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RESEARCH

Structural Dynamics of Inter-city Innovation Networks in China: A Perspective From TERGM

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Abstract

Innovation networks play a key role in advancing knowledge transfer, collaboration, and technological progress across sectors and regions. Central to the understanding of the mechanisms driving such networks is their dynamic evolution and structure. Much of the literature explores spatial and socio-economic drivers of innovation networks, focusing on geographic, institutional, and cultural influences. However, many of these studies tend to overlook the intricate properties that govern the behavior and dynamics of these networks. This study seeks to address this research gap, delving deeper by investigating Chinese intercity innovation networks between 2007 and 2018. Specifically, we examine: (i) the preferential attachment dynamics within intercity innovation networks, (ii) transitivity effects that underscore the interconnectedness of these networks, and (iii) the persistence and recurrence of connections. We find that cities show indeed a remarkable tendency to form ties with others that already have numerous connections. Such transitivity effects are important in highlighting the formation of innovation clusters. Moreover, the influence of link memory suggests that past collaborations significantly determine future partnerships, similar to the persistent nature of relationships in agglomeration theories.

Keywords Social Network Analysis · TERGM · Diffusion of innovation · City innovation · Patenting

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1 Introduction

The evolution from Exponential Random Graph Models (ERGMs) to Temporal Exponential Random Graph Models (TERGMs) represents a significant shift in inferential social network modeling, moving from capturing static structures to incorporating the dynamics of network evolution over time. While ERGMs model the probability of observing a static network based on specific structural configurations, TERGMs extend this by integrating the temporal dependencies that characterize how networks evolve (Snijders et al. 2010; Broekel and Bednarz 2019; Filippetti and Zinilli 2023). However, despite the promise of TERGMs for capturing intricate temporal patterns, their empirical application has been somewhat limited. This is primarily due to a dearth of suitable longitudinal network data and the challenge of identifying compelling use cases where the temporal dynamics offer substantial additional insights over and above static models (Leifeld et al. 2018).

Against this background, this study shifts attention to the exploration of a large-scale, real-world empirical social network from a TERGM perspective, namely *innovation networks*. The latter are defined as networks of actors or regions interlinked in joint R&D activities. The investigation of structures and dynamics within innovation networks has attracted increasing interest in the recent past. This interest stems from the notion that participating in collaborative innovation activities is essential for knowledge production and diffusion (Grillitsch and Nilsson 2015; Morrison et al. 2013, among others). Numerous research works have emerged, notably emphasizing a geographical and spatial economics perspective, which examines the interaction between spatial entities, typically regions, in collaborative innovation endeavors (refer to Scherngell 2021 for a comprehensive overview). A growing trend in network science is integrating network analysis with spatial and socioeconomic factors, emphasizing the need for a better understanding of the specific network structural elements driving innovation networks (Lomi et al. 2016; Kireyev and Leonidov 2018; Wang and Yang 2022). Though still in its early stages, network analytic approaches are increasingly contributing to regional research on innovation networks, recognizing that network structural properties are fundamental to the understanding of the dynamics between interconnected spatial entities that interact in innovation activities.

Aligning with this emerging trend, our research aims to provide a more comprehensive understanding of the intricate nature of collaborations in innovation activities. In our empirical analysis, we shift attention to the case of innovation networks across Chinese cities. Focusing on aggregated spatial entities rather than organizations, our work lies in the research stream that has a strong interest in investigating structures and dynamics of such networks from a regional/city perspective (Scherngell 2021). This stream takes the distinct perspective offered by inter-city analysis, shifting attention to meso-level dynamics of knowledge exchange and collaboration, and emphasizing the crucial role of regional characteristics and policy environments. Moreover, the city-level lens offers a broader view of the innovation ecosystem, revealing patterns and trends that cannot be captured when focusing solely on individual actors or institutions.

By focusing on China in our empirical work, we study one of the most dynamic countries in terms of innovation over the past two decades. In this time period, China has not only enhanced its comprehensive innovation capacity, but also witnessed the remarkable evolution of its innovation network. From a policy perspective, the implementation of the innovation-driven development strategy has spawned diverse cross-region innovation collaboration demands. Particularly in the context of China's highly unequal distribution of innovation resources, peripheral regions urgently seek collaborations with other regions to tap into region-external knowledge sources. Inter-regional innovation cooperation is also increasingly becoming a crucial component of national innovation-driven development strategies as governments actively promote coordinated development of regional innovation. These efforts have shaped China's cross-regional innovation network in a profound way. In spite of the unique context of transformation and development, the Chinese innovation network shares similarities with other countries; that is, they have typical non-random network attributes, such as scale-free and small-world characteristics (Gay and Dousset 2005; Fleming et al. 2007; Stuck, et al. 2016; Li et al. 2015a, b; Pan et al. 2020). This suggests that cross-regional innovation linkages in China are not random or independent, but are endogenously shaped by network configuration, and exogenously by other factors, as in other countries. Additionally, some studies have investigated the typological features of China's innovation network and found clear evidence of preferential attachment and transitivity (Li et al. 2015a, b; Sun and Liu 2016; Zhou et al. 2017). Using ERGM models, a few studies further confirmed network structural effects as the main driving force in the evolution of China's innovation networks (Sun and Peng 2021; Dai et al. 2022).

Against this background, this study explores how specific network structural mechanisms influence the dynamics of these joint innovation activities. For our empirical foundation, we use an extensive and unique dataset, capturing joint innovation activities through co-patents among applicants spread across Chinese cities from 2007 to 2018. The latter reflects—in contrast to academic or project-based networks—technological co-development that is more proximate to commercially oriented R&D activities (see, e.g., Lata et al. 2015). By this, we aim to capture more market-driven innovation collaborations, offering deeper insights into the dynamics and impacts of such networks on regional and global innovation landscapes. In our study, we give attention to the connections and knowledge sharing at the micro (or individual) level of these networks, even as we examine the larger network dynamics at the city level. Recognizing the significance of these interactions across different levels, we aim to shed light on the mechanisms that drive innovation and collaboration within these systems. While the macro-level provides an aggregated perspective, it often serves as an essential lens through which the intricacies and dynamics of the micro-level can be more coherently deciphered and interpreted (Lomi et al. 2016). In the study at hand, the interactions and collaborations between applicants (micro-level) are embedded within the larger trend of co-patenting across cities. The city view helps in contextualizing these individual activities because they can be part of larger patterns or trends. Looking at the broader context, we are able to spot patterns, key areas of innovation, or even repeated themes that are not evident at the micro-level. Moreover, when we align our analysis with other macroeconomic indicators, it enables us to compare specific innovation contexts with those in other regions or cities, providing insights for benchmarking and strategic positioning. Accordingly, we intend to combine insights from network science with socio-economic discussions at the inter-city level in this study.

From a regional innovation perspective, previous works have highlighted the benefits of networks for regional innovation capabilities and efficiency, especially in times of rising costs for innovation, increasing uncertainty and risks, and rapidly changing global demand patterns (Breschi and Lenzi 2016; Broekel 2012; De Noni et al. 2017; Maggioni et al. 2007). Therefore, identifying drivers for cross-region interactions in innovation activities has become one of the main research issues, not only in a scientific context but also in a policy realm. Empirical studies so far have typically employed concepts and techniques from spatial interaction theory to explore drivers for cross-region innovation networks, often in relation to the proximity concept (Boschma 2005). Here, special emphasis has been put on how different types of proximities – such as geographical proximity, but also technological, cultural, or institutional proximities – affect collaborations in innovation activities between actors located in different regions (e.g., Vieira et al. 2022; Lim and Han 2023). While previous research also emphasizes the importance of network structural mechanisms that may be at stake in the formation and development of such networks, they stay rather vague in their empirical approach to identify such network structural mechanisms. This is mainly related to the usage of traditional spatial interaction models in this context that are not able to incorporate and estimate consistently endogenous network structural effects. The endogenous structural effects help to explain emergent properties of inter-city innovation networks, such as the formation of clusters, the emergence of influential hubs, and the dynamics of innovation flow. In addition, broader empirical insights on drivers for cross-region innovation networks are scarce for China, in particular at more detailed geographical levels below provinces, although the sustainable development of such cross-region collaboration networks is viewed as one of the main levers to increase the innovation capability of China as a whole (see, e.g., Yao et al. 2020).

Recent research has looked into what drives innovation networks between Chinese cities, mainly focusing on the effects of geographical proximity, technological proximity, and high-speed railways connection (Dong et al. 2021; Tang et al. 2022; Yao and Li 2022); only very few studies have considered structural network effects (Gao et al. 2024). This study aims to bridge the existing research gaps by exploring previously overlooked factors that drive the innovation networks between Chinese cities. We specifically shift our attention to how network structural mechanisms influence the dynamics of collaboration in joint innovation activities across Chinese cities. We move from the usually employed spatial interaction approach to the perspective of network inferential models given that conventional spatial interaction models require assumptions of independence between observations, and fail to incorporate endogenous structural effects of the observed network. Accordingly, the objective of the study is to estimate the role of endogenous network structural effects for shaping inter-city innovation networks across China. By network structural mechanisms, we refer to network relational drivers shaping the dynamics of a network. Such attributes can refer to node and dyad-specific characteristics determining the global structure and dynamics of a network from local configurations. Stochastic approaches capable of estimating such effects, in combination with other exogenous factors, are referred to as Exponential Random Graph Models (ERGMs) (Robins et al. 2007; Rivera et al. 2010). Few studies have used ERGMs to analyze the driving mechanisms behind inter-city innovation networks, with exceptions like Dai et al. (2022) who focused on scientific collaboration networks using two periods of co-publication data. Moving away from this, we shift our focus to technological collaboration and use the temporal version of ERGMs, namely TERGM, designed to address inter-temporal dependence in longitudinally observed networks (Leifeld et al. 2018). The examination of social networks is progressively focusing on understanding shifts over time, as longitudinal data analysis typically offers greater insights for interpreting network evolution and assessing the influence of its design on individual nodes (Steglich et al. 2010). We opt for TERGM to clarify the observed network structure over traditional statistical models, given its foundation on the premise of node and link (connection) interdependence.

The study at hand departs from existing literature in at least two major aspects: *First*, it is pioneering in investigating endogenous network structural effects while at the same time controlling for proximity effects at a very detailed geographical breakdown for Chinese regions (cities). This dual focus on endogenous and exogenous effects not only advances theoretical frameworks but also provides actionable insights for regional policy-making in China and globally. *Second*, it takes a TERGM perspective to study endogenous drivers for inter-city innovation networks, specifically through mechanisms of preferential attachment, transitivity, and link memory offering a novel lens to examine how innovation networks evolve and sustain over time.

The remainder of the study is organized as follows. Section 2 discusses the conceptual background, critically summarizing the theoretical debate on how different network structural effects drive dynamics of innovation networks. Section 3 formulates the problem for structural determinants and hypotheses, focusing on the role of preferential attachment, transitivity, and link memory in Chinese inter-city innovation networks. Section 4 explains in some detail the data and derives the temporal exponential random graph model as an instrument to capture such endogenous network structural effects. Section 5 presents the empirical results, starting with some descriptive elements that set the foundation for subsequent model estimations and their interpretations. Section 6 concludes the study, offering a summary, final remarks, policy recommendations, and suggestions for future research.

2 Conceptual Background: Structural Networks Effects in Inter-city Innovation Networks

The identification and estimation of factors influencing the dynamics of collaboration networks in joint innovation activities have gained increasing interest over the past decade. This is due to the growing importance of networks in modern innovation processes in times of rising R&D costs, growing complexity of knowledge production, and the related uncertainty of research processes (see OECD 1992, among others). In particular, the rising costs of R&D are often cited as one fundamental motivation for innovating actors to engage with and become embedded in innovation networks, as these may foster synergies between such actors in the network, and the emergence of a critical mass of the new knowledge. Moreover, innovating actors well embedded in networks may benefit from mutual learning and gain more effective access to complementary knowledge. This becomes increasingly vital in complex innovation environments that require a broader set of specialized competencies (see Granovetter 1985; Powell et al. 1996; Gulati 1998; Chesbrough 2006; Provan et al. 2007; Gilsing et al. 2008, among many others). From a regional perspective, the embedding in networks, particularly when distinguishing between intra- and cross-regional networks, has garnered increased attention in research (see Scherngell 2021 for an overview)[1]and has been intensively explored from angle of the proximity framework (Boschma 2005; Balland et al. 2013) shifting attention to the role of various types of proximity, especially geographical proximity.

Recently, scholars have emphasized that relying solely on the "traditional" proximity framework is inadequate for comprehending the dynamics of both cross-city and cross-regional innovation networks. This approach overlooks the endogenous network structural effects frequently discussed in social network analysis (see, e.g., Barthélemy 2011). A few recent works have therefore incorporated empirical drivers, referred to as network structural effects, to explain cross-regional innovation networks. Among these are the work of Bergé (2017), which focuses on the role of network distance in cross-regional networks, and studies by Neuländtner and Scherngell (2020) and Gao et al. (2024). The latter two, investigating the European and Chinese cases respectively, delve into the effects of simple network structural mechanisms, such as the gap in degree centralities (i.e., the number of network links) between two regions, on their likelihood to form additional network links. Even fewer studies shift attention to explaining endogenous network effects, as these are very difficult to be incorporated in classical spatial interaction frameworks and related estimation techniques. Broekel and Hartog (2013) employ an exponential random graph model to estimate determinants of cross-regional chemical R&D

[1] Recognizing the growing significance of networks for innovation, regional innovation capability is increasingly seen as a function of its position within webs of cross-region collaborations in innovative activities (Wanzenböck et al. 2014). From a geography of innovation perspective, the geographical nature of cross-city and cross-regional innovation networks has garnered particular interest (Feldman 1994). This emphasizes the geographically localized essence of innovation, which can be broadened by opening up network channels to other cities or regions, increasingly independent of close geographical proximity. These considerations triggered a whole literature stream investigating drivers for the geography of innovation networks (see Scherngell 2021 for an overview), mostly empirically addressed from a spatial interaction perspective. In this stream of literature, the proximity framework holds a central role (Boschma 2005; Balland et al. 2013). It hypothesizes that various types of proximity, especially geographical proximity in contrast to other forms like cognitive or technological proximity, are conducive to stimulating innovation networks between two regions. Furthermore, it examines how these different forms of proximities facilitate the establishment of cross-city network links. The empirical literature in this respect—by and large—points to an increased networking intensity across geographical space, but the majority of links still being geographically localized, and to important technological, cultural and institutional proximity effects shaping cross-regional innovation networks.

collaboration networks in Germany. A recent work by Dai et al. (2022) explores scientific collaboration networks in China.

In this study, we intend to contribute to this literature stream, shifting much greater emphasis on such network structural mechanisms, going beyond existing works, both conceptually and methodologically by employing methods from temporal exponential random graph models (TERGM, see Sect. 4.6). Conceptually we extend previous literature by stressing the importance of specific endogenous network structural mechanisms—derived from social network analysis—largely neglected so far. *First*, we stress the crucial role of preferential attachment mechanisms being at stake in the formation of links in innovation networks across nodes (see, e.g., Newman 2003; Leydesdorff and Rafols 2011), i.e., cities in this study. Preferential attachment is assumed to reinforce the dominance of established players and to contribute to the emergence of innovation hubs where clusters of nodes with high connectivity form around specific topics, technologies, or geographical spaces. As cities and regions with a high degree of connectivity continue to attract new links, they become even more central to the network and can become entrenched in their position of influence. Apart from the idea that cities with more collaborations attract even more partnerships, there are other factors influencing how cities form co-patenting links. Social network theory suggests that homophily is frequently the driving factor behind participants in a network choosing their partners (Zinilli et al. 2023). In simpler terms, actors who are "similar" are preferred when choosing a partner. The tendency for similar entities to associate with one another often plays a more foundational role in determining network structures than other factors.[2] When examining cross-city innovation networks, cities with similar technological development or those that share similar contexts – such as cities located in the same region – often drive collaborations (Gao et al. 2024).

Second, the specific structural mechanisms related to the creation of "cliques" in the network have been widely stressed in the literature, referred to as transitivity (Watts and Strogatz 1998; Hilbert et al. 2016). Transitivity describes the tendency for nodes to form clusters or groups within a network (Broekel and Bednarz 2019). In the context of innovation networks, transitivity is assumed to play a significant role in determining how links between nodes form and evolve over time, facilitating the spread of ideas and knowledge within clusters or groups of cities or regions (Burt 2007). As nodes within a cluster become more closely connected, they may develop shared or complementary technological priorities or goals, and can collaborate more easily on developing new ideas and innovations. However, as a disadvantage, transitivity may also contribute to the formation of "echo chambers" within innovation

[2] While geographical proximity can influence partnerships, the role a city plays as a hub in the network, highlighted by its high number of patents indicative of its vibrant innovative activity, might be even more significant. Emerging innovation areas might thus prioritize linking with established patent hubs over geographically nearby cities. On one hand, this can create a barrier to entry for new cities or regions struggling to establish the necessary connections, but on the other hand, hubs can act as hotspots of innovation and knowledge exchange, facilitating the flow of information and resources between regions in the network (Hua et al. 2021). Consequently, it is crucial to consider both homophily and other exogenous factors alongside endogenous ones in innovation networks.

networks, where groups of nodes become isolated from the wider network and may become resistant to new ideas or perspectives. This can lead to a lack of diversity and technological lock-ins, and can limit the potential for cross-disciplinary collaborations and knowledge exchange (Del Vicario et al. 2017).

Third, we believe that a temporal perspective is essential when investigating drivers for cross-city innovation networks. Prior acquaintance has been described at the organizational level as one of the most important drivers for partner choice in networks (Paier and Scherngell 2011), but has been largely neglected when investigating drivers for cross-city innovation networks. From a network science perspective, this is referred to as link memory, i.e., the tendency of nodes in a network to form connections with nodes they have interacted with previously, either directly or indirectly (Uzzi 1997; Rivera et al. 2010). This promotes the development of long-term collaborations and partnerships between cities, based on trust and shared understandings leading to more successful outcomes of the joint innovation activities. However, like transitivity, link memory can also contribute to the formation of "lock-in" effects, where nodes become stuck in existing patterns of collaboration and are resistant to change or innovation (Kilduff and Tsai 2003).

In our modeling approach, as described in the subsequent section, we shift attention to these significant network structural mechanisms as drivers for cross-regional innovation networks in China. Undoubtedly, the methodology of social networks offers a comprehensive toolkit to investigate these foundational factors. Moreover, we juxtapose them with the "traditional" drivers related to proximity, by controlling for some spatial and technological proximity dimensions in the model (see Sect. 4.5). This not only provides new insights into the role of network structural effects but also facilitates the identification of how these structural effects might influence the roles of geographical and technological proximity in the formation of innovation networks.

3 Problem Formulation for Structural Determinants and Hypotheses

Against these conceptual considerations, our analytical strategy applied to the case of Chinese inter-city innovation networks proceeds in two steps. First, we characterize our networks in terms of preferential attachment, transitivity, and link memory. Second, we use Temporal Exponential Random Graph Models (TERGM) to test these three structural statistics along with other exogenous statistics. During the formation of innovation networks, the preferential attachment mechanism and transitivity (or triadic closure) substantially influence the final structural and functional features of a network (Glückler 2007; Liu et al. 2015). The work by Barabási and Albert (1999) is a seminal study that proposes preferential attachment as the underlying mechanism responsible for the formation of scale-free networks. The concept of preferential attachment in network science is closely associated with another well-known concept, the Matthew effect, which describes the phenomenon where "The rich get richer, and the poor get poorer" (Merton 1968). Preferential attachment suggests that the likelihood of forming additional links increases based on the

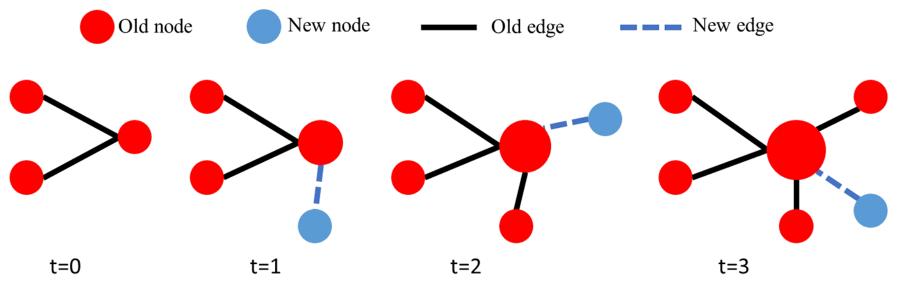

Fig. 1 Representation of preferential attachment mechanism

number of links a node already has. As innovation networks result from a continuous growth process due to the addition of new nodes and links, observing preferential attachment processes in inter-city innovation networks allows us to understand the real topology of the network. In undirected inter-city systems related to co-patenting, the inclination of cities to form patent collaborations embodies aspects of preferential attachment — i.e. the increased probability of central cities (in terms of patenting connections) to become even more pivotal. As a result of this attachment mechanism, cities that are hubs in the patent network gain new collaborations based on the collaborations they have already established. Therefore, in empirical studies focused on co-patenting activities between cities, preferential attachment is viewed as a mechanism that confers cumulative benefits, leading to varied levels of influence or significance within the network of cities involved in co-patenting. In several real networks (e.g., knowledge and innovation systems), preferential attachment and growth coexist. Following the classic linear preferential attachment implemented by Barabási and Albert (1999), the preferential attachment is given by:

$$\prod(k_i) = \frac{k_i}{\sum_j k_j}$$

Here, the probability that a link of the new node connects to node i, denoted as $\Pi(k)$, depends on the degree, k_i. Preferential attachment is a probabilistic mechanism, where the new node will tend to link with the node that already has many links in the network. Let $G(N, E)$ be an undirected graph; N is a set of nodes (e.g. Chinese cities), E representing the edge between nodes. A new node at time $T = 1$ is likely to link with the nodes that have the most edges, given a snapshot taken at time $t = 0$. Similarly, this process continues for the remaining times. As a result of this process, some cities become much more central than others. Figure 1 shows the representation of the preferential attachment mechanism across four time periods.

In Appendix Table 4, we present the average preferential attachment scores ($\Pi(k)$) for Chinese cities from 2007 to 2018. Additionally, the appendix delineates the number of new links activated for each city across the waves. In the context of intercity co-invention patent networks, preferential attachment may arise due to agglomerative factors. It is widely recognized that population and economic activity are spatially concentrated. Agglomeration refers to the concentration of economic activity and resources in specific regions or areas and plays a crucial role in the development of innovation and technology clusters in China (Fan et al. 2021). In the case of intercity networks, agglomeration may lead to a concentration of R&D activities in certain regions and clusters, which could result in preferential attachment as firms or researchers (both in the private and public sector) seek to collaborate with those who are already well-connected within these clusters. This could further reinforce the network structure, leading to the emergence of a scale-free topology, which in turn could attract even more collaborations due to the benefits of being part of a dense and well-connected network. As a result, cities with high centrality have more developed economies, higher R&D investments, and higher innovation performance than cities with low centrality. The preferential attachment process affords cities with high centrality a greater level of importance and influence within the network. This is because these cities have more connections or collaborations, making them more attractive to new partners seeking to join the network, and reinforcing their position as key players in the intercity networks of co-invented patents.

Hypothesis 1 Inter-city innovation networks in China show preferential attachment mechanisms.

We argue that the formation of collaborative ties in these networks is influenced by the agglomeration of economic activities and resources, as evidenced by previous studies. Empirical evidence supports this notion, suggesting that cities with higher centrality exhibit stronger ties and attract more collaborations over time. Transitivity (or triadic closure) suggests that if two nodes are connected to a common third node, they are likely to connect with each other (Broekel and Bednarz 2019). This can be shown by the number of triangles in a network. Such triangles are typically interpreted as indicators of social capital in knowledge and innovation networks (Coleman 1988), potentially enhancing trust among nodes as they work toward common objectives. Ter Wal (2014) confirmed the significance of transitivity (or triadic closure) in the evolution of a biotech network based on co-invented patents, emphasizing the role of transitivity in forming triads or clusters within a network. The study highlights that as the network grows and becomes more interconnected, the effects of geographic proximity may decrease, and the tendency towards triadic closure may become a more powerful mechanism for generating longer-distance collaboration ties. Consequently, transitivity mechanisms become a more powerful vehicle for generating new collaboration ties as the network evolves and grows. Additionally, using co-patenting data, Filippetti and Zinilli (2023) highlight the significance of transitivity effects in the development of innovation networks within European areas.

Assuming we refer to the same network mentioned earlier, nodes exhibit a tendency to form links with nodes with whom they share at least one mutual connection. Figure 2 illustrates transitive ties across four time periods.

Hypothesis 2 Transitivity mechanisms promote the formation of co-invented patent activity in the intercity networks.

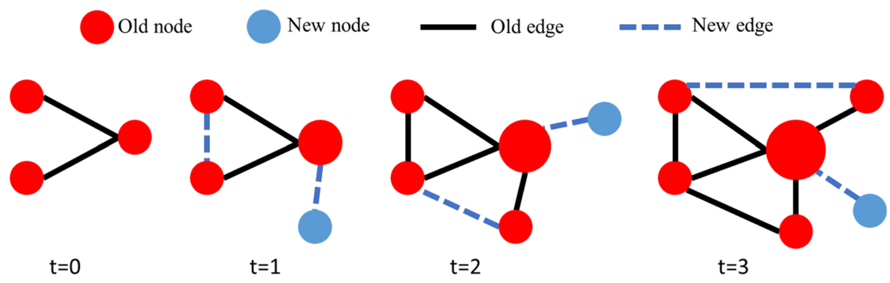

Fig. 2 Representation of transitive ties

By investigating the impact of transitivity mechanisms on the formation of co-invented patent activity within intercity networks, we seek to contribute to a deeper understanding of the dynamics driving innovation collaboration across geographical boundaries. Proving Hypothesis 2 will not only advance theoretical knowledge in the field of network science but also provide practical insights for policymakers and stakeholders aiming to foster innovation and economic development in intercity contexts.

Link memory denotes the propensity of network ties to form or persist based on the network's past tie history. This concept captures the idea that the creation of new ties in a network is influenced by both its current structure and the historical formation of ties. Link memory, in the context of cities' co-patenting activities, emphasizes the inclination of patenting ties between cities to continue over time. It suggests that co-patenting collaborations between cities are more probable if such collaborations have taken place previously. The consistent nature of these co-patenting ties, or in the patterns of recurrent collaborations, is a fundamental characteristic of such patenting networks and, more broadly, of relational systems. Bauer et al. (2022) investigated patent collaboration in a specific technological domain. They found that if an inventor pair has previously shared patents, they are more inclined to continue collaborating. These jointly obtained patents from the past signify a track record of effective collaboration, potentially enhancing the odds of their sustained partnership in subsequent innovations. In the context of co-patenting in Europe, Filippetti and Zinilli (2023) show that edge memory plays a significant role. This phenomenon indicates that co-patent linkages between cities persist over time, reflecting enduring collaborative relationships between entities across diverse geographical areas. Such past successes establish a foundation of trust, experience, and synergy between the inventor pair, fostering continued joint efforts in future ventures.

Hypothesis 3 Previous collaborations will positively influence the likelihood of future collaborations in co-invented patent activity within intercity networks.

By hypothesizing that previous collaborations positively influence the likelihood of future collaborations in co-invented patent activity within intercity networks, we aim to shed light on the mechanisms driving collaboration dynamics and network evolution. Proving H3 will contribute to a deeper understanding of how historical collaboration patterns shape the formation and persistence of collaborative ties ultimately informing strategies to foster innovation and collaboration in intercity contexts.

In co-patenting networks, the dynamics of cumulative advantages, network closure, and persistent collaboration have had little empirical representation in models like ERGMs. Few studies have so far delved into examining the temporal consistency of these approaches, especially in the context of patent collaboration dynamics. Both empirical evidence and theoretical perspectives highlight the importance of understanding that the effects of network dynamics are functions of the co-patenting process.

4 Data and Method

4.1 Data

In order to trace inter-city innovation networks in China, we make use of data on co-patent activities reflecting technological co-development and more proximate to market R&D activities, in contrast to project-based R&D or scientific collaborations (see, e.g. Lata et al. 2015; Scherngell 2021). The patents dataset we use is sourced from the Chinese State Intellectual Property Office (SIPO), which covers all invention patent application information from 2007 to 2018. Given the insufficient detail about the inventors in the dataset, we are not able to find the addresses of inventors. Thus, we investigated the address of each non-individual applicant. Using the co-applicant relationships, we constructed the innovation network. Specifically, if a patent has three applicants from cities A, B and C, then there exist three co-patenting collaborations between city-pair A-B, A-C and B-C.

4.2 Dependent Variable

The dependent variable represents the presence or absence of a co-patent linkage between two Chinese cities (n = 257) spanning the years 2007 to 2018. A linkage between two cities is established when at least two entities, be they companies or institutes from different cities, jointly apply for a patent. Thus, our primary unit of analysis is the dyad. We constructed an undirected network to describe inter-city patent relationships based on applicant regions. In this network, the cities are represented as vertices, while links denote relationships between them. Given the 257 cities, V_i represents the i_{th} city. An adjacency matrix $A = [a_{ij}]$ indicates patent collaboration between cities, where $a_{ij} = 1$ indicates collaboration between two cities and $a_{ij} = 0$ means no collaboration. Self-loops (i.e., links where a city connects to itself) are excluded. This binary approach captures the activation of links, revealing dynamics such as preferential attachment and triadic closure. By observing these transitions, we assess whether nodes with existing connections attract new links or participate in forming closed loops. To represent the dynamic mechanism of innovation collaboration and to mitigate the influence of patent application data fluctuations, we divided the entire period into four sub-periods.

4.3 Structural Network Level Variables

We consider preferential attachment, transitivity, and link memory as the endogenous structural features. The term *GWDegree* is used to model the degree distribution and capture the skewed degree distribution (network concentration or preferential attachment) in ERGMs (Young et al. 2023). For the transitivity effect, we use the *GWESP* statistic, and for link memory, we use the memory statistic. We include four variables at the structural network level:

- Edge statistic (edges) represents the number of edges in the network. This measure captures the network density effect and can be treated as a "base rate" analogous to the intercept term in OLS.

$$\sum_{i<j} y_{ij}$$

- *Geometrically weighted degree statistic (GWDegree),* this comes with gk(α) indicating the exponential weight function and helps to model the observed network's degree distribution.

$$\sum_k g_k(\alpha)D_k(y)$$

  Broadly, *GWDegree* enables the modeling of preferential-attachment processes. Specifically, a negative coefficient for this statistic indicates the presence of preferential attachment, while a positive coefficient suggests anti-preferential attachment (Hunter 2007). In our study, the decay parameter is consistently fixed, first at 0.1 and then at 0.5 (following Wang et al. 2023); in both instances, the parameters remain unchanged.
- *Geometrically weighted edgewise shared partner statistic (GWESP)* is a function of the edgewise shared partner statistics $\mathrm{ESP_k(y)}$, which represents the number of unordered connected pairs *(i, j)* (partners) that are both connected to exactly *d* other nodes:

$$e^{\alpha}\sum_{k=1}^{n-2}\left\{1-(1-e^{-\alpha})^{k}\right\}ESP_k(y)$$

  Here, $ESP_k(y)$ refers to the number of edges with exactly *k* shared partners, and α is a decay parameter. A larger decay parameter indicates slower decay (Hunter 2007). A positive coefficient for this statistic points to a tendency towards triadic closure in the network. For computational ease, the decay parameter for *GWESP* was first set to 0.1 and then to 0.5 (following Leifeld et al. 2018; Wang et al. 2023). In both scenarios, the parameters remain unchanged.

- *Link Memory* captures the temporal processes specified in the model without reflecting other network structures. Essentially, it denotes a dyadic stability memory term—indicating whether ties and non-ties at a certain time persist in the subsequent time frame. This captures the consistency (or inconsistency) of the links over time (Leifeld et al. 2018).

4.4 Node Level Variables (Control Variables)

The node level variables capture the effects of some relevant city characteristics on cross-city joint innovation activities. Referring to the common practice in existing literature, we select the following variables from the "China Urban Statistical Yearbook" to describe the characteristics of cities (e.g. Sun and Peng 2021).

- *Capital* is a dummy variable to capture the impact of administrative hierarchy on collaborative innovation among cities. If the city is a provincial city, the value equals 1, otherwise is 0.
- *Education* represents the number of college students per 100 urban residents. It measures the impact of urban education development on urban innovation capacity.
- *Gdp* is per capita GDP and deflated to constant 2010 levels using the consumer price index. This variable captures the potential impact of comprehensive economic factors on urban innovation capacity.
- *Population* is the number of residents in a city. This variable is used to control the population size effects on urban innovation capacity.

4.5 Dyad Level Variables

Apart from the generally used variables in related literature, we also consider other variables that reflect the characteristics of China, including the rapid development of urban agglomerations and high-speed railways (Yang et al. 2022). The variables we have chosen are as follows:

- *Same province* equals 1 if two cities belong to the same province, and 0 otherwise. Cities belonging to the same province share similar institutional environments and have lower transaction costs in the process of innovation collaboration.
- *Same region* is another dummy variable to indicate institutional proximity. Cities within the same urban agglomeration tend to have more frequent and closer economic ties spontaneously. Besides, the Chinese government has largely promoted innovation coordination in the inner urban agglomeration regions in recent years (Ma et al. 2023). The scope of the region is defined according to Fang (2020).
- *Geographic Distance* is measured by the Euclidean distance between the geometric centers of two cities.
- *Technological Distance* represents the technological distance between two cities, determined by the differences in their technological domain distributions.

This variable serves as a common proxy for cognitive distance, reflecting the costs associated with bridging different technological fields to innovate. A detailed calculation method can be found in Gao et al. (2024).
– *HSR* is set to 1 if two cities are directly connected by a high-speed railway without any transfers required, and 0 otherwise.

4.6 The Temporal Exponential Random Graph Model

To account for inter-temporal dependence in longitudinally observed networks, we use the Temporal Exponential Random Graph Model (TERGM), an extension of the Exponential Random Graph Model (ERGM) (Hanneke et al. 2010; Leifeld et al. 2018). The TERGM is especially well-suited for the study of knowledge and innovation networks. It employs a Markov structure, allowing us to estimate a network's transition between two consecutive time periods using various structural network configurations (e.g., *GWDegree* and *GWESP*) and network exogenous characteristics (Zinilli 2016; Zinilli and Cerulli 2023). TERGM allows us to observe the networks at discrete and equidistant time points. The SAOM model (Stochastic Actor-Oriented Model) has also been applied to longitudinal networks (Balland 2012; Balland et al. 2013). For an in-depth understanding of the empirical comparison of the two models, we refer to Leifeld and Cranmer (2019). We selected the TERGM over the SAOM, which is based on actor-based behavioral assumptions, as we are modeling an inter-city network (Block et al. 2018; Park and Newman 2004). TERGM offers statistical inference procedures that account for the non-independence of network ties and the potential for network autocorrelation. This approach provides more robust estimation and hypothesis testing compared to traditional models, which might not address the unique challenges of network data analysis adequately. Moreover, TERGM is designed explicitly to model the dynamics of network data over time, taking into account dependencies and interrelationships between network ties. Traditional models, such as generalized linear models, typically do not consider the complex dependencies inherent in network data, potentially leading to biased or misleading results. As a result, we use the TERGM to describe observed network structures because it operates on the assumption of node and link dependence (through the so-called Markov dependence).

In the typical ERGM, the likelihood of seeing a specific network is determined by a set of statistics h from the network N (for instance, counts of transitive triads or attributes linked to pairs). The factor $c(\theta)$ takes into account the chances of other possible networks that could form with the given nodes.

$$P(N,\theta) = \frac{\exp\left(\theta^T h(N)\right)}{c(\theta)}$$

The TERGM expands upon the ERGM. Instead of determining the probability of a network at a specific time, t, based just on counts of its current subgraphs, it also incorporates data from previous networks up to t-K:

$$P\left(N^t|N^{t-K},\ldots,N^{t-1},\theta\right)=\frac{\exp\left(\theta^T h\left(N^t,N^{t-1},\ldots,N^{t-K}\right)\right)}{c\left(\theta,N^{t-K},\ldots,N^{t-1}\right)}$$

The assumption here is that the statistics derived from networks between $t-K$ and t capture all the relationships evident in the network at time t. Assuming that earlier networks in a time sequence do not influence later ones, the likelihood of seeing the networks within a specific timeframe can be deduced by multiplying the probabilities for each specific time:

$$\mathrm{P}(\mathrm{N}^{\mathrm{K}+1},\ldots,\mathrm{N}^{\mathrm{T}}|\,\mathrm{N}^{1},\ldots,\mathrm{N}^{\mathrm{K}},\theta)=\prod_{\mathrm{t}=\mathrm{K}+1}^{\mathrm{T}}\mathrm{P}\left(\mathrm{N}^{\mathrm{t}}|\mathrm{N}^{\mathrm{t}-\mathrm{K}},\ldots,\mathrm{N}^{\mathrm{t}-1},\theta\right)$$

The equation describes the joint probability as the product of conditional probabilities for the network at each time step t, given the networks from $t-K$ up to $t-1$. The TERGM undertakes that the transition from Y_{t-1} to Y_t is generated according to an exponential random graph distribution with the specific parameter θ (Leifeld and Cranmer 2019). When estimating the ERGMs, or its extension such as the TERGM, the normalization constant $c(\theta)$ in the case of ERGM or $c\left(\theta,N^{t-K},\ldots,N^{t-1}\right)$ in the case of TERGM is frequently an impediment (except for very small networks) since an analytical calculation is not possible. This is because it requires summation over all possible networks. Usually, to address this issue a Monte Carlo-Markov maximum likelihood estimation (MCMC-MLE) is used. For TERGMs, maximum pseudolikelihood with bootstrap confidence intervals (Desmarais and Cranmer 2012) and Markov chain MCMC-MLE can be used. MCMC-MLE serves as an alternative to the bootstrapped pseudolikelihood inference method. Here, we used both methods. In TERGM, a significant positive parameter indicates that the associated configurations occur more frequently than expected by chance. Conversely, a significant negative parameter suggests less frequent occurrence than expected.

Degeneracy, which occurs when the majority of the probability mass is assigned to network realizations that result in either complete or empty networks, is a problem that frequently arises when fitting ERGM (or its generalizations) with endogenous network statistics (Schweinberger 2011). Because we use structural network configurations such as Geometrically-weighted degree (*GWDegree*) and Geometrically-weighted edgewise shared partner statistic (*GWESP*), the model might not converge. It may be unable to find a better model, thus degenerating. The quality of a non-degenerated model in simulating the observed network must be further tested. For this reason, we compare the average statistical values of the observed network with the simulated networks to determine goodness-of-fit. The Goodness-of-Fit plots for the Temporal ERGM of the four networks from 2007 to 2018 is in the Appendix Fig. 4. The similarity of the two distributions indicates that our TERGM adequately describes the observed network.

Table 1 Network Statistics from 2007 to 2018

Period	Nodes	Edges	Average distance	Density	Degree centralization	Number of triangles
2007–2009	257	1.543	2,27	0,05	0,64	5.493
2010–2012	257	2.570	1.99	0,08	0,84	13.380
2013–2015	257	3.617	1,91	0,11	0,86	26.504
2016–2018	257	4.627	1,87	0,13	0,84	42.295

5 Results

5.1 Descriptive Analysis

As a complement to the TERGM exercise, we examined the evolution of network metrics over four distinct periods, spanning from 2007 to 2018. Table 1 below provides a comprehensive overview of the network statistics for each period. Specifically, it counts the number of nodes (cities) and edges, the average distance between nodes, network density, degree centralization, and the number of triangles. The average distance is the average shortest path between two nodes. Density refers to the ratio of actual links in the network to the maximum possible number of links. Degree centralization measures how much the connections in the network are concentrated around a single node or a select few (Valente et al. 2015). A triangle consists of three nodes that are interconnected with each other. This data sheds light on the temporal dynamics of the network, revealing patterns of growth, connectivity, and clustering.

Table 1 provides insights into the evolution of co-patenting relationships among Chinese cities from 2007 to 2018. Over this period, there are some interesting dynamics in the evolution of the collaborative patenting landscape. We observe an increasing number of connections between cities, as evidenced by the growing number of edges. As shown by the average edges per node, we can see how the relationships grow relative to the number of cities (nodes). Starting with 1.543 unique connections in the 2007–2009 period, the collaborations nearly tripled by 2016–2018. This increase suggests that cities were indeed actively generating more partnerships. In this co-patenting network, the average distance between two cities, which measures how closely they are connected, has decreased over time. By 2016–2018, the average distance has reduced to 1,87, suggesting that cities became more interconnected. Also, network density, which measures the level of interconnectivity of the network, increased from 0,05 in 2007–2009 to 0,13 in 2016–2018. This shift underscores the fact that over time, the network of cities became much denser, highlighting a more conducive environment of shared patenting activities. Degree centralization remained relatively high and consistent, particularly from 2010 onwards. This could imply that the co-patenting activities might be concentrated around certain key cities or hubs, possibly acting as innovation centers in patenting endeavors. Lastly, the rise in the number of triangles from 5.493 to 42.295 shows that the network is not just expanding randomly. Instead, cities seemed to form more clustered

Table 2 Evolution of new links activated across successive waves

Wave 3—> Wave 4	Wave 4—> Wave 5	Wave 5—> Wave 6
2.988	3.600	4.144

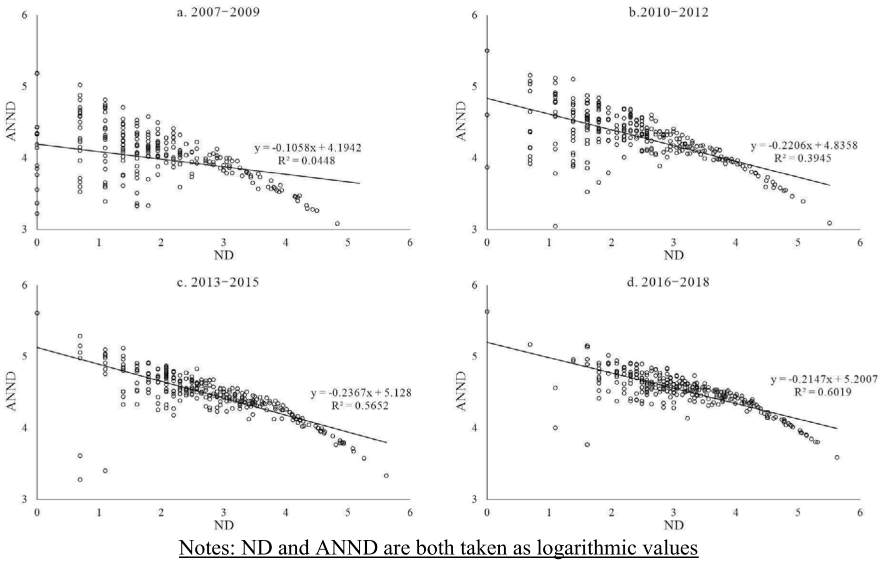

Fig. 3 The correlation between ND and ANND

groups where, if two cities were collaborating, they were likely sharing a common partner, adding another layer of connectivity.

Table 2 presents the count of new links formed between each wave and its preceding one. For each pair of consecutive waves, the value in the table represents the number of new links formed between them, illustrating the growing trend of collaborations over time.

Both Tables 1 and 2 show that the innovation network in China has been growing over time. More cities are joining in, and they are making more connections with each other. What we observe is that cities do not simply strengthen ties with their previous partners; they also form connections with new ones. This suggests that, within the Chinese landscape, the innovation network is not only growing in scale but is also evolving dynamically in terms of its structural features.

To further illustrate the evolutionary development of China's innovation network, Fig. 3 shows the correlation between the degree (ND) and the average nearest-neighbor degree (ANND) of a city at different time periods.[3] As shown in Fig. 3,

[3] The degree of a city refers to the number of cities with which it has innovation links, while the ANND refers to the average degree of other cities with which it has innovative links.

innovation networks at different periods all present significant heterogeneous characteristics, and this becomes more pronounced over time, suggesting that cities with fewer innovation partners are more likely to collaborate with cities with extensive innovation links. This result is consistent with experiences on the Chinese innovation landscape. Constrained by the extremely uneven distribution of innovation resources in China, cities with weak innovation resources encounter challenges in accessing adequate innovation support from peers of similar capacity. Thus, they are more willing to cooperate with these advantaged cities, which are more easily engaged in innovation activities. During the period spanning from 2007 to 2009, Beijing forged partnerships with 178 cities, whereas nearly 70% of cities managed to connect with fewer than 10 counterparts. As time progressed, the unequal distribution of innovation resources has intensified, leading to a growing heterogeneity within the innovation network. Between 2016 and 2018, Beijing further solidified its dominant position by collaborating with nearly 97% of cities.

5.2 Model Results: the TERGM

In this section, we present the results of the TERGM estimation, using both Maximum pseudolikelihood with bootstrap confidence intervals (MPLE) and Markov chain Monte Carlo maximum likelihood estimation (MCMC-MLE). The fitting of the models is converged for both the models; the MPLE model was estimated with 1,000 bootstrap replications to infer valid confidence intervals (a 95% confidence interval is shown around the estimates) as described by Desmarais and Cranmer (2012). The coefficients in the MPLE model are considered significant when zero is outside the confidence interval.

For Model 2 (Table 3), the goodness-of-fit plot (including the ROC curve) has been generated and can be found in the Appendix, Fig. 4. Goodness of fit analysis allows us to assess how well our model captures the observed network structure. By comparing simulated network statistics with those observed in the real data, we can verify the validity of our model. The ROC curve (in the Appendix Fig. 4.) provides an assessment of the predictive performance of our model. By plotting the trade-off between sensitivity and specificity across different threshold values, ROC curves offer insights into the model's ability to discriminate between different outcomes (presence or absence of network links). Finally, the use of both MPLE and MCMC-MLE enhances the validity of our results by evaluating the consistency and stability of our outcomes under different conditions (as a robustness check).

Small variations in the coefficient values are evident between Model 2 and Model 3 when using both the MPLE and MCMC-MLE estimation techniques. The disparities in coefficient values between the models can be attributed to the intrinsic differences between the two estimation methods. However, despite these variations, the significance and direction (sign) of the coefficients remain consistent across both models.

Model 1 focuses exclusively on endogenous variables, providing a window into the inherent dynamics of the network without exogenous variables. The *Edges* parameter quantifies the total number of connections present within the network in relation to all potential links that could be formed. Consistently across all models,

Table 3 Temporal Exponential Random Graph Model (TERGM) results for intercity co-patent network from 2007 to 2018

	Maximum pseudolikelihood with bootstrap confidence intervals (MPLE)								Markov chain Monte Carlo maximum likelihood estimation (MCMC-MLE)			
	Model 1				Model 2				Model 3			
Variable	Estimate	Boot mean	2.5%	97.5%	Estimate	Boot mean	2.5%	97.5%	Estimate	Std. Error	t value	Pr(>|t|)
Edges	-3,85	-5,88	-12,43	-3,31	-27,49	-28,53	-31,49	-26,67	-30,3	0,54	-55,66	2,20E-16 (***)
GWDegree	-20,88	-37,27	-50,68	-16,22	-3,05	-4,64	-26,89	-1,32	-0,54	0,39	-1,39	3,20E-15 (***)
Transitivity (GWESP)	2,64	4,47	2,04	13,02	0,72	0,96	0,65	4,41	1,29	0,15	8,74	2,20E-16 (***)
Dyadic stability (edge memory)	1,77	1,77	1,69	1.83	1,01	0,98	0,89	1,01	0,94	0,02	54,30	2,70E-16 (***)
Capital					0,26	0,26	0,24	0,28	0,20	0,04	4,55	7,20E-16 (***)
Education					0,17	0,17	0,16	0,19	0,16	0,006	25,22	5,38E-06 (***)
Population					0,01	0,001	0,001	0,001	0,001	0,00003	41,89	4,25E-04 (***)
Gdp					1,07	1,10	1,03	1,23	1,15	0,02	46,39	3,64E-15 (***)
Same region					0,13	0,14	0,11	0,18	0,001	0,04	0,02	2,80E-08 (***)
Same province					2,23	2,24	2,19	2,42	2,26	0,05	43,55	7,10E-16 (***)
Geo. Distance					-0,01	-0,001	-0,0002	-0,0001	-0,0001	0,00003	-3,35	1,06E-08 (***)
Tech Distance					-0,36	-0,32	-0,39	-0,19	-0,50	0,07	-7,19	6,26E-13 (***)
High-speed rail (Hsr)					0,38	0,35	0,24	0,42	0,28	0,06	4,64	3,54E-06 (***)

** $p < 0.01$; *** $p < 0.001$

this term exhibits a statistically significant negative coefficient. The negative and significant coefficient of *GWDegree* suggests a centralizing force. It seems there is a propensity to distribute ties disproportionately, amplifying the significance of certain cities over others. This can be seen as evidence of the central role some cities play in fostering connections. The concept of Triadic Closure is captured by the geometrically weighted edgewise shared partner (*GWESP*). This term evaluates the network's closure effect, essentially capturing the phenomenon of transitivity where nodes are inclined to form connections if they share mutual neighbors. With its positive coefficient, it indicates that if two cities share a common connection, they are more likely to connect themselves. This emphasizes the network's tendency for clustering, where cities are inclined to form interconnected groups. Furthermore, the positive coefficient for Dyadic stability (edge memory) is revealing, indicating that once cities form ties, they tend to maintain them over time, attesting to the resilience and stability of these connections.

When we delve into the coefficients associated with node attributes and pairwise relationships in Model 2 (the complete model), we observe that while the direction (sign) of the endogenous coefficients remains consistent, the magnitude or weight of each parameter changes. The introduction of exogenous variables modulates the relationships established by endogenous ones, potentially diminishing the initially observed effects. The significant and positive coefficient for the *Capital* variable underscores that capital cities, with their inherent advantages, are more inclined to foster connections. The *Education* variable also bears a positive and significant coefficient. Its estimate in the MPLE model suggests that cities with higher education levels are more likely to form links. *GDP* and *Population*, both with positive coefficients, suggest that cities with strong economic outputs and larger populations have a higher tendency to establish links. The formation of links in our network is also influenced by geographic proximity. The significant coefficients for *Same province* and *Same region* variables indicate that cities within the same provinces or regions are more likely to collaborate. The *Same province* variable has a higher log-odds, suggesting that cities within a shared province exhibit an even stronger tendency to form connections compared to cities in the same broader region. This could be due to more localized cultural, economic, or administrative synergies that make inter-city collaboration within a province more seamless and productive. The coefficient for *Geographical Distance* variable is negative, indicating that as the distance between two cities increases, the likelihood of collaboration between them decreases. Similarly, the *Technological Distance* coefficient suggests that differences in technological capabilities between cities can reduce the chances of collaboration. Lastly, the introduction of infrastructure such as *High-Speed Rail (HSR)* appears to have a strong impact on innovation networks. With its positive coefficient, the presence of a high-speed rail connecting two cities indicates an increased likelihood of those cities forming ties, likely serving as a conduit for enhanced collaborations.

Cross-city innovation networks in China are shaped by a dynamic interplay of various forces, both endogenous and exogenous. The network structure, represented by factors such as preferential attachment and triadic closure tendencies, provides the foundational dynamics for these networks. Central cities emerge as key nodes, amplifying the network's connectivity and acting as primary hubs for innovation. Preferential attachment (as represented by the *GWDegree* term) with a coefficient of -3.05 plays a significant role in the network dynamics. This suggests that certain cities draw in more connections, potentially due to their existing network strength. Meanwhile, external variables, from economic strengths to geographical and technological proximities, further shape the nature of connections. Additionally, infrastructural advancements, such as the introduction of High-Speed Rail, facilitate and deepen these inter-city collaborations, reinforcing the idea that connectivity, both in terms of knowledge and physical infrastructure, is important. This suggests that while the formation of ties between cities in innovation contexts is influenced by their intrinsic assets, such as infrastructural advantages or economic capability, the mechanism of preferential attachment is clearly evident. Its role appears to be more dominant among the endogenous factors.

6 Conclusions

Networks of innovating actors are nowadays considered essential for the successful generation of innovations. The capability of cities and their embeddedness in such networks has therefore attracted increasing attention in the recent past, not only in a scientific context but also by policy makers, in particular regional innovation policies. A central contemporary debate within the research stream investigating the structures and dynamics of such networks concerns the identification of drivers for collaboration in innovation activities between cities. While geographical and technological determinants have already been studied by the pioneering works in this field, more recently, emphasis has been shifted to the role of more intangible drivers for innovation networks. In this context, and inspired by network science, network structural mechanisms have gained increasing attention, but robust empirical insights are yet scarce. Against this background, this study has focused on the exploration of such network structural drivers for cross-city innovation networks in China. The study employed novel and highly detailed empirical data on cross-city innovation activities, as captured by co-patenting between applicants located in different cities. In order to capture dynamics of the network under consideration, we advance previous research that uses standard spatial interaction models (see Gao et al. 2024) by developing a temporal version of Exponential Random Graph Models (TERGM). Such models are highly suitable to incorporate endogenous network structural characteristics in predicting the innovation collaboration intensity between city pairs, controlling for standard drivers included in previous works, such as geographical or technological distance. In particular, we shift attention to preferential attachment, transitivity and network stability as potentially highly important drivers for the dynamics of cross-city innovation networks.

The results are very promising and suggest that endogenous network effects indeed play an important role for the evolution of innovation networks between cities in China. In essence, there is recognition of three important driving forces:

- *First*, the positive effect of preferential attachment indicates that well-connected cities attract more collaborations, reinforcing their centrality in the network. Cities that already have a large number of co-patents with other cities are more likely to attract new co-patents, compared to cities with a smaller number of co-patents. This could be due to a variety of factors, such as a concentration of resources or expertise in certain cities, or a tendency for researchers or companies to establish collaborations with existing partners rather than seeking out new ones. Another possibility is that cities with a higher number of co-patents may have better access to funding, resources, and expertise, which could make them more attractive collaborators for other cities. These cities may also have a higher level of visibility and reputation in the field of research or industry, which could make them more appealing partners. Moreover, researchers or companies may have a tendency to collaborate with existing partners rather than seeking out new ones. Over time, this could lead to a network in which a few cities have a much higher number of co-patents than the rest of the network.
- *Second*, transitivity emerges as an important driver, reflecting the tendency for cities within the same regional clusters to form tightly knit groups, enhancing local innovation ecosystems by representing regional hubs of innovation or centers of excellence in particular fields or industries.
- *Third*, link memory is crucial, highlighting the persistence of collaborations over time, which stabilizes the network structure. This suggests enduring and reliable partnerships that contribute significantly to innovation. Stable connections imply consistent interaction and trust among innovators, leading to sustained knowledge exchange and joint innovation efforts over time. This stability can foster the development of long-term collaborative relationships, which are crucial for achieving impactful and sustained innovation outcomes. Additionally, stable collaborations may indicate consortia within specific industries or technological domains, providing a solid foundation for future collaborative endeavors and promoting regional innovation ecosystems.

The results show that endogenous network effects significantly drive inter-city innovation networks but do not replace exogenous proximity effects, such as geographical and technological factors. Geographical distance still decreases the likelihood of collaboration between cities, as also does technological distance. Infrastructure increasing connectivity between cities, such as High-Speed Rail (HSR), also appears to have a strong impact. Overall, the main outcome and contribution of the study lies in the original estimation of structural network effects in innovation networks, specifically through the mechanisms of preferential attachment, transitivity, and link memory. While these mechanisms offer not only a novel lens to examine how innovation networks evolve and sustain over time, the study underscores the enduring relevance of geographical and relational proximities in network formation. This dual focus not only advances theoretical frameworks but also provides actionable insights for regional policymaking in China and globally. In a Chinese policy context, enabling lagging regions to participate in such networks, and to get attached to other well connected other regions becomes even more important in view of the empirical results. At the same time, the results can be an important input for regional policy makers in order to align regional policies initiated locally with the relative positioning of the region to other regions, not only in geographical and technological, but also in network space. Strategic linking with other central cities may increase the centrality of the region in the mid- to long-term.

Clearly, this study produces some interesting results, but also has some limitations that suggest directions for future research. *First*, the study is limited to technological innovation networks by focusing on inter-city co-patenting. Given that this is only one form of joint R&D activities, a comparison to other forms, such as project-based R&D collaboration, would be interesting, both in a scientific and a policy context. *Second*, the study does not control for technological or sectorial heterogeneities that have recently been increasingly discussed as an important property of innovation networks (see Neuländnter and Scherngell 2020). This would be an important complementary element in future research. *Third*, comparisons with other geographical areas, such as the US or Europe, are of great interest, in order to delineate the more China-specific from general results obtained in this study.

Appendix A

Table 4 Preferential attachment score (mean 2007-2018) and new links activated by city

City	Π(k) 2007-2018	Wave 3 -> Wave 4	Wave 4 -> Wave 5	Wave 5 -> Wave 6
Beijing	0,0409	63	18	6
Tianjin	0,0188	52	48	39
Shijiazhuang	0,0093	29	29	29
Tangshan	0,0042	10	17	26
Qinhuangdao	0,0044	10	13	16
Handan	0,0031	11	22	17
Xingtai	0,0025	7	8	7
Baoding	0,0077	21	32	28
Zhangjiakou	0,0027	7	23	11
Chengde	0,0010	4	5	9
Cangzhou	0,0030	16	9	16
Langfang	0,0049	15	19	31
Hengshui	0,0025	8	5	17
Taiyuan	0,0098	22	37	34
Datong	0,0017	6	6	23
Yangquan	0,0008	4	1	12
Changzhi	0,0031	20	14	17
Jincheng	0,0012	3	6	11
Shuozhou	0,0006	1	6	4
Jinzhong	0,0019	9	7	11

City	Π(k) 2007-2018	Wave 3 -> Wave 4	Wave 4 -> Wave 5	Wave 5 -> Wave 6
Yuncheng	0,0018	5	7	12
Xinzhou	0,0007	4	3	7
Linfen	0,0015	3	9	7
Lvliang	0,0012	3	4	6
Hohhot	0,0044	23	13	25
Baotou	0,0026	10	12	17
Wuhai	0,0011	8	3	8
Chifeng	0,0010	2	10	4
Tongliao	0,0014	2	8	10
Erdos	0,0022	5	21	16
Bayannur	0,0011	4	3	14
Shenyang	0,0137	36	39	39
Dalian	0,0118	32	33	34
Anshan	0,0044	12	30	22
Fushun	0,0026	14	13	9
Benxi	0,0011	6	7	3
Dandong	0,0019	5	9	17
Jinzhou	0,0022	3	14	15
Yingkou	0,0014	3	7	11
Fuxin	0,0018	11	9	11
Panjin	0,0013	2	6	7
Tieling	0,0012	6	5	10
Chaoyang	0,0008	2	2	2
Huludao	0,0015	9	6	13
Changchun	0,0100	26	26	39
Jilin	0,0033	10	21	20
Siping	0,0012	5	3	6
Liaoyuan	0,0005	3	0	5
Tonghua	0,0010	3	4	7
Baishan	0,0008	1	5	4
Songyuan	0,0010	4	6	2
Harbin	0,0099	27	38	45
Qiqihar	0,0014	6	3	6
Jixi	0,0006	1	2	3
Shuangyashan	0,0004	2	1	3
Daqing	0,0019	9	10	13
Jiamusi	0,0015	6	10	6
Mudanjiang	0,0010	3	6	5
Suihua	0,0009	5	4	5
Shanghai	0,0291	48	45	38
Nanjing	0,0230	50	56	39
Wuxi	0,0131	41	33	48

City	Π(k) 2007-2018	Wave 3 -> Wave 4	Wave 4 -> Wave 5	Wave 5 -> Wave 6
Xuzhou	0,0074	26	31	27
Changzhou	0,0094	30	18	29
Suzhou	0,0136	28	42	37
Nantong	0,0070	26	17	33
Lianyungang	0,0040	16	20	19
Huaian	0,0034	13	15	20
Yancheng	0,0053	25	14	14
Yangzhou	0,0065	24	15	21
Zhenjiang	0,0082	23	31	21
Taizhou	0,0047	13	19	23
Suqian	0,0025	17	11	13
Hangzhou	0,0166	38	38	45
Ningbo	0,0088	32	31	22
Wenzhou	0,0062	22	22	20
Jiaxing	0,0069	24	28	14
Huzhou	0,0047	18	15	22
Shaoxing	0,0077	25	23	31
Jinhua	0,0055	17	16	17
Quzhou	0,0028	5	12	18
Zhoushan	0,0021	9	15	11
Taizhou	0,0060	14	15	24
Lishui	0,0021	10	4	8
Hefei	0,0127	36	30	38
Wuhu	0,0033	13	16	21
Bengbu	0,0028	11	19	16
Huainan	0,0033	7	14	18
Maanshan	0,0029	8	13	20
Huaibei	0,0015	11	3	11
Tongling	0,0015	9	8	9
Anqing	0,0019	6	6	9
Huangshan	0,0017	6	4	17
Chuzhou	0,0025	12	11	9
Fuyang	0,0012	7	3	17
Suzhou	0,0016	3	4	19
Lu’an	0,0015	8	7	15
Chizhou	0,0009	5	4	6
Xuancheng	0,0020	6	8	12
Fuzhou	0,0070	14	30	23
Xiamen	0,0085	21	38	26
Putian	0,0010	1	4	10
Sanming	0,0024	11	7	16
Quanzhou	0,0043	13	13	15

City	Π(k) 2007-2018	Wave 3 -> Wave 4	Wave 4 -> Wave 5	Wave 5 -> Wave 6
Zhangzhou	0,0033	16	17	22
Nanping	0,0019	3	15	11
Longyan	0,0017	5	2	14
Ningde	0,0019	4	12	14
Nanchang	0,0074	14	35	39
Jingdezhen	0,0010	5	5	9
Pingxiang	0,0007	1	4	10
Jiujiang	0,0025	8	13	16
Xinyu	0,0007	3	4	9
Yingtan	0,0010	2	3	5
Ganzhou	0,0034	15	18	21
Ji'an	0,0019	10	15	9
Yichun	0,0025	8	16	7
Shangrao	0,0015	5	9	11
Jinan	0,0125	28	48	33
Qingdao	0,0151	49	35	41
Zibo	0,0063	15	26	29
Zaozhuang	0,0019	7	4	16
Dongying	0,0041	13	20	24
Yantai	0,0069	24	26	32
Weifang	0,0044	13	15	25
Jining	0,0046	12	17	25
Tai'an	0,0042	12	24	26
Weihai	0,0042	5	28	18
Rizhao	0,0011	4	8	5
Linyi	0,0034	5	24	22
Dezhou	0,0034	14	12	26
Liaocheng	0,0020	8	10	17
Binzhou	0,0026	9	16	28
Heze	0,0022	10	13	13
Zhengzhou	0,0133	33	34	45
Kaifeng	0,0018	9	9	10
Luoyang	0,0058	20	23	23
Pingdingshan	0,0029	5	19	21
Anyang	0,0020	5	4	19
Hebi	0,0013	5	6	5
Xinxiang	0,0034	10	15	30
Jiaozuo	0,0026	8	20	20
Puyang	0,0018	10	11	13
Xuchang	0,0045	18	24	29
Luohe	0,0008	2	4	9
Sanmenxia	0,0013	2	9	5

City	Π(k) 2007-2018	Wave 3 -> Wave 4	Wave 4 -> Wave 5	Wave 5 -> Wave 6
Nanyang	0,0023	4	8	20
Shangqiu	0,0010	1	3	9
Zhoukou	0,0012	2	9	8
Zhumadian	0,0008	2	0	6
Wuhan	0,0234	64	45	52
Huangshi	0,0015	6	9	12
Shiyan	0,0019	6	13	6
Yichang	0,0041	10	29	13
Xiangyang	0,0027	6	15	21
Ezhou	0,0009	5	3	7
Jingmen	0,0014	7	2	14
Xiaogan	0,0024	7	15	16
Jingzhou	0,0030	7	19	14
Huanggang	0,0025	10	10	12
Xianning	0,0012	6	5	12
Suizhou	0,0007	3	8	1
Changsha	0,0168	43	52	38
Zhuzhou	0,0042	18	22	22
Xiangtan	0,0038	16	15	22
Hengyang	0,0020	5	11	8
Yueyang	0,0016	3	7	12
Changde	0,0020	15	11	10
Zhangjiajie	0,0004	2	1	3
Yiyang	0,0011	5	1	8
Chenzhou	0,0015	4	5	9
Yongzhou	0,0008	5	5	5
Huaihua	0,0009	4	3	4
Loudi	0,0009	1	2	9
Guangzhou	0,0199	52	37	45
Shaoguan	0,0022	8	15	11
Shenzhen	0,0185	37	49	46
Zhuhai	0,0066	30	20	27
Shantou	0,0030	11	8	14
Foshan	0,0083	29	32	31
Jiangmen	0,0044	17	11	13
Zhanjiang	0,0038	16	9	22
Maoming	0,0023	18	9	9
Zhaoqing	0,0024	11	8	18
Huizhou	0,0029	10	14	21
Meizhou	0,0014	7	6	10
Shanwei	0,0003	0	2	4
Heyuan	0,0012	2	12	12

City	Π(k) 2007-2018	Wave 3 -> Wave 4	Wave 4 -> Wave 5	Wave 5 -> Wave 6
Qingyuan	0,0025	9	13	22
Dongguan	0,0077	28	29	37
Zhongshan	0,0045	17	16	23
Chaozhou	0,0009	4	3	4
Jieyang	0,0014	1	6	7
Yunfu	0,0010	5	4	5
Nanning	0,0054	17	25	25
Liuzhou	0,0036	12	16	11
Guilin	0,0028	6	16	14
Wuzhou	0,0009	4	3	9
Beihai	0,0022	10	11	11
Qinzhou	0,0008	4	6	7
Yulin	0,0005	2	0	5
Hechi	0,0010	4	3	2
Laibin	0,0006	3	1	3
Chongzuo	0,0008	3	9	3
Haikou	0,0051	15	24	16
Danzhou	0,0007	4	5	1
Chongqing	0,0123	27	50	38
Chengdu	0,0192	35	54	44
Zigong	0,0023	8	11	19
Panzhihua	0,0021	7	5	13
Luzhou	0,0017	9	6	14
Deyang	0,0022	10	11	12
Mianyang	0,0035	18	13	25
Suining	0,0007	2	3	7
Neijiang	0,0010	3	8	4
Leshan	0,0009	2	4	12
Nanchong	0,0012	3	12	6
Meishan	0,0009	3	5	9
Yibin	0,0018	7	5	18
Dazhou	0,0007	2	4	5
Yaan	0,0021	4	13	16
Ziyang	0,0007	2	3	9
Guiyang	0,0078	20	34	23
Zunyi	0,0019	6	7	9
Anshun	0,0011	1	4	6
Bijie	0,0010	4	7	7
Kunming	0,0091	25	38	37
Qujing	0,0016	1	13	15
Yuxi	0,0016	8	9	4
Baoshan	0,0005	1	1	7

City	Π(k) 2007-2018	Wave 3 -> Wave 4	Wave 4 -> Wave 5	Wave 5 -> Wave 6
Lijiang	0,0003	0	2	0
Puer	0,0008	5	3	7
Lincang	0,0005	1	2	7
Lasa	0,0020	2	12	16
Xi'an	0,0187	52	49	41
Tongchuan	0,0006	1	2	5
Baoji	0,0017	6	12	13
Xianyang	0,0031	10	11	23
Weinan	0,0013	8	5	14
Yan'an	0,0011	4	4	7
Hanzhong	0,0017	8	16	7
Yulin	0,0023	9	5	17
Ankang	0,0008	4	7	3
Shangluo	0,0010	5	2	2
Lanzhou	0,0077	19	39	28
Jinchang	0,0013	8	7	4
Baiyin	0,0017	6	4	11
Pingliang	0,0005	3	4	2
Jiuquan	0,0013	7	5	10
Dingxi	0,0006	2	7	4
Xining	0,0042	15	23	28
Yinchuan	0,0043	12	22	12
Shizuishan	0,0016	2	9	10
Wuzhong	0,0008	4	1	9
Zhongwei	0,0013	3	7	6
Urumqi	0,0055	24	26	30
Karamay	0,0017	2	7	9

Appendix B

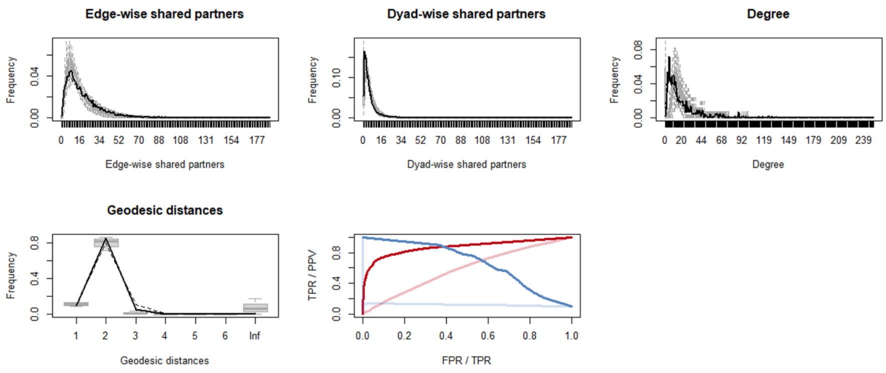

Fig. 4 Model goodness of fit for the TERGM (Model 2)

The validity of the results is determined using a goodness-of-fit analysis. In our case, the goal of the goodness-of-fit is to compare simulated and observed network matrices along a vector of values, which include edge-wise shared partners, dyad-wise shared partners, degree distribution, geodesic distances, and the ROC curve. The black thick line represents the observed network's distribution of statistics, while the gray area represents the matching confidence intervals from the simulated networks. The goodness-of-fit results indicate that our TERGM accurately describes the observed network.

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References

Balland PA (2012) Proximity and the evolution of collaboration networks: Evidence from research and development projects within the global navigation satellite system (GNSS) industry. Reg Stud 46:741–756

Balland PA, De Vaan M, Boschma R (2013) The dynamics of interfirm networks along the industry life cycle: The case of the global video game industry, 1987–2007. J Econ Geogr 13:741–765. https://doi.org/10.1093/jeg/lbs023

Barabási A-L, Albert R (1999) Emergence of scaling in random networks. Science 286:509–512

Barthélemy M (2011) Spatial networks. Phys Rep 499(1–3):1–101

Bauer V, Harhoff D, Kauermann G (2022) A smooth dynamic network model for patent collaboration data. AStA Adv Stat Anal 106:97–116. https://doi.org/10.1007/s10182-021-00393-w

Bergé LR (2017) Network proximity in the geography of research collaboration. Pap Reg Sci 96(4):785–816

Block P, Koskinen J, Hollway J, Steglich C, Stadtfeld C (2018) Change we can believe in: Comparing longitudinal network models on consistency, interpretability and predictive power. Soc Netw 52(1):180–191

Boschma R (2005) Proximity and innovation: A critical assessment. Reg Stud 39:61–74. https://doi.org/10.1080/0034340052000320887

Breschi S, Lenzi C (2016) Co-invention networks and inventive productivity in US cities. J Urban Econ 92:66–75. https://doi.org/10.1016/j.jue.2015.12.003

Broekel T, Bednarz M (2019) Disentangling link formation and dissolution in spatial networks: An application of a two-mode STERGM to a project-based R&D network in the German biotechnology industry. Netw Spat Econ 18:677–704

Broekel T (2012) Collaboration intensity and regional innovation efficiency in Germany—a conditional efficiency approach. Ind Innov 19:155–179. https://doi.org/10.1080/13662716.2012.650884

Broekel T, Hartog M (2013) Determinants of cross-regional R&D collaboration networks: An application of exponential random graph models. The geography of networks and R&D collaborations, pp 49–70

Burt RS (2007) Brokerage and closure: An introduction to social capital. OUP Oxford

Chesbrough H (2006) Open innovation: A new paradigm for understanding industrial innovation. In: Chesbrough H, Vanhaverbeke W, West J (eds) Open innovation: Researching a new paradigm. Oxford University Press, pp 1–12

Coleman JS (1988) Social capital in the creation of human capital. Am J Sociol 94:S95–S120

Dai L, Derudder B, Cao Z et al (2022) Examining the evolving structures of intercity knowledge networks: The case of scientific collaboration in China. Int J Urban Sci. https://doi.org/10.1080/12265934.2022.2042365

De Noni I, Ganzaroli A, Orsi L (2017) The impact of intra- and inter-regional knowledge collaboration and technological variety on the knowledge productivity of European regions. Technol Forecast Soc Chang 117:108–118. https://doi.org/10.1016/j.techfore.2017.01.003

Del Vicario M, Zollo F, Caldarelli G, Scala A, Quattrociocchi W (2017) Mapping social dynamics on facebook: The brexit debate. Soc Netw 50:6–16

Desmarais BA, Cranmer SJ (2012) Statistical mechanics of networks: Estimation and uncertainty. Phys A 391(4):1865–1876

Dong ZJ, Xu L, Cheng JH et al (2021) Major factors affecting biomedical cross-city R&D collaborations based on cooperative patents in China. Scientometrics 126(3):1923–1943

Fan F, Dai S, Zhang K, Ke H (2021) Innovation agglomeration and urban hierarchy: Evidence from Chinese cities. Appl Econ 53(54):6300–6318

Fang CL (2020) The atlas of China's urban agglomerations. Science Press, Beijing

Feldman M (1994) The geography of innovation. Kluwer Academic Publishers, Boston

Filippetti A, Zinilli A (2023) The innovation networks of city-regions in Europe: Exclusive clubs or inclusive hubs? Pap Reg Sci 102(6):1169–1192

Fleming L, King C III, Juda AI (2007) Small worlds and regional innovation. Organ Sci 18(6):938–954

Gao, Y., Scherngell, T., & Neuländtner, M. (2024). Drivers for inter-city innovation networks across Chinese cities: Modelling physical versus intangible effects.Chin Geogr Sci 1–16

Gay B, Dousset B (2005) Innovation and network structural dynamics: Study of the alliance network of a major sector of the biotechnology industry. Res Policy 34(10):1457–1475

Glückler J (2007) Economic geography and the evolution of networks. J Econ Geogr 7:619–634
Granovetter M (1985) Economic action and social structure: The problem of embeddedness. Am J Sociol 91(3):481–510
Gilsing V, Nooteboom B, Vanhaverbeke W, Duysters G, Van Den Oord A (2008) Network embeddedness and the exploration of novel technologies: Technological distance, betweenness centrality and density. Res Policy 37(10):1717–1731
Grillitsch M, Nilsson M (2015) Innovation in peripheral regions: Do collaborations compensate for a lack of local knowledge spillovers? Ann Reg Sci 54(1):299–321. https://doi.org/10.1007/s00168-014-0655-8
Gulati R (1998) Alliances and networks. Strateg Manag J 19(4):293–317
Hanneke S, Fu W, Xing EP (2010) Discrete temporal models of social networks. Electron J Stat 4:585–605
Hilbert M, Oh P, Monge P (2016) Evolution of what? A network approach for the detection of evolutionary forces. Soc Netw 47:38–46
Hua L, Yang Z, Shao J, Jin D (2021) The impact of the preferential attachment level on the innovation network structure and innovation efficiency. Discret Dyn Nat Soc 2021:1–11
Hunter DR (2007) Curved exponential family models for social networks. Soc Netw 29(2):216–230
Kilduff M, Tsai W (2003) Social networks and organizations. Sage
Kireyev A, Leonidov A (2018) Network effects of international shocks and spillovers. Netw Spat Econ 18(4):805–836
Lata R, Scherngell T, Brenner T (2015) Integration processes in European research and development: A comparative spatial interaction approach using project based research and development networks, co-patent networks and co-publication networks. Geogr Anal 47(4):349–375
Leifeld P, Cranmer SJ (2019) A theoretical and empirical comparison of the temporal exponential random graph model and the stochastic actor-oriented model. Netw Sci 7:20–51
Leifeld P, Cranmer SJ, Desmarais BA (2018) Temporal exponential random graph models with btergm: Estimation and bootstrap confidence intervals. J Stat Softw 83:1–36
Leydesdorff L, Rafols I (2011) How do emerging technologies conquer the world? An exploration of patterns of diffusion and network formation. J Am Soc Inform Sci Technol 62(5):846–860
Li D, Wei YD, Wang T (2015a) Spatial and temporal evolution of urban innovation network in China. Habitat Int 49:484–496
Li DD, Wang T, Wei YD et al (2015b) Spatial and temporal complexity of scientific knowledge network and technological knowledge network on China's urban scale. Geogr Res 34(3):525–540
Lim H, Han C (2023) National borders transcended: The impact of geographical proximity on the growth of global innovation networks among cities in East Asia. Int J Urban Sci 27(4):570–598
Liu X, Derudder B, Liu Y (2015) Regional geographies of intercity corporate networks: the use of exponential random graph models to assess regional network-formation. Pap Reg Sci 94:109–126
Lomi A, Robins G, Tranmer M (2016) Introduction to multilevel social networks. Soc Netw 100(44):266–268
Ma HT, Xu XF, Jiang KL (2023) The evolutionary characteristics and innovation effects of technological knowledge polycentricity in Chinese urban agglomerations. Acta Geograph Sin 78(02):273–292. https://doi.org/10.11821/dlxb202302002
Maggioni MA, Nosvelli M, Uberti TE (2007) Space versus networks in the geography of innovation: A European analysis. Pap Reg Sci 86(3):471–494
Merton RK (1968) The Matthew effect in science: The reward and communication systems of science are considered. Science 159(3810):56–63
Morrison A, Rabellotti R, Zirulia L (2013) When do global pipelines enhance the diffusion of knowledge in clusters? Econ Geogr 89:77–96. https://doi.org/10.1111/j.1944-8287.2012.01167.x
Neuländtner M, Scherngell T (2020) Geographical or relational: What drives technology-specific R&D collaboration networks? Ann Reg Sci 65(3):743–773
Newman MEJ (2003) The structure and function of complex networks. SIAM Rev 45(2):167–256. https://doi.org/10.1137/S003614450342480
OECD (1992) Technology and the economy. OECD, Paris
Paier M, Scherngell T (2011) Determinants of collaboration in European R&D networks: Empirical evidence from a discrete choice model. Ind Innov 18(1):89–104
Pan X, Pan X, Ai B et al (2020) Structural heterogeneity and proximity mechanism of China's inter-regional innovation cooperation network. Technol Anal Strateg Manag 32(9):1066–1081
Park J, Newman ME (2004) Statistical mechanics of networks. Phys Rev E 70

Powell WW, Koput KW, Smith-Doerr L (1996) Interorganizational collaboration and the locus of innovation: Networks of learning in biotechnology. Adm Sci Q 41(1):116–145
Provan KG, Fish A, Sydow J (2007) Interorganizational networks at the network level: A review of the empirical literature on whole networks. J Manag 33(3):479–516
Rivera MT, Soderstrom SB, Uzzi B (2010) Dynamics of dyads in social networks: Assortative, relational, and proximity mechanisms. Ann Rev Sociol 36:91–115
Robins G, Snijders T, Wang P, Handcock M, Pattison P (2007) Recent developments in exponential random graph (p*) models for social networks. Soc Netw 29:192–215
Scherngell T (2021) The geography of R&D collaboration networks. Handbook Reg Sci 869–887
Schweinberger M (2011) Instability, sensitivity, and degeneracy of discrete exponential families. J Am Stat Assoc 106:1361–1370
Snijders TA, Van de Bunt GG, Steglich CE (2010) Introduction to stochastic actor-based models for network dynamics. Soc Netw 32(1):44–60
Steglich C, Snijders TA, Pearson M (2010) Dynamic networks and behavior: Separating selection from influence. Sociol Methodol 40(1):329–393
Stuck J, Broekel T, Revilla DJ (2016) Network structures in regional innovation systems. Eur Plan Stud 24(3):423–442
Sun P, Peng SY (2021) Development mechanism of cohesive subgroups' urban innovation networks in the yangtze river delta: Based on the valued ERGM. Econ Geogr 41(9):22–30. https://doi.org/10.15957/j.cnki.jjdl.2021.09.003
Sun Y, Liu K (2016) Proximity effect, preferential attachment and path dependence in inter-regional network: A case of China's technology transaction. Scientometrics 108:201–220
Tang C, Qiu P, Dou J (2022) The impact of borders and distance on knowledge spillovers—Evidence from cross-regional scientific and technological collaboration. Technol Soc 70
Ter Wal AL (2014) The dynamics of the inventor network in German biotechnology: Geographic proximity versus triadic closure. J Econ Geogr 14(3):589–620
Uzzi B (1997) Social structure and competition in interfirm networks. Adm Sci Q 42(1):37–69
Valente TW, Palinkas LA, Czaja S, Chu KH, Brown CH (2015) Social network analysis for program implementation. PLoS ONE 10(6)
Vieira ES, Cerdeira J, Teixeira AAC (2022) Which distance dimensions matter in international research collaboration? A cross-country analysis by scientific domain. J Informet 16(2)
Wang S, Yang L (2022) The Network Structure of Innovation Networks. Netw Spat Econ 22:65–96. https://doi.org/10.1007/s11067-021-09556-3
Wang Z, Fellows IE, Handcock MS (2023) Understanding networks with exponential-family random network models. Soc Netw. https://doi.org/10.1016/j.socnet.2023.07.003
Wanzenböck I, Scherngell T, Brenner T (2014) Embeddedness of regions in European knowledge networks. A comparative analysis of inter-regional R&D collaborations, co-patents and co-publications. Ann Reg Sci 53(2):337–368
Watts DJ, Strogatz SH (1998) Collective dynamics of 'small-world' networks. Nature 393(6684):440–442. https://doi.org/10.1038/30918
Young LE, Tang JL, Schneider JA (2023) Demographic and HIV status diversities as mechanisms of social integration and segregation among Black sexual and gender minorities enrolled in a community-based social network intervention. Soc Netw 73:51–61
Yang L, Wang J, Yang Y (2022) Spatial evolution and growth mechanism of urban networks in western China: A multi-scale perspective. J Geog Sci 32(3):517–536
Yao L, Li J (2022) Intercity innovation collaboration and the role of high-speed rail connections: Evidence from Chinese co-patent data. Reg Stud 56(11):1845–1857
Yao L, Li J, Li J (2020) Urban innovation and intercity patent collaboration: A network analysis of China's national innovation system. Technol Forecast Soc Chang 160
Zhou C, Zeng G, Cao XZ (2017) Chinese inter-city innovation network's structure and city innovation capability. Geogr Res 36(7):1297–1308
Zinilli A, Pierucci E, Reale E (2023) Organizational factors affecting higher education collaboration networks: Evidence from Europe. Higher Educ 1–42
Zinilli A, Cerulli G (2023) Link prediction and feature relevance in knowledge networks: A machine learning approach. PLoS ONE 18(11):e0290018. https://doi.org/10.1371/journal.pone.0290018
Zinilli A (2016) Competitive project funding and dynamic complex networks: Evidence from projects of national Interest (PRIN). Scientometrics 108(2):633–652