Polycentricity and Technological Diversification: Divergent Pathways Across Chinese Urban Regions

Abstract: This paper examines how polycentricity shapes technological diversification in Chinese urban regions. Beyond morphological and functional dimensions, we introduce knowledge polycentricity, reflecting the balance of innovation across technological domains. Using patent data (2006–2020), diversification is measured via relative relatedness density and estimated through fixed-effects and instrumental variable models. Findings highlight intra-regional functional polycentricity as the main driver, while other dimensions mainly act through interactions. Developmental heterogeneity produces distinct diversification pathways. Results call for innovation policies tailored to polycentricity characteristics and diversification strategies.

Keywords: polycentricity, technological diversification, knowledge collaboration, patent, China, polycentric urban regions

JEL codes: O31, R11, R12

1 Introduction

Polycentric urban regions (PURs), defined as territories with multiple, relatively proximate centers with balanced development (Derudder et al., 2022), are widely regarded as an empirical reality, an analytical framework, and a normative goal for territorial development policies (Harrison et al., 2023). Much of the scholarly attention devoted to PURs stems from the purported economic benefits associated with polycentric development; however, empirical findings often diverge, with some reporting insignificant or even negative correlations (Dadashpoor et al., 2023). These inconclusive findings suggest the need for more nuanced approaches that account for the underlying structural forces shaping regional economic development.

One such perspective is technological diversification, which has gained salience in knowledge-driven economies where innovation is a key driver of growth (Solow, 1957; Frenken et al., 2007; Neffke et al., 2011). Jacobs (1969) first emphasized the benefits of diversified urban economies, arguing that they foster new ideas and knowledge spillovers, creating opportunities for innovation. Building on this, research has demonstrated that new economic activities tend to emerge from technologically related pre-existing activities, a process known as regional branching or regional diversification (Frenken & Boschma, 2007; Boschma & Frenken, 2011).

Regional diversification entails a balance between similarity and diversity in regional capabilities. While overlapping capabilities (such as shared skills and know-how) facilitate communication and collaboration, excessive similarity may lead to cognitive lock-in (Nooteboom, 2000; Neffke et al., 2011). This raises questions about (1) how different types of capabilities (related or unrelated) shape the diversification process, and (2) in geographical terms, how their sources (local or external) influence this process. PURs offer a promising spatial context for addressing this question. Their functional connectivity and morphological configurations combine cognitive proximity with diversity across centres, potentially enabling collaboration while avoiding redundancy and stimulating innovation. Knowledge collaboration is particularly relevant among the various indicators used to capture such functional connectivity (e.g., human mobility, transportation infrastructure, commuting patterns). It not only facilitates the transfer of capabilities but also serves as a measurable proxy for polycentricity within and beyond regions (Li & Phelps, 2018). Viewing regional diversification through the lens of knowledge collaboration and polycentricity opens new analytical ground: enriching the diversification literature with spatial-structure insights, and advancing polycentricity studies with a capability-based understanding of regional economic outcomes.

China's ongoing innovation-driven growth, particularly within its rapidly developing urban regions (URs), provides a compelling context for examining these dynamics. These urban regions, characterized by increasing interconnectivity and regional divisions of labor, offer a valuable setting for exploring the interplay between polycentricity and diversification. While some studies have begun investigating this relationship, they primarily focused on general innovation outcomes. For example, Li and Du (2022) analysed the effects of *morphological* polycentricity (the spatial distribution and size balance of cities within a region) on urban innovation capacity using patent counts. Ma and Xu (2022) complemented this by adopting a *functional* perspective (relational flows and interactions among cities in urban networks) and examining regional innovation performance based on scientific publications. However, little attention has been paid to how morphological and functional polycentricity may jointly influence technological diversification. While morphological polycentricity provides the spatial foundation for the diffusion of knowledge and innovation, functional polycentricity captures the functional intensity of intercity knowledge flows. When considered jointly, these two dimensions shape a urban region's physical and relational connectivity and the channels through which knowledge can circulate and recombine. This interaction can enable technological diversification, particularly when the urban region's internal knowledge base is complex and distributed. This provides a rationale for examining the combined influence of morphological and functional polycentricity and points to the importance of a third perspective: the internal structure of knowledge production within the urban region.

To address this, we introduce knowledge polycentricity, which captures the internal complexity of a urban region's technological structure. Knowledge polycentricity reflects the degree to which innovation activities are distributed across multiple technological domains within a urban region, thereby representing the polycentricity of its knowledge base. A higher level of knowledge polycentricity indicates a more diversified and decentralized knowledge structure, unlike systems concentrated in a few core technologies. By incorporating knowledge polycentricity into the analysis, we acknowledge that the drivers of regional diversification in urban regions are rooted in their inherent multiplexity, manifested through spatial structure, intercity connectivity, and internal knowledge organization. This integrated framework motivates our empirical approach, which systematically examines how these multiple dimensions of polycentricity, both individually and interactively, shape technological diversification in Chinese urban regions.

To operationalize this framework, we draw on patent data from the China National Intellectual Property Administration (CNIPA). We distinguish between locally and externally sourced knowledge by identifying patent collaboration within *versus* beyond regional boundaries, which we use to construct measures of intra- and extra-regional functional polycentricity (*FP_intra* and *FP_extra*). We measure knowledge polycentricity (*KP*) using the International Patent Classification (IPC) information and morphological polycentricity (*MP*) using the LandScan™ High Resolution Global Population Dataset. Employing instrumental variable (IV) techniques for these polycentricity metrics, we establish the causal relationship between polycentricity and diversification.

The remainder of this paper is structured as follows. Section 2 reviews the relevant literature and positions this study within ongoing debates on polycentricity, technological diversification, and their interrelationship. Section 3 introduces the data, variables, and empirical models. Section 4 presents the results, showing that intra-regional functional polycentricity serves as the main driver of technological diversification, while other dimensions exert influence primarily through interaction effects. Section 5 discusses the mechanisms underlying these patterns, highlighting the divergent pathways of polycentricity across urban regions with different development levels. Finally, Section 6 concludes by linking the findings to differentiated innovation policy implications and outlining future research avenues on the underlying mechanisms, methodological refinements, cross-context comparisons, and institutional factors shaping regional diversification.

2 Literature review

2.1 Polycentricity and its effects

2.1.1 Defining polycentricity: morphological, functional and knowledge-based

Polycentricity is often examined from two perspectives: (1) morphological polycentricity, which emphasizes the balance of the regional spatial structure as reflected by the equilibrium of the urban hierarchy (Kloosterman & Lambregts, 2001; Meijers, 2005), and (2) functional polycentricity, which focuses on the distribution of various functions resulting from interactions among urban centers (De Goei et al., 2010; Green, 2007; Albrechts, 2001). Scholars have argued that these dimensions, while different, are intrinsically linked (Burger & Meijers, 2012; Burger et al., 2014; Li & Phelps, 2018). An ideal-typical PUR has both a balanced spatial morphology and dynamic functional interactions (Dadashpoor et al., 2023).

Among the various functional linkages connecting cities, a key aspect of functional integration is inter-city knowledge collaboration, driven by interactions among individuals, enterprises, and universities. Such collaborations are central to economic development (Lüthi et al., 2013). These knowledge collaboration networks, which operate across both intra- and extra-regional scales (Li & Phelps, 2018), enable PURs to function as both *incubators* of new trends, knowledge, and innovation and as *hubs* connecting cities within and beyond their regional boundaries (Gottmann, 1957). Consequently, attention is increasingly paid to knowledge flows as a lens for understanding and measuring functional polycentricity (Li & Phelps, 2017; Li & Phelps, 2018).

Building on this, Ma and Xu (2022) propose a third perspective on polycentricity, knowledge polycentricity, which they define as '*a situation... where a group of cities maintain similar levels of importance in terms of their knowledge production and knowledge collaboration*'. While their approach reframes morphological and functional polycentricity in terms of knowledge flows, it remains rooted in a spatial-relational logic, emphasizing the balance and connectivity of cities. Different from their approach, our study proposes a new interpretation of knowledge polycentricity that focuses on the internal structure of a region's knowledge systems, specifically, the extent to which innovation activities are diversified across multiple technological domains within a region. This complements morphological and functional polycentricity by capturing the complexity of the regional knowledge systems. Importantly, we view knowledge polycentricity as a necessary foundation for understanding how morphological and functional polycentricity may jointly influence technological diversification—shaping not only the channels through which knowledge flows, but also the substance and variety of what flows.

Together, morphological, functional, and knowledge polycentricity capture complementary dimensions of regional polycentricity—spatial structure, intercity connectivity, and internal knowledge organization—highlighting that regional diversification in urban regions is shaped by the interplay of multiple, coexisting structural and relational mechanisms. This integrated perspective motivates our empirical analysis of various dimensions of polycentricity and their role in regional innovation dynamics.

2.1.2 Theoretical underpinnings and uncertain effects of polycentricity

The theoretical logic of the effects of polycentricity can be understood through two interrelated conceptual lenses: agglomeration economies *versus* agglomeration diseconomies and borrowed size *versus* agglomeration shadows (Dadashpoor et al., 2023). The first perspective suggests that increased urban density can generate agglomeration benefits that enhance economic productivity (Li et al., 2022; Ting & Lin, 2013; Veneri & Burgalassi, 2012), but it can also produce diseconomies such as congestion and pollution (Brinkman, 2016; Chen & Zhou, 2017; Duranton & Puga, 2001; Meijers et al., 2016). Polycentric development is often viewed as being advantageous because it offers a spatial configuration that helps balance these positive and negative externalities (Yan & Wang, 2022). The second perspective considers the 'borrowed size' effect, where smaller cities benefit from their proximity to larger ones (Alonso, 1973; Camagni et al., 2016), while a central city may simultaneously exert 'agglomeration shadows' on its adjacent small cities, thereby hindering their development (Sun et al., 2019; Meijers & Burger, 2017). Empirical studies suggest that borrowed size effects tend to outweigh agglomeration shadows in interconnected, balanced urban regions where physical proximity and accessibility to large cities can be exploited (Meijers, 2007; Meijers et al., 2016).

However, a growing body of empirical research suggests that adopting polycentricity as a normative goal is not scientifically well-supported (Groth et al., 2011; Richardson & Jensen, 2000; Waterhout et al., 2005). Studies focusing on the relationship between polycentricity and economic performance frequently report insignificant (Malý, 2016; Ouwehand et al., 2022) or even negative results (Veneri & Burgalassi, 2012; Brezzi & Vereni, 2015). The influence of specific contexts and the complex dynamics of the processes also present challenges to the putative efficacy of polycentricity (Yang et al., 2024; Schmitt et al., 2015). Collectively, this impedes establishing a robust connection between polycentricity and its assumed causal relationship to positive economic outcomes (Dadashpoor et al., 2023).

2.2 Technological diversification and influencing factors

2.2.1 (Un)related diversification: development as an evolutionary process

Given the limited empirical support for polycentricity's economic benefits, often measured through aggregate indicators such as gross domestic product (GDP), diversification offers a more structural and evolutionary perspective on regional development (Frenken et al., 2023). Regional economies evolve through related diversification, where new industries emerge from existing ones based on cognitive proximity (Hidalgo & Hausmann, 2009; Neffke et al., 2011). Accordingly, technological diversification is defined as the dynamic process through which a region expands from not having to having a specialization in new technological fields, reflecting the evolutionary nature of innovation (Frenken & Boschma, 2007; Neffke et al., 2011). This path-dependent process leads to more complex and interconnected technologies (Balland et al., 2019; Davies & Maré, 2021; Mewes & Broekel, 2022; Rigby et al., 2022), which are correlated with higher added value and stronger economic development (Hidalgo & Hausmann, 2009; Frenken et al., 2023).

Although *related* diversification is more frequently observed, *unrelated* diversification also matters. The distinction lies in the difference between path renewal (the shift of activities towards new but related areas) and new path creation (the emergence of entirely new industries or products) (Isaksen & Trippl, 2014). Unrelated diversification offers specific advantages: by engaging in economically distinct activities, regions can reduce their vulnerability to sector-specific shocks, industrial decline, or technological transformations, thus enhancing their long-term resilience (Frenken et al., 2007). However, new economic activities often draw on a mix of both related and unrelated capabilities (Boschma, 2017), combining both. This emphasizes the need to move beyond the dichotomy between related and unrelated diversification and instead consider a spectrum of relatedness—that is, *the extent to which* emerging activities are (un)related to the region's current knowledge base (Whittle & Kogler, 2020).

2.2.2 Capabilities and a spatial lens in considering technological diversification

Recent research on regional diversification has examined patterns across product, industry, and technological spaces (Hidalgo & Hausmann, 2009; Neffke et al., 2011; Rigby, 2015). These studies highlight that existing local capabilities—defined as a composite of infrastructure, natural resources, institutional endowments, knowledge, and skills (Frenken et al., 2023)—are a prerequisite for the emergence of new regional activities (Boschma, 2017). This has led to debates on which capabilities most influence diversification (Tanner, 2014; Boschma, 2017), with a growing emphasis on those that foster new specializations rather than merely maintain existing ones (Frenken et al., 2023; Boschma, 2017). While much research on the sources of capabilities for technological diversification focuses on *intra*-regional dynamics (Bathelt & Storper, 2023), an expanding body of literature highlights the critical role of *extra*-regional knowledge flows in capturing capabilities (Boschma & Iammarino, 2009) and their ability to enhance a region's knowledge accumulation and industrial upgrading (Neffke et al., 2011; Andersson et al., 2013), especially when the external knowledge is related to, yet distinct from the existing local knowledge bases (Boschma & Frenken, 2011; Miguelez & Moreno, 2018).

The acquisition of capabilities is a fundamental driver of regional diversification. Since such capabilities can be acquired both intra- and extra-regionally, understanding the dynamics of regional diversification requires *a spatial perspective* (Boschma, 2017). Regions or countries, especially those with different development levels, have different underlying spatial mechanisms during diversification (Boschma & Capone, 2016; Petralia et al., 2017). As regional diversification depends on local dynamics and how knowledge and resources are organized and accessed across space, polycentricity—as a specific spatial configuration—offers a valuable lens to examine these spatial mechanisms. Given this, we investigate whether and how different forms of evolving polycentricity influence regional technological diversification in Chinese urban regions.

2.3 Polycentricity and technological diversification in Chinese urban regions

2.3.1 State-led polycentric development and its innovation implications

Rather than a primarily market-driven phenomenon, China's polycentric regional development has evolved gradually within a framework of government-led initiatives and urbanization processes. Since the late 1980s, policies have emphasized the balanced growth of cities of different sizes, aiming to control the scale of large cities while promoting medium-sized cities and small cities (Sun et al., 2019; Wu & Zhang, 2007). Towards the end of the 20th century, influenced by European experiences, China began emphasizing the importance of polycentric development in regions to achieve more sustainable and balanced growth (Cheng & Shaw, 2018). A major turning point came with the introduction of the *chengshiqun* (city clusters or urban regions) concept, institutionalized in the *2014 National New-Type Urbanization Plan*. These clusters, arguably characterized by dense inter-city connections and economic complementarity, have become key spatial units in national planning (Wu, 2016; Derudder et al., 2022). Under this 'planned polycentrism', the state promotes functional integration among cities to boost regional competitiveness, foster economic upgrading, and stimulate innovation (Li & Du, 2022; Dadashpoor et al., 2023).

This 'planned polycentrism' has, in recent years, become closely intertwined with the state's broader ambition to become a global innovation leader. Initiatives such as *Made in China 2025* and *Industry 4.0* have emphasized innovation as a central pillar of national competitiveness (Li, 2018; Li & Rigby, 2023). This ambition is reflected in China's rapid growth in R&D investment—among the highest globally—and in its efforts to enhance intellectual property protection and encourage indigenous innovation (Bosworth & Yang, 2000; Liegsalz & Wagner, 2013; China Power Team, 2019; Li & Rigby, 2023). While these initiatives have placed emphasis on innovation, the relationship between polycentricity and innovation, particularly technological diversification, is insufficiently explored. Existing research has provided some initial insights. For example, research suggests that Chinese urban regions often exhibit higher levels of morphological (measured by the spatial distribution of academic publications) than functional polycentricity (measured by the intensity of inter-city co-authored papers) (Ma & Xu, 2022). This suggests that while spatial structures may appear polycentric, the functional integration needed to support collaboration and knowledge exchange remains underdeveloped. Furthermore, studies have demonstrated that highly polycentric urban regions in both morphological and functional terms tend to exhibit higher levels of knowledge innovation, suggesting a strong link between polycentric development and a region's knowledge stock and innovation base (Ma & Xu, 2022).

2.3.2 The role of multidimensional polycentricity in technological diversification

While the above studies point to a positive relationship between polycentricity and regional innovation, they leave open important questions regarding how morphological and functional polycentricity, both independently and in combination, shape technological diversification. Moreover, the role of a region's internal knowledge structure remains underexplored. These gaps motivate our study, which aims to clarify how different dimensions of polycentricity (morphological, functional, and knowledge-based) affect technological diversification in Chinese urban regions.

Polycentric structures may influence diversification in multiple and potentially contrasting ways. First. a higher degree of morphological polycentricity, reflected in a more spatially balanced distribution of cities, may facilitate diversification by reducing overconcentration and enabling the development of multiple centers with distinct technological profiles. However, without strong inter-city coordination, spatial balance alone may lead to fragmentation, limiting agglomeration economies and knowledge spillovers. Second, functional polycentricity based on intra-regional knowledge flows can enhance internal knowledge exchange, support inter-city division of labor, and foster local specialization, encouraging diversification through the recombination of proximate capabilities. Extra-regional functional polycentricity, based on outward linkages beyond the urban region, may broaden the scope for diversification by exposing cities to non-local knowledge pools and new technological domains. Third, knowledge polycentricity captures the extent to which a region's innovation activities are spread across multiple technological domains. A broadly distributed and thematically varied knowledge base may enhance opportunities for recombination and learning, but without sufficient connectivity, its potential for driving technological diversification may remain underutilized.

These dimensions do not operate in isolation. Interactions between them—such as between intra- and extra-regional functional polycentricity, or between morphological and functional polycentricity—may generate synergies or tensions that shape diversification in context-specific ways. For instance, spatial balance may reinforce the effects of functional integration by enabling more cities to participate in knowledge flows, or it may dilute functional concentration and reduce coordination efficiency. Similarly, external linkages may complement internal flows by injecting novelty, but also compete for institutional attention and resources. A strong knowledge base may only support diversification when coupled with internal integration or external connectivity. As such, the direction and magnitude of polycentricity's effects depend not only on each dimension, but also on how they interact.

Moreover, the impacts of polycentricity are likely to vary across urban regions with different administrative hierarchies, development levels, and spatial contexts. Cities in urban regions with higher administrative status or more mature institutional environments often have greater autonomy and capacity to mobilize resources, build collaborative infrastructures, and connect with external networks (Yang et al., 2024). Therefore, it is not straightforward what relationship to expect between polycentricity and regional technological diversification. Figure 1 summarizes the conceptual framework discussed above, illustrating the multidimensional structure of polycentricity and its potential pathways shaping technological diversification. This study empirically tests the effects of morphological polycentricity, intra- and extra-regional functional polycentricity, and knowledge polycentricity—both independently and through their pairwise interactions—and examines how these effects vary across different types of Chinese urban regions, contributing to a more nuanced understanding of the heterogeneous innovation dynamics underlying polycentric development.

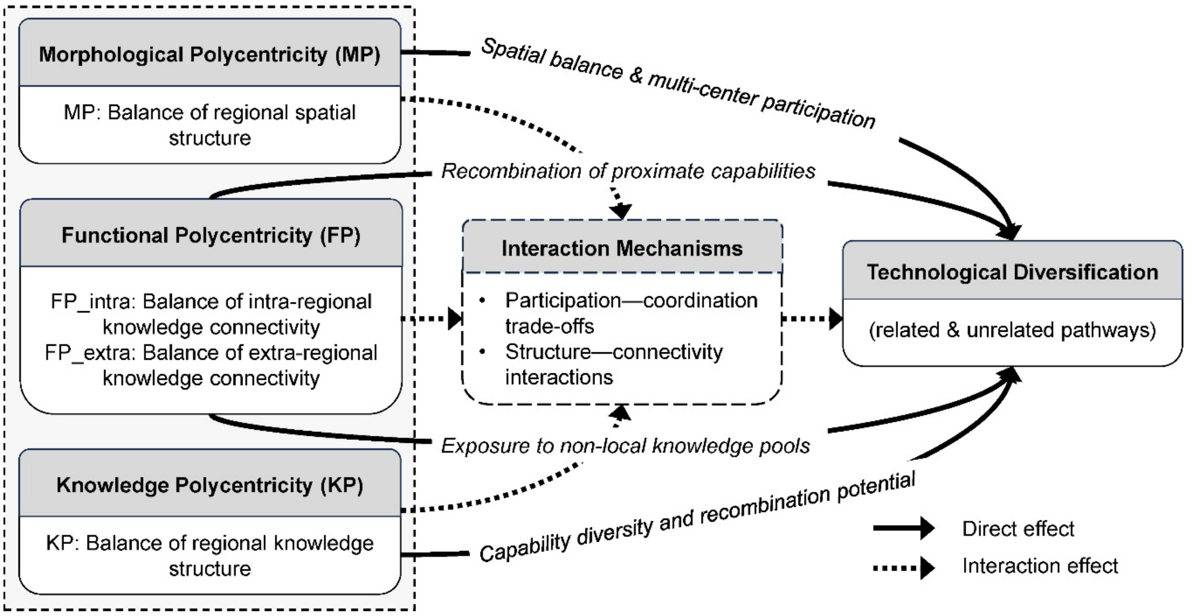

Figure 1: Conceptual framework linking multidimensional polycentricity and technological diversification

3 Data and methodology

3.1 Study region

The 19 Chinese urban regions (Figure 2), spanning both coastal eastern and inland central/western areas and accounting for over 75% of China's urban population and 85% of its GDP, exhibit significant development disparities due to varying geographic, economic, and policy factors. According to the *National New Urbanization Plan* (2021–2035), these 19 urban regions are further divided into two tiers that broadly reflect their development levels in terms of economic scale and population size (see Appendix A):

1. Tier 1 URs: These are ten more developed urban regions, comprising (1) urban regions with international influence: YRD (Yangtze River Delta), PRD (Pearl River Delta), BTH (Beijing-Tianjin-Hebei); and (2) urban regions with national influence: YRM (Yangtze River Middle-Reach), CHC (Chengdu-Chongqing), SDP (Shandong Peninsula), WTS (West

Coast of the Straits), ZY (Central Plain), GZH (Guangzhong Plain), BBW (Gulf of Tonkin). Geographically, these urban regions are concentrated along China's eastern coast and major river deltas, primarily occupying areas with favorable access to maritime trade and fertile alluvial plains.

2. Tier 2 URs: These comprise the remaining nine less developed urban regions, which aim to establish regional influence: HAC (Harbin-Changchun), CSL (Southern of Liaoning), DZ (Central Yunnan), QZ (Central Guizhou), HBEY (Hohhot-Baotou-Ordos-Yulin), JZ (Central Shanxi), LX (Lanzhou-Xining), TSM (Tianshan Mountains Northern Slopes), NXTH (Ningxia-Yellow River). These urban regions exhibit a more inland and geographically dispersed distribution, extending into northern and western areas, often characterized by more varied terrain.

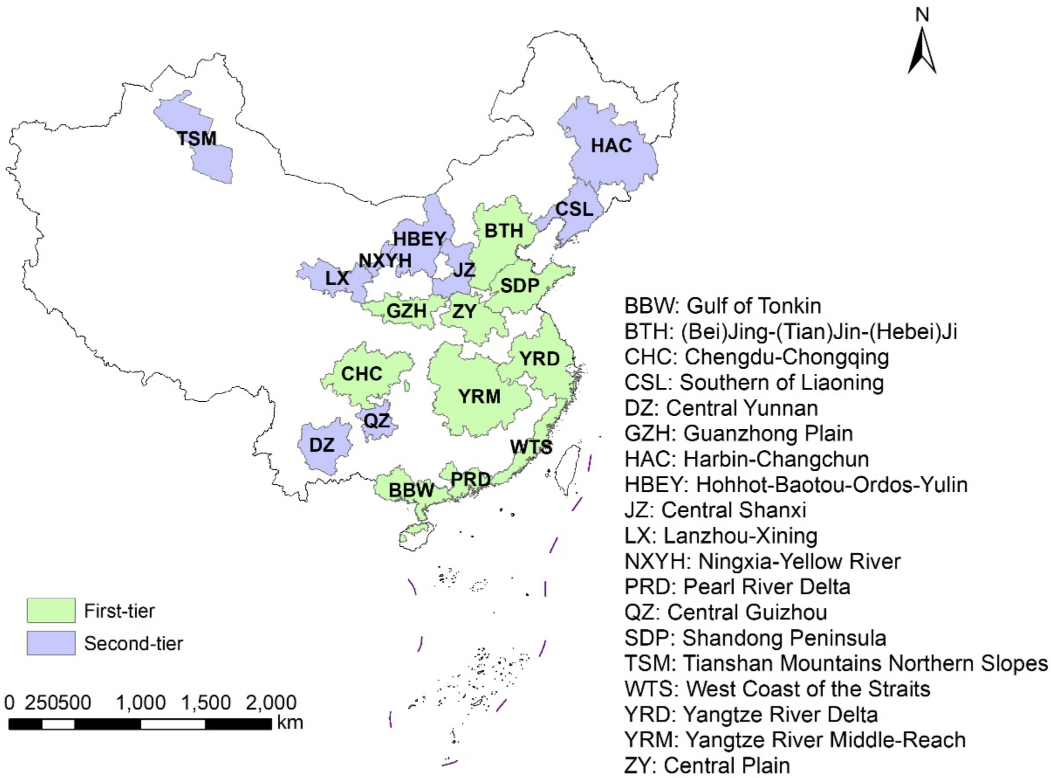

Figure 2: 19 Chinese urban regions

3.2 Data sources

This study uses Chinese patent data to analyze the interplay between technological diversification and polycentricity. While patent data have well-known limitations (Hoekman et al., 2009; Li & Du, 2022), their availability across different spatial levels (e.g., cities, regions, and national systems) and over extended time periods makes them suitable for our evolutionary analysis at the urban-region level.

We use patent data from CNIPA (http://www.cnipa.gov.cn/), encompassing over 20 million invention patents from 2006 to 2020. We focused exclusively on invention patents, which are widely recognized as the most technically demanding and frequently used in innovation network studies (Wang et al., 2022). The dataset provides comprehensive information on each patent, including applicant names and addresses[1], application date, and International Patent Classification (IPC) codes. To determine the geographical location of each patent, we extracted applicant addresses and geocoded them using the Amap API (https://lbs.amap.com/) to identify the cities to which the patents are associated. The IPC was used to classify the technology category of the patents.

Data processing involved constructing two primary datasets. (1) A City-Technology Matrix was constructed to derive technological diversification (*DIV*) and knowledge polycentricity (*KP*); and (2) a City-City Collaboration Matrix was constructed to derive (intra- and extra-regional) functional polycentricity *(FP_intra* and *FP_extra*):

1. City-Technology Matrix: Each patent with IPC information was assigned to a city based on the applicant's address. The city-level IPC information from this matrix was then aggregated to the urban-region scale[2], serving as a proxy for each urban region's technological capability.
2. City-City Collaboration Matrix: We selected patents with multiple applicants to identify inter-city collaborations. After geocoding applicant addresses, we retained only collaborations within mainland China. This resulted in a dataset of 39,681 collaborative patents from 2006 to 2020 (approximately 10.28% of the total patents in these urban regions). These collaborative patents were then aggregated to the urban-region scale and categorized as intra- or extra-regional collaborations[3].

Morphological polycentricity (*MP*) was measured using the LandScan™ High Resolution Global Population Dataset (Dobson et al., 2000). This dataset presents the global population distribution in 1 km^2 grids, which has been widely used in polycentricity studies (e.g., Meijers, 2005; Burger & Meijers, 2012; Derudder et al., 2021). *MP* captures the spatial form and demographic balance of

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[1] In line with established practice in innovation geography studies, the geographical location of each patent is determined by the address of its applicant(s). In China, this approach provides a reliable proxy for the actual site of invention, as multilocational firms generally file patents at the location where inventive activities occur rather than concentrating all registrations at their headquarters (Zhang & Rigby, 2022).

[2] Each urban region analyzed in this study consists of multiple cities delineated according to the *National New Urbanization Plan* and the official planning documents. After geocoding the patent applicant addresses, we identified the corresponding city for each patent and then aggregated all patents from cities belonging to the same urban region to obtain the total patent counts at the urban-region level.

[3] 'Patents with multiple applicants' denotes patents involving two or more cities, excluding those with single applicants or collaborations within the same city. After geocoding the applicants' addresses, we then assigned these patents to collaborating cities using full counts. 'Intra-regional' collaborations indicate that both cities are within the focal urban region; 'extra-regional' collaborations indicate that one city within and the other is outside the focal urban region.

urban regions and provides the spatial foundation for innovation, as population distribution shapes urban vitality and the spatial context for knowledge interaction (Bettencourt et al., 2007). In this study, we examine how population-based *MP*, together with patent-based *FP* and *KP*, independently and jointly shapes the process of technological diversification in Chinese urban regions.

3.3 Variable construction

3.3.1 Independent variables: polycentricity of Chinese urban regions

Polycentricity in this study is measured from three perspectives: morphological polycentricity (*MP*), functional polycentricity (*FP_intra and FP_extra*), and knowledge polycentricity (*KP*). Two often-used methods for quantifying polycentricity are the standard deviation and rank-size-based approaches (Derudder et al., 2021). In this study, we adopted the standard deviation-based approach (Green, 2007) to calculate *MP*, *FP_intra, FP_extra*, and *KP* using Equations (1)-(3). The rank-size-based approach is used as a robustness check and is presented in Appendix B.

$$MP = 1 - \frac{\sigma_M}{\sigma_{Mmax}} \tag{1}$$

$$FP = (1 - \frac{\sigma_F}{\sigma_{Fmax}}) \times \Delta \tag{2}$$

$$KP = 1 - \frac{\sigma_K}{\sigma_{Kmax}} \tag{3}$$

In Equation (1), σ_M is the standard deviation of the urban population of individual cities within a urban region[4]; and σ_{Mmax} represents the maximum possible standard deviation, defined as the standard deviation in a urban region with a hypothetical two-city structure where one city has no population. *MP* ranges from 0 (no polycentricity) to 1 (an ideal-typical urban region where all cities are equally large) (Yang et al., 2024).

In Equation (2), the calculation methods for σ_F and σ_{Fmax} are analogous to those for σ_M and σ_{Mmax}. With σ_F and σ_{Fmax} derived from *intra*- and *extra*-regional collaborations based on the City-City Collaboration Matrix, Equation (2) is used to calculate *FP_intra* and *FP_extra*, respectively. *FP_intra* measures the internal functional balance of cities within a urban region, while *FP_extra* captures the extent to which these cities functionally connect with those outside the urban region. This distinction between the two allows us to examine how internal and external knowledge linkages may differentially influence regional technological diversification. Δ represents the

[4] The urban population of each city is calculated as follows. First, a population density file is generated for each city, and individual grids are ranked by population size. Next, a density cut-off is set at the 95th percentile of the city's gridded population, selecting the top 5% most populated grids. These grids are then grouped into clusters based on eight-cell adjacency. Clusters containing more than 100,000 inhabitants and covering an area of at least 3 km² are identified as 'urban centers'. Finally, the total population of all identified urban centers within each city is summed to calculate the urban population (Yang et al., 2024).

network density of patent collaborations among cities, introduced to ensure that the value of functional polycentricity is zero when there is no patent collaboration between cities (Green, 2007). Δ is the ratio of the actual number of existing connections to the total number of possible connections in a complete network.

In Equation (3), σ_K represents the standard deviation of patent applications across all technology categories within a urban region, while σ_{kmax} denotes the maximum possible standard deviation when all patent applications are concentrated in a single technology category. Unlike *MP* and *FP*, which reflect spatial and functional dimensions of polycentricity, *KP* is introduced as a novel indicator specially designed to capture the *polycentricity of knowledge* within a urban region. By examining the distribution of technology domains, *KP* reflects the internal technological structure of the urban region, indicating the degree to which innovation activities are diversified or specialized. Incorporating *KP* enables us to move beyond spatial and functional perspectives to account for the influence of internal knowledge structure on technological diversification. This more comprehensive approach combining *MP*, *FP*, and *KP*, reflects the multiplex nature of urban regions and aligns with the integrated framework outlined in the introduction[5].

Figures C in Appendix C illustrate the varying patterns of multiple dimensions of polycentricity across 19 Chinese urban regions from 2008 to 2020.

3.3.2 Dependent variable: technological diversification of Chinese urban regions

Regional technological diversification is measured through emerging new technologies in a region (Santoalha, 2019). Following a co-specialization approach, we first calculated the revealed technological advantage (RTA) based on the relatedness between technology pairs (Equations (4)-(6)) (Tanner 2014; Boschma et al. 2015; Kogler & Whittle 2018; Balland et al. 2019; Kogler et al., 2023).

$$RTA_{i,j,t} = \frac{Patent_{i,j,t} / \sum_j Patent_{i,j,t}}{\sum_i Patent_{i,j,t} \,/ \sum_{i,j} Patent_{i,j,t}} \tag{4}$$

$$x_{i,j,t} = \begin{cases} 1, \; RTA_{i,j,t} \geq 1 \\ 0, \; RTA_{i,j,t} < 1 \end{cases} \tag{5}$$

$$\phi_{j,j'} = \frac{\sum_i M_{i,j} \, M_{i,j'}}{\max\,(k_{j,o}, k_{j',o})} \tag{6}$$

where $RTA_{i,j,t}$ captures the specialization of urban region *i* in technology *j* at time *t* compared to the national average. If $RTA_{i,j,t} \geq 1$, urban region *i* is considered to have a comparative advantage in technology *j* at time *t*. $k_{j,o}$ in Equation (6) represents the number of urban regions exhibiting RTA in technology *j* in the study period and $M_{i,j}$ is the two-mode matrix of urban region *i* and technology *j*. If the pairwise conditional probability that a urban region specializes in both

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[5] Although this study examines the impact of polycentricity on technological diversification, the concept of knowledge polycentricity can also be extended to other domains, such as industrial diversification, by adapting the corresponding structural indicators.

technologies *j* and *j'* is higher, the two technologies are indicated to have a greater degree of relatedness $\phi_{j,j'}$. Based on this, the relatedness density is calculated as follows:

$$Density_{i,j,t} = \frac{\sum_{j'} x_{i,j',t} \cdot \phi_{j,j',t}}{\sum_{j'} \phi_{j,j',t}} \tag{7}$$

$$\omega_{i,j,t} = \frac{Density_{i,j,t} - \langle Density_{i,t} \rangle_O}{\sigma_O(Density_{i,t})} \tag{8}$$

where $x_{i,j',t}$ is a dummy variable indicating whether urban region *i* has RTA in technology *j'* at time *t*. $Density_{i,j,t}$, reflects the existing technological capabilities, serving as a foundation for innovation in technology *j* in urban region *i* at time *t*. To avoid statistical biases caused by the urban region's inherent technological capabilities, the relative relatedness density $\omega_{i,j,t}$ is then calculated using a *z*-score by comparing the density of existing technologies with the average density of all non-specialized technologies ($\langle Density_{i,t} \rangle_O$) in the region. A positive value of ω indicates related diversification, and a negative value indicates unrelated diversification. Finally, average scores of ω are calculated to describe the overall level of regional technological diversification (Zheng & Ran, 2021) (Equations (9)-(10)).

$$d = \begin{cases} 1, RTA_{i,j,t-1} < 0.1 \; and \; RTA_{i,j,t} \geq 1 \\ 0, else \end{cases} \tag{9}$$

$$Diversification_{i,t} = \frac{1}{n}\sum_{j=1}^{n} \omega_{i,j,t} \tag{10}$$

where the condition for diversification occurrence *d* is defined as shown in Equation (9), and the total number of such occurrences is represented by *n* in Equation (10). Following the approach of Hidalgo and Hausmann (2009) and Petralia et al. (2017), the critical condition for a region transitioning from having no presence in a technology (RTA very low) to specialization is set as $RTA < 0.1$. Robustness checks relaxing this threshold to $RTA < 0.5$ yielded consistent results (see Appendix B).

This diversification indicator offers a new measurement approach based on established methods. In line with the recognition that new activities often draw upon both related and unrelated capabilities (Boschma, 2017), $Diversification_{i,t}$ in Equation (10) incorporates a normalized, continuous measure of relative relatedness density (ω). This allows for a more nuanced differentiation between related and unrelated diversification along a spectrum, moving beyond binary distinctions and reflecting the extent to which emerging activities are (un)related to the region's current knowledge base. A higher value indicates that the urban region tends to achieve innovation in fields closely related to its existing knowledge base; conversely, a lower value suggests a tendency towards innovative activities in unrelated fields. While this approach captures the degree of technological diversification in a urban region, it does not categorize diversification strictly as related or unrelated. Therefore, to ensure the robustness of our findings, we constructed alternative separate count variables for related and unrelated diversification events based on the sign of ω, as detailed in Appendix B.

3.4 Model specifications

All variables used for the econometric model, including control variables[6], are presented in Table 1. Descriptive statistics and the correlation matrix are shown in Appendix D. No significant multicollinearity is observed among the variables. We included the interaction terms between each two of *MP, FP_intra, FP_extra, and KP* in the models in a stepwise manner to see if their combined effects on technological diversification are statistically significant. We used the following fixed-effects panel model specification to estimate the impact of different forms of polycentricity on diversification in Chinese urban regions.

$$\begin{aligned} DIV_{it} = {} & \beta_1 MP_{it} + \beta_2 FP\_intra_{it} + \beta_3 FP\_extra_{it} + \beta_4 KP_{it} + \beta_5 (MP_{it} * FP\_intra_{it}) \\ & + \beta_6 (MP_{it} * FP\_extra_{it}) + \beta_7 (MP_{it} * KP_{it}) \\ & + \beta_8 (FP\_intra_{it} * FP\_extra_{it}) + \beta_9 (FP\_intra_{it} * KP_{it}) \\ & + \beta_{10} (FP\_extra_{it} * KP_{it}) + \beta_{11} GDP_{it} + \beta_{12} TER_{it} + \beta_{13} EDU_{it} \\ & + \beta_{14} STE_{it} + \beta_{15} HRP_{it} + \beta_{16} WEB_{it} + \mu_i + \lambda_t + \epsilon_{it} \end{aligned} \tag{11}$$

where μ_i represents individual (urban region) fixed effects, λ_t denotes time-fixed effects, and ϵ_{it} is a random error term. All independent variables were lagged by one period to dampen potential endogeneity and were z-standardized in the regression models. Robust standard errors were clustered at the urban-region level to account for heteroscedasticity and serial correlation.

To address potential endogeneity concerns arising from reverse causality, we applied instrumental variable (IV) techniques. The construction and validation of IVs are detailed in Appendix E.

Moreover, given that the impact of polycentricity may vary across urban regions, we employed a group-wise regression approach to explore this heterogeneity and examine whether the effects of polycentricity differ significantly across urban regions at different levels of economic development, with results presented in the following section.

[6] Apart from the current controls, we also tested fiscal expenditure on science and technology (*STE*) to capture government support for innovation. This variable was excluded from the final specification due to multicollinearity with existing controls and to maintain model parsimony and statistical validity.

Table 1: Variables used in the regression analysis

	Variables	Description	Abbreviation	Year
Dependent variable	Technological diversification	Average relative technology density in the urban region.	*DIV*	2008, 2011, 2014, 2017, 2020
Main independent variable	Morphological polycentricity	Spatial distribution and balance of population centers in the urban region.	*MP*	One-year lag (2007, 2010, 2013, 2016, 2019)
	Knowledge polycentricity	Distributional balance across technology domains in the urban region indicating internal technological structure.	*KP*	Three-year moving window (2006~2008, 2009~2011, 2012~2014, 2015~2017, 2018~2020)
	Functional polycentricity (intra-regional)	Distributional balance of intra-regional patent collaborations between cities in the urban region.	*FP_intra*	
	Functional polycentricity (extra-regional)	Distributional balance of extra-regional patent collaborations between cities within and outside the urban region.	*FP_extra*	
Control variable	Economic level	Average GDP per capita of cities in the urban region.	*GDP*	One-year lag (2007, 2010, 2013, 2016, 2019)
	Industrial structure	Share of tertiary industry GDP in the urban region.	*TER*	
	Education level	Proportion of the population with at least secondary education in the urban region.	*EDU*	
	Transport infrastructure	Volume of highway road passenger traffic in the urban region.	*HRP*	
	Communication infrastructure	Number of broadband internet access users in the urban region.	*WEB*	

4 Results

4.1 The interplay between polycentricity and diversification

Models 1-9 in Table 2 present full-sample baseline regression results, which include the polycentricity variables and progressively incorporate their pairwise interaction terms. Intra-regional functional polycentricity (*FP_intra*) consistently shows a statistically significant positive effect, whereas extra-regional functional polycentricity (*FP_extra*) and morphological polycentricity (*MP*) are not statistically significant as standalone variables. This suggests that polycentricity based on intra-regional functional linkages is a key driver of diversification in Chinese urban regions. Knowledge polycentricity (*KP*) only shows a statistically significant positive effect in Model 3 (0.628*)[7] and Model 9 (0.746*), indicating that the benefit of the regional knowledge base is more salient when interacting with other forms of polycentricity.

The structural contrast between morphological polycentricity and intra-regional functional polycntricity observed in Figure C in Appendix C (i.e., urban regions that are more morphologically polycentric tend to have less balanced intra-regional functional linkages) may, in fact, reflect a complementary relationship between the two in their effects on diversification. The statistically significant positive coefficients of the interaction between morphological polycentricity and intra-regional functional polycentricity in Model 3 (0.421***) and Model 9 (0.485**) indicate that spatial dispersion may unlock the potential of intra-regional functional linkages. Conversely, the interaction between intra- and extra-regional functional polycentricity shows a statistically significant negative impact in Model 6 (-0.164**) and Model 9 (-0.345**), suggesting a potential trade-off between internal and external functional linkages in driving diversification. One possible explanation is that urban regions with more internally balanced functional structures may be less dependent on external connections to develop diversification or may face coordination constraints when both intra- and extra-regional linkages are simultaneously strong, thereby resulting in diminishing marginal returns.

The control variables show that a higher economic level (*GDP*), a more developed industrial structure (*TER*), and improved transport infrastructure (*HRP*) significantly promote diversification, specifically contributing to more related diversification. In contrast, a higher education level (*EDU*) and more developed communication infrastructure (*WEB*) are inclined to promote more unrelated diversification.

Notably, Model 9 exhibits the highest coefficients for the statistically significant variables and the highest R^2 value. This indicates that including a comprehensive set of variables optimizes the model's explanatory power.

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[7] Numbers are standardized coefficients (β). Asterisks indicate statistical significance (* p<0.1, ** p<0.05, *** p<0.01). This notation applies throughout the text.

4.2 Heterogeneity among urban regions

Before examining the heterogeneous effects among urban regions, Figure 3 illustrates the patterns of technological diversification in 19 Chinese urban regions. It shows an overall increasing trend from 2008 to 2020, reflecting a broader exploration of technological domains. However, notable disparities exist. For example, several central and western urban regions exhibited a rapid increase in diversification value after 2017, possibly driven by supportive local industrial policies introduced around that time.

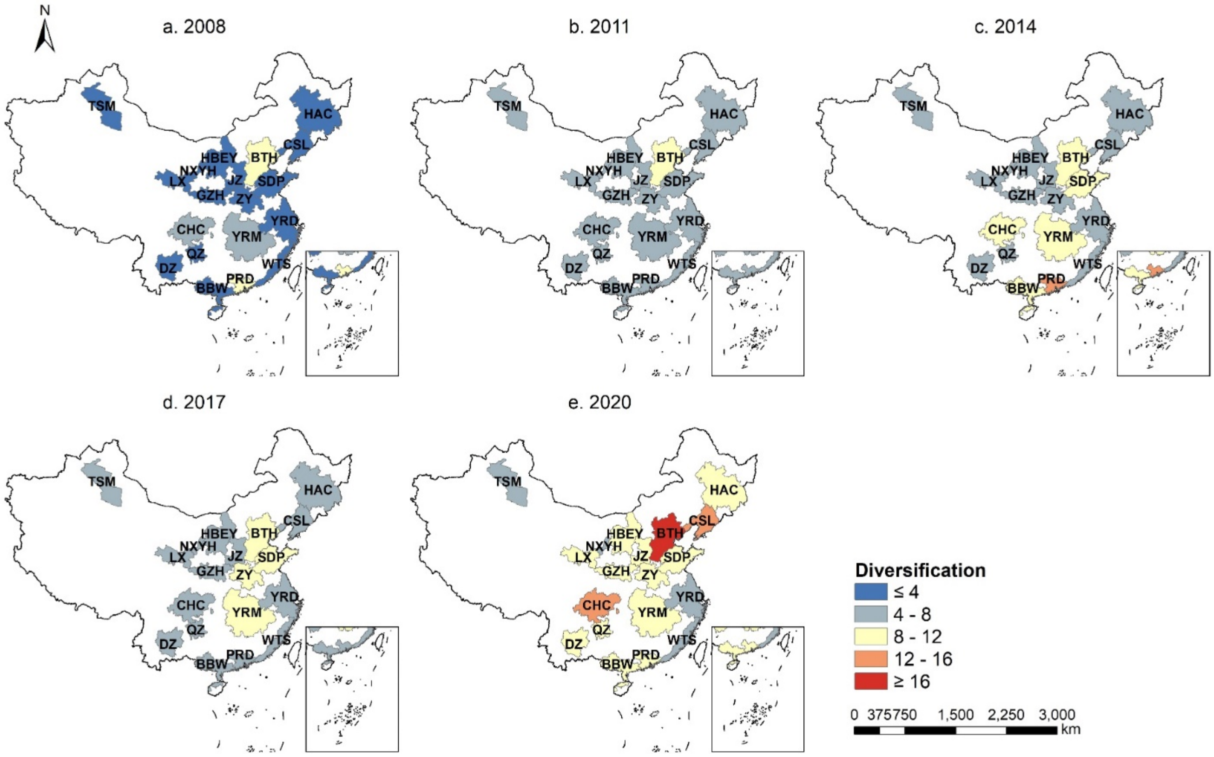

Figure 3: Technological diversification in 19 Chinese urban regions, 2008-2020.

The spatial pattern of diversification differs markedly between tiers. Among Tier 1 urban regions, which generally host more advanced innovation systems, the levels and directions of diversification vary considerably. Beijing-Tianjin-Hebei (BTH) stands out with consistently high diversification (*DIV*) values, indicating strong related diversification. Chengdu-Chongqing (CHC) shows a gradual move toward stronger related diversification, while the Pearl River Delta (PRD) shows mixed patterns between related and unrelated types. Most other Tier 1 urban regions, including the Yangtze River Delta (YRD), the Shandong Peninsula (SDP), the West Coast of the Straits (WTS), the Gulf of Tonkin (BBW), the Yangtze River Middle-Reach (YRM), the Central Plain (ZY), and the Guangzhong Plain (GZH), display persistently low *DIV* values, signifying a dominance of unrelated diversification.

In contrast, Tier 2 urban regions follow a different trajectory. Although their overall *DIV* values remain relatively low, their diversification pathways are more incremental (related) rather than exploratory (unrelated). Because unrelated diversification typically requires higher technological capability and absorptive capacity that these less developed urban regions often lack (Boschma, 2017; Kretschmer & Symeou, 2024). Thus, most Tier 2 urban regions, such as Harbin-Changchun

(HAC), Hohhot-Baotou-Ordos-Yulin (HBEY), Central Shanxi (JZ), Lanzhou-Xining (LX), Central Yunnan (DZ), Central Guizhou (QZ), the Tianshan Mountains Northern Slopes (TSM), and the Ningxia-Yellow River (NXYH), are still in the early phase of developing related diversification. Only a few, such as Southern of Liaoning (CSL), which exhibit relatively high *DIV* values, show emerging signs of transitioning toward a more advanced stage of related diversification. This pattern reflects a capability-constrained and path-dependent trajectory in Tier 2 urban regions, focusing on strengthening existing technological trajectories instead of branching into entirely new and unrelated domains.

Building on these descriptive patterns, Models 9a and 9b in Table 2 further examine how different forms of polycentricity and their interactions influence diversification across different tiers of Chinese urban regions, revealing patterns that differ from those observed in the full-sample results. In Tier 1 urban regions, the effects of intra-regional functional polycentricity (2.427***), knowledge polycentricity (2.087**), and their interaction (1.812***) vary with the prevailing diversification mode. In urban regions dominated by related diversification, such as Beijing-Tianjin-Hebei (BTH) and Chengdu-Chongqing (CHC), core cities (e.g., Beijing and Tianjin in BTH as well as Chengdu and Chongqing in CHC) play a central role in driving collaborations (both internal and external ones). The strong internal connectivity and diverse knowledge bases in these urban regions jointly reinforce cumulative, path-dependent growth, forming a complementary relationship between internal collaboration and knowledge base. In contrast, in urban regions dominated by unrelated diversification, such as the Yangtze River Delta (YRD), the Shandong Peninsula (SDP), the West Coast of the Straits (WTS), the Gulf of Tonkin (BBW), the Yangtze River Middle-Reach (YRM), the Central Plain (ZY), and the Guangzhong Plain (GZH), these positive coefficients primarily indicate a reduction in unrelated diversification, as stronger internal linkages and broader knowledge bases help redirect innovation toward more proximate technological fields. The Pearl River Delta (PRD), which displays a mixed pattern of related and unrelated diversification, likely exhibits both mechanisms.

In Tier 2 urban regions, related diversification constitutes the prevailing pattern and is driven mainly by morphological polycentricity (3.766***) and intra-regional functional polycentricity (1.799***), underscoring the importance of spatial structure and external knowledge sourcing in promoting incremental, path-dependent expansion within related technological domains in less-developed contexts. However, morphological polycentricity plays a conditional role in these urban regions, as knowledge polycentricity (−0.699**) and its interaction with morphological polycentricity (−1.139**) are statistically significant and negative. This indicates that higher spatial dispersion weakens the efficiency of local knowledge utilization. In most urban regions such as Central Yunnan (DZ) and Hohhot-Baotou-Ordos-Yulin (HBEY), this reflects weak integration capability under spatial dispersion, while in transitional urban regions like Southern of Liaoning (CSL), moderate dispersion can still facilitate cross-domain exploration, though with diminishing returns. A more compact urban form therefore appears more conducive to concentrating and exploiting endogenous knowledge in Tier 2 urban regions.

The interaction between intra- and extra-regional functional polycentricity exhibits statistically significant effects in both Tier 1 and Tier 2 urban regions but with contrasting signs (-0.454* and 0.500**, respectively). This suggests that the contribution of extra-regional functional polycentricity to diversification is contingent on the development level of the urban regions. In Tier 2 urban regions, where intra-regional functional structures tend to be more balanced (e.g. see Central Yunnan and Hohhot-Baotou-Ordos-Yulin in Figure C in the Appendix C), external linkages can more effectively complement internal ones, resulting in a positive interaction effect. In contrast, in Tier 1 urban regions, such as Beijing-Tianjin-Hebei (BTH) and Chengdu-Chongqing (CHC), where collaborations are often established by core cities, external collaborations tend to reinforce existing core-periphery patterns and thus yield limited additional effects when combined with internal ones.

The discrepancies between the group-wise and full-sample results likely stem from two main sources. First, different underlying mechanisms in Tier 1 and Tier 2 urban regions may lead to divergent effects for certain variables (e.g., morphological polycentricity and extra-regional functional polycentricity), offsetting each other in the full sample. Second, the full-sample estimates of specific interaction terms may be disproportionately shaped by the dominant statistical influence of one group. For example, the negative coefficient of the interaction between intra- and extra-regional functional polycentricity in the full sample, despite its positive effect in Tier 2, suggests that Tier 1 urban regions primarily drive the overall estimate.

Table 2: Regression results

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 9a *Tier1 URs*	Model 9b *Tier2 URs*
MP		-0.508	-0.414	-0.690	-0.629	-0.498	-0.435	-0.531	-0.478	-0.674	3.766***
		(0.941)	(0.876)	(1.002)	(0.916)	(0.926)	(0.931)	(0.935)	(0.971)	(0.931)	(0.886)
FP_intra		0.811**	1.328***	0.840**	0.755**	0.733*	0.844**	0.768*	1.196***	2.427***	0.254
		(0.395)	(0.269)	(0.377)	(0.398)	(0.425)	(0.391)	(0.398)	(0.438)	(0.701)	(0.838)
FP_extra		-0.122	-0.261	-0.268	-0.164	-0.125	-0.123	-0.245	-0.396	-0.751	1.799***
		(0.199)	(0.223)	(0.285)	(0.215)	(0.174)	(0.201)	(0.275)	(0.359)	(0.529)	(0.527)
KP		0.467	0.628*	0.554	0.514	0.463	0.475	0.541	0.746*	2.087**	-0.699**
		(0.344)	(0.329)	(0.361)	(0.367)	(0.340)	(0.357)	(0.392)	(0.382)	(0.939)	(0.314)
*MP*FP_intra*			0.421***						0.485**	-0.843	-0.145
			(0.125)						(0.233)	(0.954)	(0.313)
*MP*FP_extra*				0.261					0.022	0.182	1.594***
				(0.251)					(0.329)	(0.306)	(0.195)
*MP*KP*					0.148				0.241	0.020	-1.139**
					(0.180)				(0.324)	(0.359)	(0.491)
*FP_intra*FP_extra*						-0.164**			-0.345**	-0.454*	0.500**
						(0.082)			(0.280)	(0.258)	(0.206)
*FP_intra*KP*							0.153		0.234	1.812***	-0.028
							(0.119)		(0.253)	(0.364)	(0.153)
*FP_extra*KP*								0.204	0.047	0.108	0.310
								(0.238)	(0.283)	(0.354)	(0.297)
GDP	1.753***	1.832***	2.038***	1.933***	1.913**	1.898***	1.869***	1.974***	2.432***	1.933	1.888***
	(0.547)	(0.571)	(0.574)	(0.628)	(0.617)	(0.582)	(0.537)	(0.624)	(0.767)	(1.258)	(0.472)
TER	3.784*	5.745**	4.926*	5.943**	5.829**	5.770**	5.729**	5.790**	4.988*	5.463	6.918***

	(2.078)	(2.417)	(2.473)	(2.338)	(2.460)	(2.391)	(2.415)	(2.489)	(2.600)	(4.384)	(1.549)
EDU	-0.411**	-0.313**	-0.313**	-0.296**	-0.309**	-0.312*	-0.322**	-0.315*	-0.318**	-0.219	-0.520**
	(0.165)	(0.157)	(0.152)	(0.146)	(0.157)	(0.158)	(0.152)	(0.159)	(0.150)	(0.298)	(0.215)
HRP	0.676*	0.885**	0.736*	0.930**	0.877*	0.925**	0.889**	0.919**	0.807***	0.102	0.339
	(0.410)	(0.402)	(0.376)	(0.419)	(0.404)	(0.362)	(0.377)	(0.390)	(0.453)	(0.693)	(0.444)
WEB	-0.191***	-0.182***	-0.195***	-0.198***	-0.192**	-0.182***	-0.171***	-0.184***	-0.195***	-0.245**	0.021
	(0.048)	(0.060)	(0.061)	(0.070)	(0.063)	(0.059)	(0.064)	(0.058)	(0.078)	(0.098)	(0.088)
Observations	95	95	95	95	95	95	95	95	95	50	45
Region-fixed	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time-fixed	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.550	0.578	0.569	0.577	0.574	0.575	0.576	0.575	0.583	0.499	0.807

Notes: * p<0.1 ** p<0.05 *** p<0.01.

Robust standard errors shown in parentheses are clustered at the urban-region level.

5 Discussion

The differentiated effects of polycentricity on diversification in Chinese urban regions arise from the interplay among its morphological, functional, and knowledge dimensions, which together shape whether diversification proceeds through related or unrelated trajectories. The most influential driver, intra-regional functional polycentricity, reflects how evenly innovation activities are distributed and functionally connected among multiple centers. A higher level of intra-regional functional polycentricity reduces coordination costs and enhances knowledge exchanges (De Noni et al., 2017). It also allows peripheral cities to access complementary resources from core cities, strengthening localized spillovers, which in turn facilitate the recombination of proximate capabilities and foster related diversification (Qiao and Wu, 2024; Mewes and Broekel, 2020; Boschma, 2017; Wanzenböck et al., 2025).

While this highlights the importance of balanced internal connectivity for enhancing related diversification, excessive internal collaboration reduces the need for external or cross-domain inputs, which hinders exploration of distant technological fields in urban regions where unrelated diversification dominates. This finding confirms that internal integration fosters cumulative, path-dependent trajectories but constrains exploratory innovation once network balance becomes overly inward-looking (Kogler et al., 2023; Li and He, 2024; De Noni et al., 2021; Miguelez and Moreno, 2018). A stronger degree of intra-regional functional polycentricity therefore tends to channel innovation into more cohesive and path-dependent trajectories rather than steering it toward unrelated paths.

The effects of other forms of polycentricity suggest that the benefits of a diverse knowledge base are realized only when spatial and functional structures create effective channels for knowledge recombination. Two main pathways can be identified among Chinese urban regions dominated by related diversification. The first pathway, represented by Beijing-Tianjin-Hebei (BTH) and Chengdu-Chongqing (CHC), features a highly diversified knowledge base and a core-dominated internal structure among Tier 1 urban regions. Major cities such as Beijing, Tianjin, Chengdu, and Chongqing control most collaborative activities. This concentration supports cumulative, path-dependent growth but restricts diffusion to peripheral cities. Under such circumstances, external collaborations established by the cores tend to reinforce existing hierarchies rather than complement internal linkages (Xie & Su, 2021; Zhang et al., 2025; Benoit & Belderbos, 2024), thereby reducing their marginal contribution to related diversification.

The second pathway, mainly found in Tier 2 urban regions, represents incremental related diversification driven by spatial balance and outward connectivity. A balanced spatial structure enables the emergence of multiple local innovation centers, while outward linkages introduce new but cognitively proximate knowledge. These external connections are complemented by the balanced internal linkages typical of these urban regions, which revitalize endogenous capabilities and continuously support related diversification (Frenken et al., 2007; Andersson et al., 2013; Boschma, 2017). However, the efficiency of this related path may be constrained when the knowledge base is widely distributed but lacks sufficient coordination, leaving these potential synergies underexploited.

In urban regions dominated by unrelated diversification, particularly most Tier 1 cases, a balanced internal network structure, especially when combined with a diversified knowledge base, tends to reinforce path-dependent growth and limit exploration into more distant technological domains. Yet when extensive external linkages form a counteracting relationship with internal connections, they can break this structural constraint and stimulate exploration into distant and unrelated technological domains (Wanzenböck et al., 2025; Miguelez and Moreno, 2018; Qiao and Wu, 2024).

6 Conclusion

This paper systematically examined how multidimensional polycentricity—morphological, functional, and knowledge-based—shapes technological diversification in Chinese urban regions. By integrating fixed-effects and instrumental variable models, we identified causal relationships and revealed distinct diversification mechanisms across development levels.

6.1 Main findings

Both polycentricity and innovation are central topics in regional studies, yet their interrelationship remains underexplored (Xue et al., 2025). The strategic significance of polycentricity for innovation lies in the recognition that innovation diffusion depends not only on co-location but also on internal and external knowledge networks (Xue et al., 2025). When these interactions operate within broadly distributed regional knowledge bases, they form the foundation of a multidimensional polycentricity framework that links with innovation dynamics.

Despite this conceptual potential, empirical research on polycentricity and innovation (Li & Du, 2022; Ma & Xu, 2022) have mainly examined single dimensions of polycentricity and on general innovation outcomes. Li and Du (2022) found a negative link between morphological polycentricity and innovation capacity, whereas Ma and Xu (2022) revealed that functional polycentricity is strongly associated with regional innovation base. Yet, the functions and mechanisms of different forms of polycentricity remain insufficiently studied within the geography of innovation, particularly regarding regional diversification (Balland & Boschma, 2021; Balland & Rigby, 2017; Xue et al., 2025). This study advances the literature by establishing the causal links between multidimensional polycentricity and technological diversification, revealing distinct patterns across development levels.

Our empirical findings demonstrate that technological diversification is shaped by different dimensions of polycentricity, both independently and interactively. In particular, intra-regional functional polycentricity emerges as a key driver of technological diversification in Chinese urban regions. Other forms of polycentricity influence diversification primarily through their interactions with intra-regional functional polycentricity: morphological polycentricity enhances its positive effect, while extra-regional functional polycentricity tends to weaken it. Knowledge polycentricity, in turn, becomes statistically significant only in the presence of these interactions, acting as a crucial underlying factor that amplifies the effects of spatial and functional structures.

These findings contrast with those of Li and Du (2022), who argued that a city's innovation capacity is negatively influenced by morphological polycentricity because polycentric urban development may weaken agglomeration spillovers. In our analysis, however, morphological polycentricity exerts a positive effect and only when combined with intra-regional functional polycentricity, which, among the different dimensions examined, emerges as the most important driver of diversification. This difference may be attributed to the distinct indicators and conceptual approaches used. Our study employs a dynamic and structural indicator, technological diversification, rather than a static measure of innoavation capacity (patent counts), and it considers multiple dimensions of polycentricity rather than morphological polycentricity alone. At the same time, our result aligns with previous findings showing that, although the development of functional polycentricity generally lags behind that of morphological polycentricity in China (Yue et al., 2019; Chen et al., 2021; Tang & Dou, 2022; Ma & Xu, 2022), functional polycentricity constitutes a more critical condition for urban regions to operate as innovation incubators (Ma & Xu, 2022) and to achieve superior performance (Meijers et al., 2018).

Beyond the general patterns identified above, we also find that these dynamics vary across urban regions. In Tier 1 urban regions, intra-regional functional polycentricity and knowledge polycentricity reinforce each other as key drivers of diversification. In contrast, in Tier 2 urban regions, morphological polycentricity and extra-regional functional polycentricity play a dominant role. The negative interaction between knowledge and morphological polycentricity further indicates a conditional role for the latter: while a polycentric morphological structure may enhance the benefits of external linkages, it may also offset the positive effect of a polycentric knowledge structure on diversification. Finally, whereas Tier 1 urban regions face diminishing marginal returns from external linkages, Tier 2 urban regions tend to benefit more from them.

6.2 Policy implications

Since the Chinese government officially introduced the concept of urban regions as key spatial units for coordinated urbanization in 2014[8]. the urban-region framework has been increasingly shaping the country's regional development discourse. *The 15th Five-Year Plan Recommendations* released in October 2025 further highlighted five major urban regions—Beijing-Tianjin-Hebei (BTH), Chengdu-Chongqing (CHC), the Yangtze River Delta (YRD), the Pearl River Delta (PRD), and the Yangtze River Middle-Reach (YRM)—as high-quality growth poles. These urban regions, classified as Tier 1 urban regions with national influence, are intended to enhance cross-regional innovation cooperation and market integration. Building on this context, our findings have implications for understanding how future regional coordination initiatives might integrate differences in development levels and diversification pathways across urban regions.

Although the five major urban regions serve as national growth poles, their diversification trajectories differ. BTH and CHC are dominated by related diversification, whereas the YRD and the PRD display a stronger tendency toward unrelated diversification[9]. Since the launch of the

[8] See the *National New Urbanization Plan (2014-2020)*, available at: https://www.gov.cn/zhengce/2014-03/16/content_2640075.htm

[9] For example, in Beijing-Tianjin-Hebei (BTH), Beijing focuses on information technology and scientific

Beijing–Tianjin–Hebei Coordinated Development Strategy in 2017, initiatives such as the relocation of research institutes, the establishment of university campuses in Xiong'an New Area, and the creation of intercity innovation platforms have facilitated knowledge diffusion from Beijing and Tianjin to to peripheral areas in Hebei. Further reinforcing such internal linkages could help consolidate intra-regional functional polycentricity and promote a more inclusive and balanced pattern of related diversification.

In contrast, Tier 2 urban regions such as Central Yunnan (DZ) and Hohhot-Baotou-Ordos-Yulin (HBEY) also exhibit related diversification but remain at earlier stages. Although their internal structures are relatively balanced, they often lack sufficiently diversified knowledge bases. External connectivity is therefore particularly critical, as it introduces new but cognitively proximate knowledge that complements internal networks, helps compensate for limitations in their knowledge bases, and supports related diversification. For example, DZ has broadened its knowledge base by participating in *Belt and Road* science and technology cooperation projects that channel technological resources from coastal and Southeast Asian regions. In the longer term, policies initiatives could further leverage such external linkages to stimulate regional upgrading, particularly combined with investments that enhance local absorptive capacity through education, research, and digital infrastructure (Brunetti et al., 2020; Miguelez & Moreno. 2015; Qian & Jung, 2017)

Furthermore, the diversification pathways of Tier 2 urban regions differ from those of more developed ones not only in their development levels but also in their strategic focus. Tier 1 urban regions tend to advance frontier innovation sectors, whereas Tier 2 cases would benefit more from building on local resource endowments, such as geographical advantages in Yunnan (in DZ) or energy base in Inner Mongolia (in HBEY), to cultivate specialized industries. Tier 2 urban regions, especially those located along the Yellow River Basin, e.g., Lanzhou-Xining (LX) and the Ningxia-Yellow River (NXYH), could also place stronger emphasis on ecological protection and green transformation, which are already becoming key components of their diversification agendas. Continued investment in transportation and logistics infrastructure would further reinforce regional integration and consolidate the foundations for sustainable innovation (Chen & Li, 2021; Shi et al., 2024).

Taken together, China's regional coordination strategies would benefit from an approach that not only accounts for differences in development (more developed vs. less developed urban regions) but also recognizes the coexistence of distinct diversification paths (related vs. unrelated) within similar levels of development. Greater attention to variations in spatial structure, functional linkages, and knowledge bases would be essential for designing future national and regional innovation frameworks. A multidimensional, path-sensitive policy orientation that fosters the synergy among morphological, functional, and knowledge-based polycentricity is likely to provide a more

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innovation, Tianjin specializes in advanced manufacturing, and Hebei undertakes industrial transfer from the two core cities and developing supporting sectors. In contrast, the Yangtze River Delta (YRD) has evolved from its foundational electronics base into new and emerging domains such as new energy vehicles, biomedicine, and fintech.

sustainable route toward long-term technological diversification and innovation-led regional growth.

6.3 Contributions and future avenues

Overall, this study makes several contributions to the literature. Theoretically, it bridges the fields of polycentricity and technological diversification by conceptualizing their multidimensional interplay. Methodologically, it introduces a continuous indicator of relatedness-based diversification and applies novel instrumental variables to identify causal effects. Empirically, it uncovers how different dimensions of polycentricity—morphological, functional (intra- and extra-regional), and knowledge-based—independently and interactively shape diversification trajectories across urban regions at varying development levels. These contributions lead to differentiated policy recommendations that align spatial and functional structures with knowledge bases to promote diversified innovation development across urban regions.

However, it has several limitations that open up avenues for future research. First, the underlying mechanisms require further empirical investigation, for example, whether and how knowledge spillovers within and between sectors serve as critical channels through which different forms of polycentricity influence diversification. Second, the unified indicator of diversification proposed in this study remains an exploratory attempt to operationalize Boschma's (2017) perspective on the coexistence of related and unrelated diversification. Future research could refine this measure and develop more sophisticated approaches to capture these dynamics within a unified analytical framework. Third, a comparative analysis could reveal whether China exhibits patterns that diverge from those observed in other regions, e.g., Randstad in the Netherlands, particularly regarding technological complexity and relatedness within urban regions. This would offer valuable insights into the applicability of Smart Specialization Strategies in the Chinese context. Fourth, the current study does not fully account for the role of institutional factors in shaping diversification outcomes. For example, the struggle with developing unrelated diversification in Beijing-Tianjin-Hebei may reflect insufficient policy support for peripheral cities, constraining their absorptive capacity for new technologies. Addressing these limitations in future research would enable a more comprehensive understanding of how urban configurations shape regional technological diversification.

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