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Technological diversification in China: the role of intra- and extra-regional collaboration

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ABSTRACT
This study investigates how intra- and extra-regional collaborations affect regional technological diversification in Chinese urban regions (URs), using a continuous indicator that places diversification along a spectrum from related to unrelated. Based on patent co-application data from 2001 to 2020, we analyse the intensity, technological diversity and the correlation of intra- and extra-regional collaborations. Our results show that the effects of (1) intra-regional collaboration intensity on related diversification and (2) extra-regional collaboration diversity on unrelated diversification are both curvilinear. In addition, extra-regional intensity and the correlation between intra- and extra-regional collaborations foster related diversification. Moreover, economic disparities within URs reinforce, rather than weaken, the positive influence of intra-regional intensity and intra–extra technological correlation on related diversification. These results challenge conventional assumptions and highlight the importance of coordinated collaboration structures in promoting regional diversification, especially under uneven regional development conditions.

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1. Introduction

Over the past few decades, firms and industries have experienced technological diversification due to increasing product complexity (Breschi et al., 2003; Giuri et al., 2004; Rosenberg, 1976). Regions that effectively leverage this technological branching can continuously diversify into new areas, thereby gaining long-term competitiveness (Balland et al., 2018). Research in evolutionary economic geography has demonstrated that regional diversification positively impacts productivity (Rocchetta et al., 2021), enhances innovation capabilities (Wang et al., 2016) and contributes to economic resilience (He et al., 2022). Understanding how regions diversify their technological capabilities and what factors support this process is crucial for designing effective policies aimed at sustainable development and competitiveness (Feng et al., 2020).

Meanwhile, in innovation geography, a relational perspective has emerged exploring various forms of regional innovation collaborations, often focusing on co-patenting and co-publishing (Bathelt et al., 2004; Bathelt & Glückler, 2011). While many studies focus on patterns and mechanisms of innovation collaborations either within or between regions separately, few consider both types in conjunction (Sun, 2016). Recently, the importance of cross-regional cooperation has attracted attention, especially in the context of the European Union's Smart Specialization Strategy (Balland & Boschma, 2021; Boschma & Iammarino, 2009; Elekes et al., 2019; Kogler et al., 2023; Neffke et al., 2018). For instance, Santoalha (2019) investigated the role of regional cooperation in promoting diversification across 226 European regions, highlighting that intra- and inter-regional cooperation must evolve together to avoid potential lock-in effects and maximise the opportunities for regional diversification, especially in less developed regions. Yet, less is known about

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whether these findings apply to other national contexts with distinct institutional settings and regional dynamics.

In the case of China, research indicates that regions with stronger diversification capabilities are primarily located in the eastern part of the country, whereas the central and western regions show comparatively weaker effects (Mao & He, 2019). This variation is likely driven by internal economic inequalities within these regions. In regions where cities are more evenly developed and possess comparable absorptive capacities, collaboration tends to yield better outcomes. Conversely, substantial economic gaps between cities can hinder effective knowledge transfer and absorption (Li et al., 2020; Ye et al., 2019). China's rapid economic development has been marked by pronounced spatial unevenness, leading to one of the highest levels of regional inequality globally (Fleisher et al., 2010). However, the extent to which such disparities condition the relationship between collaboration and diversification remains under-explored in the literature.

Against this backdrop, Chinese urban regions (URs) provide a compelling context for examining these dynamics. On the one hand, URs differ from single cities in that they integrate multiple proximate yet functionally distinct cities into broader economic and technological entities, and can therefore be regarded not only as geographical spaces but also as economic units formed and steered by central policies and inter-city dynamics (Boschma, 2004). On the other hand, in China, national initiatives – such as the Yangtze River Delta (YRD) integration and the Guangdong-Hong Kong-Macao Greater Bay Area – promote cross-city coordination and technological upgrading, while persistent economic gaps between constituent cities within URs may hinder knowledge flows and integration. Studying Chinese URs therefore enriches our understanding of regional diversification mechanisms in contexts marked by both integration and disparity.

This study draws on a longitudinal panel dataset covering 19 Chinese URs from 2001 to 2020, aiming to address the following research question: How do different aspects of intra- and extra-regional technological cooperation, both independently and jointly, influence regional diversification? Furthermore, how do these effects vary across URs with different levels of internal economic disparities? The next section reviews the literature on regional diversification and the role of collaboration therein. Section 3 outlines the data and methodology. Section 4 presents the empirical results, including an overview of diversification and collaboration patterns, a topology of Chinese URs based on the diversification–disparity relationship, and regression analyses. Finally, Section 5 concludes by summarising the main findings and suggests directions for future research.

2. Regional diversification and collaborations in technology space

2.1. Diversification beyond the related/unrelated dichotomy

While the Marshall versus Jacobs debate remains largely unresolved, Frenken et al. (2007) introduced the concept of related variety, emphasising that it is not just the diversity of industries that matters, but also their interconnectedness (De Noni & Ganzaroli, 2024). The technological relatedness among different industries within a region fosters incremental growth through agglomeration economies and shapes the long-term dynamics of regional industrial structures. This evolutionary process, referred to as regional diversification, involves the restructuring of regional economies by encouraging the development of industries that are technologically related to existing sectors (Neffke et al., 2011).

Recent research on regional diversification can be traced back to the product space study by Hidalgo et al. (2007) and the work on regional branching by Frenken and Boschma (2007). These studies demonstrate that regions do not diversify randomly; rather, they accumulate capabilities that are closely linked to their existing knowledge base (Boschma et al., 2013; Boschma et al., 2015; Boschma & Iammarino, 2009; Neffke et al., 2011) and to the knowledge base of nearby regions with which they closely interact (Rigby, 2015). This reliance on a region's capabilities positions regional diversification as a path-dependent and evolutionary process that encompasses not only the region's current capabilities but also those from its historical and present context (Arthur, 1989; David, 1985).

Given its path-dependent nature, diversification can be categorised into two types: 1) related diversification, involving path renewal toward new but related activities and 2) unrelated diversification, involving path creation in entirely new sectors or products (Isaksen & Trippl, 2014). Related diversification is more prevalent and generally prioritised due to its lower risks and costs (Balland & Boschma, 2021; Boschma, 2017; Hidalgo et al., 2018). However, heavy reliance on overlapping capabilities can lead to cognitive lock-in, where participants become less innovative (Nooteboom, 2000). In contrast, unrelated diversification, though rarer, can drive radical shifts in local capabilities and foster long-term innovation by engaging with non-overlapping knowledge bases (Neffke et al., 2011). This type of diversification is more common in larger or more developed cities, with most other cities relying on nonlocal resources, such as high-speed rail connections, multinational corporations and external collaborations, to achieve it (Castaldi et al., 2017; Neffke et al., 2018). Despite its higher risks and costs, unrelated diversification can promote structural change and enhance regional economic resilience by reducing vulnerability to sector-specific shocks (Boschma & Capone, 2015; Boschma & Frenken, 2012; Essletzbichler, 2007).

The binary distinction between related and unrelated diversification likely overstates things. Boschma (2017) argued that the distinction is more a matter of degree than a strict separation, with related and unrelated activities being combined unevenly. For regional technological development to thrive, the cognitive proximity between the regional knowledge base and external knowledge should be balanced: neither too small (leading to overly similar learning process) nor too large (hindering effective absorption) (Boschma & Frenken, 2012). Several studies have moved beyond the traditional related/unrelated dichotomy by combining both types of diversification. For instance, Boschma (2017) emphasised the need to examine how different combinations of existing activities, whether related or unrelated, local or non-local, can foster new regional activities. Accordingly, the empirical analysis employs an integrated indicator that positions related and unrelated diversification at opposite ends of a spectrum. While measured along a continuum, this approach does not dissolve their conceptual distinction, but instead allows us to assess the orientation of regional diversification within a unified analytical framework.

2.2. The role of intra- and extra-regional collaborations

Understanding the factors that drive the emergence of new industries and technological activities in regional economies has become a key focus in economic geography (Kogler et al., 2023). Collaborative networks are essential in the process of knowledge production, enabling regions to build capabilities through collaboration, which in turn attracts knowledge inputs and fosters new industries (De Noni et al., 2018). Given the limited capacity of regional actors to absorb external information (Simon, 1955), they often seek new knowledge in close proximity – within their cognitive domains, networks and local environments – resulting in widespread intra-regional collaborations. Opportunities to acquire knowledge from distant sources are often scarce, particularly when that knowledge is tacit (Gertler, 2003; Lin et al., 2023). As a result, knowledge diffusion tends to be geographically constrained (Balland et al., 2020; Balland & Rigby, 2017; Jaffe et al., 1993), which can lead to regional lock-in and over-specialisation.

This is where external connections become critical (Balland & Boschma, 2021; Boschma & Frenken, 2010; Boschma & Lambooy, 1999; Glückler, 2007; Grabher, 1993; Kogler et al., 2023). External connections serve two distinct but interrelated functions. First, it keeps regional actors informed about new ideas emerging elsewhere (Elekes et al., 2019; Fitjar & Rodríguez-Pose, 2011; Neffke et al., 2018). Second, it introduces new sources of variety into the region, helping to prevent regional lock-in and potentially fostering diversification (Grabher, 1993; Kogler et al., 2023). Nonetheless, simply increasing the number of external collaborations is insufficient. To effectively enhance regional diversification, external collaborations should ideally complement and integrate with intra-regional collaborations, thus ensuring efficient knowledge absorption and integration (De Noni & Ganzaroli, 2024; Isaksen, 2014; Kogler et al., 2023; Sun & Cao, 2015).

While the importance of intra- and extra-regional collaborations is well recognised, it remains unclear how their specific aspects and interactions shape regional diversification (Balland & Boschma, 2021; Kogler et al., 2023). Recent studies suggest that the intensity of collaboration, measured by the volume or frequency of connections, reflects the strength of knowledge flows and potentially shapes diversification trajectories. Specifically, stronger intra-regional collaboration intensity may facilitate related diversification, as the knowledge exchanged is often contextually relevant and complementary to existing capabilities (Balland et al., 2020; Kogler et al., 2023). Conversely, stronger extra-regional collaboration intensity can drive unrelated diversification, introducing novel knowledge from outside the region that is less familiar but potentially transformative (Boschma, 2017; Neffke et al., 2018). This reflects the higher potential for radical path creation in entirely new sectors, as external connections allow regions to access non-local knowledge bases that are less cognitively proximate (Neffke et al., 2011).

However, excessively high collaboration intensity, whether within or beyond the region, can undermine its positive effects due to rising coordination costs, cognitive overload and diminishing marginal returns (Crescenzi et al., 2016). As collaboration networks become denser, actors need to allocate more managerial attention to coordinating multiple ties and aligning heterogeneous knowledge bases, which reduces the net benefits of additional collaborations (Anzola-Román et al., 2019; Broekel, 2012; Kobarg et al., 2019; Lin, 2017). At the same time, very dense networks can expose actors to excessive and often redundant information, making it harder to identify and absorb valuable knowledge efficiently (Broekel, 2012). Beyond a certain threshold, these coordination and cognitive costs likely outweigh the benefits of new knowledge inflows, resulting in a non-linear, inverted U-shaped effect of collaboration intensity on innovation outcomes (De Noni et al., 2017; Qiao & Wu, 2024; Wang et al., 2024a; Xie et al., 2022; Xu & Zeng, 2021). Therefore, we propose *H1a* and *H1b*:

> H1a: Higher intensity of intra-regional collaboration promotes related technological diversification, while excessive intensity may inhibit related diversification.

> H1b: Higher intensity of extra-regional collaboration promotes unrelated technological diversification, while excessive intensity may inhibit unrelated diversification.

In parallel, the technological diversity of collaborations, defined as the range of different technological domains involved, promotes unrelated technological diversification by expanding opportunities for knowledge recombination (Fleming, 2001). Within regions, empirical evidence shows that collaboration spanning multiple technological domains facilitate entry into technologies less related to the existing regional portfolio, highlighting the role of internal diversity in pushing regions beyond established development paths (Kogler et al., 2023; Miguelez & Moreno, 2018). Beyond regional boundaries, technological diversity in extra-regional collaborations can compensate for missing local capabilities by providing access to non-redundant external knowledge and global research and development (R&D) networks, thereby helping regions overcome path dependence and explore new, unrelated technological trajectories (Kogler et al., 2023; Mewes & Broekel, 2020; Miguelez & Moreno, 2018; Simone, 2023).

Yet, when technological diversity becomes too extensive, its positive effects may diminish. Combining increasingly distant knowledge domains raises cognitive distance and coordination costs, making communication, interpretation, and integration more challenging (Yoo & Lee, 2022). Given finite absorptive capacity, regions may struggle to effectively absorb and recombine highly diverse knowledge inputs, so that additional diversity yields diminishing returns rather than further gains (Belitski et al., 2024; De Noni et al., 2017). Empirical studies across multiple levels consistently show that collaboration breadth and technological variety enhance innovation performance only up to a point, beyond which their effects weaken or turn negative, resulting in inverted U-shaped patterns (Kobarg et al., 2019; Ning & Guo, 2022; Wang et al., 2024a). Therefore, we propose *H2a* and *H2b*:

> H2a: Higher technological diversity of intra-regional collaborations promotes unrelated technological diversification, while excessive diversity may inhibit unrelated diversification.

> H2b: Higher technological diversity of extra-regional collaborations promotes unrelated technological diversification, while excessive diversity may inhibit unrelated diversification.

Beyond their independent effects, we also examine whether intra- and extra-regional collaborations jointly influence regional diversification outcomes (De Noni et al., 2017). Prior research suggests that collaboration within and across regions can be complementary, and that their combined configuration is more likely to foster diversification than either dimension alone (Santoalha, 2019). Specifically, we focus on the technological correlation between intra- and extra-regional collaboration portfolios, which captures the degree of knowledge alignment across spatial scales. While the technological diversity of each collaboration type broadens the scope for exploring new and unrelated technological domains to a certain extent (see *H2a* and *H2b*), technological correlation indicates whether external capabilities are compatible with, and can be effectively integrated into, the region's existing knowledge base. When external capabilities are related to the regional knowledge base, they can substantially increase the likelihood of new related technologies entering the region, thereby promoting related diversification through effective recombination and integration (Balland & Boschma, 2021; Kogler et al., 2023). Hence, we propose *H3*:

H3: Higher technological correlation between intra- and extra-regional collaborations promotes related technological diversification.

2.3. In Chinese URs with internal economic disparities

China's technological development has progressed rapidly, with patents serving as a key indicator of innovation output. Between 1985 and 2015, patent applications in China skyrocketed from 3423 to 689,270. By 2012, China had surpassed both the US and Japan in patent filings, becoming the world's largest patent holder. However, this explosive growth in patent numbers has sparked debate, as some scholars and policymakers argue that quantity-driven patent policies may not effectively enhance economic development, and that diversification may offer a more comprehensive measure of innovation quality. During the same period, China expanded its patent domains from 468 to 611 four-digit International Patent Classification (IPC) codes, achieving significant breakthroughs in fields such as quantum computing and aerospace. Yet substantial challenges remain in key midstream industries, such as high-end equipment, advanced materials and semiconductors, which are vital for global competitiveness.

Several studies have examined the spatial distribution of technological diversification in China and its determinants, focusing on the role of patent numbers, population, gross domestic product (GDP) (Wang et al., 2015), high-speed rail connections (Chen & Guo, 2023) and foreign multinational enterprises (Qiao et al., 2024). Most of this research is conducted at the provincial level, with limited attention to URs, which have become increasingly important in national innovation strategies. The inclusion of the Beijing-Tianjin-Hebei Coordinated Development in the national agenda marked a turning point, followed by initiatives such as the Yangtze River Delta integration, the Guangdong-Hong Kong-Macao Greater Bay Area and the Chengdu-Chongqing twin-city economic circle. These strategies highlight URs as key arenas for fostering industrial upgrading and technological advancement. Despite this policy emphasis, technological activity within many URs remains spatially uneven. In response, some local governments have begun advocating cross-regional cooperation to channel resources to peripheral cities and reduce internal disparities. For example, Shanghai's Science and Technology Innovation Action Plan encourages collaboration across jurisdictions to support high-quality development across the Yangtze River Delta.

While the role of collaboration in fostering regional diversification is attracting growing policy interest, empirical research at the UR level remains limited. One exception is Jiang (2024), who examined how regional collaboration and local knowledge bases contribute to breakthrough inventions. At the same time, although policies increasingly promote collaboration as a means to overcome internal unevenness, its effectiveness may be conditioned by internal economic disparities and therefore does not automatically translate into region-wide diversification outcomes. Such disparities can fragment knowledge flows within URs, as absorptive capacity and coordination resources tend to be concentrated in core cities, enabling them to benefit disproportionately from collaboration while peripheral cities remain marginalised (Nijman & Wei, 2020; van Oort & Lambooy, 2021). Empirical evidence from China further shows that large core–periphery gaps trap technological spillovers within metropolitan cores and weaken inter-city diffusion (He et al., 2021). Pronounced internal disparities also disrupt industrial linkages and undermine regional economic resilience and the capacity for evolutionary transformation (Liang et al., 2025), both of which are key conditions for successful diversification. As a result, more balanced URs, characterised by smaller internal disparities, are expected to derive greater diversification benefits from collaborations, whereas highly unequal URs may experience more uneven and limited outcomes. This implies that the effect of collaboration on technological diversification is conditional on the degree of internal economic unevenness. Accordingly, we propose our final hypothesis:

H4: The positive effects of intra- and extra-regional collaborations on technological diversification are weaker in URs with higher internal economic disparities.

3. Methodology

3.1. 19 Chinese URs

The 19 URs examined in this study span both the more developed eastern areas and the inland central and western areas of China. Together, they account for over 75% of the national urban population and contribute more than 85% of GDP (see Table A1 in Appendix A in the online supplemental data). Beyond their demographic and economic weight, these URs often host dense science, technology and innovation (STI) infrastructures – such as universities, research institutes, industrial parks and high-speed rail networks – that provide the institutional and physical basis for inter-city knowledge exchange and collaborative innovation. However, due to differences in location, economic foundations and policy environments, these URs exhibit considerable variation in their regional influence and strategic importance. Therefore, the 19 URs were categorised into three tiers in the National New Urbanization Plan (2021–2035) (Figure 1). A detailed description of each tier is provided in Appendix A in the online supplemental data.

3.2. Patent data

We use patent data from the China National Intellectual Property Administration (CNIPA, http://www.cnipa.gov.cn/), which provides information such as patent name, type, application and grant date, main International Patent Classification (IPC) code, and applicant names. The full dataset includes over 20 million records from 2001 to 2020. We focus exclusively on invention patents, excluding utility model and design patents, as invention patents are technically more substantial and widely used in innovation network studies (Wang et al., 2022).

To capture collaborations, we identify co-applicant patents involving applicants from different URs, following the approach of Kogler et al. (2023). We first exclude patents applied solely by individuals, as their addresses are not publicly available. We then retain patents with two or more applicants and retrieve their addresses using the Amap API (https://lbs.amap.com/) based on the applicants' names. This yields a dataset of 24,001 inter-city co-applicant invention patents from 2001 to 2020 across mainland China. These collaborations are then aggregated to the UR level and classified as either intra-regional or extra-regional linkages.[1]

3.3. Dependent variable

In evolutionary economic geography, regional technological diversification refers to the entry of regions into technological fields in which they were not previously specialised, reflecting the dynamic evolution

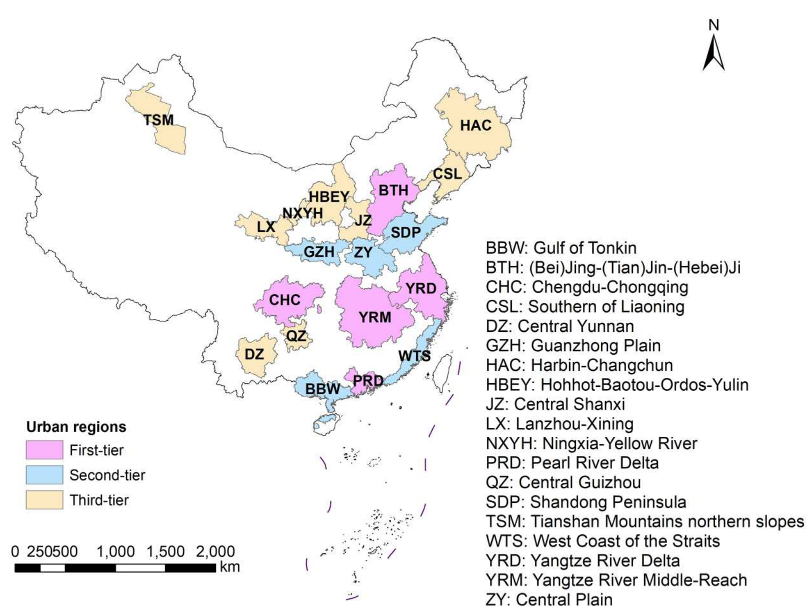

Figure 1. Chinese urban regions.
Source: the authors.

of regional technological structures through the development of new capabilities (Boschma & Frenken, 2012; Hidalgo et al., 2007; Kogler et al., 2023). Empirically, diversification is identified as the emergence of new technological specialisations between consecutive periods. To capture a region's relative level of specialisation in each technological domain, we first construct revealed technological advantage (RTA) (Hidalgo et al., 2007; Kogler et al., 2023; Neffke et al., 2011; Whittle & Kogler, 2020):

$$RTA_{i,j,t} = \frac{Patent_{i,j,t} / \sum_j Patent_{i,j,t}}{\sum_i Patent_{i,j,t} / \sum_{i,j} Patent_{i,j,t}} \tag{1}$$

$$x_{i,j,t} = \begin{cases} 1, & RTA_{i,j,t} \geq 1 \\ 0, & RTA_{i,j,t} < 1 \end{cases} \tag{2}$$

The RTA index measures the specialisation of UR i in technology j compared to the national average. If RTA ≥ 1, UR i is considered to have a comparative advantage in technology j. Using a binary matrix based on RTA values, we then calculate the technology proximity matrix between technology pairs (Hidalgo et al., 2007). Following a co-specialisation approach in the diversification literature (Balland et al., 2018; Boschma et al., 2015; Kogler et al., 2023; Kogler & Whittle, 2018; Tanner, 2014), if the pairwise conditional probability that a UR specialises in both technologies is higher, the two technologies are indicated to have a greater degree of relatedness:

$$\phi_{j,j'} = \frac{\sum_i M_{i,j} M_{i,j'}}{max(k_{j,o}, k_{j',o})} \tag{3}$$

where $k_{j,o}$ and $k_{j',o}$ represent the number of URs that exhibit RTA in technology j and technology j' in the study period, respectively. By measuring the proximity between technology j and all other technologies in UR i, we assess how closely a new technology is related to the UR's existing technological portfolio. This relationship is captured by relatedness density, which reflects the extent to which new technologies build on the UR's current capabilities:

$$Density_{i,j,t} = \frac{\sum_{j'} x_{i,j',t} \cdot \phi_{j,j',t}}{\sum_{j'} \phi_{j,j',t}} \tag{4}$$

where $x_{i,j',t}$ is a dummy variable indicating whether UR i has RTA in technology j' in year t. It captures the existing technological base of UR i, representing the capabilities that firms may draw upon when innovating in technology j in year t. A UR's own technological capabilities also influence its ability to diversify into areas with high technological density. To control for potential statistical biases arising from these inherent capabilities, we introduce relative relatedness density, calculated using z-score standardisation:

$$\omega_{i,j,t} = \frac{Density_{i,j,t} - \langle Density_{i,t} \rangle_O}{\sigma_O(Density_{i,t})} \tag{5}$$

where O denotes the set of technologies in UR i in year t that have not yet reached specialisation. The average density $\langle Density_{i,t} \rangle_O$ and its standard deviation $\sigma_O(Density_{i,t})$ are calculated within this set. The relative technology density index $\omega_{i,j,t}$ measures technology j's density relative to others in O. A negative $\omega_{i,j,t}$ indicates a relatively small stock of technology j, suggesting unrelated diversification, whereas a positive $\omega_{i,j,t}$ reflects a relatively large stock, implying related diversification. This index provides a nuanced distinction between related and unrelated diversification and facilitates comparisons across URs. Based on the relative technology density, we calculate the average value to capture the overall level of a UR's technological diversification (Zheng & Ran, 2021):

$$Diversification_{i,t} = \frac{1}{n} \sum_{j=1}^{n} \omega_{i,j,t} \tag{6}$$

$$d = \begin{cases} 1, & RTA_{i,j,t-1} < 0.1 \text{ } and \text{ } RTA_{i,j,t} \geq 1 \\ & 0, \text{ } else \end{cases} \tag{7}$$

where n is the number of diversification events, the condition for diversification occurrence d is defined in Equation (7). Following Hidalgo and Hausmann (2009) and Petralia et al. (2017), a UR is considered to diversify into a technology if it transitions from no presence (RTA < 0.1) to specialisation (RTA > 1). The average relative technology density not only reflects the extent of diversification in a UR but also indicates the orientation of its innovation activities. A higher value suggests a tendency toward innovation in related fields, while a lower value implies a shift toward unrelated domains.

3.4. Independent variables

In geographical terms, technology collaborations can take two forms: intra-regional and extra-regional. Intra-regional collaborations occur between patent applicants from different cities within the same UR, while extra-regional collaborations involve a first applicant from one UR and co-applicants from cities in other URs. Building on the methodologies of Kogler et al. (2023) and De Noni and Ganzaroli (2024), we extend the analytical scope to include not only the intensity and technological diversity of both collaboration types, but also the technological alignment between their knowledge portfolios.

3.4.1. Intensity of collaborations

We quantify the intensity of intra- and extra-regional collaborations using a fractional indicator that captures the share of patents involving collaboration in UR i. Specifically, $INT.INTRA_{i,t}$ denotes the number of patents co-applied by applicants from different cities within the same UR i at year t, while $INT.EXTRA_{i,t}$ refers to the number of patents involving at least one co-applicant from a different UR. Both indicators reflect the relative importance of collaborative activities in a UR's innovation output.

$$INT.INTRA_{i,t} = \frac{PATINTRA_{i,t}}{PAT_{i,t}} \tag{8}$$

$$INT.EXTRA_{i,t} = \frac{PATEXTRA_{i,t}}{PAT_{i,t}} \tag{9}$$

$PAT_{i,t}$ denotes the total number of patent applications filed in UR i in year t, $PATINTRA_{i,t}$ refers to the number of these applications involving multiple applicants, all of whom are based in UR i, whereas $PATEXTRA_{i,t}$ refers to applications involving multiple applicants, with at least one applicant from outside UR i. In Equations (8) and (9), the value ranges from 0 to 1.

3.4.2. Technological diversity and correlation of collaborations

We use the Herfindahl-Hirschman Index (HHI) to measure the concentration of technological portfolios associated with both intra- and extra-regional collaborations:

$$TECH.DIV.INTRA_{c,i,t} = \sum_{c} \left(\frac{PATINTRA_{c,i,t}}{PAT_{i,t}}\right)^2 \tag{10}$$

$$TECH.DIV.EXTRA_{c,i,t} = \sum_{c} \left(\frac{PATEXTRA_{c,i,t}}{PAT_{i,t}}\right)^2 \tag{11}$$

where c represents the IPC classes. Higher values of the HHI indicate greater technological concentration, meaning that a UR's collaborative patents are focused in fewer technological domains, while lower values suggest broader technological diversity.

While we examine intra- and extra-regional collaborations separately in terms of their intensity and technological diversity, we also consider their joint effects on diversification (De Noni et al., 2017; Santoalha, 2019). These joint effects are captured by the technological correlation between intra- and extra-regional collaboration portfolios, which is defined as follows:

$$TECH.PROP.INTRA_{c,i,t} = \frac{PATINTRA_{c,i,t}}{\sum_c PATINTRA_{c,i,t}} \tag{12}$$

$$TECH.PROP.EXTRA_{c,i,t} = \frac{PATEXTRA_{c,i,t}}{\sum_c PATEXTRA_{c,i,t}} \tag{13}$$

These two indicators represent the proportion of intra- and extra-regional collaborative patents in each technological category, reflecting the technological composition of internal and external collaborations for UR i in year t. We then construct $COR.EXTRA.INTRA_{i,t}$ by calculating the Pearson correlation coefficient between the two indicators. A correlation close to 1 indicates that the focal UR engages in extra-regional collaborations in the same technological domains it already develops internally, implying a high degree of technological alignment between intra- and extra-regional collaborations. Conversely, values close to − 1 suggest that the external knowledge accessed through extra-regional collaborations differs significantly from the intra-regional knowledge base.

3.5. Moderating variable

To assess how internal economic conditions shape the effects of collaboration on technological diversification, we introduce regional economic disparity as a moderating variable. Specifically, we use the coefficient of variation (CV) of gross domestic product per capita (GDPpc) across its constituent cities, denoted as *CV.GDPpc*. GDPpc is a widely used indicator of economic performance that enables consistent comparison of economic levels across cities. The CV measures the relative dispersion of GDPpc within a UR, standardising variability and allowing for comparison across URs. A higher value of *CV.GDPpc* indicates greater internal economic disparity within the UR.

3.6. Econometric model

In addition to the main explanatory variables, we include three control variables to account for structural differences across URs. Economic strength (GDP), measured by the average GDP of cities in the UR, captures the overall development level and potential resource base for innovation. Human capital (HUM), defined as the proportion of the population with at least a secondary education, reflects the knowledge capacity that underpins innovation and technology absorption. Industrial structure (TER), proxied by the share of tertiary industry[2] in GDP, indicates the service-oriented economic base that is often associated with higher innovation intensity. All variables used in the econometric models are presented in Table 1. Descriptive statistics and the correlation matrix are shown in Table B1 in Appendix B in the online supplemental data, with no significant multicollinearity observed.

Table 1. Variables employed in the analysis.

	Variable	Description	Abbreviation	Year
Dependent variable	Regional technological diversification	Average relative technology density of the UR	*DIV*	2005, 2010, 2015, 2020
Independent variables	Intensity of intra-regional collaborations	Share of the number of intra-regional collaborations in total patents applications	*INT.INTRA*	Five-year moving window[4] (2001-2005, 2006-2010, 2011-2015, 2016-2020)
	Intensity of extra-regional collaborations	Share of the number of extra-regional collaborations in total patents applications	*INT.EXTRA*	
	Technological diversity of intra-regional collaborations	Herfindahl-Hirschman Index measuring how concentrated the technology classes are in intra-regional collaborations	*TECH.DIV.INTRA*	
	Technological diversity of extra-regional collaborations	Herfindahl-Hirschman Index measuring how concentrated the technology classes are in extra-regional collaborations	*TECN.DIV.EXTRA*	
	Technological correlation of intra- and extra-regional collaborations	Pearson correlation between the technological distribution of extra- and intra-regional collaborations	*COR.EXTRA.INTRA*	
Moderating variable	Economic disparities	Coefficient of variation (CV) of gross domestic productivity per capita (GDPpc) of cities in the UR	*CV.GDPpc*	One-year lag (2004, 2009, 2014, 2019)
Control variables	Economic strength	Average GDP of cities in the UR	*GDP*	
	Human capital	Proportion of the total population with at least a secondary education in the UR	*HUM*	
	Industrial structure	Share of tertiary industry GDP in the UR	*TER*	

Based on Hypotheses 1–3, we estimate fixed-effects panel regression models to assess how intra- and extra-regional collaborations influence technological diversification, both separately and jointly:

$$DIV_{it} = \beta_0 + \beta_1 INT.INTRA_{it} + \beta_2 INT.INTRA^2_{it} + \beta_3 TECH.DIV.INTRA_{it} + \beta_4 TECH.DIV.INTRA^2_{it} + \beta_5 C_{it} + \delta_i + \gamma_t + \epsilon_{it} \tag{14}$$

$$DIV_{it} = \beta_0 + \beta_1 INT.EXTRA_{it} + \beta_2 INT.EXTRA^2_{it} + \beta_3 TECH.DIV.EXTRA_{it} + \beta_4 TECH.DIV.EXTRA^2_{it} + \beta_5 C_{it} + \delta_i + \gamma_t + \epsilon_{it} \tag{15}$$

$$DIV_{it} = \beta_0 + \beta_1 TECH.DIV.INTRA_{it} + \beta_2 TECH.DIV.EXTRA_{it} + \beta_3 COR.EXTRA.INTRA + \beta_4 C_{it} + \delta_i + \gamma_t + \epsilon_{it} \tag{16}$$

where C_{it} represents the control variables, ε_{it} denotes the error term, and β is the parameter to be estimated. To account for unobserved heterogeneity across urban regions and over time, we include both region δ_i and year γ_t fixed effects. Since the independent variables vary in scale, we apply z-score standardisation to ensure comparability of the coefficients across models. For control variables, we use the natural logarithm (ln) transformation to reduce skewness and maintain consistent scaling.

3.7. Dealing with endogeneity

While the fixed-effects regression models provide useful insights into the relationship between collaboration and technological diversification, the possibility of endogeneity remains a concern. In particular, reverse causality may affect the estimated effects of intra- and extra-regional collaboration. Regions that have already achieved higher levels of related or unrelated technological diversification may themselves become more attractive collaboration partners. For instance, a diversified, especially unrelated, technological profile can signal broader knowledge bases and stronger absorptive capacity, thereby attracting more heterogeneous extra-regional partners. In such cases, observed collaboration intensity may partly reflect the outcomes of prior diversification rather than its cause, introducing bias into standard regression estimates.

To address this concern, we adopt an instrumental variable (IV) approach based on historical firm-level investment data in 1992. A valid instrument should satisfy two conditions: it must be correlated with contemporary collaboration patterns (relevance), and it should affect current technological diversification only through its impact on collaboration, rather than through a direct channel (exclusion restriction). Historical investment relationships reflect early structural heterogeneity and industrial complementarities between cities, which may have facilitated knowledge flows by enhancing innovation capability and narrowing technological distance (Wang et al., 2024b).

Importantly, we do not use historical investment volumes directly. Instead, these data are employed to construct instruments that proxy structural and technological conditions relevant to the configuration of intra- and extra-regional collaboration. Given the long temporal gap, these historical structural conditions remain plausibly exogenous to recent patterns of technological diversification. By focusing on investment-derived structural and technological dimensions, our instruments are expected to influence contemporary technological diversification primarily through the collaboration channel, thereby mitigating concerns about a direct effect on current diversification outcomes. Details of instrument construction and diagnostic tests for instrument validity and strength are provided in Appendix C in the online supplemental data.

4. Results

4.1. Regional diversification and collaboration patterns

Before presenting the regression results, we first provide a visual and descriptive overview of the regional diversification and collaboration patterns in Chinese URs. Figures 2 and 3 illustrate the temporal evolution of these patterns over the study period. In Figure 2, URs shaded in red indicate a stronger tendency towards

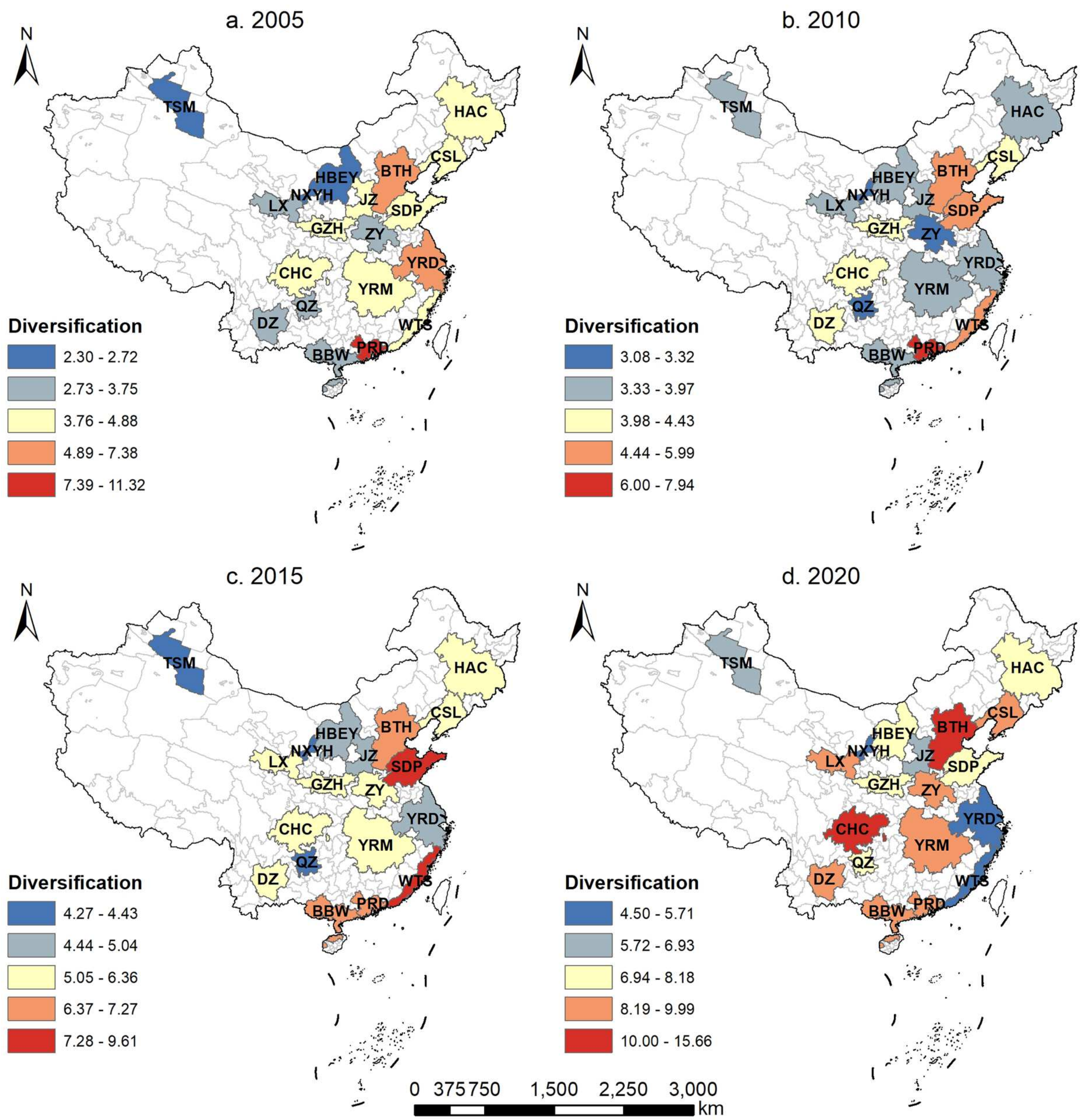

Figure 2. Technological diversification in Chinese urban regions.
Source: the authors.

more related diversification, blue reflects a greater extent of more unrelated diversification, while yellow represents a more balanced diversification profile.

Regional diversification varies significantly among URs. By 2020, URs like Beijing–Tianjin–Hebei (BTH), Chengdu–Chongqing (CHC), Yangtze River Middle-Reach (YRM), Central Plain (ZY) and Southern of Liaoning (CSL) exhibited high levels of related diversification, while the Yangtze River Delta (YRD) and the West Coast of the Straits (WTS) shifted towards more unrelated diversification. The economically advanced coastal URs , e.g., BTH, the YRD and the Pearl River Delta (PRD), have followed different diversification paths due to their distinct industrial dynamics. For instance, the YRD, spanning Shanghai, Jiangsu, Zhejiang and Anhui, shows a trend towards unrelated diversification, reflecting its diverse economic base: Shanghai has a comprehensive industrial structure, Jiangsu focuses on foreign investment and large-scale industries, Zhejiang emphasises export-driven, small-scale manufacturing, while Anhui mainly absorbs industrial transfers, characterised by state-owned enterprises. In contrast, the BTH, dominated by Beijing and Tianjin, is driven by high-end technological innovation, while the

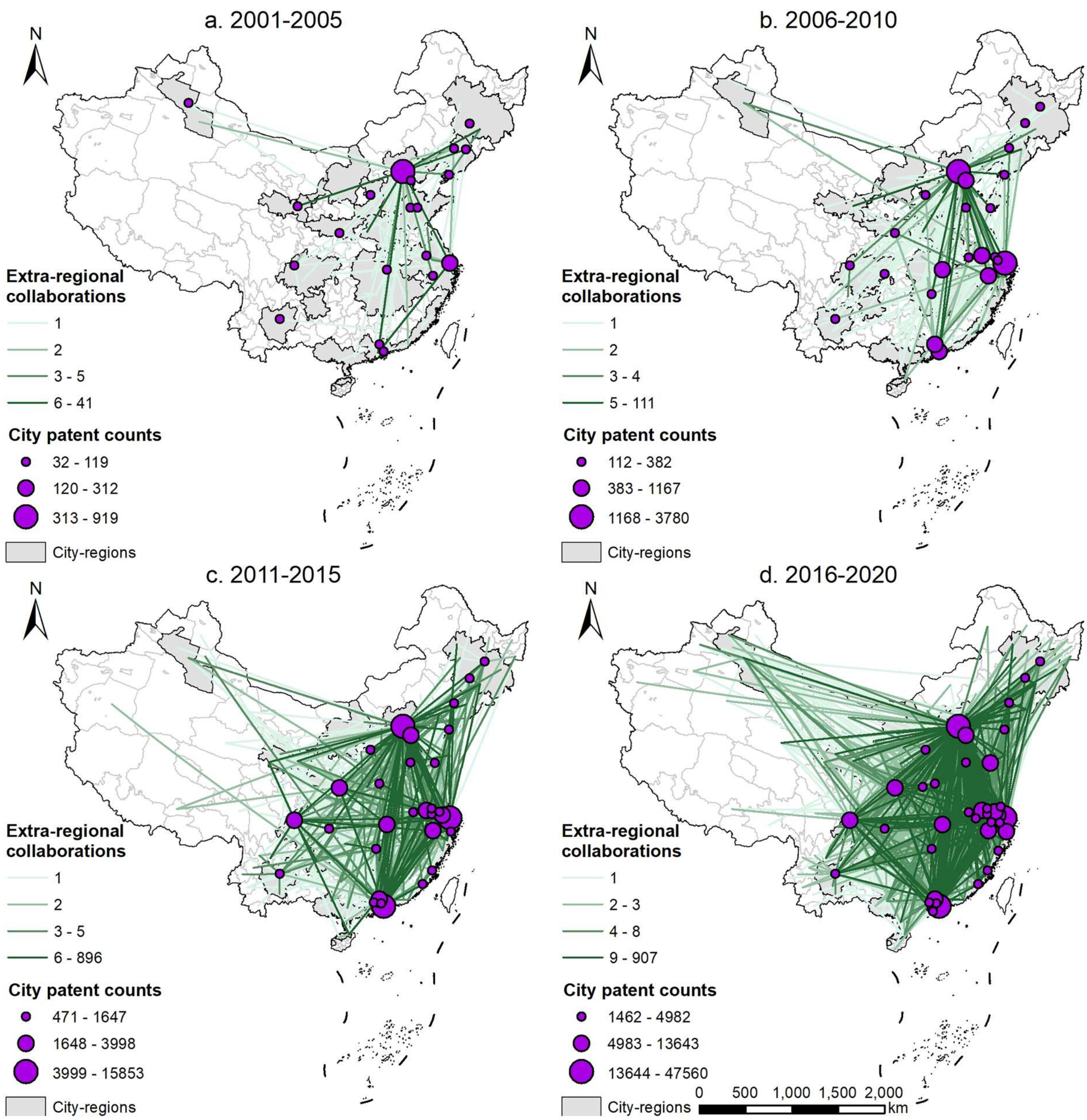

Figure 3. Extra-regional collaborations and city patent counts.
Source: the authors.

PRD, centred in Guangdong, relies on specialised manufacturing clusters, with most cities, except Guangzhou and Shenzhen, focusing on low-end manufacturing. These contrasting strategies highlight the varied pathways to diversification among China's leading URs.

Figure 3 depicts the geography of extra-regional collaborations, with green edges representing collaboration intensity and purple nodes indicating the number of patents. Since the 2000s, BTH has established strong external linkages with both the YRD and the PRD, which have gradually intensified over time. By the end of the first decade, these extra-regional collaborations had formed a diamond-like structure connecting BTH, the YRD, the PRD and CHC, with their core cities emerging as major hubs for invention patents.

Collaborative patents constitute a small portion of the total patents, with most URs having less than 10% of their patents derived from collaborations (see Appendix D in the online supplemental data for intra- and extra-regional shares). The YRD, a patent leader, has seen growth in both intra- and extra-regional collaborations; however, its extra-regional collaboration has declined since 2005, despite maintaining the highest

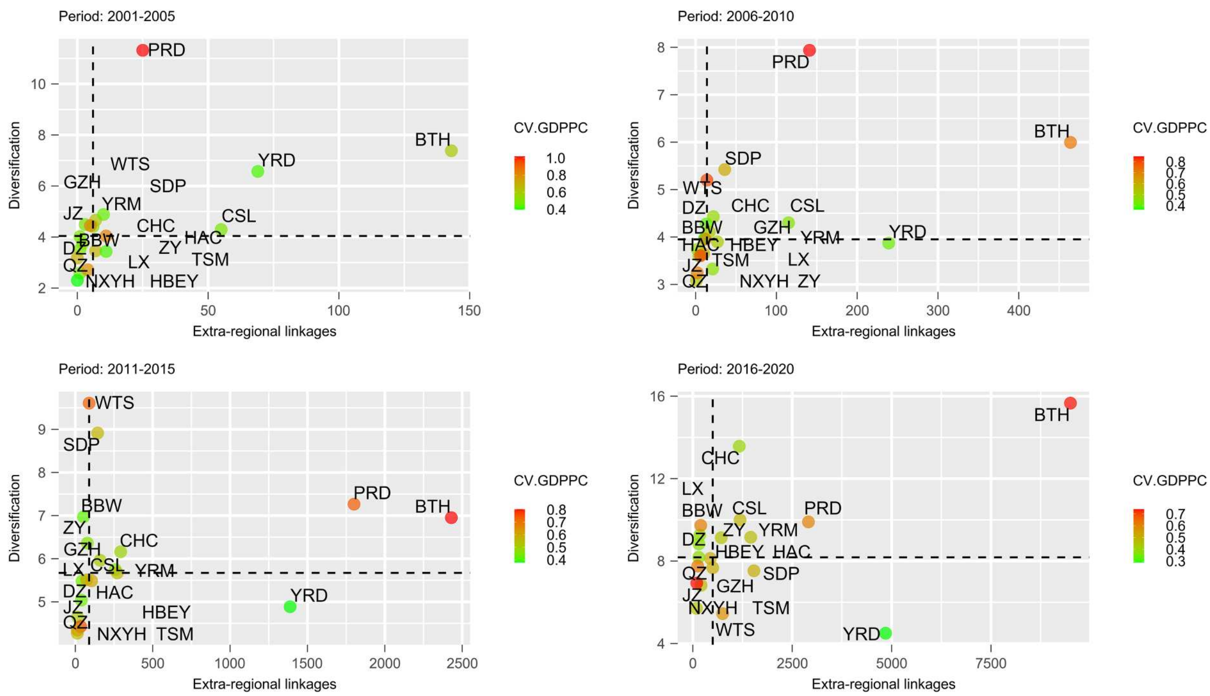

Figure 4. Relationship between extra-regional linkages, diversification, and economic disparities.
(Note: The vertical and horizontal dashed lines represent the median values of extra-regional linkages and diversification, respectively). Source: the authors.

level of intra-regional collaboration. This aligns with its shift toward more unrelated diversification. In contrast, BTH has consistently maintained the highest level of extra-regional collaboration, nearly double that of the YRD from 2016 to 2020, alongside steady growth in related diversification, reaching the highest level by 2020. Additionally, the YRD and BTH exhibit contrasting trends in economic disparities: the YRD achieved the most balanced economy by 2020, while BTH experienced a sharp increase in disparities, becoming the most uneven UR in China.

Figure 4 highlights economic disparities in Chinese URs. URs in the upper-right quadrant are characterised by a higher degree of extra-regional collaboration and more related diversification, often accompanied by greater internal economic disparities. BTH stands out as a notable example in this group. Due to space limitations, a detailed case analysis of BTH is provided in Appendix E in the online supplemental data.

4.2. The role of different aspects of intra- and extra-regional collaboration

Table 2 presents the regression results. Model 1 incorporates only control variables. Models 2 and 3 correspond to *H1* and *H2*, with Model 2 focusing on intra-regional collaboration (*H1a* and *H2a*) and Model 3 on extra-regional collaboration (*H1b* and *H2b*). Model 4 corresponds to *H3*.

H1 is partially supported. Model 2 shows that intra-regional collaboration intensity (*INT.INTRA*) exhibits a significant inverted U-shaped relationship with related diversification, indicating that excessive intensity of internal collaboration is associated with a decline in related diversification outcomes, thus supporting *H1a*. In contrast, Model 3 shows that extra-regional collaboration intensity (*INT.EXTRA*) has a significant positive linear effect on related diversification, but no evidence of an inverted U-shaped relationship is found; therefore, *H1b* is not supported.

H2 is also partially supported. The technological diversity of intra-regional collaboration (*TECH.DIV.INTRA*) does not show a statistically significant effect on unrelated diversification, providing no support for *H2a*. In contrast, the technological diversity of extra-regional collaboration (*TECH.DIV.EXTRA*) exhibits a significant inverted U-shaped relationship with unrelated diversification (given that lower values of the diversification index indicate a stronger tendency towards unrelated diversification), suggesting that while moderate diversity is beneficial, excessive external diversity may inhibit unrelated diversification, thus supporting *H2b*.

Table 2. Regression results of fixed effects models.

	Model 1	Model 2 H1a&H2a (intra)	Model 3 H1b&H2b (extra)	Model 4 H3
INT.INTRA		0.583*(0.323)		
INT.INTRA^2		−0.326*(0.177)		
INT.EXTRA			0.571*(0.302)	
INT.EXTRA^2			−0.100(0.124)	
TECH.DIV.INTRA		−0.172(0.727)		−0.146(0.255)
TECH.DIV.INTRA^2		0.016(0.147)		
TECH.DIV.EXTRA			−0.948***(0.300)	−0.176(0.154)
TECH.DIV.EXTRA^2			0.297***(0.088)	
COR.EXTRA.INTRA				0.625*(0.358)
GDP	1.168***(0.306)	0.845***(0.287)	0.932***(0.348)	1.149***(0.306)
HUM	−1.455*(0.804)	−1.390*(0.806)	−1.309*(0.758)	−1.431*(0.816)
TER	4.924***(1.370)	5.048***(1.441)	4.181***(1.466)	5.057***(1.427)
Region-fixed	Yes	Yes	Yes	Yes
Time-fixed	Yes	Yes	Yes	Yes
Observations	76	76	76	76
R^2	0.523	0.512	0.538	0.511

Note: *p*-values are denoted as follows: * $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$. Robust standard errors shown in parentheses are clustered at the UR level.

Finally, *H3* is supported. Model 4 shows that stronger technological correlation between intra- and extra-regional collaborations significantly promotes related technological diversification.

Overall, these results highlight that intra-regional collaboration intensity and extra-regional collaboration diversity both show curvilinear effects, the former on related diversification and the latter on unrelated diversification. This implies that internal intensity enhances related diversification up to a threshold before diminishing returns set in, while external diversity initially fosters unrelated diversification but becomes less effective once excessive heterogeneity creates coordination challenges. In addition, extra-regional collaboration intensity and the technological correlation between intra- and extra-regional collaborations exert positive effects on related diversification. These findings are broadly consistent with previous studies emphasising the central role of localised innovation dynamics and spatially proximate collaboration (Balland, 2012; Boschma & Frenken, 2010), and highlighting that the integration between intra- and inter-regional knowledge bases is crucial for enhancing diversification outcomes (De Noni & Ganzaroli, 2024; Santoalha, 2019).

We examine the robustness of our findings to alternative variable measurements. For independent variables, we use different approaches to calculate intensity, technological diversity and correlation of collaboration. Specifically, for *INT.INTRA* and *INT.EXTRA*, we re-run the models by replacing fractional scores with integer scores, using only the numerators of Equations (8) and (9), $PATINTRA_{it}$ and $PATEXTRA_{it}$, respectively. For *TECH.DIV.INTRA* and *TECH.DIV.EXTRA*, we re-run the models by replacing the Herfindahl-Hirschman Index (HHI) with the Shannon Entropy Index.[3] For *COR.EXTRA.INTRA*, we re-run the models by replacing the Pearson correlation with the Spearman Correlation method. For dependent variables, the definition of technological diversification is refined to increase robustness: the elasticity inherent in the definition of technological diversification provided in Equation (7) allows for the relaxation of the $RTA_{i,j,t-1}$ assumption to capture a broader range of diversification events (Petralia et al., 2017). Specifically, the condition for diversification is relaxed to $RTA_{i,j,t-1} < 0.5$ and $RTA_t \geq 1$. This revised diversification variable is then incorporated into the regression model. The above alternatives all yield consistent results, confirming the robustness of our results.

4.3. Economic disparities: does it matter for the effect of collaboration?

We are particularly interested in whether economic disparities condition the relationship between collaboration and diversification. Therefore, Table 3 tests *H4* by introducing interaction terms between internal economic disparities (*CV.GDPpc*) and different dimensions of collaboration. Model 1 shows that intra-regional collaboration intensity (*INT.INTRA*), which displayed a curvilinear effect in Table 2, now exerts a consistently positive influence (β = 2.902, $p < 0.05$) on related diversification once disparities are incorporated. Moreover, its interaction with *CV.GDPpc* is positive and significant (β = 3.452, $p < 0.05$), indicating

Table 3. Regression results considering the moderating effect of economic disparities (CV.GDPpc).

	Model 1 H4 (intra)	Model 2 H4 (extra)	Model 3 H4 (intra&extra)
INT.INTRA	2.902**(1.228)		
INT.INTRA^2	−0.919(0.917)		
INT.EXTRA		1.563*(0.892)	
INT.EXTRA^2		0.774(0.824)	
TECH.DIV.INTRA	−1.054(2.589)		−0.165(0.262)
TECH.DIV.INTRA^2	−0.034(0.608)		
TECH.DIV.EXTRA		−0.911(2.078)	−0.137(0.242)
TECH.DIV.EXTRA^2		−0.002(1.166)	
COR.EXTRA.INTRA			1.699*(1.031)
CV.GDPpc	2.806(2.695)	1.759(1.824)	1.784**(0.858)
*CV.GDPpc*INT.INTRA*	3.453**(1.321)		
*CV.GDPpc*INT.INTRA*^{2}	−0.905(1.244)		
*CV.GDPpc*INT.EXTRA*		1.525(1.335)	
*CV.GDPpc*INT.EXTRA*^{2}		0.967(0.964)	
*CV.GDPpc*TECH.DIV.INTRA*	−1.023(3.462)		
*CV.GDPpc*TECH.DIV.INTRA*^{2}	−0.178(0.794)		
*CV.GDPpc*TECH.DIV.EXTRA*		−0.009(3.074)	
*CV.GDPpc*TECH.DIV.EXTRA*^{2}		−0.432(1.707)	
*CV.GDPpc*COR.EXTRA.INTRA*			4.217**(1.952)
Controls	Yes	Yes	Yes
Region-fixed	Yes	Yes	Yes
Time-fixed	Yes	Yes	Yes
Observations	76	76	76
R^2	0.601	0.585	0.567

Note: *p*-values are denoted as follows: * $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$. Robust standard errors shown in parentheses are clustered at the UR level.

that greater internal inequality reinforces rather than weakens the benefits of intra-regional collaboration, which contradicts *H4*.

For extra-regional collaboration intensity (*INT.EXTRA*), the results are robust across both tables. While already positive in Table 2 (β = 0.571, $p < 0.1$), the coefficient becomes larger in Table 3 (β = 1.563, $p < 0.1$), suggesting a stronger positive effect. However, its interaction with disparities is insignificant, implying that the positive impact of external intensity remains robust across varying levels of internal disparities and is not moderated by them. This likely reflects that external intensity captures the openness of URs to non-local knowledge flows, which are typically channelled through core cities acting as gateways (Breschi & Lenzi, 2017). By redistributing external knowledge to other constituent cities, core cities mitigate the potential constraining role of internal disparities, thereby sustaining the positive effect of external intensity.

Regarding the technological diversity of extra-regional collaboration (*TECH.DIV.EXTRA*), the U-shaped relationship identified in Table 2 disappears in Table 3: both the linear and quadratic terms lose significance, and their interactions with disparities are also insignificant. This suggests that the previously observed curvilinear pattern was largely driven by differences in inequality across URs. That said, the benefits of external diversity are conditional: they require strong absorptive capacity and alignment with local knowledge bases to be effectively realised (Boschma, 2017; Cohen & Levinthal, 1990). Once disparities are considered, which themselves capture differences in absorptive and coordination capacities, the marginal contribution of external diversity becomes negligible. Technological diversity of intra-regional collaboration (*TECH.DIV.INTRA*) is also statistically insignificant in Table 3, and none of its interactions with disparities reach significance.

In contrast, the effect of technological correlation between intra- and extra-regional collaborations (*COR.EXTRA.INTRA*) remains statistically significant and positive in Table 3 (β = 1.699, $p < 0.1$), consistent with Table 2. Moreover, its interaction with *CV.GDPpc* is also significant and positive (β = 4.217, $p < 0.05$), indicating that the benefit of technological alignment across boundaries is even stronger in URs with greater internal inequality. This suggests that when disparities are high, stand-alone diversity is insufficient, as local absorptive and coordination capacities are uneven. In such contexts, aligning intra- and extra-regional knowledge bases becomes particularly valuable, as it bridges structural gaps and facilitates knowledge circulation across the UR.

In sum, the evidence rejects *H4*: internal economic disparities do not weaken collaboration effects but shape them in different ways: reinforcing the positive effects of intra-regional intensity and cross-regional technological alignment on related diversification, while leaving the effects of external intensity largely unaffected and nullifying the previously observed curvilinear effect of external diversity.

5. Discussion and conclusions

5.1. Main findings

This study investigated how different dimensions of intra- and extra-regional technological collaboration shape regional technological diversification in Chinese urban regions (URs), with particular attention to the moderating role of internal economic disparities. Using instrumental variable estimations to address potential endogeneity concerns, we strengthen the causal interpretation of the collaboration–diversification relationship. Three main findings emerge.

First, different dimensions of collaboration exert distinct and non-linear effects on regional diversification. Intra-regional collaboration intensity exhibits an inverted U-shaped relationship with related diversification, indicating that moderate levels of internal collaboration facilitate capability recombination along existing technological paths, whereas excessive intensity leads to diminishing returns. In contrast, the technological diversity of extra-regional collaboration shows an inverted U-shaped relationship with unrelated diversification, suggesting that external knowledge variety initially enables regions to explore technologically distant domains but becomes less effective once cognitive and coordination costs rise. Meanwhile, extra-regional collaboration intensity consistently promotes related diversification, underscoring the role of sustained external linkages in reinforcing existing technological trajectories.

Second, beyond their independent effects, the alignment between intra- and extra-regional collaboration portfolios plays a pivotal role. A higher technological correlation between internal and external collaborations significantly strengthens related diversification, indicating that diversification is driven not only by internal or external collaboration individually, but also by the effective integration of external knowledge into the regional knowledge base.

Third, internal economic disparities fundamentally condition how collaboration translates into diversification. Contrary to the common expectation that inequality weakens collaboration outcomes, internal disparities selectively amplify the positive effects of intra-regional collaboration intensity and intra–extra technological correlation on related diversification. Rather than uniformly shaping all dimensions of collaboration, disparities reinforce those mechanisms that rely on intensive local, technologically aligned recombination. Taken together, these findings highlight that regional diversification depends not only on the presence of collaboration, but on how collaboration is structured, technologically aligned and embedded in internal economic conditions.

5.2. Comparison with existing studies

Our findings both align with and extend existing literature in three main ways. First, while most previous studies often associate external collaboration primarily with unrelated diversification (e.g., Kogler et al., 2023; Li & He, 2024; Qiao et al., 2024), we show that extra-regional collaboration intensity in Chinese URs predominantly reinforces related diversification. Moreover, we find that intra-regional collaboration intensity and the technological diversity of extra-regional collaboration exert inverted U-shaped effects on related and unrelated diversification, respectively, highlighting that both excessive internal intensity and excessive external diversity can generate diminishing returns. These results suggest that external linkages do not necessarily induce radical technological shifts, but may instead consolidate existing technological trajectories when external knowledge is selectively absorbed and recombined with local capabilities (Liao et al., 2025; Miguelez & Moreno, 2018; Sedita et al., 2022).

Second, existing research on the joint effects of intra- and extra-regional collaboration has largely focused on the balance of collaboration volume (e.g., De Noni et al., 2017; Santoalha, 2019; Sun & Cao, 2015). By explicitly examining technological alignment between intra- and extra-regional collaboration portfolios, our analysis demonstrates that technological correlation plays a central role in shaping related diversification outcomes. This extends prior studies by emphasising that effective diversification depends not only on the scale of collaboration, but also on the compatibility between external knowledge and the regional knowledge base (Balland et al., 2018; Kogler et al., 2023; Miguelez & Moreno, 2018; Tanner, 2016).

Third, most prior research contrasts regions at different development levels, such as core versus peripheral or advanced versus lagging regions, primarily in the European context, when assessing the role of collaboration in diversification (e.g., Balland & Boschma, 2021; Barzotto et al., 2019; De Noni et al., 2018; Santoalha, 2019). In contrast, our analysis focuses on internal economic disparities within URs. By shifting attention from inter-regional to intra-regional inequality, we show that collaboration outcomes depend not only on whether a region is more developed or peripheral, but also on how capabilities and resources are distributed within the region itself. These findings underscore the importance of institutional context and spatial scale in shaping the collaboration–diversification relationship and caution against directly transferring insights from European regional contexts to other national settings.

5.3. The moderating role of internal economic disparities

A central contribution of this study lies in revealing that internal economic disparities reshape the functioning of collaboration within URs. In URs characterised by pronounced internal disparities, technological capabilities, skilled labour and coordination resources are unevenly concentrated in leading cities (Pinheiro et al., 2025). This configuration facilitates fine-grained matching and stronger Marshallian externalities through intensive intra-regional collaboration (Caragliu et al., 2016). Consequently, leading cities are more likely to diversify into complex but related activities, while lagging cities tend to diversify into simpler related activities (Balland et al., 2020; Pinheiro et al., 2025). This asymmetric, path-dependent process consolidates the core–periphery configuration and increases the marginal returns to intra-regional collaboration intensity, while simultaneously deepening related diversification trajectories at the UR level (Caragliu et al., 2016).

The same uneven capability structure also helps explain why the effect of technological alignment between intra- and extra-regional collaboration is amplified. External knowledge accessed through extra-regional linkages can partly substitute for missing local relatedness; however, this channel is most effective where a strong internal capability base already exists (Gao et al., 2021; Kogler et al., 2023; Yeung, 2021). Accordingly, technologically advanced cities are better positioned to exploit related external technologies, reinforcing their existing related diversification trajectories (Bürscher & Scherngell, 2024; Liao et al., 2025). In contrast, lagging areas within the same UR are less able to access or utilise similar opportunities, concentrating the benefits of intra–extra technological correlation in core cities and further strengthens their related diversification paths (Freitas et al., 2024).

These findings have important policy implications: under conditions of uneven development, reducing disparities is not a prerequisite for collaboration-led diversification; rather, policy effectiveness depends on how collaboration is governed. First, policies should 1) prioritise coordination mechanisms that strengthen intra-regional collaboration, particularly by institutionalising cooperation across jurisdictions and 2) enhance the technological alignment between internal and external linkages through structured platforms such as joint R&D programmes and inter-city governance arrangements. Second, in unequal URs, enhancing the orchestrating role of leading cities, while facilitating effective knowledge diffusion to lagging cities through formal collaboration networks and shared innovation infrastructures, may yield greater diversification benefits than simply expanding the intensity or diversity of external collaboration.

5.4. Limitations and future avenues

While this study offers important insights, several limitations point to avenues for future research. First, while patent data offer important advantages in capturing codified technological innovation, they underrepresent organisational, service-related and incremental innovation (Griliches, 1998; Haščič & Migotto, 2015; Pavitt, 1985). As a result, our findings pertain to patent-observed technological diversification. To the extent that non-patented innovation is relatively more prevalent in economically weaker parts of unequal URs and relies more strongly on collaboration (Asheim & Gertler, 2006; Fritsch & Slavtchev, 2011; Lundvall, 1992), incorporating such innovation could potentially further amplify the moderating role of internal economic disparities identified in this study.

Second, relatedness in regional diversification has a twofold characteristic: similarity and complementarity (Boschma, 2017; Makri et al., 2010). Our current measure of the correlation between intra- and extra-regional relationships, based on the proportion of shared technologies, assumes that a higher similarity in technology proportions indicates greater correlation. Further research could explore how the complementarity of collaborations influences diversification in Chinese URs.

Third, while this study focuses on economic disparities within urban regions, future research could extend the framework by incorporating other dimensions of internal inequality, such as infrastructure provision or institutional capacity, and by examining their potential mediating roles in the relationship between collaboration and diversification.

Finally, some studies suggest that regions are not standalone economic entities and that the knowledge structure within firms is crucial, potentially more significant than the city itself (Zhang & Rigby, 2022). The capabilities within firms and the flow of knowledge across firm boundaries – both within and between regions – are vital for regional diversification.

Notes

1. We do not include Sino-foreign collaborations, as these involve cross-border factors – such as multinational firm strategies and foreign direct investment – that fall beyond the scope of this study. We focus on domestic inter-city linkages, which account for only a small proportion of all collaborations (approximately 14%). The large counterpart, intra-city ties, are excluded as they are primarily shaped by micro-level dynamics – such as within-city institutional arrangements and local university–industry connections – that may amplify local effects and distort the analysis of interactions among constituent cities within URs.
2. According to the Industrial Classification for National Economic Activities (GB/T 4754-2011) issued by the National Bureau of Statistics of China, the tertiary industry refers to service sectors and includes, e.g., information transmission, software and information technology services; financial services; scientific research and technical services; and education.
3. $TECH.DIV.INTRA_{c,i,t} = -\sum_c \frac{PATINTRA_{c,i,t}}{PAT_{i,t}} \cdot ln\left(\frac{PATINTRA_{c,i,t}}{PAT_{i,t}}\right)$, $TECH.DIV.EXTRA_{c,i,t} = -\sum_c \frac{PATEXTRA_{c,i,t}}{PAT_{i,t}} \cdot ln\left(\frac{PATEXTRA_{c,i,t}}{PAT_{i,t}}\right)$, where c represents the IPC classes. The higher the Shannon entropy index, the more diversified the distribution of collaboration across the IPC classes.
4. The moving window serves two key purposes: first, it smooths out short-term cyclical fluctuations that may introduce noise into patent-related metrics; second, it accounts for the lagged effects of the independent variables to mitigate potential endogeneity.

Disclosure statement

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Data availability statement

Data are available from the corresponding author upon reasonable request.

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