects as well.

As for the variables that measure the connection of the city with the global networks, node-level indicators are used, that is, statistics that measure the relative position of the nodes in the network. It is important to underline that, in this case, the nodes of the global network are cities (and not patent owners as in the case of local networks) and the links are collaborations between actors located in different cities. We use three indicators to measure the position of the city in the global network. First, *degree centrality* measures the number of links adjacent to each city relative to the maximum number of links it can have given the number of nodes in the network. This indicator measures the relative prominence or importance of a node in the network.

The second indicator is the *proportion of extra-regional links*, that is, the number of links that the city maintains with other cities located outside Latin America out of the total number of links that the city maintains with other cities. Finally, we include an indicator that measures brokerage in the global network. For this purpose, we calculate the *gatekeeper* index proposed by Gould and Fernandez (1989), which measures the extent to which a given city is connected to pairs of Latin American and non-Latin American cities that are disconnected from each other.

As explained in the theoretical framework, these indicators measuring the city's connection to the global network can have both positive and negative effects on innovation: although centrality, extra-regional orientation and the brokerage role can facilitate innovation processes, excessive levels of these indicators could generate negative effects on innovation in cities when the costs of occupying these positions in the global network outweigh the benefits.

All explanatory variables are lagged by one period since, according to our theoretical framework, networks can influence innovation processes, which would lead to future increases (or reductions) in patenting levels. To control for potential complementarity between local and global networks in innovation, our estimations consider the interactions of local network variables with global network variables. Furthermore, to control for factors other than networks that may determine patenting levels in cities, the models include a set of control variables. First, city size and agglomeration of innovators are controlled for by considering the number of inventors and the number of patent owners located in each city. Second, to control for the technological specialization of cities, we include the number of technological fields in which the city patents, using the patent technological code. Third, the number of patents registered in the previous period is used to control for other unobserved factors that may determine patenting levels in cities, such as the evolution of the local economy or investments in technological development. Since these variables are highly correlated, their inclusion in the models could generate collinearity problems. To address this issue, we perform a factor analysis that allows to group them into fewer dimensions. The factor analysis shows that a single factor is adequate to replace all these control variables, even while maintaining more than 80% of the variance they contribute (see Appendix A3). Therefore, the variable *factor* is created and included in the models to control for the above aspects. Appendix A4 presents descriptive statistics for all variables used in the analysis, as well as the correlation matrix.

To differentiate whether the effects of local and global networks occur because the city improves or because it ranks above other cities, our models follow the so-called within-between approach (Allison 2009). This approach allows to explicitly model variations in patenting levels explained by cities' characteristics as well as by variations in such characteristics through time. The estimated models can be expressed as follows:

$$y_{i,t} = \beta_0 + \beta_1(x_{i,t-1} - \bar{x}_i) + \beta_2\bar{x}_i + \beta_x{}' \; X_{i,t} + \varepsilon_{i,t}$$

In this equation, $y_{i,t}$ represents each city's patenting levels, $x_{i,t-1}$ its local and global network indicators, and $X_{i,t}$ is a vector of control variables. β_1 estimates the within-city effects coefficients. This coefficient measures how variations each city records in its independent variables (its local and global networks) influence its level of patenting. This allows to observe to what extent the improvements that a city achieves in the configuration of its local network and its position in the global network lead to increases in its patenting levels.

β_2 represents the between-cities effects coefficients, which measure how the average level recorded by each city for its local and global networks' variables in relation with values obtained by other cities may influence its patenting levels. This allows to estimate to what extent when a city has better (local and/or global) network configurations than other cities then it will innovate more than those other cities.

According to H1, for the variables measuring the structure of the local network, only β_1 should be statistically significant. This would imply that at the local scale, it only matters that the city improves its network properties, while it is not relevant to compete with (and eventually outperform) other cities. On the other hand, according to H2, for the variables measuring the connection of the city to global networks, both β_1 and β_2 should be statistically significant (with β_2 having a stronger effect on the dependent variable than β_1). This result would mean that on a global scale, it is not so important to improve its position, but to occupy better positions in the network than those occupied by other cities.

Although the limited availability of city-level data in Latin America constrains the strategies available to address potential endogeneity issues, several elements of our empirical design help to mitigate potential biases. First, given that the model considers the mean of the independent variables for each city ($\bar{x}_i$), it allows controlling for the effect of time-fixed characteristics of each city (Allison 2009; Hill et al. 2021; Li 2013). This allows controlling for unobserved structural factors of the cities that are related to the local capacities and that may be influencing their patenting levels, such as the educational level, the institutional framework or the business environment. Second, potential reverse causality or omitted variable biases can be reduced by using control variables that vary between each period and lagged explanatory variables. According to Bellemare et al. (2017), the use of lagged explanatory variables is justified when it has theoretical foundations. Since our theoretical framework argues that local and global networks can facilitate innovation processes that may lead a city to generate more patents in the future, our use of lagged explanatory variables is well justified. These econometric strategies have been widely used in the empirical literature on patent networks facing similar endogeneity problems (e.g., de Araujo et al. 2019; Fleming et al. 2007; Galaso and Kovářík 2021; Schilling and Phelps 2007; van der Wouden and Rigby 2019). Nevertheless, the results should still be interpreted with caution.

The dependent variable (i.e., the number of patents registered in each city) is a count variable that takes strictly positive integer values, therefore, the most appropriate strategy for our regressions is to use Generalised Linear Models, specifically Poisson models. To verify that this is the most suitable alternative, we performed overdispersion tests, which found no evidence to indicate the presence of overdispersion (thus, it is not necessary to use Negative Binomial models).

As noted above, the process of extracting the network backbone—retaining only the most relevant interactions—necessarily reduces the number of nodes and links, resulting in a relatively small final sample. Accordingly, we removed all the interactions between local and global network variables that were not statistically significant. These interactions were not central to testing our hypotheses, and excluding them contributes to address the small sample problem by reducing the number of estimated parameters. Additionally, the econometric models are estimated using standard error adjustments appropriate for small-n samples. Following Liang and Zeger (1986) and MacKinnon and White (1985), these adjustments involve applying a scalar correction to the standard errors, calculated as $(m(N-1))/[(m-1)(N-p)]$, where m is the number of cities, p the number of parameters, and N the total number of observations. Finally, Appendix A5 presents robustness checks, the results of which provide additional support for our main findings (Tables A5.1 A5.2).[1]

4 | Results

The results of our estimations, presented in Table 2, confirm our two hypotheses. First, for the local network variables, the models show that only the within-city effects are relevant to explain innovation. Thus, improvements in all three indicators of local networks are associated with increases in city innovation over the following period. In other words, when cities manage to improve their average reach, increase the clustering in their local networks, or when they improve their small-world property, then they achieve further increases in innovation.

Given that the between-city effects are not significant for the local network variables in any of the models, these improvements are independent of whether cities have better or worse local networks than those of other cities. That is, as long as cities achieve improvements in their local networks, their innovation will be increased, even if their local networks are less conductive to innovation compared to local networks in other cities.

Secondly, regarding global networks, we find that both within- and between-city effects are relevant in explaining innovation. But in fact, the between-city effects seem to be more relevant. This implies that those cities that occupy more central positions in the global networks and those with a higher proportion of their connections linked to cities outside the region obtain, on average, better innovation outcomes than those obtained by other—more peripheral and regionally oriented—cities.

This finding confirms our second hypothesis, indicating that, unlike with the local networks, in the global network, cities seem to compete with each other. To do so, cities need to position themselves in more central locations of the global network than other cities and focus their connections outside the region more than other cities do. By doing so, and outperforming other territories on the global network, these cities will gain a better access to the knowledge flows that circulate through global pipelines, which will lead them to obtain better innovation outputs.

Some variables measuring the city's position in the global network show results that go beyond our hypotheses. In particular, we find that playing a gatekeeper role, that is, being in an intermediary position between Latin American and non-Latin American cities, is associated with worse innovation outcomes. This negative effect of gatekeeper roles in global networks has been documented in previous research (Bianchi et al. 2023a) and seems to reflect the cost that some territories cover by maintaining links with unrelated actors. A cost associated with efforts in interpretation and translation of information obtained from different sources. Although broker positions can generate benefits for innovation, sometimes the cost of performing them can outweigh the positive effects.

Finally, the interactions between the local network variables and those of the global network present results in line with the literature (Breschi and Lenzi 2013, 2016; Coffano et al. 2017). Of particular interest is the interaction between the local networks and the gatekeeper position in global networks. Our results suggest that, while the gatekeeper variable may reflect the costs of maintaining global links for peripheral cities, the interaction between a gatekeeper position and the structure of local networks can mitigate these costs. In other words, when a city has a cohesive local network (whose nodes are close to each other), with high clustering and small-world property, then the costs of being a gatekeeper in global networks can be attenuated and/or its benefits can be enhanced. This may imply that the negative effects of occupying gatekeeper positions could be strongly conditioned by the weaknesses of local innovation systems in Latin America, which are often characterized by highly

TABLE 2 | Poisson regressions.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9
Intercept	2.463***	2.480***	2.473***	2.476***	2.479***	2.470***	2.463***	2.477***	2.469***
	(0.097)	(0.096)	(0.099)	(0.099)	(0.097)	(0.101)	(0.092)	(0.091)	(0.094)
Between-city effects									
Factor	1.827***	1.805***	1.747***	1.873***	1.880***	1.808***	1.783***	1.778***	1.734***
	(0.256)	(0.254)	(0.259)	(0.261)	(0.254)	(0.264)	(0.240)	(0.238)	(0.244)
Local network variables									
Reach	−0.051			−0.032			−0.032		
	(0.103)			(0.107)			(0.099)		
Clustering		0.066			0.116			0.071	
		(0.121)			(0.121)			(0.114)	
Small world			−0.064			−0.048			−0.047
			(0.107)			(0.111)			(0.104)
Global network variables									
Centrality	0.928***	0.901***	0.890***				0.687**	0.653**	0.673**
	(0.276)	(0.277)	(0.280)				(0.289)	(0.292)	(0.296)
Gatekeeper	−1.779***	−1.776***	−1.679***	−1.022***	−1.103***	−0.971***	−1.555***	−1.565***	−1.501***
	(0.319)	(0.323)	(0.327)	(0.255)	(0.267)	(0.257)	(0.319)	(0.322)	(0.328)
Extra regional links				0.307***	0.304***	0.297***	0.194*	0.192*	0.183
				(0.107)	(0.103)	(0.108)	(0.110)	(0.108)	(0.112)
Within-city effects									
Factor	−0.106***	−0.090***	−0.115***	−0.024	−0.089***	−0.115***	−0.107***	−0.087***	−0.106***
	(0.023)	(0.024)	(0.026)	(0.015)	(0.024)	(0.026)	(0.023)	(0.024)	(0.026)
Local network variables									
Reach	0.201***			0.100**			0.209***		
	(0.040)			(0.042)			(0.049)		
Clustering		0.086*			0.062			0.087*	
		(0.050)			(0.049)			(0.050)	
Small world			0.117**			0.105*			0.113*
			(0.058)			(0.058)			(0.059)
Global network variables									
Centrality	0.204***	0.101*	0.087				0.200***	0.165**	0.156**
	(0.061)	(0.060)	(0.060)				(0.063)	(0.066)	(0.066)
Gatekeeper	−0.187***	−0.141***	−0.071	−0.033***	−0.060***	0.006	−0.186***	−0.166***	−0.114**
	(0.045)	(0.043)	(0.049)	(0.012)	(0.015)	(0.015)	(0.045)	(0.045)	(0.052)
Extra regional links				−0.042	−0.062	−0.065*	0.013	−0.105**	−0.107**
				(0.044)	(0.039)	(0.039)	(0.052)	(0.043)	(0.043)
Interaction of local and global networks									
Reach*Centrality	−0.065***						−0.068***		
	(0.021)						(0.024)		
Clustering*Gatekeeper		0.110***			0.111***			0.087***	
		(0.031)			(0.031)			(0.033)	
Small World*Gatekeeper			0.111***			0.125***			0.078**
			(0.033)			(0.030)			(0.035)

(Continues)

TABLE 2 | (Continued)

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9
Over.disp_pv	0.983	0.344	0.378	0.987	0.328	0.426	0.981	0.421	0.462
Disp_ratio	0.617	1.069	1.050	0.602	1.078	1.024	0.616	1.027	1.005
AIC	406.028	425.535	426.134	436.954	427.898	427.586	407.087	420.605	421.415
BIC	429.427	448.934	449.533	458.225	451.297	450.984	434.739	448.257	449.067
Log likelihood	−192.014	−201.768	−202.067	−208.477	−202.949	−202.793	−190.543	−197.302	−197.707
Num. obs.	62	62	62	62	62	62	62	62	62
Num. groups: name	31	31	31	31	31	31	31	31	31

Note: Standard errors in parentheses, with small sample adjustment.
Source: Authors based on PatentsView data.
*$p < 0.1$.
**$p < 0.05$.
***$p < 0.01$.

fragmented networks. Therefore, as cities across the region succeed in strengthening their local networks, they may also be better positioned to benefit from their integration into global networks.

5 | Discussion and Conclusion

In this paper, we have investigated how the effects of local and global networks operate on cities. At the local scale, what is important is that the city manages to improve its network configuration over time, enabling local actors to connect with each other forming networks with topologies that are more conducive to innovation. Specifically, the evolution of the local network toward greater proximity between its nodes, the formation of clusters and the combination of these structures in the property known as a small-world network will have a positive impact on the city's innovation processes. This evolution is independent of what the networks in other cities are like. That is, whether a city has a better or worse local network configuration than other cities is not as relevant as whether the city's network is progressively improving over time, evolving toward the structures mentioned above.

This finding is particularly important for lagging territories and for cities in developing countries. In these cases, local capacities for the formation of networks associated with innovation processes tend to be weak in comparison with leading regions on a global scale. Their actors tend to cooperate little with each other, operating in isolation, and orienting their links outward, so that their local networks tend to be poorly connected (Bianchi et al. 2023b). However, according to our findings, the weakness of local networks in backward territories does not prevent them from contributing to innovation. Local networks of these territories could also facilitate innovation processes to the extent that they manage to gradually improve their configuration: by increasing their levels of closeness, clustering or small world, these local networks will have a positive impact on innovation.

This is not the case for global networks. As the results of our models show, the connection of a city to the global network can be positive for innovation in the territory. But this influence will depend mainly on the position of the city in the network compared to the position of other cities. In other words, on a global scale there seems to be a kind of competition between cities to capture the resources that flow through the global network and that can facilitate innovation processes. For cities in developing countries, this result underscores the importance of improving their relative positions in the global network, moving away from the periphery, since, as Calignano (2022) suggests, not all peripheral positions are the same. To the extent that a city manages to position itself better than others in the global network, then it will obtain improvements in its innovation processes. Therefore, we can conclude that, in innovation networks, cities should improve locally and compete globally.

These findings have important implications for future research. First, for research on innovation and networks, the results point to the importance of differentiating between evolution and competition among territories. Previous studies focused on developing regions, such as Latin America, has documented that innovation networks tend to be structurally weak, highly fragmented, strongly dependent on global connections (Bianchi et al. 2020, 2023b), and lacking the critical mass of local linkages required to sustain self-sufficient system functioning (Dutrénit and Puchet 2011). However, the distinction between the dynamics of network evolution and competition within these networks remains largely unexplored in this body of research. According to our findings, this aspect is relevant for understanding innovation, since it would allow future studies to delve into questions such as, for example, the different rates of evolution in the networks of different territories and their impact on innovation and development. Do the territories follow different paths (and rates) in the development of their local networks and their connection to the global network? It would also be possible to analyze whether there are different forms of competition among territories through their networks: can different competitive strategies of territories be found through the networks? It would also be interesting to delve deeper into the possible interaction between the two factors: to what extent is the evolution of networks in territories conditioned by competition between them and vice versa?

Latin American studies on innovation and development have highlighted systemic failures, particularly in feedback loops (Erbes et al. 2010; Yoguel and Robert 2010; Arocena and

Sutz 2000), describing Latin American innovation systems as immature (Rapini et al. 2009). A key factor is the weakness of external connectivity to global networks and absorptive capacities, linked to the absence of a critical mass in local networks (Bianchi et al. 2023b; Erbes et al. 2010; Arocena and Sutz 2000; Dutrénit and Puchet 2011). Our paper can contribute to this debate by highlighting how the local and global networks may strengthen feedback loops. In light of this, one might ask: do Latin American cities benefit more from strengthening their local absorptive capacity than from direct integration into global networks? Or is it a combination of both? Our findings suggest that cities with underdeveloped local networks may benefit more from strengthening internal absorptive structures, while better-integrated cities (e.g., large capitals or innovation hubs) may already be positioned to compete globally and enhance innovation outcomes.

Although our study does not aim to explore the interaction between local and global networks in depth, its findings also have relevant implications for future research in this line. In particular, the result regarding the interaction between a city's gatekeeper position in the global network and the structure of its local networks suggests that structural disadvantages faced by Latin American cities may be limiting the potential benefits of their connections to global innovation networks. In this regard, future research could investigate whether certain characteristics of cities in developing countries, such as industrial specialization or policy incentives, may influence the way local and global networks interact.

In addition, our findings may also contribute to the ongoing debate on the importance of city size in fostering innovation and economic development. In this regard, as Frick and Rodríguez-Pose (2017) show, megacities tend to support growth only in very large countries with complex urban systems, whereas small and medium-sized cities are more conducive to development in most other national contexts. The authors highlight that the benefits of large cities depend on the presence of adequate urban infrastructure, effective governance, and an economic base oriented toward sectors with increasing returns (e.g., services, high-tech industries). In the context of developing countries, many cities face significant deficiencies in these dimensions, limiting their capacity to absorb and exchange knowledge within innovation networks. Investing in these enabling conditions would be key to allowing a broader set of Latin American cities to improve their local networks while integrating into global networks.

The literature on global financial networks can offer valuable insights for interpreting our findings. For example, in light of the work by Robinson et al. (2022), we can consider that cities successfully integrated into global innovation networks are not merely those endowed with talent or knowledge, but rather those that are connected to the critical infrastructures that organize global flows of capital and information. Thus, financial connectivity serves as an enabling condition that determines who can participate in global innovation, and under what terms.

Our findings can also be examined in light of the increasing role of digital transformation. Drawing on the findings of Trincado-Muñoz et al. (2023), digital connectivity can be seen as a strategic bridge linking local with global innovation networks. Many Latin American cities face a dual disconnection: weak integration into global innovation networks and internal fragmentation within their local innovation ecosystems. In this context, digital connectivity can play a critical mediating role—if effectively leveraged—to articulate fragmented local networks by connecting traditionally disconnected sectors, and to enable alternative forms of international integration through the active adoption of global digital standards, participation in shared technological architectures, and use of enabling digital infrastructures.

Finally, our study also has relevant implications for public policy. On the one hand, the results can guide policies that promote the formation of networks at the local level. Cooperation between local actors can improve network configurations, which would positively impact the development of innovations. On the other hand, with respect to the city's connections with global networks, our findings indicate that territories should also take into account how other cities are performing, given that there is a competition between them. Therefore, policymakers should be strategic in the type of connections they seek to foster with the outside world, for example, by encouraging extra-regional links or collaborating with other cities that are, in turn, disconnected from each other, so that the city in question is placed in a brokerage position. This type of strategies could be crucial to foster innovation processes and promote the development of territories.

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Conflicts of Interest

The authors declare no conflicts of interest.

Endnotes

[1] As robustness checks, we estimate two sets of alternative models (see Appendix A5). First, models that include all interaction terms between local and global network variables, including those that are not statistically significant (Table A5.1). Second, models without using standard error adjustments for small-n samples (Table A5.2). The results of these alternative models are qualitatively the same as those obtained in the original specification.

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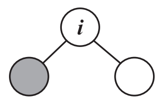
Appendix A

A1. Latin American Cities Included in the Analysis

City	Country	Number of patents (2006–2017)
São Paulo	Brazil	596
Mexico City	Mexico	322
Rio de Janeiro	Brazil	270
Santiago	Chile	235
São José dos Campos	Brazil	167
Buenos Aires	Argentina	152
Monterrey	Mexico	94
Cadereyta Jiménez	Mexico	85
La Habana	Cuba	81
Bogotá	Colombia	55
Hermosillo	Mexico	50
Jundiaí	Brazil	47
Porto Alegre	Brazil	44
Campinas	Brazil	41
Camaçari	Brazil	28
Belo Horizonte	Brazil	27
Montevideo	Uruguay	25
Brasilia	Brazil	21
Medellín	Colombia	21
Corinto	Brazil	18
Ciudad Apodaca	Mexico	16
Florianópolis	Brazil	14
Heroica Veracruz	Mexico	14
Concepción	Chile	12
Santa Fe	Argentina	12
San Nicolás de los Garza	Mexico	11
Rosario	Argentina	10
Valparaíso	Chile	10
Araraquara	Brazil	5
Juiz de Fora	Brazil	5
Valparaíso de Goiás	Brazil	4

Source: Authors based on PatentsView data.

A2. Variable Description Table

Indicator	Calculation	Clarification
Reach: $R(g)$	$R(g) = \frac{\frac{1}{N}\sum_{i\neq j}\frac{1}{d_{i,j}}}{N-1}$ where: • N is the number of nodes (innovators) in the network. • $d_{i,j}$ is the shortest path distance between nodes i and j. • $\frac{1}{d_{i,j}}$ is set to 0 when $d_{i,j} = \infty$ (i.e., nodes are disconnected).	
Clustering: $T(g)$	$T(g) = \frac{T_{\text{obs}}(g)}{T_{\max}(g)}$ Where: • $T_{\text{obs}}(g)$ is the number of closed triad. • $T_{\max}(g)$ is the number of possible closed triad.	This is the ratio of the count of triangles and connected triples in the graph
Small world: SW (g)	$\text{SW}(g) = R(g)xT(g)$	
Centrality: $DC(i)$	$\text{DC}(i) = \frac{d(i)}{n-1}$ where: • $d(i)$ is the number of links adjacent to node i • n is the number of nodes in the network and, therefore, $n-1$ is the maximum value that the numerator can reach	In our study, $d(i)$ is the number of cities with which city i collaborates and n is the number of cities in the network Centrality is the Degree Centrality of the node
Gatekeeper: $G(i)$	In a network where nodes can be categorized into two groups (e.g., white and gray nodes), node i occupies a coordinator position between two other nodes when: • it connects two nodes that are disconnected from each other, and • the nodes in between i belong to different categories (one is gray, the other one is white)  $G(i)$ is the standardized brokerage scores, of nodes for which i is a broker of this type	In our study the two categories of nodes are: Latin American cities and non-Latin American cities Node i is always a Latin American city

(Continues)

(Continued)

A3. Factor Analysis

Kaiser–Meyer–Olkin factor adequacy

Call: KMO (r = controls)

Overall MSA = 0.8

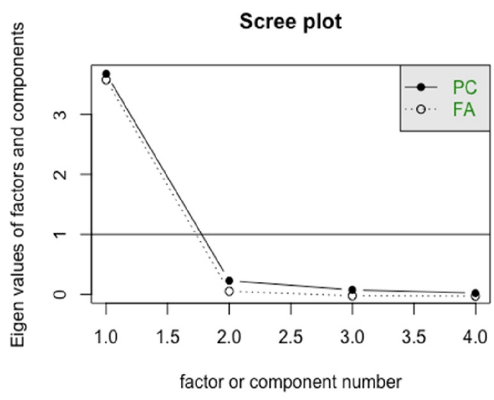
MSA for each item

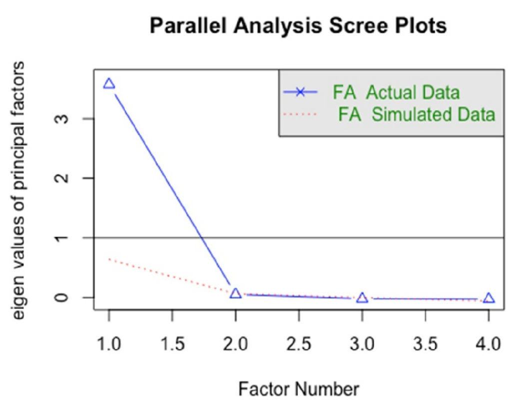
Number of patents	Number of owners	Number of inventors	Number of technological fields
0.72	0.82	0.79	0.93

Bartlett test of homogeneity of variances

Data: controls

Bartlett's $K^2 = 528.8$, df = 3, p-value < 2.2e-16





Note: Both the MSA and the Bartlett test results indicate that performing a factor analysis with our data is perfectly adequate. Regarding the most appropriate number of factors, both the Scree plot curve and the Parallel Analysis Scree Plots suggest the use of one single factor.

Source: Authors based on PatentsView data.

A4. Descriptive Statistics and Correlation Table

ID	Variable	Mean	SD	Median	Min	Max	1	2	3	4	5	6	7	8
1	Patents	26.63	41.38	9.00	1.00	219	1.00	0.94	−0.03	0.45	−0.02	0.79	0.74	0.21
2	Factor	0.05	1.08	−0.41	−0.62	4.64	0.94	1.00	−0.05	0.41	−0.05	0.87	0.87	0.22
3	Reach	0.13	0.26	0.00	0.00	1.00	−0.03	−0.05	1.00	0.41	0.66	−0.13	−0.09	−0.24
4	Clustering	0.12	0.31	0.00	0.00	1.00	0.45	0.41	0.41	1.00	0.72	0.41	0.41	0.05
5	Small world	0.05	0.19	0.00	0.00	1.00	−0.02	−0.05	0.66	0.72	1.00	−0.08	−0.04	−0.16
6	Centrality	0.03	0.03	0.01	0.00	0.17	0.79	0.87	−0.13	0.41	−0.08	1.00	0.92	0.36
7	Gatekeeper	3.81	13.08	−0.87	−0.88	84.28	0.74	0.87	−0.09	0.41	−0.04	0.92	1.00	0.21
8	Extra regional links	0.50	0.39	0.59	0.00	1.00	0.21	0.22	−0.24	0.05	−0.16	0.36	0.21	1.00

A5. Alternative Models

TABLE A5.1 | Models using more interactions.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9
Intercept	2.465***	2.478***	2.473***	2.474***	2.478***	2.470***	2.465***	2.475***	2.470***
	(0.097)	(0.096)	(0.098)	(0.099)	(0.097)	(0.101)	(0.091)	(0.091)	(0.093)
Between-city effects									
Factor	1.823***	1.795***	1.754***	1.876***	1.880***	1.808***	1.779***	1.765***	1.737***
	(0.255)	(0.255)	(0.258)	(0.261)	(0.254)	(0.264)	(0.239)	(0.239)	(0.243)
Local network variables									
Reach	−0.051			−0.037			−0.031		
	(0.103)			(0.107)			(0.099)		
Clustering		0.061			0.114			0.066	
		(0.122)			(0.122)			(0.115)	
Small world			−0.062			−0.047			−0.046
			(0.107)			(0.111)			(0.103)
Global network variables									
Centrality	0.930***	0.897***	0.903***				0.694**	0.648**	0.677**
	(0.275)	(0.277)	(0.280)				(0.288)	(0.293)	(0.296)
Gatekeeper	−1.786***	−1.761***	−1.696***	−1.022***	−1.102***	−0.971***	−1.566***	−1.547***	−1.507***
	(0.317)	(0.324)	(0.327)	(0.255)	(0.268)	(0.257)	(0.318)	(0.323)	(0.328)
Extra regional links				0.308***	0.306***	0.297***	0.191*	0.194*	0.184*
				(0.107)	(0.103)	(0.108)	(0.109)	(0.109)	(0.112)
Within-city effects									
Factor	−0.090***	−0.158***	−0.107***	−0.031	−0.086***	−0.116***	−0.092***	−0.150**	−0.103***
	(0.025)	(0.060)	(0.030)	(0.022)	(0.026)	(0.027)	(0.025)	(0.060)	(0.030)
Local network variables									
Reach	0.193***			0.127**			0.203***		
	(0.041)			(0.051)			(0.049)		
Clustering		0.101*			0.084			0.101*	
		(0.052)			(0.088)			(0.052)	

(Continues)

TABLE A5.1 | (Continued)

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9
Small world			0.120**			0.102			0.114*
			(0.059)			(0.074)			(0.059)
Global network variables									
Centrality	0.199***	0.063	0.094				0.194***	0.129*	0.158**
	(0.060)	(0.067)	(0.061)				(0.063)	(0.073)	(0.067)
Gatekeeper	−0.226***	−0.054	−0.091	−0.018	−0.060***	0.006	−0.225***	−0.084	−0.123*
	(0.052)	(0.083)	(0.063)	(0.030)	(0.015)	(0.015)	(0.052)	(0.084)	(0.064)
Extra regional links				−0.037	−0.061	−0.065*	0.018	−0.103**	−0.105**
				(0.045)	(0.039)	(0.039)	(0.052)	(0.043)	(0.043)
Interaction of local and global networks									
Reach*Centrality	−0.078***						−0.083***		
	(0.023)						(0.026)		
Reach*Gatekeeper	0.051			−0.017			0.052		
	(0.036)			(0.034)			(0.036)		
Reach*Extra regional links				−0.037					
				(0.039)					
Clustering*Centrality		0.110						0.104	
		(0.090)						(0.090)	
Clustering*Gatekeeper		0.225**			0.120***			0.195**	
		(0.099)			(0.043)			(0.100)	
Clustering*Extra regional links					−0.016				
					(0.053)				
Small World*Centrality			−0.019						−0.009
			(0.035)						(0.035)
Small World*Gatekeeper			0.087			0.125***			0.066
			(0.056)			(0.031)			(0.056)
Small World*Extra regional links						0.003			
						(0.038)			
Over.disp_pv	0.955	0.366	0.354	0.088	0.328	0.429	0.914	0.502	0.482
Disp_ratio	0.688	1.056	1.063	1.280	1.078	1.023	0.735	0.985	0.995
AIC	405.964	426.046	427.855	440.005	429.807	429.581	407.036	421.298	423.349
BIC	431.490	451.572	453.380	465.531	455.333	455.107	436.815	451.077	453.128
Log likelihood	−190.982	−201.023	−201.927	−208.003	−202.904	−202.790	−189.518	−196.649	−197.674
Num. obs.	62	62	62	62	62	62	62	62	62
Num. Groups: name	31	31	31	31	31	31	31	31	31

Note: Standard errors in parentheses.
Source: Authors based on PatentsView data.
*$p < 0.1$.
**$p < 0.05$.
***$p < 0.01$.

TABLE A5.2 | Main models without small sample adjustment.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9
Intercept	2.463***	2.480***	2.473***	2.476***	2.479***	2.470***	2.463***	2.477***	2.469***
	(0.097)	(0.096)	(0.099)	(0.099)	(0.097)	(0.101)	(0.092)	(0.091)	(0.094)
Between-city effects									
Factor	1.827***	1.805***	1.747***	1.873***	1.880***	1.808***	1.783***	1.778***	1.734***
	(0.256)	(0.254)	(0.259)	(0.261)	(0.254)	(0.264)	(0.240)	(0.238)	(0.244)

(Continues)

TABLE A5.2 | (Continued)

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9
Local network variables									
Reach	−0.051			−0.032			−0.032		
	(0.103)			(0.107)			(0.099)		
Clustering		0.066			0.116			0.071	
		(0.121)			(0.121)			(0.114)	
Small world			−0.064			−0.048			−0.047
			(0.107)			(0.111)			(0.104)
Global network variables									
Centrality	0.928***	0.901***	0.890***				0.687**	0.653**	0.673**
	(0.276)	(0.277)	(0.280)				(0.289)	(0.292)	(0.296)
Gatekeeper	−1.779***	−1.776***	−1.679***	−1.022***	−1.103***	−0.971***	−1.555***	−1.565***	−1.501***
	(0.319)	(0.323)	(0.327)	(0.255)	(0.267)	(0.257)	(0.319)	(0.322)	(0.328)
Extra regional links				0.307***	0.304***	0.297***	0.194*	0.192*	0.183
				(0.107)	(0.103)	(0.108)	(0.110)	(0.108)	(0.112)
Within-city effects									
Factor	−0.106***	−0.090***	−0.115***	−0.024	−0.089***	−0.115***	−0.107***	−0.087***	−0.106***
	(0.023)	(0.024)	(0.026)	(0.015)	(0.024)	(0.026)	(0.023)	(0.024)	(0.026)
Local network variables									
Reach	0.201***			0.100**			0.209***		
	(0.040)			(0.042)			(0.049)		
Clustering		0.086*			0.062			0.087*	
		(0.050)			(0.049)			(0.050)	
Small world			0.117**			0.105*			0.113*
			(0.058)			(0.058)			(0.059)
Global network variables									
Centrality	0.204***	0.101*	0.087				0.200***	0.165**	0.156**
	(0.061)	(0.060)	(0.060)				(0.063)	(0.066)	(0.066)
Gatekeeper	−0.187***	−0.141***	−0.071	−0.033***	−0.060***	0.006	−0.186***	−0.166***	−0.114**
	(0.045)	(0.043)	(0.049)	(0.012)	(0.015)	(0.015)	(0.045)	(0.045)	(0.052)
Extra regional links				−0.042	−0.062	−0.065*	0.013	−0.105**	−0.107**
				(0.044)	(0.039)	(0.039)	(0.052)	(0.043)	(0.043)
Interaction of local and global networks									
Reach*Centrality	−0.065***						−0.068***		
	(0.021)						(0.024)		
Clustering*Gatekeeper		0.110***			0.111***			0.087***	
		(0.031)			(0.031)			(0.033)	
Small World*Gatekeeper			0.111***			0.125***			0.078**
			(0.033)			(0.030)			(0.035)
Over.disp_pv	0.983	0.344	0.378	0.987	0.328	0.426	0.981	0.421	0.462
Disp_ratio	0.617	1.069	1.050	0.602	1.078	1.024	0.616	1.027	1.005
AIC	406.028	425.535	426.134	436.954	427.898	427.586	407.087	420.605	421.415
BIC	429.427	448.934	449.533	458.225	451.297	450.984	434.739	448.257	449.067
Log likelihood	−192.014	−201.768	−202.067	−208.477	−202.949	−202.793	−190.543	−197.302	−197.707
Num. obs.	62	62	62	62	62	62	62	62	62
Num. groups: name	31	31	31	31	31	31	31	31	31

Note: Standard errors in parentheses.
Source: Authors based on PatentsView data.
*$p < 0.1$.
**$p < 0.05$.
***$p < 0.01$.