Intercity Coopetition and Regional Innovation: The Role of Urban Polycentricity

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Abstract: Intercity coopetition—the dynamic interplay between cooperation and competition—is central to regional innovation, enabling knowledge exchange across cities. However, the spatial organization of these dynamics among functionally diverse cities and their implications for regional innovation outcomes remain underexplored. This study examines how urban polycentricity, captured through the balance of intercity coopetition relations, affects regional innovation performance. Methodologically, we develop an intercity coopetition index that incorporates both geographical overlap in collaboration networks and technological proximity. Empirically, we draw on longitudinal patent co-application data from nineteen Chinese urban regions between 1990 and 2022. Using fixed effect and instrumental variables models, we find that a balance in cooperation alone has a negative effect on regional innovation. In contrast, regional innovation performance is driven by the interaction between the strength of competitive ties and the balance of competition across cities. We conclude by discussing the policy implications of these findings for fostering spatially coordinated innovation systems.

Keywords: Intercity coopetition; Urban polycentricity; Regional innovation performance; Patents; China

1. Introduction

Innovation, built on the development and integration of new knowledges, is widely seen as a key source of regional competitiveness (Boschma, 2004). Although innovation often originates at the firm level, few firms can sustain it independently (Corbo et al., 2023). To overcome internal limitations such as resource limitations and knowledge gaps, firms increasingly engage in partnerships that involve both cooperation and competition, a strategic logic known as 'coopetition' (Brandenburger and Nalebuff, 1996). Rather than cooperation and competition simply coexisting, coopetition entails that both are strategically balanced, allowing knowledge sharing while managing tensions around trust, control, and rivalry (Dagnino, 2009). These dynamics are not confined to firms; they scale up to the regional level. Just as firms coopete to enhance innovation, cities form intercity partnerships to access external knowledge, infrastructure, and institutional complementarities (De Noni et al., 2017). Cities cooperate to build joint innovation platforms while competing for talent, capital, and recognition. This duality drives intercity knowledge flows and shapes the spatial organization of regional innovation systems (Zhang et al., 2025). Therefore, intercity coopetition has become a key feature of innovation-driven urban and regional development.

Building on these insights, recent literature has increasingly focused on the positions of cities within cooperative and/or competitive knowledge networks in regional settings by analyzing their patterns and performances through co-patent, co-publication, or technology transfer data (Breschi and Lenzi, 2016; Van der Wouden and Rigby, 2019; Zhang et al., 2025). Much of this research focuses on operationalizing coopetition (e.g., coopetition inferred from inventors in different locations) and the mechanisms driving it (e.g., the conditions under which coopetition emerges and unfolds). However, despite these attempts, intercity coopetition is often assumed to produce homogenous regional effects, overlooking the inherently asymmetric, uneven, and selective nature of knowledge diffusion (Miguelez and Moreno, 2017; Giuliani, 2007). Gatekeeper cities, for instance, can strategically restrict the diffusion and circulation of valuable knowledge to maintain competitive advantages (Breschi and Lenzi, 2015), while recipient cities may either benefit from these cooperative advantages or struggle due to these competitive pressures. Thus, the spatial configurations between functionally diverse cities may influence how knowledge diffuses within regional urban systems and, in turn, regional innovative performance (De Noni et al., 2017). However, this remains an underexplored area of research.

Against this backdrop, this paper advances the literature by integrating urban polycentricity into the analysis of intercity coopetitive relations. Traditionally, polycentricity has been defined as 'a means to achieve both a more balanced spatial pattern of development and a higher level of international territorial competitiveness by the area at stake' (Meijers & Romein, 2003, p. 173). While some research has examined the internal structure of single metropolitan areas (e.g., Zhang et al., 2017; Pan et al., 2024; Yu et al., 2022), a substantial body of work has long conceptualized polycentricity at inter-urban and interregional scales (e.g., Zhang et al, 2022; Derudder et al., 2022). We adopt the concept of an urban region (UR)—a territorially integrated system of proximate yet functionally distinct cities—as the scale for analyzing polycentricity and innovation dynamics. Recent studies show that high-technology development is often regionally dispersed, with firms, research institutions, and talent flows crossing city boundaries (Xue et al., 2025). Actors innovate as part of regional systems whose capabilities depend on both the strengths of individual cities and their interaction structure (Stuck et al., 2016). However, innovative capacity is unevenly distributed, with core cities frequently dominating (Rodríguez-Posé & Wilkie, 2016). Analyzing polycentricity at the UR scale therefore enables a more nuanced understanding of the geography of innovation, capturing the balance, or the lack thereof, of innovation functions among multiple cities.

Building on this foundation, this study proposes a novel conceptual and methodological framework to assess polycentric structures and analyze their impact on regional innovation performance. At the conceptual level, we measure urban polycentricity based on the functional attributes of cities, specifically their coopetitive capacities in knowledge exchange. We argue that a polycentric urban configuration may foster effective knowledge diffusion by enabling cities to engage in a balance in terms of coopetitive behaviors. In such a setting, newly generated information or ideas may rapidly circulate among all network members and are recombined with their own knowledge, thereby improving regional innovation performance (Breschi and Lenzi, 2016).

At the methodological level, we build upon the framework Demuynck et al. (2023) developed to capture the directional intensity of coopetition between cities by analyzing the overlap in their external linkages. In their approach, external linkages are functional connections that cities maintain within a region, such as flows of people, goods, or information. When two cities exhibit similar sets of flows serving the same function, they are considered to be competing for influence or attraction from the same external sources. Conversely, cooperation is more likely when cities are strongly connected and serve complementary geographic markets. We extend this approach by incorporating cities' technological similarities into their coopetitive relations. The idea is that the similarity of technological resources among cities may affect their coopetitive behaviors. On the one hand, technology similarity can reduce collaboration costs and facilitate mutual learning, enabling cities to better absorb and apply each other's ideas and technologies (cooperation) (Qian et al., 2024). On the other hand, excessive technological homogeneity may lead cities with similar knowledge bases to perceive each other as competitors, intensifying rivalry (competition) (Krammer, 2018).

Based on this reasoning, we assume intercity cooperation is more likely to occur when cities have non-overlapping external networks and complementary technological structures. At the same time, competition tends to arise between cities that operate in similar technological domains and maintain overlapping external networks. We empirically test these arguments based on a large dataset of patents in 19 Chinese urban regions (URs) for the period 1990-2022. The focus on these Chinese URs is particularly relevant for examining the link between urban polycentricity and regional innovative performance, as urban polycentricity has become a key normative goal in Chinese planning discourse.

The remainder of this paper is organized as follows. In the next section, we derive our research hypotheses from the literature. Section 3 describes the construction of our key network variables and presents the empirical models to be tested and the data. Section 4 discusses the empirical results and comments on the robustness checks to detect and control for possible endogeneity. Finally, Section 5 concludes with an overview of our main findings and avenues for further research.

2. Theoretical background and derivation of hypotheses

2.1 Conceptualizing coopetition in the context of regional innovation networks

Initially developed in business and organizational studies (Walley, 2007), the concept of coopetition has been increasingly applied in the context of city networks and regional innovation systems (Luongo et al., 2023; Feser, 2023; Zhang et al., 2025). Conceptualized as the dynamic interplay between cooperation and competition, coopetition is considered a strategy that leverages the advantages of both dimensions (Bouncken et al., 2015). In an urban context, cities provide cooperation by offering knowledge, infrastructure, or technological resources to others and receive cooperation by tapping into external capabilities not available locally (Breschi and Lenzi, 2016). At the same time, cities actively compete to attract talent, investment and technological advantages, while others may be targets in these competitive strategies (Galvin et al., 2020). By combining these dynamics, intercity coopetition enables asymmetric but complementary relationships, facilitating knowledge flows, supporting joint technology development, and allowing for the distribution of risks and costs across city networks (Corbo et al., 2023).

Previous studies have employed various approaches to measuring coopetition, often emphasizing cooperation over competition. Cooperation has been assessed using indicators like the number of collaborations with others (Zhao et al., 2023), network-based measures of social proximity (Breschi and Lenzi, 2016), and the co-location of creative individuals within urban environments (van der Wouden and Rigby, 2019). In contrast, competition has been less frequently examined, and when it has, it has primarily been measured through indicators such as market concentration and variations in sales at the production level (Galvin et al., 2020). More recently, studies have integrated both cooperation and competition within a unified framework, drawing from ecological or network theories (Demuynck et al., 2023; Zhang et al., 2025; Liu et al., 2025). These approaches conceptualize intercity coopetition based on (dis)similarities in network structures, emphasizing that *cities cooperate when they have strong intercity connections and complementary market structures, whereas they compete when their geographic markets overlap*. This line of research advances previous indices by capturing the asymmetry of intercity relations, highlighting that a city may serve as a provider without receiving an equivalent. Such asymmetry arises from the uneven distribution of indirect connections a city maintains through its direct ties with others.

This coopetition index primarily adopts a *horizontal* perspective, emphasizing geographical similarity as a key determinant of collaboration. We extend this approach by incorporating a *vertical* perspective, assessing whether cities exhibit technological similarity in their innovation activities. While direct city-level evidence remains scarce, firm-level studies highlight a trade-off in technological similarity when seeking innovative partners. On the one hand, a moderate level of technological similarity facilitates cooperation, as firms operating in related technological domains share overlapping knowledge bases, which reduces collaboration costs and promotes mutual learning (Krammer, 2016). Besides, greater technological similarity accelerates knowledge assimilation and commercial exploitation (Carnahan et al., 2010). On the other hand, excessive similarity may limit learning opportunities, as cities with nearly identical technological portfolios are more likely to perceive each other as rivals rather than cooperative partners (Frenken, 2006). Conversely, very low similarity hinders cooperation, as the absence of a shared knowledge base creates absorptive capacity barriers, making it difficult to exchange and apply each other's knowledge effectively (Qian et al., 2024).

Building on this perspective, we construct a coopetition index that integrates geographical (dis)similarity in external networks and technological (dis)similarity (Figure 1). Specifically, we assume that cities are more likely to cooperate when they have non-overlapping external linkages and complementary technological profiles, while competition arises when both networks and technologies overlap. In empirical terms, geographical similarity is identified based on the overlapping portion of a city's external linkages with other cities (Demuynck et al., 2023); technological similarity is quantified based on the co-occurrence of International

Patent Classification (IPC) codes within city-level patents portfolios (Park and Yoon, 2017) (section 3.2.1).

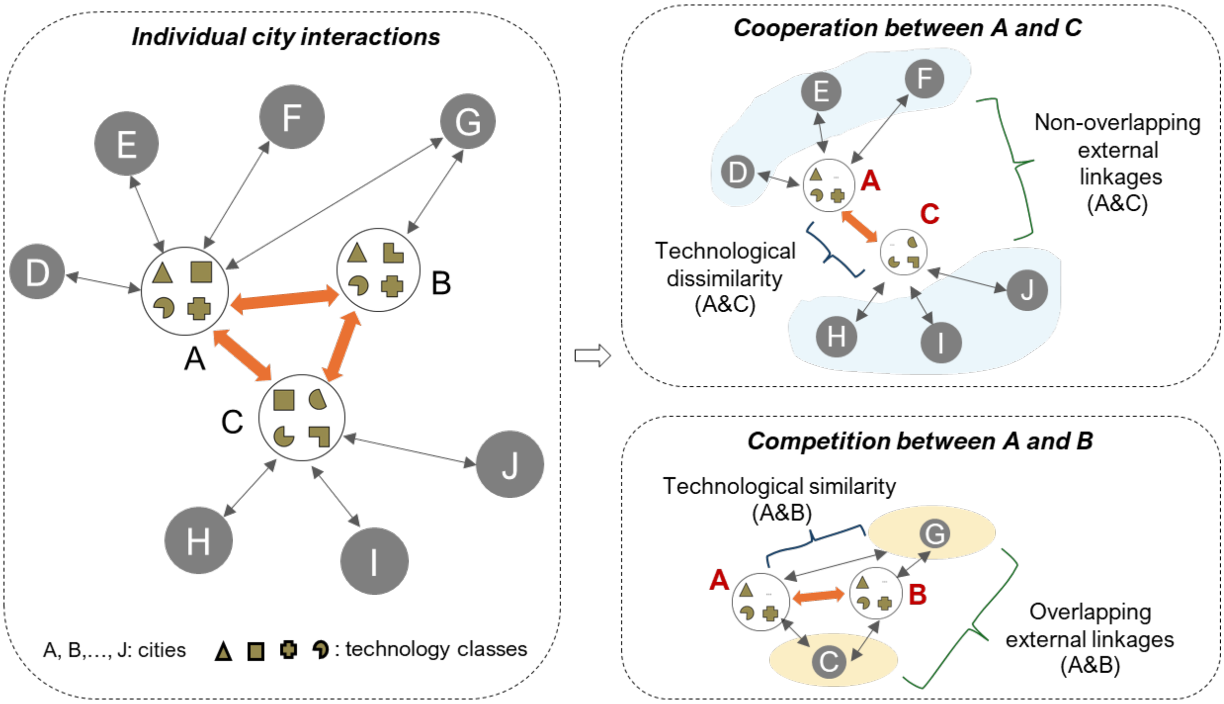

Figure 1 From individual city interactions to coopetition structures.

2.2 Rethinking urban polycentricity: A coopetitive perspective

Urban polycentricity has been widely recognized as a key element in both scientific inquiry and spatial development policies. It is both an analytical framework for examining real-world urban phenomena and a politically significant component in normative spatial planning goals (Derudder et al., 2022). Despite its increasing use in different geographical settings, polycentricity is typically situated within a regional context and conceptualized in both morphological and functional terms. The morphological dimension considers the size and distribution of cities; the functional dimension, on the other hand, considers the economic specialization and interaction among cities (Rauhut, 2017).

Building on these dimensions, we incorporate cities' coopetitive behaviors into the functional understanding of polycentricity. The relative positions of cities in coopetitive networks directly shape how regional innovation patterns are organized and distributed. For example, China's Greater Bay Area (GBA) is moving towards a polycentric-cooperative model, particularly among its major cities. Hong Kong specializes in financial expertise, global networking, and high-quality research; Shenzhen absorbs knowledge from Hong Kong but has surpassed it in AI, biotech, and electronics; and Dongguan and Foshan are transitioning from manufacturing hubs to high-tech innovators (Ma and Xu, 2023). These cities engage in relatively balanced cooperation while maintaining distinct innovation strengths (Daniel et al., 2015). In contrast, the Chengdu-Chongqing (CHC) region reflects a more monocentric-competitive dynamic. Chengdu has developed a strong IT sector, aerospace industry, and defense science, attracting top R&D centers (Qin, 2015); Chongqing, historically an industrial hub, benefits from knowledge spillovers but struggles to transition into a high-tech economy (Bao et al., 2019). Although the two cities are broadly equally important and boast similar ambitions—both aiming to become the CHC region's leading city—the competition between them is uneven, with

Chengdu exerting greater competitive pressure and capturing a disproportionate share of resources and institutional support (Cheshmehzangi and Tang, 2022).

In empirical terms, we define coopetitive polycentric structures as URs in which cities both provide and receive cooperation and pose and face competition in relatively balanced proportions. This balance indicates that no single city dominates the functional landscape; instead, multiple centers share influence and rely on each other in ways that foster mutual interdependence. In contrast, when these roles are heavily skewed—such that a few cities predominantly provide or capture cooperation while others remain largely dependent—the result is a more monocentric structure, where innovation capacity and decision-making power are concentrated in a limited number of dominant cities.

While our approach is grounded in the functional tradition—examining how cities structure territorial dynamics by supplying functions to other cities (Rauhut, 2017)—it extends this perspective by explicitly quantifying the balance of directional cooperation and competition roles. Rather than relying solely on network centrality to infer interdependence (e.g., Thomas and Schmidt, 2022), we adopt a function-based morphological perspective, operationalized in two steps. Using the cooperation network as an example, we first transform intercity co-patenting flows into directed cooperation networks, measuring each city's strength in providing/receiving cooperation. Second, we aggregate these directional ties at the regional level and use a morphological-based index to assess how evenly these cooperative functions are spatially distributed within the UR (Figure 2). A similar procedure is applied to competition networks. However, the calculation of intercity ties differs, as it draws on the non-overlap of external linkages combined with technology similarity (see section 3.2.1).

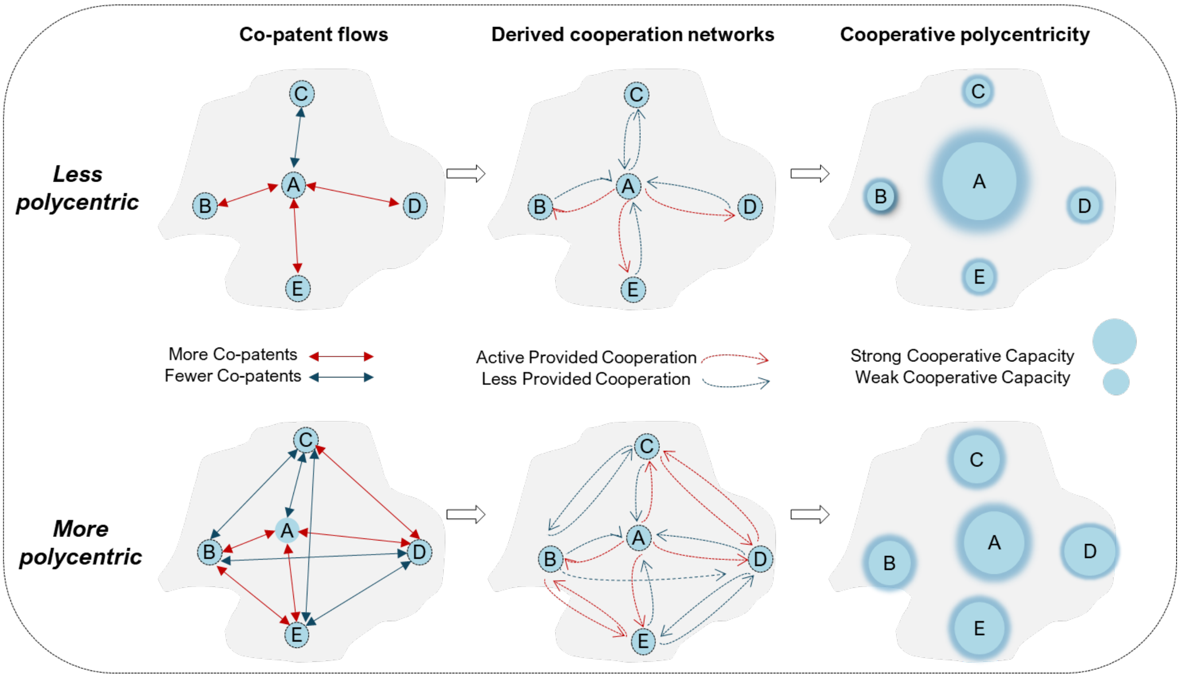

Figure 2 From co-patent networks to cooperative polycentric structures.

2.3 Linking urban polycentricity and regional innovation performance: Five hypotheses

The relationship between urban polycentricity and regional innovation performance is rooted in the literature on spatial agglomeration and, more specifically, in the evolutionary view of regional innovation systems. These connections have been conceptualized through several key mechanisms: net-agglomeration benefits that can be optimized through polycentric development (Agarwal et al., 2012), socioeconomic diversity that are generators of creative economies (Florida et al., 2008), and polycentric organizations of firms at the micro level (Li and Du, 2021). We extend these discussions by framing our hypotheses through a function-based morphological perspective, distinguishing between cooperative and competitive polycentric structures.

A cooperative polycentric structure is characterized by two key features: reciprocal (though not necessarily equal) knowledge diffusion and a decentralized cooperation system. For instance, if city A provides knowledge to B and C, while B also provides knowledge to A and C, they act as both generators and transmitters of knowledge, ensuring that this region does not become overly reliant on a few dominant cities. In more complex regional settings, structural holes (i.e., gaps in knowledge flows between groups) often emerge as close-knit cities concentrate on their unique advantage (Raman and Grover, 2020), limiting external diffusion. However, polycentric development helps bridge these gaps by distributing brokerage roles more evenly, allowing intermediary cities to facilitate connections between otherwise unlinked cities (Wall, 2018). Moreover, the balanced distribution of cooperation opportunities fostered by polycentric development extends beyond geographical linkages (i.e., cities establishing new cooperative ties beyond their existing networks) to include technology diversity (i.e., a more even distribution of technological specialization across cities). In other words, knowledge cooperation is not only spatially distributed but also functionally balanced, ensuring that innovation benefits stem from both broader geographic reach and complementary technological capabilities. Thus, we hypothesize that polycentric structures enhance regional innovation performance, regardless of whether a city provides or receives cooperation (as the cumulative effects remain consistent):

H1a: A higher degree of polycentricity in provided cooperation—a balanced distribution of cooperation provided by cities within a UR—enhances regional innovation performance.

H1b: A higher degree of polycentricity in received cooperation—a balanced distribution of cooperation received by cities within a UR—enhances regional innovation performance.

The key features of competitive polycentric structures mirror those of cooperative structures, but they differ in that cities strive to outperform each other rather than collaborate. Given the scarcity of direct evidence linking intercity competition to regional innovation performance, we begin by discussing the dual effects of competition within metropolitan environments and extend this perspective to regional systems. In competitive environments, cities drive each other towards continuous improvement through rivalry-driven learning and innovation races (Galvin et al., 2020). However, according to the theories of strategic knowledge protection, excessive competition increases the likelihood that cities with higher knowledge stock will prioritize retaining exclusive access to cutting-edge information to prevent rivals from catching up (Gast et al., 2019). At the same time, excessive competition reinforces agglomeration overshadowing—a phenomenon in which spatial competition among nearby cities results in some (smaller) cities hosting fewer innovation resources than they usually would (Burger et al., 2015). A competitive polycentric structure offers a balance between these extremes. In such a system, no single city monopolizes resources or exerts unilateral influence over others while remaining immune to competitive pressures. Instead, it preserves the cumulative 'benefits' from competition while mitigating the risks of excessive rivalry. Therefore, we propose the following hypotheses:

H2a: A higher degree of polycentricity in posed competition—a balanced distribution of competition posed by cities within a UR, enhances regional innovation performance.

H2b: A higher degree of polycentricity in faced competition—a balanced distribution of competition faced by cities within a UR, enhances regional innovation performance.

Next, we expect regional innovation performance to improve when there is a combination of (i) high polycentricity in cities' providing cooperation and (ii) high polycentricity in cities' facing competition. When the degree of polycentricity in competition is low, the benefits of cooperative polycentricity—i.e., the broad diffusion of knowledge—may not be fully realized. This is because there are fewer competition-driven incentives to absorb, adapt, and apply external knowledge, limiting the potential for knowledge transfer and recombination across the regional networks. Similarly, when competitive polycentricity is high while cooperation remains low, the absence of a structured knowledge-sharing mechanism may equally hinder innovation. While information may circulate rapidly, it may not be effectively absorbed and applied, as it is not exchanged through trusted cooperative partners, which may lead to less effective exploitation of new ideas (Breschi and Lenzi, 2016). Thus, an interplay between the two structures fosters regional innovation performance by integrating both knowledge exchange and rivalry-induced learning, which leads us to the final hypothesis,

H3: Combining high cooperative polycentricity and high competitive polycentricity enhances regional innovation performance.

3. Methodology

This paper aims to explore how the degree of urban polycentricity—in terms of cities providing/receiving cooperation and posing/facing competition—influences regional innovation performance. Our analysis focuses on 19 urban regions (URs) in China, as formulated in the 14^{th} National Five-year Plan (Figure 3). We use co-patent data to capture cities' coopetitive behaviors and construct corresponding polycentric structure measures. While patent-based metrics have limitations—such as measuring inventions rather than innovations (Leydesdorff et al., 2017) —they remain widely used to assess both the quality and intensity of knowledge collaboration within and across regions (Wanzenböck et al., 2014; Breschi and Lenzi, 2016; Yao and Li, 2022).

We construct a panel dataset of cities among these 19 URs from 1990[1] to 2022, based on data from *incopat.com*, which compiles patent information from the China National Intellectual Property Administration (CNIPA). *Incopat* provides detailed records, including application dates, applicants' names and addresses, IPC classifications, and other metadata, making it a well-established resource for studying innovation networks in China. For our analysis, we specifically focus on patent applications that had more than two applicants and identify intercity co-patents based on the information of applicant addresses. To measure technology similarity, we extract IPC lists from the patents, using the first four digits of the IPC code as the subclass. This leads to a total of 654 IPC classes at the 4-digit level.

[1] While intercity collaboration was limited in 1990 (average co-patent applications within URs = 12, compared with 2,462 in 2024), it was not absent. Earlier studies likewise show that China's urban network in the 1990s was highly centralised around Beijing (Zhang et al., 2021). Using 1990 as the starting point therefore enables us to capture this initial stage and trace the long-term evolution of urban networks.

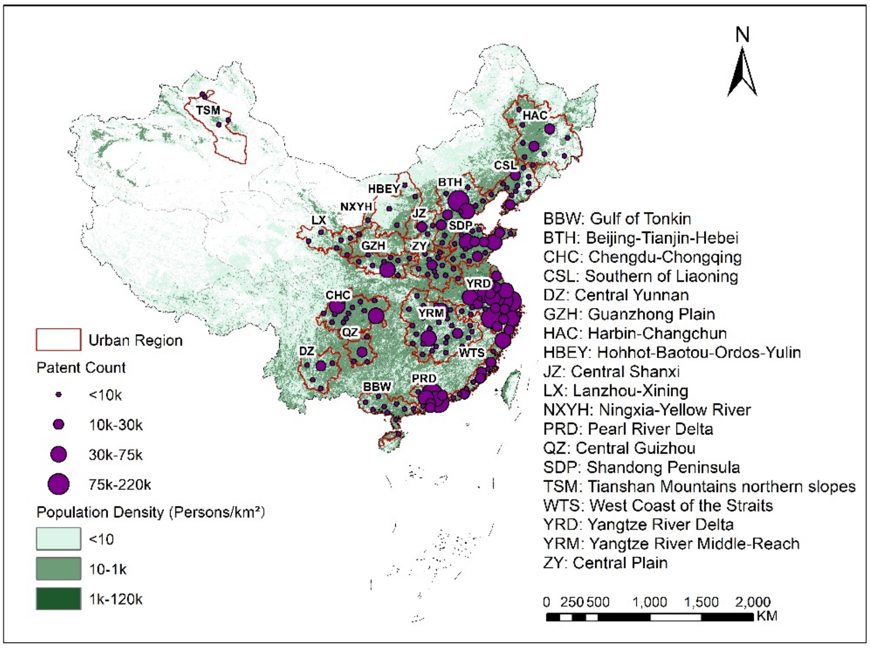

Figure 3 Spatial distribution of 19 URs and their patent output (2022)

3.1 Dependent variables

To quantify regional innovation performance (*INN.PER*), we use the log-transformed total number of patents per worker within the UR (1990-2022), measured over a three-year forward-looking window[2].

3.2 Explanatory variables

3.2.1 Quantifying intercity cooperation and competition

To assess urban polycentricity, we measure the balance of intercity cooperation and competition in the technology domain through co-patenting networks, building on the frameworks of Demuynck et al. (2023) and Qian et al. (2024). We choose patent data because they are both the output of inventive activity and the result of collaborations between actors across locations. Co-patent applications, in particular, directly reflect cooperative knowledge productions between cities, while overlaps in technological portfolios capture potential rivalry over similar innovation domains.

$$Cooperation_{i\to j} = a_{ij} * AD_{ij} * \left(1 - J_{i,j}\right) \quad (1)$$

$$Competition_{i\to j} = \left(1 - AD_{ij}\right) * J_{i,j} \quad (2)$$

Where $Cooperation_{i\to j}$ and $Competition_{i\to j}$ represents the degree of cooperation/competition provided (posed) by city i to city j. The term a_{ij} captures the direct knowledge collaboration (standardized co-patent count) between cities i and j. AD_{ij} captures the technological

[2] For instance, explanatory variables measured in 2016 are expected to affect *INN_PER* over the subsequent 2017 - 2019 period, while the same set of variables in 2019 is expected to generate effects from 2020 to 2022. This approach aligns with previous studies (De Noni et al., 2017; De Noni and Ganzaroli, 2024) and serve two key purposes : firstly, it smooths out short-term cycle fluctuations that may introduce noise into innovation metrics, and secondly, it account for the lagged effect of innovation drivers to mitigate potential endogeneity problems.

proximity dimension, reflecting indirect patent collaboration, i.e., the extent to which the city $i's$ external network complements that of city j. By contrast, $J_{i,j}$ captures the technological proximity dimension, measuring the similarity of technological portfolios between cities i and j.

AD_{ij} is calculated as:

$$AD_{ij} = \sum_{h=1}^{p} \left[\frac{a_{ih}}{\sum_{h=1}^{p} a_{ih}} * \frac{a_{ih}}{a_{ih}+a_{jh}}\right], \ i \neq j \neq h \quad (3)$$

where a_{ij}, a_{jh} and a_{ih} are the co-patent counts between cities i and j, cities j and h, and cities i and h, respectively. h is a city in a set of p cities. The fraction $a_{ih}/\sum_{h=1}^{p} a_{ih}$ measures the relative importance of city h as a collaborator for city i. The term $a_{ih}/(+a_{jh})$ reflects the degree to which city i influences the cooperation environment of city h relative to city j's influence.

$J_{i,j}$ is calculated as follows,

$$J_{i,j} = \frac{|T_i \cap T_j|}{|T_i \cup T_j|} \quad (4)$$

Where $T_i \cap T_j$ represents the number of technologies that occurred both in city i and j. $T_i \cup T_j$ represents the number of technologies that occur either in city i and j.

By applying equations (1) and (2) to all city pairs, we obtain a directional network of intercity cooperation and competition. This allows us to derive four indices per city: $Pro\_cooperation_i$ (averaged cooperation provided by city i), $Rec\_cooperation_i$ (averaged cooperation received by city i), $Pos\_competition_i$ (averaged competition posed by city i), $Fac\_competition_i$ (averaged competition faced by city i). These indexes range from zero to one, where higher values point to more provided/received cooperation or posed/faced competition.

3.2.2 Capturing coopetition intensity

Spatial balance in cities' functional attributes alone may not be sufficient to stimulate innovation. As Meijers et al. (2018) argue, polycentricity may or may not enhance regional innovation performance, depending more on the degree of functional integration—that is, the strength of functional connections between cities within URs (Vasanen, 2013)—rather than on spatial balance alone. To capture this dimension, we compute UR-level averages of cooperation (*COOP*) and competition (*COMP*). These indices measure the overall density of coopetitive interactions among constituent cities and complement the polycentricity indicators by reflecting how intensively cities engage with one another.

3.2.3 Measuring urban polycentricity

The degree of urban polycentricity is calculated by measuring 'balance' in cities' cooperation/competition index based on a standard deviation-based method (Green, 2007):

$$Poly = 1 - \frac{\sigma_{\mathrm{obs}}}{\sigma_{\mathrm{max}}} \quad (5)$$

where $Poly$ indicates the degree of polycentricity of a UR; σ_{obs} represents the standard deviation of the cooperation/competition indexes of all cities[3] in a UR; σ_{max} is a maximum

[3] Polycentricity measures are often sensitive to the number of centers (*N*) included in the analysis (Zhang & Derudder, 2019). The standard deviation–based indicator we adopt partly addresses this scale effect by combining both *N* and the balance among cities into a single composite measure (Derudder et al.,

standard deviation in a hypothetical two-city UR where one city has no cooperation (or competition) function and the other has the highest observed value. $Poly$ ranges from 0 (no polycentricity) to 1 (perfectly balanced cooperation and competition across cities). This leads us to four polycentricity indexes: polycentric provided cooperation *(POLY_PROCOOP)*, polycentric received cooperation *(POLY_RECCOOP)*, polycentric posed competition *(POLY_POSCOMP)*, and polycentric faced competition *(POLY_FACCOMP)*.

3.3 Control variables

We selected a set of control variables drawing on previous literature. Economic level (*GDP_PER*) is measured by the average GDP per capita of cities in the UR. Population density (*POP_DEN*) refers to the population per square kilometer in each UR. Human capital (*HUM_CAP*) is captured by the population with at least a secondary education in the UR. Inter-regional linkages (*INT_REG*) are measured by the number of co-patent flows across different URs.

3.4 Model

3.4.1 Fixed effect model

We use a fixed-effects panel data model (*FE*) to examine the impact of polycentricity on regional innovation performance.

$$INN\_PER_{it} = \alpha + \beta_1 POLY_{it} + \beta_2 Y_{it} + \gamma_t + \delta_i + \varepsilon_{it} \quad (6)$$

Where INN_PER_{it} is the regional innovation performance of UR i in year t. $POLY_{it}$ represents the degree of polycentricity derived from the four coopetition indexes, as well as their interaction item for UR i in year t. Y_{it} denotes a set of control variables (see above). γ_t is the time-fixed variable, δ_i is the individual fixed effect, ε_{it} is the random error term, and α, β_1, β_2 are the parameters to be estimated.

Before presenting our empirical results, we also deal with the standard range of econometric issues. The panel unit test results suggest stable relationships between variables. We then assessed three common econometric issues in multivariate regression: multicollinearity, heteroscedasticity, and autocorrelation. The Variance Inflation Factor (VIF), Breusch-Pagan, and Wooldridge test results (Table 2) suggest these issues are not relevant to our specifications.

3.4.2 Instrumental variable approach

While we hypothesize that polycentricity affects regional innovation capacity, this relationship may be biased by endogeneity: regional innovation performance may affect the extent to which a UR's spatial structure is polycentric. For instance, more innovative URs have greater resources and stronger incentives to establish collaborative networks among their constituent cities. This could, in turn, shape the observed pattern of polycentric structures. In this case, innovation is both an outcome and a driver of polycentric development. To address this

2021). The observed dispersion is then normalized against the "maximum possible standard deviation," defined for a hypothetical system of the same size where one city holds all importance and the others none. This normalization recalculates the maximum potential inequality for each UR according to its *N*, thereby making the measure scale-adjusted and enabling meaningful comparison across regions with different number of cities.

concern, we adopt an instrumental variable (IV) approach[4] to isolate the exogenous variable in polycentricity. A valid IV should be (1) correlated with the present-day polycentricity and (2) related to current innovation outcomes except through their effect on polycentricity.

Whereas previous studies often rely on IVs based on natural topology or historical polycentricity (Yang et al., 2024; Ouwehand et al., 2022), these approaches are more suited to capturing morphological polycentricity and are restricted to cross-sectional analyses. In contrast, our study focuses on the spatial balance of intercity relations using a longitudinal panel dataset spanning over 30 years. To address the limitations of prior IVs, we propose a novel IV[5] based on historical *sectoral similarity and complementarity*. The underlying idea is that URs with historically similar or complementary industrial structures are more likely to evolve into systems characterized by balanced competition or cooperation among their constituent cities.

To operationalize this, we draw on city-level firm data disaggregated at the 3-digit sectors[6] from 1960 to 1992. We compute both sectoral similarity and complementarity by considering the degree of structural overlap among cities, and aggregate these measures to the UR level to form historical polycentricity proxies. Further details on the construction of these measures are provided in Appendix A. The resulting indices serve as IVs for current polycentricity in cooperation and competition—*POLY_COOPIV* for *POLY_PROCOOP* and *POLY_COMPIV* for *POLY_POSCOMP*, respectively[7].

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[4] The IV procedure follows a two-stage steps. Firstly, we regress potential endogenous variable on the IV to obtain predicted values that are purged of endogeneity. Secondly, these fitted values are used in place of original variables in the main regression to estimate their causal relation on innovation.

[5] We also evaluated an alternative instrument for *POLY_PROCOOP* based on morphological polycentricity (constructed from the spatial distribution of city-level patent counts). Cluster-robust weak-ID diagnostics indicate that this instrument is insufficiently strong under heteroskedasticity, rendering associated 2SLS inference unreliable; we therefore do not rely on this specification in our preferred results.

[6] These sectors include third-level classifications. At the first level are broad includes industries such as construction, catering and real estate, which are further divided into more specific sectors – for example, residential building construction and construction installation within the construction industry.

[7] Although our analysis includes four main independent variables—*POLY_PROCOOP*, *POLY_RECCOOP*, *POLY_POSCOMP*, and *POLY_FACCOMP*—the first two and the last two are highly symmetric in both conceptual and empirical patterns, as shown in Table 1 and Figure 4. Given that the registered enterprise data used to construct our instruments represent stock rather than flow measures, we simplify the analysis by constructing only two IVs: one for the cooperative polycentricity pair (*POLY_PROCOOP*) and one for the competitive polycentricity pair (*POLY_POSCOMP*).

Table 1 Variables and description statistics in regression models

Variables		Description	Abbr.	Min	Max	Mean	Std.	Year
Dependent variable	Regional innovation performance	Total number of patents per worker within the UR	*INN_PER*	1.37	1226	126	198	1992, 1995, 1998,…, 2016, 2019, 2022
Independent variable	Polycentric provided cooperation	Balance degree between UR cities in providing cooperation	*POLY_PROCOOP*	0.00	0.96	0.46	0.35	Three-year moving window (1990-1992, 1993-1995, 1996-1998, …, 2017-2019, 2020-2022)
	Polycentric received cooperation	Balance degree between UR cities in receiving cooperation	*POLY_RECCOOP*	0.00	0.97	0.46	0.36	
	Polycentric posed competition	Balance degree between UR cities in posing competition	*POLY_POSCOMP*	0.00	0.98	0.69	0.24	
	Polycentric faced competition	Balance degree between UR cities in facing competition	*POLY_FACCOMP*	0.00	0.99	0.68	0.23	
	Cooperation	Averaged regional cooperation	*COOP*	0.00	0.50	0.13	0.12	
	Competition	Averaged regional competition	*COMP*	0.00	0.19	0.02	0.03	
Control variable	Economic level	GDP per capita	*GDP_PER*	1209	180608	34033	33854	One-year lag (1991,1994,1997, 2000,…,2015, 2018,2021)
	Population density	Population per square kilometer	*POP_DEN*	64	992	411	235	
	Human capital	Total Population with at least secondary education	*HUM_CAP*	10032	5045761	823072	974669	
	Inter-regional linkages	Number of co-patent flows across different URs	*INT_REG*	0	2789	123	352	
Instrumental variable	Polycentric sectoral complementarity	Balance degree between UR cities in industrial structural complementarity	*POLY_COOP_IV*	0.00	0.96	0.46	0.36	Three-year moving window (1960-1962, 1963-1965, …, 1987-1989, 1990-1992)
	Polycentric sectoral similarity	Balance degree between UR cities in industrial structural similarity	*POLY_COMP_IV*	0.00	0.98	0.65	0.32	

Note: All variables are log-transformed in the models, but the statistics in this table reflect the pre-transformed values

4. Results

4.1 Typologies of Chinese URs in regional innovation networks

Before conducting the regression analysis, we present the averaged values of four polycentricity indices for the 19 URs over the period 1990-2022, shown in Figure 4. The left panel shows each UR's polycentricity based on provided cooperation (horizontal axis) and posed competition (vertical axis). The right panel shows polycentricity based on received cooperation and faced competition. The 19 URs are categorized as central, eastern and western to highlight regional differences. Circle size indicates the average annual patent output (1990 to 2022).

Several key patterns emerge. Overall, URs with stronger innovation outcomes tend to display more balanced roles. The Yangtze River Delta (YRD) stands out as the most polycentric region, followed by the Yangtze River Middle-Reach (YRM), the Shandong Peninsula (SDP), and Chengdu-Chongqing (CHC). Interestingly, while the Pearl River Delta (PRD) and Beijing-Tianjin-Hebei (BTH) have been previously identified as highly polycentric (e.g., Demuynck, 2022), they no longer top the list even though they still have relatively high scores. Prior studies emphasize that these URs are morphologically polycentric (based on population distributions (Yue et al., 2025)) or functionally polycentric (based on headquarter-subsidiary connections (Zhao et al., 2017) or intercity commuting flows (Chen et al., 2020)). In contrast, our findings suggest that in BTH and the PRD, the distribution of cities' functional influence is more uneven than indicated by these morphological or commuting-based patterns. In fact, Beijing (in BTH), Guangzhou and Shenzhen (in the PRD) provide cooperation functions that are five times stronger than those of other cities within their respective URs. Other less polycentric URs, such as Ningxia-Yellow River (NXYH), Tianshan Mountains northern slopes (TSM) and Hohhot-Baotou-Ordos-Yulin (HBEY), are primarily located in the western or central regions.

Another notable observation is the positive association between cooperative and competitive polycentricity: URs that are more balanced in cooperation also tend to be more balanced in competition. Nonetheless, overall levels of polycentricity are higher in competition (0.70 for posed, 0.69 for faced) than in cooperation (0.44 for provided, 0.43 for received), suggesting that competitive pressures are more evenly distributed across cities than cooperative engagements. In other words, cities are more equal in how they compete than in how they cooperate. Finally, the similarity between the left and right panels implies a degree of symmetry between spatial distributions of cities' active (providing/posing) and passive (receiving/facing) roles. While past research often highlights the asymmetry in intercity relationships—where a city may provide significantly more knowledge than it receives or vice versa (Yang et al., 2024) —our findings show that the asymmetry of intercity ties does not result in substantial differences in polycentricity scores across the roles of provider and receiver. This is because, although individual ties are directional, they are derived from from the same network: each directed tie increases the 'provided' value of one city and the 'received' value of another. As a result, the distribution of values across cities tends to mirror each other, leading to consistent polycentricity scores regardless of directionality, whether in the context of cooperation or competition.

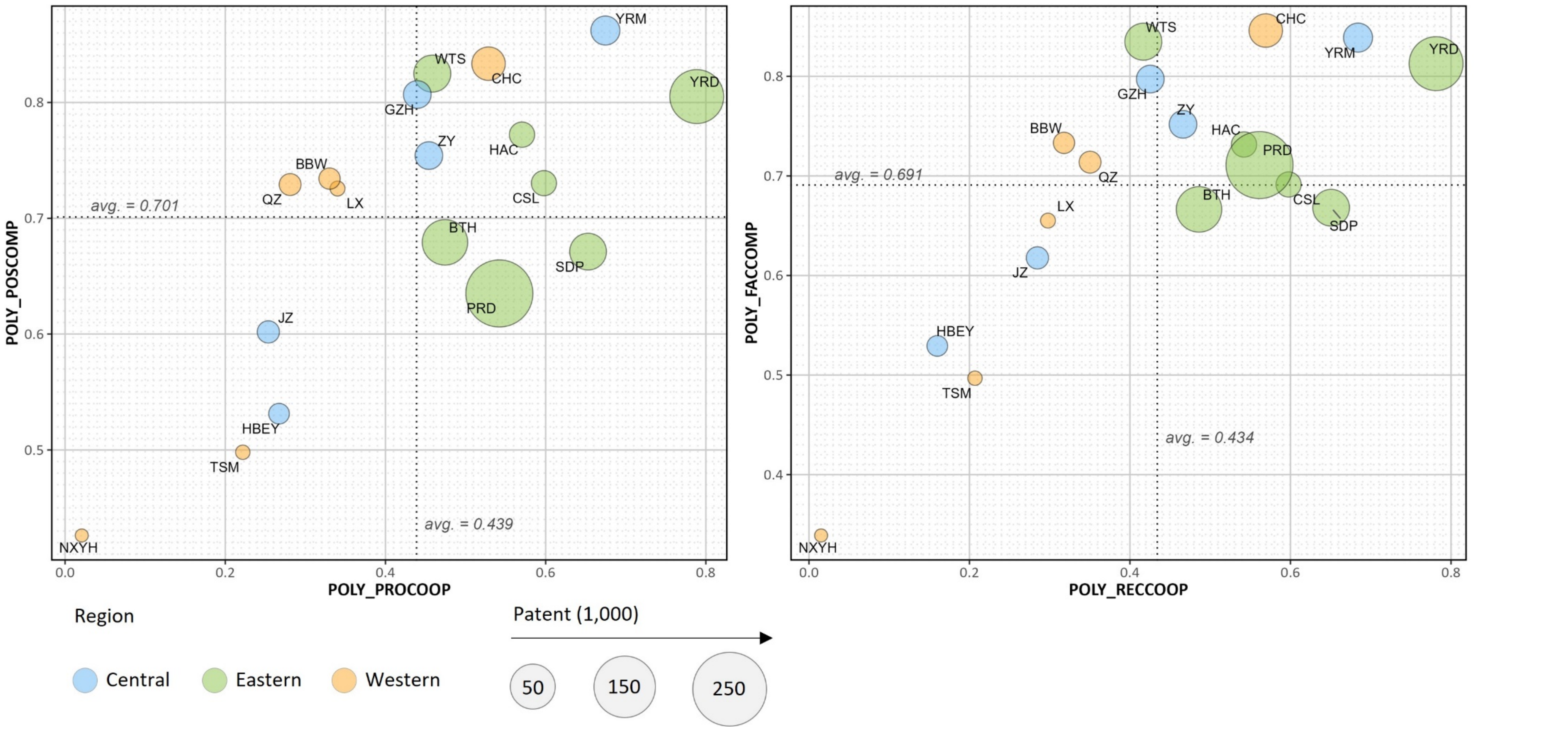

Figure 4 Relations between cooperative and competitive polycentricity in 19 URs: provided-posed (left) and received-faced (right)

Note: YRD: Yangtze River Delta; YRM: Yangtze River Middle-Reach; SDP: Shandong Peninsula; CSL: Southern of Liaoning; HAC: Harbin-Changchun; PRD: Pearl River Delta; CHC: Chengdu-Chongqing; BTH: Beijing-Tianjin-Hebei; WTS: West Coast of the Straits; ZY: Central Plain; GZH: Guanzhong Plain; LX: Lanzhou-Xining; BBW: Gulf of Tonkin; QZ: Central Guizhou; HBEY: Hohhot-Baotou-Ordos-Yulin; JZ: Central Shanxi; TSM: Tianshan Mountain Northern Slopes; DZ: Central Yunnan; NXYH: Ningxia-Yellow River

4.2 Regression analysis

4.2.1 The role of polycentricity in regional innovation

Stepwise regression results of the *FE* model are reported in Table 2. All the models include the UR fixed effects to control for the unobserved and time-invariant heterogeneity across URs, as well as the year fixed effects to control for the unobserved macroeconomic cycles that also drive the dynamics of innovation. The average R^2 values of all seven models are above 0.84, pointing to a sizeable explanatory power of our models. We now discuss each model in turn.

Model 1 serves as the baseline model and includes only the control variables. Unsurprisingly, the baseline model results suggest that regional innovation is positively associated with GDP per capita (*GDP_PER*) and Human capital (*HUM_CAP*). Inter-regional linkages (*INT_REG*) also exhibit a robust positive effect, highlighting the role of external connectivity in supporting knowledge creation. In contrast, the effect of population density (*POP_DEN*) is less consistent. While it is statistically significant in Model 1, this is no longer the case in *Models 2* to *7* after measures of polycentricity are introduced. This suggests that the benefits of population density may be mediated or overshadowed by the structure of intercity relationships.

Models 2 through 5 test the main effects of polycentricity on innovation outcomes. The results show that the impact of polycentricity on cities' cooperative behaviors is negative or not significant, contrary to our initial expectations. Specifically, in *Models 2* and *3*, an increase in the polycentricity degree in cooperation—both provided (*POLY_PROCOOP*) and received (*POLY_RECCOOP*)—is associated with a notable decline in innovation output. This suggests that a greater balance in how cities provide or receive cooperation within a region may dilute innovation gains. *Models 4* and *5* show that the polycentric structure of cities' competition (*POLY_POSCOMP* and *POLY_FACCOMP)* has no statistically significant association with innovation outcomes. As a consequence, hypotheses *H1a, H1b, H2a* and *H2b* are rejected.

These findings contrast with the normative view that balanced intercity structures inherently enhance innovation outcomes through greater integration and synergy (cf. Meijers, 2005). However, our results are consistent with recent studies, such as Caset et al. (2023), who found a negative association between regional polycentricity and economic productivity, and Li and Du (2021b), who identified a negative causal relationship between polycentricity and innovation capacity. These findings align with a broader stream of literature suggesting that polycentric structures may fail to generate the concentrate effects critical for high innovation performance (Parr, 2002; Brezzi and Veneri, 2015). In our operationalization, polycentricity is defined solely in terms of balanced functional roles—without accounting for the strength of intercity linkages—which can simply reflect a dispersion of functions across multiple centres (Green, 2007). In URs with low network connectivity, such balance does not guarantee the integration and dynamic exchange necessary for innovation-led growth (Meijers, 2018). We examine this argument in the next subsection.

Models 6 and 7 introduce the interaction effects between cooperative polycentricity and competitive polycentricity. The results indicate that although cooperative polycentricity and competitive polycentricity individually have negative or insignificant effects, their interactions are positive. Specifically, the interaction between polycentricity provided cooperation and posed competition (*PROCOOP*POSCOMP) (Model 6),* and the interaction between polycentric received cooperation and faced competition (*RECCOOP*FACCOMP) (Model 7).* Thus, hypothesis *H3* is accepted. These findings suggest that regional innovation performance improves when URs simultaneously maintain a balanced structure in both cooperation and competition. This extends prior firm-level studies on coopetition (e.g., Gnyawali and Park, 2011) by demonstrating that, at a regional scale, evenly distributed cooperative and competitive polycentricity improves regional innovation performance.

Table 2 The influence of polycentricity on regional innovation

Variables	Model 1 /	Model 2 POLY_PROCOOP *H1a*	Model 3 POLY_RECCOOP *H1b*	Model 4 POLY_POSCOMP *H2a*	Model 5 POLY_FACCOMP *H2b*	Model 6 PROCOOP*POSCOMP *H3*	Model 7 RECCOOP*FACCOMP *H3*
Main							
POLY_PROCOOP		-0.15(0.06)**				-0.20(0.06)**	
POLY_RECCOOP			-0.13(0.06)**				-0.17(0.07)**
POLY_POSCOMP				-0.11(0.12)		-0.03(0.01)	
POLY_FACCOMP					-0.07(0.10)		-0.06(0.10)
GDP_PER	0.59(0.10)***	0.59 (0.12)**	0.62(0.13)***	0.64(0.14)***	0.60(0.13)***	0.57(0.13)***	0.60(0.13)***
POP_DEN	0.44(0.20)**	0.23(0.24)	0.22(0.27)	0.07(0.35)	0.13(0.34)	0.08(0.35)	0.03(0.59)
HUM_CAP	0.58(0.08)***	0.74(0.12)**	0.71(0.12)***	0.64(0.12)***	0.65(0.12)***	0.79(0.12)***	0.77(0.13)***
INT_REG	0.16(0.32)***	0.19(0.04)**	0.18(0.04)***	0.17(0.04)***	0.18(0.04)***	0.18(0.04)***	0.17(0.04)***
COOP*COMP							
PROCOOP*POSCOMP						0.13(0.05)**	
RECCOOP*FACCOMP							0.11(0.05)**
Constant	-12.35	-13.33	-13.19	-11.55	-11.72	-12.92	-12.61
R^2	0.84	0.84	0.85	0.86	0.86	0.84	0.86
VIF	3.26	3.59	3.91	3.17	3.10	3.08	3.26
Breusch-Pagan	0.36	0.33	0.38	0.31	0.32	0.32	0.33
Wooldridge test	0.22	0.20	0.21	0.20	0.18	0.18	0.18
UR fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	627	627	627	627	627	627	627

****p*< 0.01, ***p*< 0.05, **p*< 0.1.*

4.2.2 Beyond polycentricity: does coopetition matter?

The results above indicate that achieving spatial balance in cities' functional attributes alone does not necessarily drive innovation. To investigate whether the effect of polycentricity depends on the intensity of intercity interactions, we introduce variables capturing the average level of cooperation (*COOP*) and competition (*COMP*) within each UR. Models 1 and 2 test their direct effects, while Models 3–6 incorporate their interaction terms with the four polycentricity measures (*COOPPOLY_PROCOOP*, *COOPPOLY_RECCOOP*, *COMPPOLY_POSCOMP*, *COMPPOLY_FACCOMP*; see Table 3).

Models 1 and 2 show that both *COOP* and *COMP* are positively associated with regional innovation outcomes, highlighting the importance of cooperative and competitive dynamics. Turning to interaction effects, we find that their effect differs notably. *Models* 5 and 6 reveal that the interaction between competition density and polycentricity structure (*PROCOOP*POSCOMP, RECCOOP*FACCOMP*) is positive. In other words, polycentricity contributes to innovation only when coupled with a sufficiently strong competitive density among cities. We calculate the turning points based on the marginal effects to identify the thresholds at which polycentricity begins to have a positive effect. Specifically, we find that the positive effect of polycentricity on innovation emerges when the competition strength exceeds 0.15 and 0.14 in *Models 5* and 6, respectively. However, these thresholds are only surpassed in a few instances—especially by three URs: the Pearl River Delta (PRD), Shandong Peninsula (SDP), and Beijing-Tianjin-Hebei (BTH), and only in selected years after 2015.

In contrast, *Models* 3 and 4 show that the interaction term between polycentricity and cooperation density (*COOP*POLY_PROCOOP, COOP*POLY_RECCOOP)* is not statistically significant. This suggests that while cooperation plays a positive role in fostering innovation, its effect is not significantly enhanced by a more balanced distribution of cooperative roles among cities. One explanation is that cooperative interactions—while sometimes organic—are often shaped by government-led initiatives in Chinese URs, with dominant core cities driving much of the collaborative agenda (Wu and Zhang, 2022). Such administratively driven arrangements may produce a formal balance in cooperative roles but do not necessarily generate the reciprocal, innovation-enhancing exchanges required to strengthen the link between cooperation and polycentricity. Competitive dynamics, by contrast, are largely market-driven and arise organically; when competition is balanced across cities in a polycentric UR, it can reinforce innovation by incentivizing specialization, differentiation, and continuous upgrading.

Table 3 The interaction effect between coopetition strength and polycentricity

Variables	Model 1 COOP	Model 2 COMP	Model 3 COOP* POLY_PROCOOP	Model 4 COOP* POLY_RECCOOP	Model 5 COMP* POLY_POSCOMP	Model 6 COMP* POLY_FACCOMP
Main						
COOP	0.17 (0.07)**		0.19(0.08)**	0.20(0.09)**		
COMP		0.13(0.04)**			0.11(0.04)**	0.13(0.05)**
POLY_PROCOOP			-0.14(0.09)*			
POLY_RECCOOP				-0.12(0.11)		
POLY_POSCOMP					-0.02(0.13)	
POLY_FACCOMP						-0.02(0.09)
COOP* POLY_PROCOOP			0.06(0.09)			
COOP * POLY_RECCOOP				0.10(0.09)		
COMP*POLY_POSCOMP					0.13(0.06)**	
COMP*POLY_FACCOMP						0.14(0.06)**
GDP_PER	0.51(0.13)**	0.62(0.12)***	0.47(0.12)**	0.49(0.11)***	0.58(0.16)**	0.62(0.13)***
POP_DEN	0.14(0.21)	0.08 (0.20)	0.11(0.17)	0.09(0.17)	0.15(0.32)	0.06(0.26)
HUM_CAP	0.63(0.11)***	0.60(0.10)***	0.77(0.10)**	0.75(0.10)***	0.66(0.14)**	0.61(0.11)**
INT_REG	0.16(0.04)**	0.15(0.04)**	0.15(0.04)**	0.14(0.03)***	0.14(0.04)**	0.15(0.04)**
Constant	-10.86	-11.00	-13.33	-13.19	-11.70	-10.93
R^2	0.86	0.88	0.85	0.85	0.86	0.88
VIF	3.21	3.25	3.76	4.13	2.55	2.55
Breusch-Pagan	0.25	0.18	0.22	0.38	0.17	0.16
Wooldridge test	0.21	0.18	0.21	0.21	0.20	0.22
UR fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	627	627	627	627	627	627

****p*< 0.01, ***p*< 0.05, **p*< 0.1.*

4.2.3 Dealing with endogeneity

The second-stage results of our IV models are reported in Appendix B, alongside the standard tests for the relevance and exogeneity of the instruments. Across all model specifications, both the tests on the relevance of the excluded instruments and the test of identification provide evidence for the validity of our IVs. Furthermore, the endogeneity test results suggest that *POLY_PROCOOP* and *POLY_POSCOMP* can be treated as exogenous. The results of the IV model corroborate those in Table 2 in the text. Specifically, we confirm the negative relationship between cooperative polycentricity and regional innovation performance. The effect of competitive polycentricity remains statistically insignificant, while the interaction between cooperative and competitive polycentricity remains positive. Moreover, although the magnitude of the IV-estimated coefficients is larger, they are broadly comparable to those obtained in the baseline models reported in Table 2 in the main text.

4.2.4 Robustness check

We implement two robustness checks to assess the stability of our findings. Prior work has noted that polycentricity measures are sensitive to the number and size of cities, and a standard-deviation–based index may overlook core–periphery asymmetries (Brezzi & Veneri, 2015). To address this concern, we replace the standard-deviation–based polycentricity index with a Gini-based measure that captures inequality in the distribution of cities' functional roles (providing/receiving cooperation; posing/facing competition) within each UR. The equations and full results are reported in Appendix C. Relative to the baseline (Table 2), the Gini-based estimates show that the effect of polycentricity turns positive—for both the cooperation- and competition-based measures—and remains so when interaction terms are included. This is consistent with the interpretation that the Gini-based index emphasizes dispersion: higher values indicate that functional capacity is more widely shared across cities (rather than concentrated in a single core), a configuration associated with stronger regional innovation. While confiriming our main arguments, these results also highlight the sensitivity of polycentricity measurement and the need to align index choice with the theoretical dimension under investigation.

Second, we re-estimate all models on two subperiods—2000–2019 and 2010–2019—to exclude major external shocks (the 1997–98 Asian financial crisis, the 2008–09 global crisis, and post-2019 COVID-19 effects). The main results are unchanged: coefficient signs and statistical significance mirror the full-period estimates, with only modest shifts in magnitude as expected from shorter windows. These estimates are reported in Appendix D.

5. Discussion and conclusion

In this paper, we examined whether the polycentric structure of cities' coopetition influences regional innovation performance. Drawing on city-pair co-patent data from nineteen Chinese URs over the period 1990-2022, we employ a fixed effect model combined with an instrumental variable approach to identify causal relationships. This paper makes three key contributions. Conceptually, we move beyond traditional definitions of polycentricity—typically based on population balance or network centrality (Chen et al., 2020; Münter and Volgmann, 2020)—by focusing on the spatial distribution of directional coopetition roles: cities as providers or receivers of cooperation and as initiators or targets of competition. This allows for a more nuanced assessment of whether innovation functions are widely shared or concentrated in a few dominant cities. Methodologically, we develop an improved indicator of coopetition, building on Demuynck et al. (2023) and Zhang et al. (2025). We extend their approach by (i) applying it to innovation networks and (ii) incorporating both geographic proximity and technological similarity. Empirically, this operationalization of polycentricity provides a basis for detecting functional imbalances and guiding policy measures to promote a more balanced distribution of innovation capabilities, an approach consistent with the priorities articulated in recent policy initiatives in China.

Before presenting the regression results, a preliminary application of our framework reveals a critical pattern: cooperation is more strongly associated with regional polycentricity than competition. URs with higher levels of cooperative polycentricity tend to exhibit stronger cooperative ties among cities (correlation coefficient = 0.60). This relationship stems from how our cooperation index is constructed—emphasizing geographical non-overlap in collaboration networks and technological complementarity between cities. In polycentric regions, where the cooperation function between cities is more evenly distributed, these conditions are more likely to occur: cities are distinct enough to have non-overlapping cooperation spheres yet diverse enough in their technological specializations to foster complementary innovation. In contrast, competition is only weakly correlated with polycentricity (correlation coefficient = 0.17). This may reflect the fact that competitive dynamics are more directly shaped by factors such as local policy incentives and centralized resource allocation (Wang and Deng, 2022) rather than spatial structure alone. These findings align with earlier studies suggesting that Chinese URs exhibit clear spatial differences in how cities engage in competitive and cooperative innovation activities (Demuynck, 2022; Zhang et al., 2025).

Next, we find that polycentric development in cooperation—whether in the form of providing or receiving cooperation—is negatively associated with regional innovation performance. This reflects the dilution of agglomeration externalities often observed in highly polycentric systems (Sun et al., 2019). Similarly, competitive polycentricity alone does not significantly affect innovation performance. However, this does not imply that polycentric development lacks value. In fact, we find that polycentricity can enhance innovation performance under two conditions: (i) when cooperative polycentricity is accompanied by competitive polycentricity and (ii) when competitive polycentricity is coupled with sufficient overall competition strength. These findings suggest that polycentricity's effectiveness depends not on its individual dimensions but on the interplay between functional roles and underlying intensity, highlighting the importance of balance and integration in regional innovation systems.

These findings have important implications for spatial planning discourse in China. While the Chinese government has emphasized polycentric development as a guiding principle in territorial planning—aiming to balance the growth of small, medium, and large cities (Liu et al., 2018)—we argue that functional connectivity, rather than structural balance alone, should be the primary objective. Fostering a landscape that supports both strong intercity cooperation and competition is essential. Achieving this requires targeted, region-specific strategies. For example, the Yangtze River Delta (YRD) already exhibits advanced intercity cooperation, supported by established collaborative platforms such as the '*Integrated Intellectual Property Trading Platform*'. In such regions, efforts to strengthen coopetitive capacity should be prioritized or at least developed together with broader polycentric planning. In less integrated URs, by contrast, promoting functional strength and connectivity should be a priority. This may require allocating more resources to core cities, which can act as connective hubs that facilitate broader knowledge diffusion despite potentially reinforcing a more hierarchical urban structure.

Our research contributes to an emerging stream of scholarship that calls for stronger linkages between the literatures on the geographies of innovation and polycentric URs (Xue et al., 2025). As Galvin et al. (2020) argue, firms often engage in co-opetition, a dynamic that makes changes in innovation outcomes visible primarily at the network level. This logic extends to cities: intercity co-opetition is most effective when cities recognize their positions and interdependencies within broader networks, as coordination and alignment are strongest when actors are aware of their connections and roles. At the same time, innovative activity is well established as being neither uniform nor random across space (Hospers et al., 2012), with innovation systems playing a central role in producing and reproducing spatial inequalities. In this context, polycentricity provides a valuable lens for examining both the structural distribution of innovation outcomes and the active roles cities assume in shaping innovation (e.g., whether they primarily provide or receive cooperation), a dimension often overlooked in prior research that has emphasized structure over agency (e.g., Li & Du, 2021). By incorporating the latter, our analysis shows that knowledge production remains marked by unevenness, not only in outcomes, but also in the intentions and strategies through which cities cooperate and compete. Overall, polycentricity offers a critical framework for capturing these dynamics, though much remains to be explored within this perspective.

While our analysis offers a broad overview of coopetition polycentric dynamics across Chinese URs and their impact on regional innovation performance, the regression results risk reifying cities or URs as monolithic actors, abstracting away from the complexities and heterogeneities within them. To better capture the lived realities of these dynamics, future research would benefit from in-depth case studies that explore how these processes unfold in specific locations. For instance, examining a particular UR in greater detail—identifying which cities or firms engage in coopetition, how polycentric structures are functionally organized, and how power relations shape these dynamics—could provide a more grounded understanding of coopetition in practice. On the analytical front, several limitations suggest avenues for improvement. First, our coopetition index is partly based on technological similarity. This is a stylized representation of coopetition dynamics, which inevitably simplifies complex realities. For example, technological similarity can also facilitate collaboration through mutual understanding. This points to the possibility of a nonlinear relationship between technological relatedness and cooperation. Future work could test this by incorporating nonlinear specifications (e.g., quadratic terms) to capture potential inverted U-shaped effects. More broadly, this connects to an ongoing debate in economic geography: whether specialization or diversity more effectively fosters technological change and innovation (Santoalha, 2019), and how these relationships may shift when spatial dimensions of coopetition are considered.

Future research could explore whether coopetition is more likely to emerge within narrowly specialized urban economies or whether diverse technological environments provide a stronger basis for such dynamics. Second, our study does not explicitly examine the underlying mechanism through which polycentricity affects regional innovation. Investigating processes such as cities suffering from agglomeration shadow or benefiting from borrowed size (as in Li and Schmidt, 2024) could offer a detailed understanding of the disaggregated spatial dynamics that underlie broader patterns of regional innovation.

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Appendix A

To construct IVs for *POLY_PROCOOP*, we measure the degree of historical sectoral complementarity between each pair of cities within a UR using the following formula,

$$Complementarity_{ij} = \frac{|A_i \, \Delta \, A_j|}{|A_i \cup A_j|} \tag{1}$$

Where A_i and A_j represent the sets of dominant industries in city i and j respectively. Δ is the symmetric difference between the two sets. This index captures the extent to which cities specialize in non-overlapping industrial sectors, thereby reflecting structural complementarity in their economic structures.

To construct IVs for POLY_POSCOMP, one might expect to use 1- $Complementarity_{ij}$ given the use of $1 - J_{i,j}$ and $J_{i,j}$ (technological dissimilarity and similarity) in the main model's computation of cooperation and competition. However, we instead adopt a sectoral similarity index, as inverting the complementarity measure can overstate similarity when complementarity is already low—particularly in historical industrial data starting from 1960, which underpins the IVs. The similarity index is defined as,

$$Similarity_{ij} = \sum_{k} \min \left(\frac{N_{ik}}{N_i}, \frac{N_{jk}}{N_j}\right) \quad (2)$$

Where N_{ik} and N_{jk} are the number of registered enterprises in sector k in city i and j, respectively. N_i and N_j are the total number of registered enterprises in city i and j, respectively. This index captures the extent to which two cities have overlapping sectoral structures. Subsequently, the UR-level similarity and complementarity indices are computed by aggregating these measures to the UR level to form historical polycentricity proxies. Notably, the main model begins in 1990 when patenting activity and intercity cooperation are already observable, making the use of $1 - J_{i,j}$ empirically appropriate in our context.

Appendix B

We discuss the possible endogeneity issues by the statistics provided in Appendix Table 1 and 2. The former table reports to what extent polycentricity can be effectively explained by the IV while the latter shows the full estimates with interaction items also instrumented. The IVs are tested both separately and simultaneously. More specifically, we ran (1) two regressions in which we instrumented the cooperative and competitive polycentricity by the historical polycentricity constructed based on sectoral similarity and complementarity, respectively (*POLYCOOP_IV*, *POLYCOMP_IV*), and (2) one regression in which the two instruments and their interaction are included simultaneously. The Underidentification, Weak identification, and Overidentification tests were used to evaluate the validity, relevance, and coherence between the instrumental variables.

According to Appendix Table 1, the Anderson statistics are significant across all specifications, suggesting that the IVs are correlated with the endogenous variable. In the Weak identification test, the Cragg-Donald Wald F statistic for the instruments, POLYCOOP_IV, POLYCOMP_IV, are greater than that of Stock-Yogo critical values at 10% maximal IV size at the 5% confidence interval (Appendix Table 1 (1) and (2)). These results show the validity of the above two IVs. In Model (3) in which the two instruments and their interaction are introduced simultaneously, the p-value of Sargan statistic (0.99>0.10) indicates there is no over-identification problem, i.e., the existence of more IVs than the endogenous variable is valid. We then test the endogeneity of polycentricity with the Durbin-Wu-Hausman test. The statistic is insignificant at the p<0.05 level, suggesting that endogeneity issue is not a concern in our estimates.

Table 1. The first stage result of FE-IV model

	POLYCOOP_IV (1)	POLYCOMP_IV (2)	Interaction_IV (3)
Underidentification test			
Anderson canon. corr. LM statistic	3.01**	3.82**	42.88**
Weak identification test			
Cragg-Donald Wald F statistic	12.96	17.23	16.85

Stock-Yogo critical values (10% maximal IV size)	16.38	16.38	16.38
Overidentification test	/	/	10.07
Sargan statistic	/	/	0.99
Endogeneity test			
Durbin-Wu-Hausman	0.05	0.05	

****p< 0.01, **p< 0.05, *p< 0.1.*

Table 2. The second stage result of FE-IV model

Variables	POLY_PROCOOP (1)	POLY_POSCOMP (2)	POLY_PROCOOP* POLY_POSCOMP (3)
POLY_PROCOOP	-0.50(0.21)*		-0.69(0.33)*
POLY_POSCOMP		-0.07(0.28)	-0.09(0.30)
POLY_PROCOOP* POLY_POSCOMP			0.12(0.04)**
GDP_PER	0.70(0.14)***	0.65(0.20)**	0.63(0.32)**
POP_DEN	0.05(0.26)	0.24(0.26)	0.08(0.25)
HUM_CAP	0.82(0.20)***	0.63(0.14)***	0.62(0.12)***
INT_REG	0.20(0.05)***	0.16(0.05)**	0.15(0.04)**
R^2	0.94	0.95	0.95
Observation	209	209	209
Year FE	Yes	Yes	Yes
Region FE	Yes	Yes	Yes

****p< 0.01, **p< 0.05, *p< 0.1.*

Appendix C

The Gini index captures inequality in the distribution of cities' functional roles (providing/receiving cooperation, posing/facing competition) within a region. It is defined as:

$$Poly = 1 - \frac{\sum_{i=1}^{N}\sum_{j=1}^{N}|x_i - x_j|}{2N^2\mu}$$

Where N is the number of cities in the UR, x_i represents the cooperation/competition indexes of city i. μ is the mean of x_i across all cities. This formulation normalizes inequality relative to the system's average, with values ranging from 0 (complete imbalance, i.e. highly concentrated in one city) to 1 (perfect balance across cities). Based on this measure, we construct four Gini-based polycentricity indexes: polycentric provided cooperation (*PL_PROCOOP_GINI*), polycentric received cooperation (*PL_RECCOOP_GINI*), polycentric posed competition (*PL_POSCOMP_GINI*), and polycentric faced competition (*PL_FACCOMP_GINI*).

Table 3 The influence of polycentricity (Gini-index based) on regional innovation

Variables	Model 1 /	Model 2 PL_PROCOOP _GINI	Model 3 PL_RECCOOP _GINI	Model 4 PL_POSCOMP_ GINI	Model 5 PL_FACCOMP_ GINI	Model 6 PL_PROCOOP_GINI * PL_POSCOMP_GINI	Model 7 PL_RECCOOP_GINI * PL_FACCOMP_GINI
Main							
PL_PROCOOP_GINI		0.23(0.07)**				0.29(0.09)***	
PL_RECCOOP_GINI			0.23(0.08)**				0.26(0.07)**
PL_POSCOMP_GINI				0.03(0.10)		0.06(0.07)	
PL_FACCOMP_GINI					0.12(0.04)**		0.14(0.04)**
GDP_PER	0.59(0.10)***	0.45 (0.22)**	0.47(0.22)***	0.61(0.22)**	0.63(0.21)**	0.42(0.22)*	0.48(0.22)**
POP_DEN	0.44(0.20)**	0.21(0.21)	0.19(0.21)	0.26(0.23)	0.28(0.22)	0.22(0.16)	0.22(0.19)
HUM_CAP	0.58(0.08)***	0.61(0.14)***	0.59(0.14)***	0.61(0.15)**	0.64(0.15)***	0.66(0.14)**	0.62(0.14)***
INT_REG	0.16(0.01)***	0.19(0.04)***	0.18(0.04)***	0.18(0.04)***	0.17(0.04)**	0.16(0.05)**	0.17(0.04)***
PL_PROCOOP_GINI * PL_POSCOMP_GINI						0.14(0.06)**	
PL_RECCOOP_GINI * PL_FACCOMP_GINI							0.01(0.04)
Constant	-12.35	-10.23	-9.99	-12.06	-12.71	-10.63	-10.64
R^2	0.84	0.81	0.82	0.84	0.82	0.79	0.79
VIF	3.26	3.81	3.21	3.15	3.25	3.27	3.26
Breusch-Pagan	0.36	0.33	0.38	0.31	0.32	0.32	0.33
Wooldridge test	0.22	0.15	0.16	0.16	0.15	0.15	0.15
UR fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	627	627	627	627	627	627	627

****p< 0.01, **p< 0.05, *p< 0.1.*

Appendix D

Table 4 The influence of polycentricity on regional innovation (2000-2019)

Variables	Model 1 /	Model 2 POLY_PROCO OP	Model 3 POLY_RECCO OP	Model 4 POLY_POSCOM P	Model 5 POLY_FACCOM P	Model 6 PROCOOP*POSCOM P	Model 7 RECCOOP*FACCOMP
Main							
POLY_PROCOOP		-0.16(0.09)**				-0.18(0.10)*	
POLY_RECCOOP			-0.11(0.09)				-0.21(0.14)*
POLY_POSCOMP				-0.07 (0.07)**		0.11(0.12)	
POLY_FACCOMP					-0.12(0.05)**		0.13(0.05)**

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
	/	POLY_PROCOOP	POLY_RECCOOP	POLY_POSCOMP	POLY_FACCOMP	PROCOOP*POSCOMP	RECCOOP*FACCOMP
GDP_PER	1.03(0.17)***	0.94 (0.16)***	0.96(0.17)***	1.04(0.17)***	0.94(0.17)***	0.95(0.17)***	0.80(0.19)***
POP_DEN	-0.09(0.23)	0.02(0.20)	-0.04(0.21)	-0.12 (0.24)	-0.15(0.24)	-0.03(0.22)	-0.06(0.22)
HUM_CAP	1.09(0.26)***	0.99(0.27)**	1.02(0.28)**	1.10(0.27)***	1.24(0.27)***	1.01(0.28)**	1.18(0.27)***
INT_REG	0.07(0.04)***	0.08(0.04)**	0.08(0.04)*	0.08(0.04)***	0.05(0.03)*	0.08(0.04)**	0.05(0.04)
COOP*COMP							
PROCOOP*POSCOMP						0.85(1.18)	
RECCOOP*FACCOMP							0.07(0.03)*
Constant	-20.68	-19.05	-1.27	-20.69	-21.93	-19.15	-19.57
R^2	0.77	0.78	0.85	0.77	0.78	0.78	0.78
VIF	3.26	3.34	3.91	3.17	3.10	3.08	3.26
Breusch-Pagan	0.36	0.32	0.32	0.31	0.32	0.32	0.33
Wooldridge test	0.22	0.18	0.19	0.20	0.21	0.19	0.20
UR fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	380	380	380	380	380	380	380

Table 5 The influence of polycentricity on regional innovation (2010-2019)

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
	/	POLY_PROCOOP	POLY_RECCOOP	POLY_POSCOMP	POLY_FACCOMP	PROCOOP*POSCOMP	RECCOOP*FACCOMP
Main							
POLY_PROCOOP		-0.16(0.09)*				-0.18(0.09)*	
POLY_RECCOOP			-0.11(0.09)				-0.21(0.13)*
POLY_POSCOMP				-0.06(0.07)*		0.11(0.11)	
POLY_FACCOMP					-0.80(0.51)		-0.12 (0.05)*
GDP_PER	1.02(0.17)***	0.94 (0.16)***	0.96(0.17)***	1.04(0.17)***	0.02(0.00)***	0.95(0.17)***	0.80(0.18)*
POP_DEN	-0.09(0.23)**	0.02(0.20)	-0.04(0.21)	-0.12 (0.23)	0.20(0.20)	-0.03(0.22)	-0.06(0.22)
HUM_CAP	1.09(0.26)***	0.99(0.27)**	1.02(0.28)**	1.10(0.27)***	0.03(0.00)**	1.01(0.28)**	1.18(0.29)**
INT_REG	0.07(0.04)***	0.08(0.04)*	0.08(0.04)*	0.08(0.04)***	0.18(0.04)*	0.08(0.04)**	0.05(0.03)***
COOP*COMP							
PROCOOP*POSCOMP						0.03(0.04)	
RECCOOP*FACCOMP							0.06(0.03)***

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
	/	POLY_PROCOOP	POLY_RECCOOP	POLY_POSCOMP	POLY_FACCOMP	PROCOOP*POSCOMP	RECCOOP*FACCOMP
Constant	-20.68	-19.05	-19.38	-20.69	2.91	-19.15	-19.56
R^2	0.77	0.78	0.77	0.77	0.77	0.78	0.78
VIF	3.26	3.34	3.91	3.17	3.10	3.08	3.26
Breusch-Pagan	0.24	0.22	0.22	0.22	0.22	0.23	0.22
Wooldridge test	0.18	0.19	0.17	0.17	0.17	0.18	0.17
UR fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	190	190	190	190	190	190	190