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Abstract: Place dependence is a widely recognized concept but has rarely been quantified in existing research. Employing the Wasserstein Distance algorithm from machine learning literature and China's Annual Survey of Industrial Firms dataset, this paper introduces a novel method to measure the place dependence of industrial dynamics in Chinese cities, and explore its impact on urban economic performance. Our empirical findings confirm the presence of place dependence in Chinese cities, and show that cities diversifying into more related and complex industries tend to exhibit higher levels of place dependence. Moreover, place dependence appears to complement the effects of relatedness and complexity in enhancing urban economic performance. These findings offer important insights for regional industrial development and urban planning practices.

Keywords: Place dependence, path dependence, knowledge complexity, industrial dynamics, economic performance, China

Introduction

The concept of path dependence is well-established and extensively validated within the fields of evolutionary economics and regional development (Nelson & Winter, 1982; Boschma & Lambooy, 1999; Martin & Sunley, 2010). Hall (1994), for instance, famously characterized path dependence as the "first principle" of evolutionary economics, emphasizing its foundational role in understanding economic evolution. At its core, path dependence highlights the critical influence of historical trajectories and pre-existing industrial structures in shaping the evolutionary pathways of regional economies. Despite its widespread theoretical acceptance, path dependence remained largely qualitative and under-quantified until the pioneering work of Hidalgo et al. (2007), who introduced the relatedness density metric to operationalize the proximity between emerging economic activities and the existing capabilities of a region. This innovative indicator provided a quantitative basis to empirically capture the extent to which new industries or technologies are path-dependent.

Subsequent research in Evolutionary Economic Geography (EEG) has strongly corroborated and extended the concept of path dependence by applying the relatedness approach to various domains, including industries (Neffke et al., 2011; Boschma et al., 2013; Gao et al., 2021; Qiao & Ascani, 2025), technologies (Boschma et al., 2015; Rigby, 2015; Balland et al., 2019; Balland & Boschma, 2021; Qiao & Li, 2025), products (Zhu et al., 2017; Hidalgo et al., 2020), and occupations (Muneepeeraku et al., 2013; Farinha et al., 2019). The conceptual refinement of "related diversification" (Boschma, 2017) and the articulation of "principle of relatedness" (Hidalgo et al., 2018) have further elucidated how non-spatial factors—such as the composition of industrial and technological portfolios—influence the creation and evolution of regional economic paths. Despite these advances, the spatial dimension of path dependence, especially how place-specific assets impact regional industrial dynamics, has received relatively limited attention (Heimeriks & Boschma, 2014). Consequently, our understanding of the role of place in regional diversification processes remains underdeveloped (Martin & Sunley, 2010).

Economic geographers, however, have increasingly recognized that path dependence is fundamentally a locally contingent and emergent phenomenon, inherently embedded in place-bounded contexts (Martin & Sunley, 2010). For example, Heimeriks & Boschma (2014) argued that the production of scientific knowledge in the biotechnology sector exemplifies a process that is both path- and place-dependent, contingent on local institutional and knowledge infrastructures. Similarly, Sunley and Martin (2023) emphasize that despite the forces of globalization and digitalization, place continues to significantly shape the distribution of capabilities and resources available to firms and industries. However, the persistence of place as a critical factor in industrial development is complex to explain, as it involves the localized and highly specific interactions among a constellation of processes, which collectively give rise to the accumulation and evolution of assets and capabilities within firms and regions (Martin & Sunley, 2010). Given this complexity, it is perhaps unsurprising that the existing literature has predominantly investigated the role of place in regional economic evolution through qualitative approaches (Heimeriks & Boschma, 2014; Yang et al., 2021). Empirical quantification remains scarce, and there is, to date, no widely accepted indicator to measure the extent to which regional industrial development is fundamentally a place-dependent process. This gap highlights the need for novel methodological tools and metrics that can systematically capture the place dependent characteristics of economic evolution, thereby enriching the theoretical and empirical discourse around path dependence and regional industrial evolution.

To address this important gap in existing literature, we propose a novel indicator—place dependence—to quantitatively measure the extent to which the current spatial distribution of economic activities is aligned with historical spatial patterns. Unlike traditional measures that often overlook the temporal persistence and spatial embedding of industrial dynamics, our place dependence metric explicitly captures how industrial activities are spatially anchored over time. Leveraging the rich information contained in China's Annual Survey of Industrial Firms (ASIF) dataset, we employ the Wasserstein Distance algorithm—a dissimilarity measure algorithm widely used in the machine learning domain (Frogner et al., 2015; Panaretos & Zemel, 2019)—to rigorously quantify the degree of place dependence of industrial dynamics across Chinese cities. Our empirical findings confirm the presence of place dependence and show that cities diversifying into more related and complex industries tends to exhibit higher levels of place dependence, underscoring the spatially embedded nature of related and complex industries. Moreover, we demonstrate that place dependence not only operates independently but also complements the well-established roles of relatedness and complexity in promoting urban economic performance. The principal contribution of this study lies in the conceptualization and operationalization of place dependence indicator, which extends the relatedness-complexity diversification framework prevalent in EEG by integrating a critical spatial dimension. This advancement deepens our understanding of regional diversification processes by highlighting how industrial spatial patterns interact with path dependence and regional knowledge complexity to shape the contemporary urban economic trajectories and performance.

The structure of this paper is organized as follows: Section 2 provides a comprehensive review of the relevant literature, situating our research within the broader academic discourse. Section 3 details the data sources and methodological approach, including the technical details of place dependence indicator and a brief introduction of the relatedness-complexity framework in EEG literature. Sections 4 and 5 present descriptive analyses and empirical results, respectively, illustrating the evolution of place dependence and its economic impact. Last, Section 6 concludes by summarizing the key findings, discussing their theoretical and policy implications, and suggesting avenues for future research.

Literature Review

Revisiting place dependence

In the field of economic geography, the concept of place dependence refers to the extent to which economic activities, firms, and industries rely on specific locational attributes—such as shared infrastructure, skilled labor pools, specialized suppliers, and localized knowledge spillovers—for their sustained operation, innovation, and competitive advantage (Heimeriks & Boschma, 2014; Yang et al., 2021). This concept underscores the functional relationship between economic agents and place-specific resources that shape their productivity and strategic decisions. Two notions closely related to place dependence are path dependence (Authur, 1994; Martin & Sunley, 2006, 2010) and place attachment (Hidalgo & Hernandez, 2001; Lewicka, 2011), which, although interconnected, emphasize distinct dimensions of the spatial-economic relationship.

On the one hand, path dependence, as articulated in the work by Arthur (1994) and further elaborated in regional development literature (Martin & Sunley, 2006, 2010), highlights the importance of historical trajectories and pre-existing industrial structures in shaping the evolutionary pathways of regional economies. This perspective foregrounds how past industrial legacies and cumulative processes constrain or enable future economic diversification and spatial development (Boschma, 2017). While some studies recognize the path- and place-dependent nature of regional diversification processes (Martin & Sunley, 2010; Heimeriks & Boschma, 2014), two key limitations remain. First, the degree of place dependence is rarely quantified or operationalized in empirical research, limiting our understanding of its measurable impact. Second, existing analyses predominantly focus on the regional scale, often overlooking the micro-level variation in locational attributes within regions that influence firm behavior and industry dynamics (Vaessen & Keeble, 1995; Asheim & Coenen, 2005; Huggins et al., 2017).

On the other hand, place attachment is mainly rooted in social and psychological dimensions, centering on the emotional bonds, identity, and sense of belonging that individuals or communities develop toward a place (Hidalgo & Hernandez, 2001; Lewicka, 2011). This affective connection, while relevant to environmental psychology and community studies (Raymond et al., 2010; Manzo & Devine-Wright, 2013; Brown et al., 2015), diverges from the economic focus of place dependence.

In contrast, place dependence is primarily economically and functionally oriented, emphasizing how well a specific location meets the operational requirements and strategic needs of economic agents. It captures the tangible benefits derived from spatial factors that directly affect economic performance, such as proximity to suppliers, access to specialized labor markets, or supportive infrastructure and institutional environments.

This further leads to one of the principal mechanisms underpinning place dependence, i.e., agglomeration economies, including the three classical Marshallian sources: knowledge spillovers, thick labor markets, and specialized suppliers (Marshall, 1890; Boschma & Frenken, 2003). As the density of firms within a region increases, so too does the diversification of the local labor market, the availability of specialized suppliers, and the frequency of localized knowledge exchange, among other locational advantages. Empirical evidence consistently demonstrates that geographical proximity to specialized labor pools and supplier networks reduces transaction costs and enhances firms' productivity (Rosenthal & Strange, 2004; Andersson & Lööf, 2011), thereby strengthening their locational commitment. Additionally, agglomeration economies could also bolster firms' innovative capacity by facilitating the formal and informal exchange of knowledge and technologies (Jaffe et al., 1993; Eriksson, 2011). Especially, spatial agglomeration enables the transmission of tacit, non-codified knowledge—often described as "sticky" due to its spatially embedded nature—among local economic actors, contributing to the localized accumulation of expertise (Markusen, 1996; Breznitz et al., 2024). Consequently, agglomeration economies engender a strong degree of place dependence within industries, even when individual firms exhibit heterogeneous locational preferences. From a theoretical standpoint, agglomeration economies serve to reinforce both path dependence and place dependence by fostering cumulative causation and lock-in effects (Martin & Sunley, 2010). As firms become increasingly entrenched within agglomerated settings, the distinctive assemblage of local assets and institutional frameworks shapes their evolutionary pathways, rendering relocation or structural transformation both costly and challenging especially within Marshallian clusters (Markusen, 1996; Mathias et al., 2021). In this sense, place dependence, or the stickiness of a place, does not primarily arise from the individual locational decisions of firms or workers, but rather from the external economies generated through their spatial proximity and interaction with other firms and the local industrial milieu.

Another fundamental driver of place dependence is the spin-off processes, wherein new start-ups typically leverage the knowledge and expertise acquired from their parent firms, establishing themselves in the same location (Klepper, 2007). This spin-off model illustrates an industry evolution characterized by a continuous chain of firms that give rise to new enterprises, which subsequently generate additional spin-offs (Boschma & Frenken, 2003). This dynamic interplay of firm formation has been identified as a critical determinant driving both the rapid growth and spatial concentration of various industrial clusters. Prominent examples include the Information and Communication Technology (ICT) sector in Silicon Valley (Saxenian, 1991), the automobile industry in Detroit (Klepper, 2002), and the burgeoning e-commerce clusters in rural areas of China (Luo & Qiao, 2021). In all these examples, spin-offs predominantly opt to locate in proximity to their parent firms, thereby capitalizing on established socio-economic networks and agglomeration economies. Moreover, spin-off process and agglomeration economies might have a complementary role in reinforcing the place dependence of firms. On the one hand, spin-offs increase the density of firms in a region, which strengthens agglomeration economies. On the other hand, agglomeration economies make the location more attractive for new spin-offs, further increasing the spatial concentration (Boschma & Frenken, 2003). Together, this interdependence ensures that firms become increasingly place-dependent, as leaving the cluster would mean losing these advantages.

Measuring place dependence

As previously discussed, place dependence refers to the extent to which economic activities, firms, and industries rely on specific locational attributes. While this concept is crucial for understanding the reinforcing dynamics of regional diversification, its measurement remains inherently challenging (Martin & Sunley, 2010). Consequently, the place-dependent dimension of regional industrial dynamics is predominantly explored through qualitative analyses in the existing literature (Markusen, 1996; Heimeriks & Boschma, 2014; Yang et al., 2021). This is mainly because traditional spatial indicators commonly employed in economic geography and regional studies are insufficient for capturing the nuanced nature of place dependence. For instance, spatial Gini coefficients and Herfindahl-Hirschman Index could effectively quantify the degree of agglomeration by measuring the concentration of industries or technologies within particular geographic areas, where higher values signify greater spatial concentration (Rey & Smith, 2013;

Matsumoto et al., 2012). Similarly, spatial dependence metrics such as the Moran’s I and Getis–Ord statistics serve as proxies for spatial autocorrelation, revealing statistically significant clustering of high or low values across geographic space (Tiefelsdorf & Boots, 1995; Songchitruksa & Zeng, 2010). However, these metrics are inherently static, offering only a snapshot of spatial agglomeration or clustering patterns at a given point in time. They fail to capture the dynamic aspect of place dependence—specifically, how the reliance of economic activities within particular regions evolves over time relative to previous periods. This limitation underscores the need for more sophisticated, temporally sensitive measures to better understand the temporal dynamics of place dependence in regional industrial dynamics.

Along this line of inquiry, Yang et al. (2021) applied the standard deviation ellipse method to examine the spatial path dependence of industrial development in Beijing. By comparing the shifts in mean centers and orientations of these ellipses over different years, they provided empirical evidence supporting the notion of place dependence in regional industrial dynamics. While this approach is insightful, employing the standard deviation ellipse as a proxy for place dependence also has limitations. For instance, aggregating all firms into a single mean center risks oversimplifying the spatial complexity and results in the loss of detailed spatial distribution of industrial activities. Moreover, the method lacks standardization and scalability, which undermines its comparability across cities.

In recent years, the rapid advancement of the Wasserstein Distance in machine learning literature offers a novel and promising approach to measuring place dependence (Frogner et al., 2015; Panaretos & Zemel, 2019). Conceptually, this method quantifies the minimal cost required to transform one spatial distribution into another, thereby providing a robust metric for assessing the degree of spatial stability or change over time. Crucially, the Wasserstein Distance facilitates a continuous and interpretable measure of place dependence that is sensitive not only to the magnitude of change but also to variations in geographical distances within economic activity distributions (further technical details are provided in the methodology section). When combined with high-resolution, firm-level locational data, this technique has the potential to yield fine-grained and dynamic indicators of place dependence, thereby revealing the spatial dimension of regional industrial dynamics.

The impact of place dependence on industrial diversification and urban economic performance

The relatedness-complexity framework in EEG offers a foundational analytical toolkit for examining regional industrial diversification (Balland et al., 2019; Qiao et al., 2024). The relatedness dimension serves as a metric to assess the degree of proximity between newly developed economic activities and a region's existing industrial portfolio, thereby capturing path-dependent trajectories of industrial evolution (Boschma, 2017; He et al., 2018). Meanwhile, the complexity dimension evaluates the sophistication and technological advancement of emerging industries, providing insights into a region's capacity for technological innovation and industrial upgrading (Hidalgo, 2021; Balland et al., 2022). Despite their analytical utility, neither dimension explicitly account for place dependence—the extent to which regional industrial evolution is dependent on place-specific assets, such as localized labor markets, specialized suppliers, shared infrastructure, and geographically bounded knowledge spillovers. To address this gap, we argue that incorporating place dependence as a third dimension could enhance our understanding of regional diversification processes by revealing the impact of spatially sticky factors.

The conceptual relationship between place dependence and the established dimensions of regional diversification - relatedness and complexity - merits systematic examination. On the one hand, empirical evidence consistently demonstrates that regional diversification exhibits both path-dependent and place-dependent characteristics. This dual dependence emerges partly because the key enablers of local industrial development, including localized labor markets, specialized supplier networks, knowledge spillovers, and institutional frameworks, are inherently place-specific (Martin & Sunley, 2010). These place-contingent factors create unique regional advantages that particularly shape trajectories of related diversification (Qiao & Wu, 2024). Consequently, regions possessing strong place-based assets demonstrate greater capacity for sustaining related diversification pathways, as firms pursuing such strategies benefit disproportionately from proximity to existing industrial clusters. This dynamic gives rise to a mutually enhancing relationship between place dependence and path dependence: place dependence reinforces path-dependent processes by providing the necessary local assets for related industrial branching, while path dependence simultaneously enhances the value of place-specific factors through cumulative investment and knowledge spillovers (Strambach & Halkier, 2013).

On the other hand, the relationship between place dependence and complex industrial diversification reveals equally significant dynamics. From the perspective of combinatorial knowledge, the complexity of knowledge emerges from the integration of diverse existing knowledge elements in a particular configuration, resulting in a sophisticated and coherent system (Strambach & Klement, 2012; Tödtling & Grillitsch, 2015). These integrated knowledge components are often non-fungible and irreducible, requiring a substantial reservoir of prior knowledge to facilitate the effective recombination of complex knowledge elements (Hidalgo, 2024). Furthermore, as highlighted by Heimeriks & Boschma (2013), increasing knowledge complexity makes it progressively more difficult for a firm to independently possess the requisite skills and knowledge to solve problems alone. Consequently, the creation and diffusion of complex knowledge and technologies are frequently constrained by geographic proximity (Balland & Rigby, 2017; Cohen & Levinthal, 1990; Breschi & Lissoni, 2009; Balland et al., 2020). Firms requiring complex knowledge inputs, therefore, tend to cluster near established knowledge hubs. This interplay also generates a self-reinforcing dynamic between place dependence and complex diversification: place dependence fosters complex diversification by providing essential knowledge inputs, while complex diversification, in turn, strengthens place dependence through knowledge accumulation in specific locations. In summary, we argue that, for cities, their levels of place dependence are positively associated with regional relatedness and knowledge complexity.

Regarding economic performance, a substantial body of literature demonstrates that regions characterized by higher levels of relatedness and knowledge complexity tend to experience greater economic growth (Boschma, 2017; Cicerone et al., 2020; Hidalgo, 2021). This positive association is largely attributed to the presence of densely interconnected industrial networks and advanced capabilities, which foster innovation, productivity improvements, and economic resilience (Martin & Sunley, 2020; Xiao et al., 2025). Given the interdependent relationships identified earlier between place dependence and both regional relatedness and knowledge complexity, we propose that place dependence may serve a complementary role in enhancing urban economic outcomes. Specifically, place dependence is likely to interact synergistically with related and complex industrial networks, collectively amplifying their capacity to drive economic growth. In other words, the embeddedness of industries within a city's historical and spatial context could strengthen the benefits derived from relatedness and complexity, thereby promoting more robust and sustained improvements in urban economic performance.

Data and Methodology

Data sources

This study draws upon the Annual Survey of Industrial Firms dataset spanning the period from 1998 to 2012, as compiled and disseminated by the National Bureau of Statistics of China. The ASIF provides granular firm-level information, including firm address, four-digit industry classification codes, and employment figures. For the purposes of empirical analysis, we aggregate these firm-level observations at city-industry level, thereby facilitating the examination of industrial dynamics within urban contexts. To capture temporal stability and mitigate short-term volatility in industrial dynamics, the sample period is partitioned into five discrete, non-overlapping intervals, each encompassing three years: 1998–2000, 2001–2003, 2004–2006, 2007–2009, and 2010–2012. We acknowledge that the sample period employed in this study is not the most recent; however, given that our primary focus lies in methodological development, the existing dataset remains appropriate for our study.

It is noteworthy that the classification system for industries underwent revision during the sample period. Specifically, industry codes from 1998 to 2002 adhered to the *Industrial Classification for National Economic Activities (GB/T 4754-94)*, whereas from 2003 onward, the revised *Industrial Classification for National Economic Activities (GB/T 4754-2002)* was adopted. To maintain comparability across these periods, we harmonized the classification schemes using the concordance table developed by Brandt et al. (2012), enabling a consistent longitudinal framework for industry-level analysis. In line with existing literature (Chen, 2018), we implemented rigorous data cleaning procedures to exclude observations exhibiting implausible or inconsistent accounting records. This includes firms reporting negative values in key variables such as employment, industrial output, or new product output, as well as instances where total paid-in capital failed to reconcile with the aggregate of its reported components. These measures enhance the reliability and validity of the resulting dataset, which underpins our subsequent empirical investigation.

Consistent with the methodological approach employed by Dong et al. (2021), this study utilizes the AMAP API to conduct the geocoding process, thereby obtaining precise latitude and longitude coordinates corresponding to the reported firm addresses. To ensure the robustness and representativeness of our dataset, we exclude cities situated within the Xinjiang Uygur Autonomous Region, Xizang Autonomous Region, Inner Mongolia Autonomous Region, Qinghai Province, and Hainan Province. This exclusion is justified by the relatively limited number of observations available from these regions, coupled with their extensive geographical coverage, which may introduce spatial heterogeneity and potential bias. Additionally, cities within Shaanxi and Hunan provinces are omitted due to systematic missing values in employment data for specific years spanning 2010 to 2012. For the computation of location quotient (see details the following methodology section), only those industries that are recorded at least once in one period in every city are retained, alongside cities that maintain the presence of at least one industry in every period under consideration. This rigorous procedure ensures a consistent and balanced panel for analysis. Consequently, the finalized dataset comprises 3,580,404 valid observations during the period 1998-2012, distributed across 247 prefecture-level and higher cities, encompassing 424 distinct four-digit manufacturing industries.

Methodology

Place dependence

In this study, we introduce the place dependence indicator as a metric to quantify the spatial stickiness or inertia of industrial dynamics over time. The conceptual foundation of the place dependence is based on measuring the degree of change in the spatial distribution of industries between two time periods. To operationalize this comparison, we adopt the Wasserstein Distance algorithm (also known as Earth Mover's Distance), a metric indicator widely used in the machine learning literature to calculate the dissimilarity between images (Frogner et al., 2015; Panaretos & Zemel, 2019). The core intuition behind the Wasserstein Distance is to compute the minimal effort required to transform one spatial distribution into another. To illustrate, consider two spatial distributions, P and Q, as depicted in Figure 1. Assume that each grid cell has a uniform weight of one, and the Euclidean distance between adjacent locations—such as X_1 and X_2, X_2 and X_3, and so on—is equal to one. The transformation from P to Q can be achieved through multiple transport plans, two of which are shown in Figure 2. Transport plan A incurs a total cost of 9 units, which represents the minimum transportation cost among all feasible plans. In contrast, transport plan B requires 11 units of cost. Hence, the Wasserstein Distance between distributions P and Q is defined as 9—the lowest possible cost needed to transform P to Q. In a more formal way, the definition of Wasserstein Distance is given in formula (1), in which γ is any one transport plan belonging to the joint distribution with marginals P and Q, $m(x, y)$ gives the gives the amount of mass to move from the point x to the point y under transport plan γ, and $c(x, y)$ gives the cost of transporting a unit mass from x to y.

$$WD = \inf_{\gamma \in \Gamma(P,Q)} \iint m(x, y) c(x, y)\, dxdy \tag{1}$$

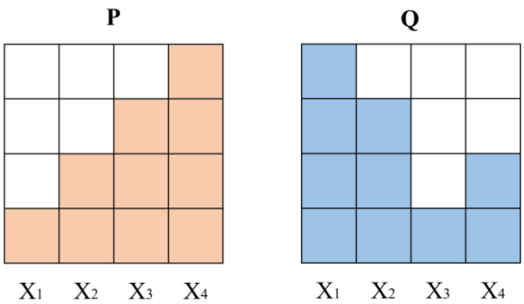
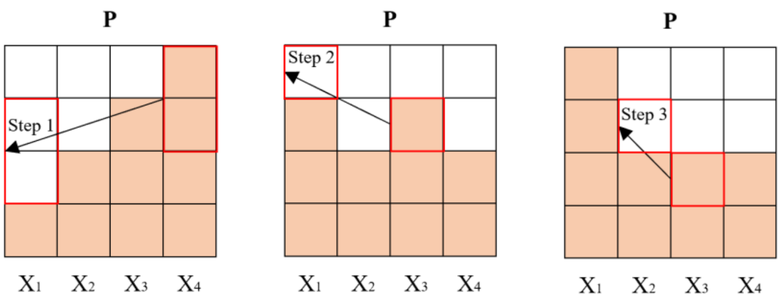
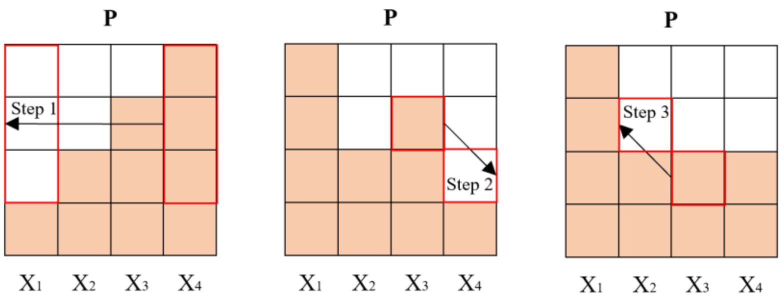


Figure 1 Two illustrative spatial distributions



Transport plan A: 2*3 + 1*2 + 1*1 = 9



Transport plan B: 3*3 + 1*1 + 1*1 = 11

Figure 2 Two illustrative transport plans

To operationalize the place dependence of industrial dynamics in the context of Chinese cities, we begin by dividing each city into 2 km × 2 km grid cells. Using the geographic coordinates (latitude and longitude) of individual firms, we assign each firm to its corresponding grid cell. By aggregating the number of employments within each grid cell, we compute the proportion of employments in each cell relative to the total employments within the city. And we repeat this procedure for each period for every city. To measure the change of spatial distributions between two consecutive periods of city *c*, we first calculate the Wasserstein Distance between these two distributions (denoted as WD_c). As formalized in formula (2), $m_{c,j,k}$ represents the proportion of employments moved from grid *j* in the later period to grid *k* in the earlier period, while $d_{c,j,k}$ denotes the Euclidean distance between grids *j* and *k*. To ensure comparability across cities of different sizes, we normalize $d_{c,j,k}$ by dividing it by the maximum possible distance between any two grids within the city, denoted as d_{max}. Taking Nanjing City as an example, as shown in Figure 3, d_{max} is the longest yellow line between two edge grids in the city, and $m_{c,j,k}$ is the proportion of employments moved from grid *j* to grid *k* when transforming the industrial spatial distribution during 2010-2012 to the one during 2007-2009, and $d_{c,j,k}$ is the distance between two grids (the length of the short yellow line). Since the Wasserstein Distance measures the spatial change of two distributions, to derive the place dependence indicator (PD_c), we subtract the square root of WD_c from 1, as shown in formula (3). The square root is applied to account for the fact that the Wasserstein Distance is derived from the arithmetic sum of products of two values, each less than one. The final value of place dependence indicator ranges from 0 to 1. A value of 0 reflects maximum change of two spatial distributions and thus minimum place dependence—this occurs when all firms in the earlier period are concentrated in one grid cell, while all firms in the later period are located in a different grid cell at the maximum distance within the city. Conversely, a value of 1 indicates perfect place dependence, where the spatial distributions of employments remain unchanged between two periods.

$$WD_c = \arg min\,(\sum_{j=1}^{n}\sum_{k=1}^{n} m_{c,j,k} * \frac{d_{c,j,k}}{d_{max}}) \quad (2)$$

$$PD_c = 1 - \sqrt{WD_c} \quad (3)$$

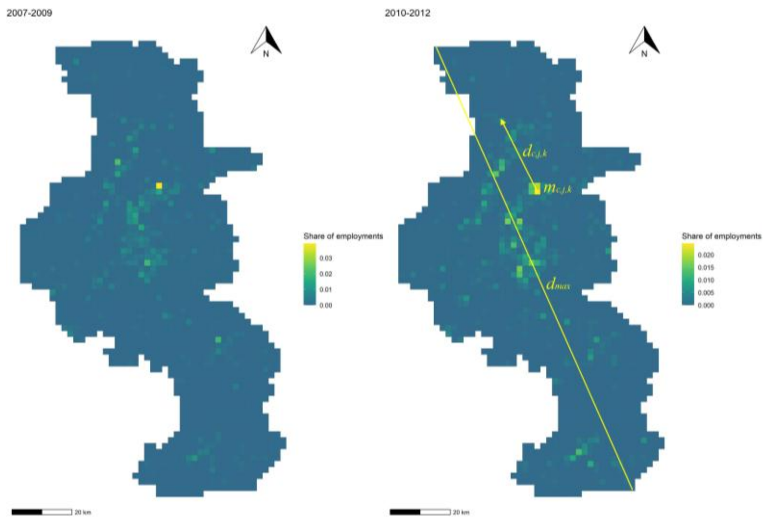


Figure 3 The industrial spatial distribution of Nanjing City

Relatedness density and knowledge complexity

To explore the relationship between place dependence and regional diversification, in this study, we adopt the relatedness-complexity framework developed by Balland et al. (2019) to systematically measure the path dependence and knowledge complexity of city industrial dynamics. Our analytical procedure begins with the computation of Revealed Comparative Advantages (RCA), operationalized according to formula (4). Specifically, the RCA for industry *i* in city *c* during period *t*, denoted as $RCA_{i,c,t}$, is defined as a binary indicator: it equals 1 if the location quotient of industry *i* in city *c* during period *t* ($LQ_{i,c,t}$) meets or exceeds the threshold of one, signalling specialization; otherwise, it is assigned a value of zero. As shown in formula (5), $LQ_{i,c,t}$ is defined as the ratio between the share of industry i's employment in city c ($employment_{i,c,t}$) in the total number of city c's employments in year t, and the share of industry i's employment in the total number of employment across all cities in year t. Building on the foundational work of Hidalgo et al. (2007), we proceed to quantify the relatedness strength (*relatedness*) between pairs of industries, which is operationalized as the conditional minimum probability that a city exhibiting a comparative advantage in one industry also demonstrates a comparative advantage in another industry, as formalized in formula (6). This metric captures the degree of cognitive proximity between industries based on their co-occurrence patterns across cities.

Subsequently, we compute the relatedness density (*relden*) of industry *i* in city *c* during period *t* as presented in formula (7). This measure represents the weighted proportion of relatedness strength linking industry *i* to all other industries in which city *c* holds a specialization, normalized by the total relatedness strength between industry i and all other industries. Intuitively, a higher relatedness density indicates that a city's current industrial portfolio is more closely aligned with the knowledge base required for the development or expansion of a specific industry, thereby increasing the likelihood of successful specialization in that industry. To analyze industrial dynamics, we define industry entry for industry i in city c during period t, denoted as $entry_{i,c,t}$, through changes in RCA values between periods $t-1$ and t, as specified in formula (8). This indicator captures the emergence of new specialization within a city-industry pair over time. Furthermore, to proxy the level of path dependence of industrial dynamics within a city, we calculate the average relatedness density of all industrial entries in city c during period t ($RD_{c,t}$), as detailed in formula (9).

$$RCA_{i,c,t} = \begin{cases} 1, & LQ_{i,c,t} \geq 1 \\ 0, & LQ_{i,c,t} < 1 \end{cases} \tag{4}$$

$$LQ_{i,c,t} = \frac{employment_{i,c,t}}{\sum_i employment_{i,c,t}} \Bigg/ \frac{\sum_c employment_{i,c,t}}{\sum_{i,c} employment_{i,c,t}} \tag{5}$$

$$relatedness_{i,j,t} = min\{P(RCA_{i,r,t} = 1 \mid RCA_{j,r,t} = 1), P(RCA_{j,r,t} = 1 \mid RCA_{i,r,t} = 1)\} \tag{6}$$

$$relden_{i,c,t} = \frac{\sum_{j \neq i} RTA_{j,c,t} * relatedness_{i,j,t}}{\sum_{j \neq i} relatedness_{i,j,t}} \tag{7}$$

$$entry_{i,c,t} = \begin{cases} 1, & RCA_{i,c,t-1} = 0 \wedge RCA_{i,c,t} = 1 \\ 0, & RCA_{i,c,t-1} = 0 \wedge RCA_{i,c,t} = 0 \end{cases} \tag{8}$$

$$RD_{c,t} = \frac{\sum_i entry_{i,c,t} * relden_{i,j,t}}{\sum_i entry_{i,c,t}} \tag{9}$$

Following the seminal approach of Hidalgo and Hausmann (2009), we employ the method of reflection to calculate the Knowledge Complexity Indicator (KCI) for industries. While this metric has faced criticism for potentially underrepresenting the complexity of economies in emerging markets such as China and India (Cristelli et al., 2013), we nonetheless adopt the KCI in this study due to its well-established relevance and robustness within the field of economic geography (Balland & Rigby, 2017; Mealy et al., 2019; Balland et al., 2019). Moreover, utilizing the KCI facilitates alignment with extant literature, thereby enhancing the comparability and interpretability of our empirical results. The computational algorithm for deriving the KCI is formalized in formulas (10)-(12). Specifically, $ECI_{c,t}$ denotes the knowledge complexity of city c during period t, while $k_{c,t}$ represents the industrial diversity of city c in period t, defined as the aggregate sum of RCA across all industries within the city ($\sum_i RCA_{i,c,t}$). Accordingly, $TCI_{c,t}$ captures the knowledge complexity of industry i during period t, and $k_{i,t}$ quantifies the ubiquity of industry i in period t, calculated as the total number of cities exhibiting an RCA in industry i ($\sum_c RCA_{i,c,t}$). The final knowledge complexity for industries, denoted as $complexity_{i,t}$, are standardized to ensure the comparability across different periods. To further characterize the aggregate knowledge complexity of industrial dynamics for a city, we compute the average knowledge complexity of industrial entries within city *c* in period *t* ($KC_{c,t}$), as specified in formula (13).

$$ECI_{c,t} = \frac{1}{k_{c,t}} \sum_i RCA_{i,c,t} * TCI_{i,t} \tag{10}$$

$$TCI_{i,t} = \frac{1}{k_{i,t}} \sum_c RCA_{i,c,t} * ECI_{c,t} \tag{11}$$

$$complexity_{i,t} = \frac{TCI_{i,t} - mean(TCI_{i,t})}{sd(TCI_{i,t})} \tag{12}$$

$$KC_{c,t} = \frac{\sum_i entry_{i,c,t} * complexity_{i,t}}{\sum_i entry_{i,c,t}} \tag{13}$$

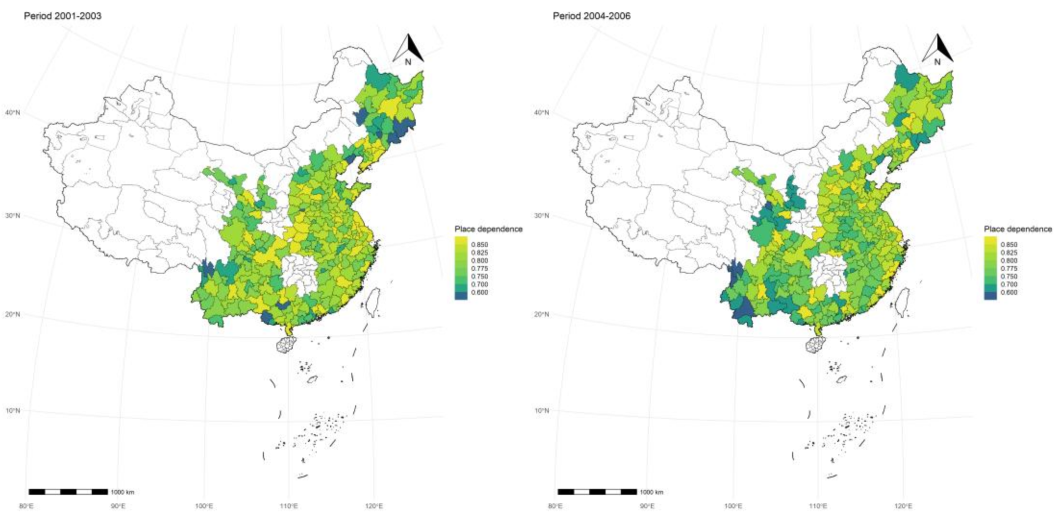
Place Dependence and Industrial Diversification of Chinese Cities

Evolution of industrial place dependence of Chinese cities

As depicted in Figure 4, our analysis begins by tracing the temporal evolution of place dependence of industrial dynamics in Chinese cities over multiple time periods. And Figure 5 further presents the calculated national and regional averages of place dependence, together providing a comprehensive overview of how this place dependence has fluctuated across both spatial and temporal dimensions. The empirical evidence reveals that the average level of place dependence among the sampled cities has remained relatively stable throughout the observed intervals, suggesting a persistent anchoring of industrial activities within specific locales. More specifically, the national average place dependence was recorded at 0.79 during the 2001–2003 period, and experienced a slight decrease to 0.78 in 2004–2006. Then it rose marginally to 0.81 in 2007–2009, before settling back to 0.78 in the 2010–2012 period. The modest increase during 2007–2009 corresponds temporally with the onset of the global financial crisis, which arguably slowed industrial restructuring and mobility, thereby intensifying firms' reliance on existing local assets and networks (Lardy & Subramanian, 2011). In general, the relatively high levels of place dependence confirm the presence of place-dependence in industrial dynamics.

When the data is disaggregated by region, a distinct spatial gradient becomes apparent, with place dependence generally declining as one moves from coastal to inland areas. This east to west gradient is especially pronounced in the final period examined (2010–2012), where economically advanced eastern cities exhibit significantly higher levels of place dependence compared to their western counterparts. This spatial distribution reflects the entrenched industrial clusters concentrated in the eastern coastal zones, regions known for their well-developed agglomeration economies and robust spin-off dynamics (Qiao et al., 2024). Such clusters generate powerful localized industrial interdependencies, reinforcing the embeddedness of firms and industries within these places and thereby elevating their place dependence.

Furthermore, this spatial pattern elucidates the relatively elevated place dependence observed in key urban centers located within central and western regions, including major direct-controlled municipalities and provincial capitals such as Chongqing, Taiyuan, Lanzhou, Wuhan, and Hefei. These cities serve as crucial nodal points within their respective regional industrial networks, leveraging concentrated resources, advanced infrastructure, and institutional support to sustain localized industrial linkages and enhance economic specialization. Their strategic roles as regional hubs enable them to maintain higher degrees of place dependence relative to surrounding less-developed areas, illustrating how place-specific assets can buffer against broader regional disparities. Collectively, these findings underscore the enduring spatial heterogeneity in industrial dynamics across China, highlighting the critical role of geographical context in shaping the stability and evolution of place dependence over time.



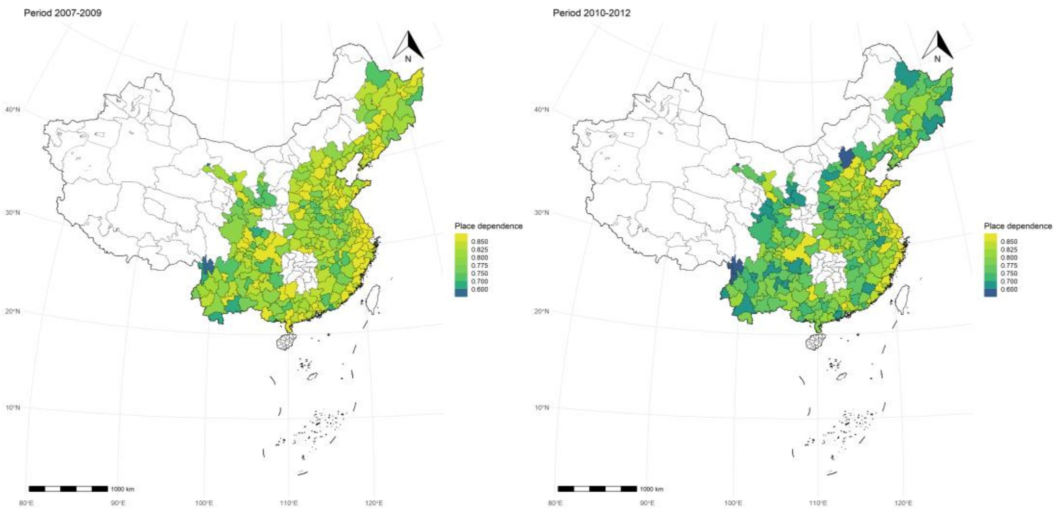


Figure 4 The spatial distribution of industrial place dependence across Chinese cities

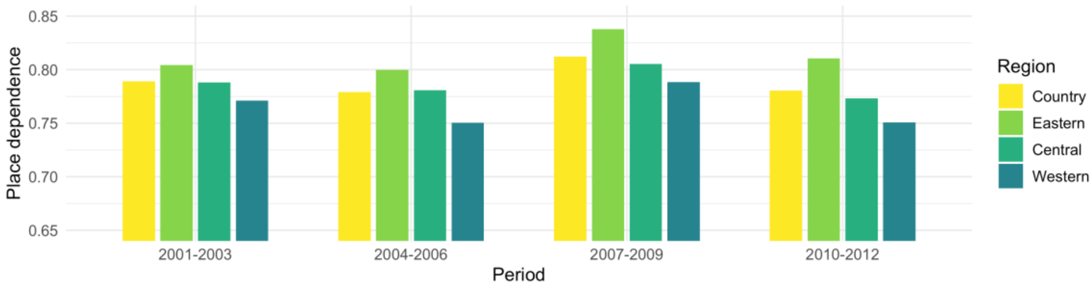


Figure 5 The average place dependence of different regions

Place dependence and path dependence

In Figure 6, we present the empirical correlation between place dependence and path dependence across sample cities. A clear and statistically significant positive correlation emerges, indicating that these two dimensions are closely intertwined rather than operating independently. This observation is consistent with the theoretical expectation outlined in the literature review, where we argue that place dependence and path dependence engage in a mutually reinforcing relationship. Specifically, the presence of place-specific assets—such as localized knowledge bases, shared infrastructure, institutional support, and specialized labour markets—facilitates the development and sustainability of related industries within a region. Conversely, the agglomeration and growth of these related industries further enhance the unique advantages of the location, creating a virtuous cycle that strengthens both place and path dependence (Martin & Sunley, 2010). This reciprocal dynamic implies that the spatial concentration of industries is not merely a product of historical accident or firm-specific strategies but is deeply embedded in the interaction between cumulative evolutionary processes and the distinct characteristics of places (Heimeriks & Boschma, 2014).

To further interrogate this relationship, we classify cities into four categories based on their relative levels of place dependence and path dependence, benchmarked against the sample averages. These categories, visualized in Figure 7, reveal a striking spatial pattern. Cities exhibiting both high place dependence and high path dependence (HH) cluster predominantly in eastern China, encompassing major provincial hubs such as Chengdu, Hefei, Kunming, Wuhan, and Zhengzhou. These cities benefit from a rich endowment of local assets and well-established industrial legacies, which together create robust environments for related industrial diversification. By contrast, cities characterized by both low place dependence and low path dependence (LL) are primarily situated in the less economically developed western regions of China, where limited local resources and weaker industrial histories constrain path- and place-dependent growth.

A quantitative assessment of the distribution across categories further underscores these spatial dynamics. As shown in Figure 8, cities classified as HH consistently represent the largest group and have increased steadily over time, reflecting the cumulative advantages that reinforce their industrial specialization and regional competitiveness. Conversely, cities with low place dependence but high path dependence (LH) are conspicuously underrepresented compared to the other categories. This asymmetry suggests that while path dependence—reflected in historical industrial patterns and established firm routines—is important, it alone is insufficient to sustain industrial development without the support of place-specific assets (Martin & Sunley, 2010). In other words, the development of related industries depends heavily on the mobilization of localized resources and networks that are characteristic of place dependence. Obviously, the comparison between cities in HH and LH types indicates that cities with strong place-specific resources tend to exhibit pronounced path-dependent industrial trajectories, while those lacking such assets struggle to maintain industrial continuity. Overall, these findings highlight the important role of place-specific assets in shaping and sustaining industrial trajectories, demonstrating that path dependence is deeply conditioned and supported by the spatial context in which it unfolds.

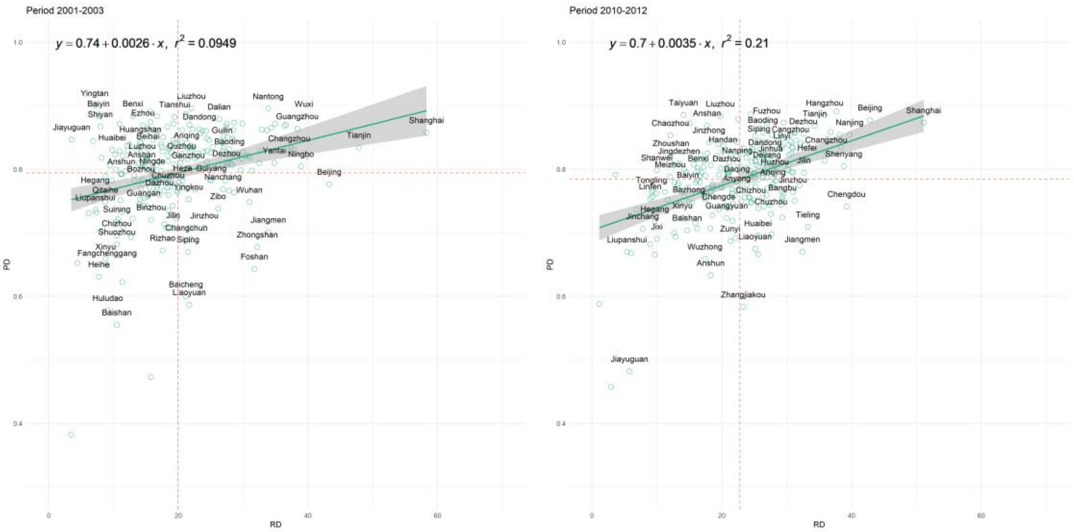


Figure 6 The correlation between place dependence and path dependence

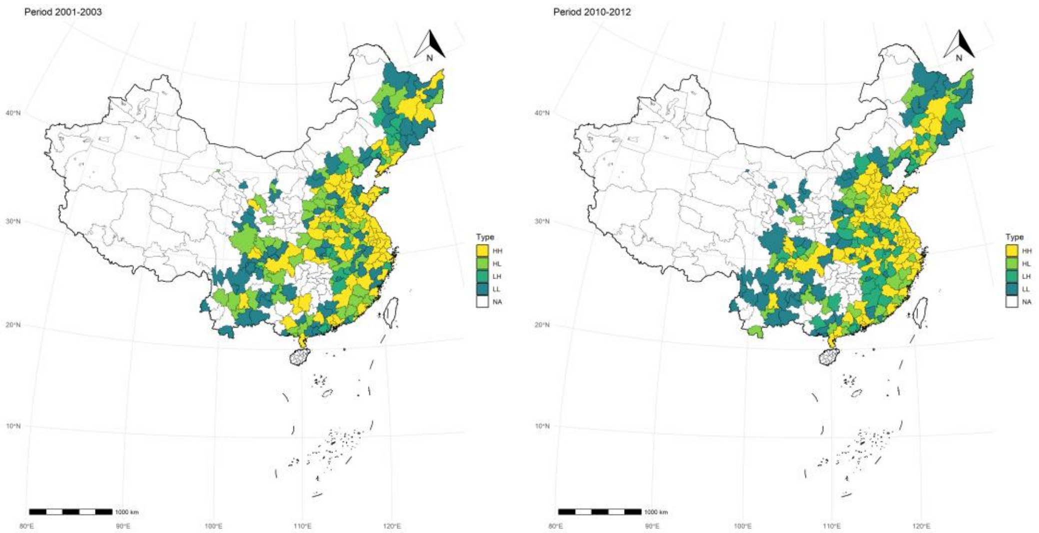


Figure 7 The spatial distribution of different types of cities by place dependence and path dependence

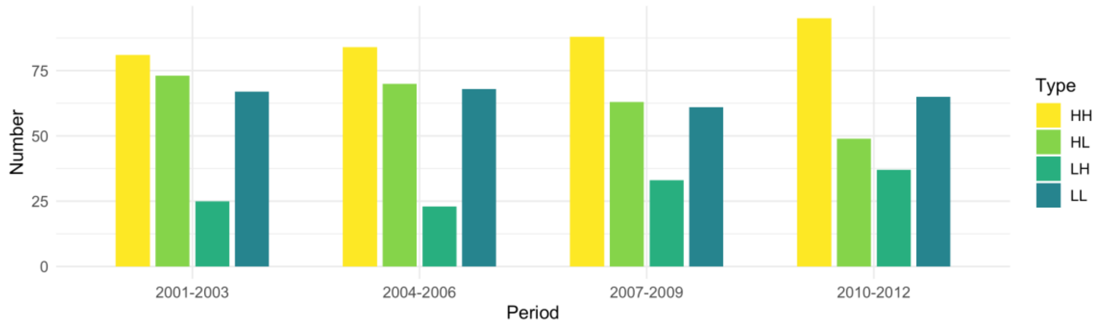


Figure 8 The number of different types of cities by place dependence and path dependence

Place dependence and knowledge complexity

In Figure 9, we further investigate the empirical relationship between place dependence and knowledge complexity of regional industrial diversification. This analysis corroborates the theoretical expectations detailed in the literature review, revealing a robust positive and statistically significant correlation between these two aspects. The underlying rationale for this association lies in the spatial concentration of complex, tacit knowledge, which typically requires frequent and nuanced face-to-face interactions for effective production, exchange, and learning (Balland & Rigby, 2017). Such localized knowledge spillovers and interactive learning processes are more easily sustained in places characterized by strong place dependence, where firms and institutions are embedded in dense social and economic networks. Importantly, our results show that both the coefficient and the explanatory power (R squared) of this relationship are remarkably higher in the 2010–2012 period compared to the earlier 2001–2003 period. This temporal intensification aligns with the accelerated pace of industrial upgrading and technological innovation witnessed in Chinese industries during this period (Brandt & Thun, 2016), suggesting that as the knowledge base and technological sophistication of industrial diversification deepen, the interplay between place dependence and knowledge complexity becomes increasingly pronounced.

Complementing this quantitative relationship, Figure 10 maps the spatial distribution of cities categorized by varying levels of place dependence and knowledge complexity. This distribution reveals a pattern strikingly similar to that found in prior analyses, with coastal economic cities and several strategically important inland provincial capitals exhibiting concurrently high levels of both place dependence and knowledge complexity (HH). Such a geographic configuration is consistent with our theoretical expectation that locations endowed with rich place-specific assets are more conducive to cultivating and sustaining complex knowledge production. Moreover, as presented in Figure 11, an examination of the relative frequency of cities across these categories reveals a clear predominance of cities that exhibit both high place dependence and high knowledge complexity. In contrast, cities characterized by low place dependence yet high knowledge complexity (LH) form the smallest subset, highlighting the inherent tension and practical difficulties of fostering sophisticated knowledge-intensive industries in environments lacking strong place-specific assets (Qiao & Li, 2025). This notable disparity further underscores the critical importance of place-specific conditions and embeddedness in enabling complex knowledge economies to thrive.

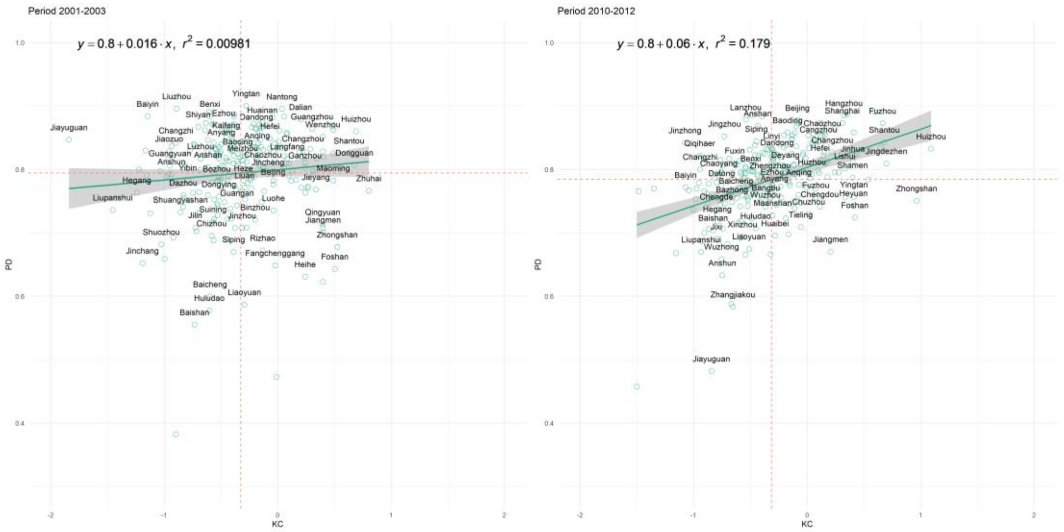


Figure 9 The correlation between place dependence and knowledge complexity

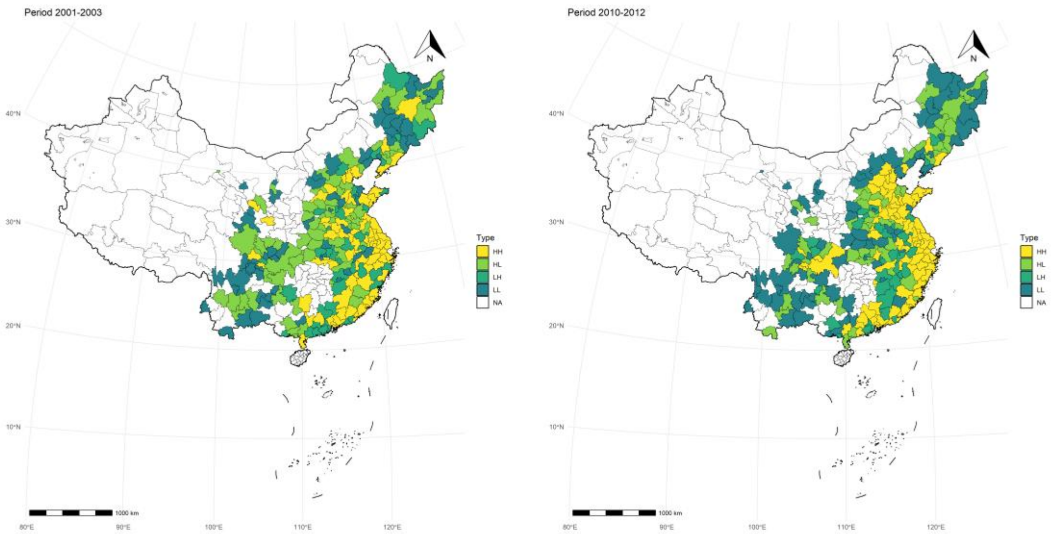


Figure 10 The spatial distribution of different types of cities by place dependence and knowledge complexity

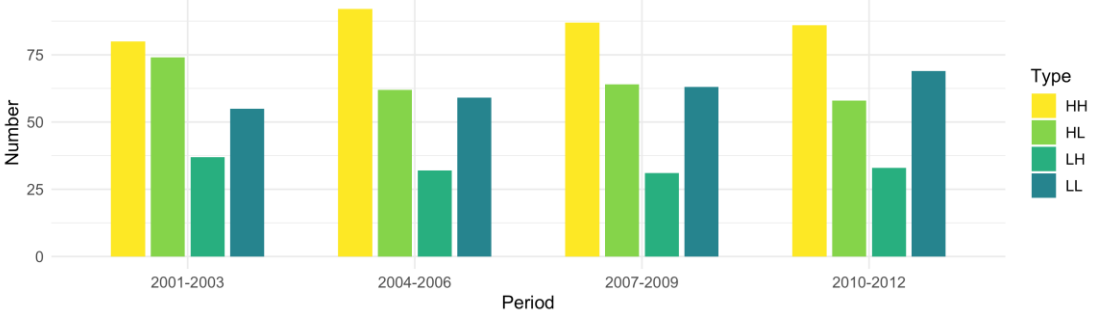


Figure 11 The number of different types of cities by place dependence and knowledge complexity

Place Dependence and Urban Economic Performance

Model specification

In this section, we undertake a comprehensive investigation into the influence of place dependence on urban economic performance, with the logarithm of GDP per capita (*pcgdp*) serving as the primary dependent variable. Our key variable of interest is city-level place dependence (*PD*), which captures the extent to which urban industrial dynamics rely on place-specific assets within cities. To explore the mutually reinforcing relationships among place dependence, path dependence, and knowledge complexity, we incorporate additional explanatory variables, including the average relatedness density (*RD*) and knowledge complexity (*KC*) of regional industrial entries, and interaction terms between *PD* and both *RD* and *KC*, thereby allowing for a nuanced understanding of how these dimensions collectively shape urban economic outcomes. In order to control for other relevant determinants of economic performance, we also include a set of control variables that reflect demographic, infrastructural, and technological conditions within cities. These controls consist of total city population (*population*), population density (*density*), fixed capital investment (*fixed*), and number of internet users (*internet*), all of which are sourced from the China Statistical Yearbook. To ensure consistency with our temporal framework, we aggregate data over three-year intervals, aligning with the defined study periods. Recognizing the importance of accounting for unobserved heterogeneity, we further incorporate province-level regional fixed effects and period fixed effects into our econometric model specification. This approach effectively controls for spatially invariant regional characteristics as well as temporal shocks that may influence economic performance across all cities. To enhance the robustness and interpretability of our results, all explanatory variables are standardized, enabling direct comparison of coefficient magnitudes across different variables. Additionally, all independent variables are one period lagged to mitigate potential endogeneity concerns arising from reverse causality.

Empirical results

Our empirical findings are systematically reported in Table 1, where we progressively change our econometric specifications to unpack the relationship between place dependence and urban economic performance. We begin with a baseline specification in column (1), where *pcgdp* is regressed solely on the variable of interest, place dependence (*PD*). The results reveal a statistically significant positive effect: a one standard deviation increase in variable *PD* is associated with an approximate 7% increase in GDP per capita. This initial finding provides strong preliminary evidence that place dependence plays a crucial role in enhancing the economic performance of cities, likely by fostering localized knowledge spillovers and supporting specialized industrial clusters.

In column (2), we extend the model by incorporating average relatedness density (*RD*) and knowledge complexity *(KC*) as additional explanatory variables. Both *RD* and *KC* exhibit positive and highly significant coefficients, reinforcing their well-documented roles in driving urban economic growth through the diversification and sophistication of local industrial structures (Balland et al., 2019). Interestingly, with the inclusion of these variables, the coefficient of *PD* loses its statistical significance, suggesting that the direct effect of place dependence on economic performance may be mediated or subsumed by the underlying mechanisms of path dependence and knowledge complexity. This finding implies a potential overlapping influence among these interconnected dimensions, warranting further exploration through interaction effects.

Accordingly, columns (3) through (5) introduce interaction terms between variables *PD* and *RD*, as well as between variables *PD* and *KC*, to capture the synergistic effects that may exist between them. The results demonstrate that both interaction terms are positive and statistically significant, indicating that place dependence not only contributes to economic growth independently but also amplifies the beneficial effects of path dependence and knowledge complexity. This substantiates the theoretical premise that localized embeddedness enhances the capacity of cities to leverage related and complex industrial diversification, thereby reinforcing urban economic development in a complementary and mutually reinforcing manner.

Finally, in column (6), we incorporate a comprehensive set of control variables—including demographic, infrastructural, and technological factors—to account for other determinants of urban economic performance. The inclusion of these controls does not substantially alter the significance or direction of the key coefficients, thereby underscoring the robustness of our results. Taken together, our empirical analysis provides compelling evidence that place dependence significantly contributes to enhancing urban economic performance, both directly and through its interaction with path dependence and knowledge complexity. These findings highlight the intricate and interdependent dynamics underpinning regional economic development, emphasizing the need to consider place-specific embeddedness alongside industrial structural characteristics in policy and academic discourse.

Table 1 Place dependence and urban economic growth

	Dependent variable:					
	pcgdp (ln)					
	(1)	(2)	(3)	(4)	(5)	(6)
PD	0.070***	0.001	0.048*	0.029	0.048*	0.045**
	(0.023)	(0.024)	(0.026)	(0.025)	(0.025)	(0.020)
RD		0.192***	0.173***	0.190***	0.178***	0.247***
		(0.028)	(0.028)	(0.027)	(0.028)	(0.023)
KC		0.099***	0.098***	0.094***	0.095***	0.043*
		(0.030)	(0.030)	(0.030)	(0.029)	(0.023)
*PD * RD*			0.102***		0.069***	0.036*
			(0.020)		(0.026)	(0.020)
*PD * KC*				0.091***	0.052**	0.049***
				(0.019)	(0.024)	(0.019)
population						-0.484***
						(0.024)
density						0.069***
						(0.019)
fixed						0.484***
						(0.046)
internet						0.098**
						(0.041)
Region FE	Yes	Yes	Yes	Yes	Yes	Yes
Period FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	977	907	907	907	907	906
R^2	0.559	0.596	0.607	0.606	0.609	0.763
Residual Std. Error	0.581	0.548	0.541	0.541	0.540	0.421
Note:	Robust standard errors in parentheses; *p<0.1; **p<0.05; ***p<0.01					

Concluding Remarks

Place dependence is innately taken by economic geographers, who claim that regional diversification is a locally contingent process and therefore is largely place-dependent (Martin & Sunley, 2010; Heimeriks & Boschma, 2014; Yang et al., 2021). In line with this observation, our study operationalizes place dependence as the degree to which the present spatial distribution of economic activities corresponds with historical spatial patterns. This definition captures the persistence and continuity of spatial economic structures over time, highlighting the extent to which economic dynamics are anchored in place-specific legacies. Despite the growing recognition of place dependence as a critical dimension of regional economic evolution, the concept has remained predominantly qualitative in the extant literature. To date, there has been a notable absence of rigorous quantitative measures capable of capturing the spatial-temporal continuity inherent in place dependence, which limits our ability to empirically validate and operationalize this important theoretical insight. Addressing this gap is essential for advancing both the academic understanding and practical assessment of how place impacts the regional diversification processes and economic performance.

To address this gap, we develop a novel method to measure the place dependence of industrial dynamics within Chinese cities. Relying on the Wasserstein Distance algorithm widely used in machine learning literature, we quantifying the place dependence by assessing the degree of continuity in the spatial distribution of industrial activities across two distinct time periods within the same city. Our empirical analysis offers several key insights. First, we confirm the presence of place dependence phenomenon in Chinese cities' industrial dynamics, and observe clear regional disparities in place dependence, which tends to decline gradually from the coastal cities towards more inland urban areas. Furthermore, our results demonstrate a positive association between place dependence and both related and complex diversification, indicating that cities with more sophisticated and interconnected industrial portfolios tend to exhibit stronger spatial continuity over time. Importantly, we also find that place dependence complements relatedness and knowledge complexity and jointly enhanced urban economic performance. These findings highlight the critical role of place dependence in regional economic evolution and underscore the necessity of integrating place dependence into EEG research.

The policy implications of our empirical findings are straightforward. Place dependence suggests that successful regional industrial development and urban planning require a deep understanding of historical spatial patterns and locally embedded economic processes. Consequently, policymakers and urban planners should prioritize strategies that reinforce existing place-based strengths, encourage related diversification, and tailor interventions to the distinct spatial characteristics of each region to effectively foster sustainable economic growth. Our results also offer important insights for the planning and development of new industrial districts in China (Xue et al., 2013). Rather than pursuing rapid, large-scale expansions that break sharply from existing economic space, new industrial district construction should be approached with greater prudence to ensure strong linkages with local advantageous assets. Specific industrial policies might be more effective if they focus more on strengthening and upgrading existing industrial clusters, rather than attempting path- and place-breaking diversification that may lack the necessary local foundations.

This paper also has several limitations that warrant further investigation. First, place dependence operates across multiple spatial scales, ranging from micro-level to broader regional and national contexts. In this study, our analysis is primarily confined within cities, which may overlook important dynamics occurring at higher or lower spatial resolutions. Future research could seek to further uncover the evolution of place dependence at micro-, meso-, and macro-level. Such approaches would allow scholars to simultaneously examine individual firm behaviours, local institutional contexts, and broader regional economic systems, thereby enriching our understanding of how place dependence emerges and interacts across different scales. Second, although we have reviewed the theoretical mechanisms underpinning place dependence, this paper does not empirically explore the full range of factors that influence its formation and evolution. Various factors such as policy interventions, institutional quality, social networks, and infrastructure endowments may play critical roles in shaping place dependence, yet these remain underexamined. Future studies could incorporate these contextual determinants to better explain variations in place dependence across different urban and regional settings. Third, our current approach primarily offers a snapshot of place dependence over specific time intervals, but the dynamic processes through which place dependence evolves — such as how shocks, technological changes, or policy interventions alter place dependence or leads to spatial leapfrogging—are not fully addressed.

Longitudinal and process-oriented studies are needed to capture the temporal dynamics and causal mechanisms at play.

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