Cities 178 (2026) 107361

Contents lists available at ScienceDirect

Cities

journal homepage: www.elsevier.com/locate/cities

Mapping semiconductor innovation clusters in China: A patent-based analysis of spatiotemporal evolution and typology

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ARTICLE INFO

Keywords:
Innovation clusters
Semiconductor industry
Spatiotemporal evolution
Patent analysis
Economic geography

ABSTRACT

Semiconductors constitute the technological foundation of the digital economy. This study examines Chinese semiconductor innovation clusters from 2003 to 2022 and documents the dominance of full-chain integration as the prevailing organizational form, which stands in contrast to specialization-driven theoretical predictions. Within integrated clusters, a clear pattern of quality heterogeneity emerges, as deeply integrated clusters with substantial critical technology engagement gradually displaced both specialized and broadly integrated alternatives. Survival analysis reveals that deep integration confers longevity advantages, with disparities intensifying during the period of geopolitical tensions and export restrictions. These advantages depend on resource foundations including urban proximity, anchor firm presence, and collaborative networks. However, design capabilities remain peripheral within technology networks, indicating persistent chokepoint vulnerabilities. Chinese semiconductor innovation clusters follow neither the American modular separation between fabless design and dedicated foundries, nor Korea's corporate-level vertical integration within chaebols, nor Europe's deep niche specialization in equipment and materials. Instead, they represent a distinctive cluster-level integration model. This study contributes to cluster theory by delineating boundary conditions under which integration outperforms specialization.

1. Introduction

The semiconductor industry constitutes the technological foundation of the modern digital economy, underpinning advances in artificial intelligence, 5G communications, cloud computing, and the Internet of Things. As geopolitical tensions reshape global technology supply chains, the spatial organization of semiconductor innovation has emerged as a critical determinant of national competitiveness and technological sovereignty (Edler et al., 2023). China presents a particularly compelling case: despite being the world's largest semiconductor consumer, the country remains dependent on foreign suppliers for critical technologies, creating vulnerabilities exposed by recent export restrictions and the dynamics of "weaponized interdependence" (Farrell & Newman, 2019; Miller, 2024). Understanding how Chinese semiconductor innovation clusters organize themselves across the value chain, including why certain organizational forms persist while others disappear, is therefore essential for grasping the evolving dynamics of global semiconductor competition.

The theoretical tension between specialization and diversification has long defined cluster development. Classical perspectives posit that specialized agglomeration builds core advantages through knowledge spillovers, input output linkages, and shared labor pools (Marshall, 1890; Porter, 1990), while diversification is viewed as a vital mechanism for fostering cross-sector innovation (Jacobs, 1969). However, recent scholarship in evolutionary economic geography (EEG) emphasizes that the capacity of a region to generate breakthrough innovation depends critically on the recombination of distinct but related knowledge capabilities (Boschma et al., 2017; Frenken et al., 2007). Empirical evidence confirms that while both pathways are valid, the accumulation of complex knowledge is increasingly spatially concentrated and contingent on the symbiotic presence of complementary industries (Balland & Rigby, 2017; Delgado et al., 2014). Yet, how these principles of relatedness translate into the organizational choices within a single, highly complex strategic industry like semiconductors remains underexplored.

The global landscape of the semiconductor industry offers a critical case study in the relationship between technological innovation and industrial organization. Leading regions have achieved success by

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https://doi.org/10.1016/j.cities.2026.107361
Received 2 August 2025; Received in revised form 27 April 2026; Accepted 1 July 2026
Available online 6 July 2026

evolving distinct architectures of innovation ecosystems rather than conforming to a single model. Silicon Valley's breakthrough lay in institutionalizing the modular separation of design from manufacturing, creating an open innovation network where specialized design houses and foundries link through standardized interfaces (Sturgeon, 2002). In stark contrast, Korea's chaebol-centered model exemplifies system-level vertical integration. Represented by Samsung and SK Hynix, its competitive strength stems from the deep coordination of cutting-edge design and precision manufacturing within a single organizational boundary, a model particularly effective for capital-intensive memory technologies (Mathews, 2006; Yeung, 2022). Europe, meanwhile, has pursued a path of niche specialization, forming knowledge-intensive innovation loops in specific domains like equipment (e.g., ASML) and materials (Balland & Boschma, 2021). Thus, competitiveness arises from a specific architecture that aligns with local institutions and knowledge bases.

Against the backdrop of global supply chain restructuring and intensifying great-power competition, building a secure and resilient semiconductor innovation system has become a core national strategy. However, significant gaps exist in understanding this state-led innovation ecosystem. First, existing research predominantly focuses on macro-level national policies or firm-level catch-up strategies (Lee & Malerba, 2017), failing to delineate the actual spatial distribution and organizational forms of semiconductor innovation activities in China (Wei & Liefner, 2012). This disconnects macro-level strategy from micro-level implementation. This gap is particularly problematic given China's emergence as both the world's largest semiconductor market and a latecomer economy following distinct institutional trajectories. Second, assessments based on output value or firm counts cannot discern a cluster's technological depth in strategic “chokepoint” segments, undermining the precision of policy interventions. Third, while U.S. and Korean experiences offer successful paradigms, it is uncertain which indigenous organizational model is more conducive to sustainable catch-up under external technological constraints. This study addresses these gaps by empirically examining the organizational logic of China's semiconductor innovation clusters.

This paper addresses these gaps by asking: does China's semiconductor innovation ecosystem follow specialization model of the USA, integration model of Korea, or a distinctive third path? We examine the prevalence and evolution of organizational forms among Chinese semiconductor innovation clusters, distinguish quality heterogeneity within integrated clusters based on critical technology engagement, investigate whether survival differentials across organizational forms are consistent with selection-based explanations, and identify the spatial distribution patterns and resource foundations associated with different cluster types.

To answer these questions, we construct a novel dataset of semiconductor innovation clusters spanning 2003–2022. We employ hexagonal grid aggregation of geocoded patent data, a robust method for capturing micro-geographic agglomeration while mitigating the modifiable areal unit problem (Arribas-Bel & Fleischmann, 2022; Kerr & Kominers, 2015). The sample covers 400,000 semiconductor-related patents across eight technology categories, enabling systematic tracking of cluster emergence, evolution, and exit over two decades. Clusters are initially classified using the Herfindahl-Hirschman Index and location quotient to distinguish diversified from specialized forms, then further differentiated by Chain Width Index measuring value chain coverage breadth and Critical Technology Ratio capturing engagement depth in strategically important segments. The analysis employs descriptive statistics, Kaplan-Meier survival analysis, technology co-occurrence network analysis, and spatial distribution mapping across three developmental phases.

Our findings reveal that Chinese semiconductor innovation clusters follow neither the firm-level specialization of the U.S. nor the firm-level vertical integration of Korea. Instead, they exhibit a distinctive pattern of cluster-level full-chain integration, defined as a systemic configuration where innovation activities spanning the complete value chain co-locate within the geographic boundary of a cluster rather than the organizational boundary of a single firm. Importantly, “full-chain” here denotes technology category coverage as measured by CWI, not the strength of co-occurrence connectivity between segments, which we examine separately through network analysis. Diversified-competitive clusters consistently account for over 80% of all clusters throughout the observation period, a pattern starkly at odds with specialization-driven predictions. Within this integrated majority, substantial quality heterogeneity exists: deeply integrated clusters with high critical technology engagement expanded from 44% to 74% between Phase I and Phase III, while broadly integrated clusters lacking technological depth remained marginal, never exceeding 11%. Systematic survival differentials emerge across organizational forms: deeply integrated clusters exhibit approximately 70% survival probability at ten years compared to roughly 30% for specialized clusters, with the pattern intensifying during external shocks when specialized clusters experienced exit rates five times higher than deeply integrated counterparts. Spatially, deeply integrated clusters concentrate in higher-tier cities, closely associated with enabling conditions including urban proximity, anchor firm presence, and dense collaborative networks. Critical technologies display distinct dynamics, with wafer materials showing persistent concentration in Beijing and Shanghai while design and wafer fabrication technologies exhibit greater volatility and opportunities for latecomer cities. However, a critical structural asymmetry persists: despite the expansion of full-chain integration, our network analysis reveals that design capabilities, particularly in EDA and advanced architecture, remain peripheral within the cluster innovation networks. This suggests that while the Chinese model has successfully integrated manufacturing and materials, it has not yet resolved the fundamental dependence on foreign intellectual property in the most strategic ‘chokepoint’ segments.

This study makes three contributions. First, we provide the first systematic empirical characterization of Chinese semiconductor innovation clusters, complementing existing studies on the United States, Korea, and Europe to enable meaningful cross-national comparison of cluster organizational forms. Our documentation of cluster-level full-chain integration as the dominant Chinese pattern reveals a distinctive model that differs from both the U.S. specialized ecosystem and Korea's firm-level vertical integration. Second, we develop an analytical framework distinguishing deeply integrated clusters from broadly integrated clusters, incorporating critical technology engagement as a key dimension that captures not only the breadth of value chain coverage but also the strategic depth of technological positioning in chokepoint segments. Third, we document systematic survival differentials across organizational forms and identify the resource foundations supporting deep integration, providing suggestive evidence consistent with survival selection as a potential mechanism shaping the observed dominance of deep integration in China's semiconductor innovation landscape.

The remainder of this paper is organized as follows. Section 2 reviews the related work. Section 3 describes the data sources, cluster identification methodology, and classification procedures. Section 4 presents the results. Section 5 discusses theoretical implications and limitations. Section 6 concludes.

2. Related work

2.1. Conceptual foundations and identification of innovation clusters

The theoretical and empirical distinction between *innovation clusters* and *industrial clusters* is fundamental. While industrial clusters are defined by the geographic concentration of production activities and input-output linkages, innovation clusters are characterized by the spatial agglomeration of knowledge creation and diffusion processes (Audretsch & Feldman, 1996; Cooke, 2001). Their core logic is not cost efficiency but accelerated learning, fueled by the localized exchange of tacit knowledge, which necessitates proximity (Breschi & Lissoni, 2009;

Carrincazeaux et al., 2001). Consequently, their identification requires data on inventive output, such as patents, rather than establishment or employment figures which capture production geography (Acs et al., 2002; Buzard et al., 2017).

Methodologically, the measurement of spatial concentration has evolved from indices of industrial specialization and market concentration toward micro-geographic techniques that mitigate the modifiable areal unit problem. Kernel density estimation and related continuous-space approaches now enable the precise identification of co-agglomeration patterns, revealing how industries linked by labor pools or knowledge flows cluster together (Duranton & Overman, 2005; Ellison et al., 2010). The shape and internal structure of agglomerations themselves carry analytical significance, as demonstrated by research linking cluster morphology to underlying economic forces (Kerr & Kominers, 2015). Recent advances apply these methods with high-resolution spatial grids to map and typologize high-tech clusters (Zandiatashbar & Hamidi, 2022; Zhao et al., 2023), while hexagonal grid systems have emerged as a robust approach to minimize edge effects and ensure uniform spatial representation. However, these sophisticated frameworks have been developed and validated predominantly in the contexts of advanced Western economies. Their application to the analysis of strategic innovation clusters in large, state-guided catching-up economies like China remains limited. This gap is particularly salient for the semiconductor industry, where the geography of innovation may diverge significantly from the geography of manufacturing.

2.2. The specialization-diversification debate and the principle of relatedness

A longstanding debate in economic geography concerns whether regional development benefits more from specialization (Marshall-Arrow-Romer externalities) or diversification (Jacobs externalities). Comprehensive reviews have synthesized decades of theoretical and empirical work on how agglomeration economies shape innovation outcomes (Carlino & Kerr, 2015). The literature has progressively synthesized these perspectives through the lens of technological relatedness. The central finding is that regions do not grow through random diversification or extreme specialization, but by branching into new activities that are technologically proximate to their existing knowledge base (Frenken et al., 2007; Hidalgo et al., 2018). Successful diversification is thus “related diversification”, a path-dependent process constrained by a region's capability endowment (Balland et al., 2019; Boschma, 2017). While this “relatedness” framework powerfully explains regional evolution across industries, it has not been systematically extended to explain organizational choices within a single, complex strategic industry.

For industries like semiconductors, characterized by a highly interdependent yet globally fragmented value chain, the critical question shifts: Should a regional cluster specialize in a particular segment (e.g., chip design) or integrate across multiple segments (e.g., design, wafer fabrication, and advanced packaging)? The prevailing inter-industry relatedness paradigm cannot adequately address this intra-industry, value-chain organizational puzzle. Crucially, not all segments are equal. Activities like design, advanced manufacturing, and equipment constitute technological chokepoints with high entry barriers, creating strategic dependencies (Shalf, 2020). A cluster can have broad chain coverage but concentrate innovation in lower-barrier downstream segments, or it can achieve deep integration in critical upstream technologies with narrower overall breadth. Research shows that organizational forms involve strategic positioning within ecosystem structures (Kapoor & Lee, 2013), and deep integration outperforms shallow coverage when tight co-optimization is required (Baldwin & Woodard, 2009). Therefore, clusters should be distinguished by both the breadth of their value chain coverage and the depth of their engagement in critical segments.

2.3. Organizational forms in the global semiconductor industry

The global semiconductor industry presents a compelling context for examining the variety of organizational forms that emerge across different regional ecosystems. The theoretical core of this debate centers on the fundamental tension between modularity and integration. Historical analyses document the industry's evolution from vertically integrated device manufacturers (IDMs) toward more modular production networks, where standardized interfaces enable deep specialization, as epitomized by the fabless-foundry model (Adner, 2017; Brown & Linden, 2009; Kano et al., 2020). This shift is grounded in the theory of architectural design, which posits that the optimal form of organization depends critically on the intensity and nature of technical interdependencies between value chain stages (Colfer & Baldwin, 2016). From a strategic management perspective, the predominant forms (IDM, fabless, and foundry) represent distinct approaches to coordinating activity and appropriating value within a complex ecosystem, each conferring different advantages for managing innovation and investment (Jacobides et al., 2018).

Empirically, these theoretical possibilities have crystallized into distinct, path-dependent regional forms. The foundational scholarship on Silicon Valley has illuminated how its unique industrial structure, characterized by interfirm mobility, informal knowledge exchange, and dense networks of specialized suppliers, enabled rapid innovation through market-based coordination rather than hierarchical integration (Bresnahan, 2001; Kenney, 2000). This American fabless model was built upon a vertically disintegrated form, characterized by specialized firms that collectively cover the value chain through market relationships. In stark contrast, Korea's dominance in memory semiconductors was achieved through a vertically integrated form orchestrated within the boundaries of large chaebols (Yeung, 2014). The geographic shift of chip-making toward East Asia reflects not merely cost advantages but complex market dynamics and strategic coupling within evolving global production networks (Yeung, 2022). Meanwhile, the internationalization of chip design activities toward Asia demonstrates how innovation complexity interacts with regional capability development (Ernst, 2005). The coexistence of these successful yet divergent forms demonstrates that multiple organizational equilibria are viable, shaped by institutional frameworks and historical trajectories. Recent work frames China's semiconductor industry as an externally driven sector in which upgrading depends on the variety of external knowledge from global value chains (Zhu et al., 2026).

The contemporary Chinese context introduces a critical new dimension: active, state-led ecosystem building under conditions of geopolitical pressure and technological catch-up. Scholarly work highlights how China's trajectory is being shaped by concerted state investment and policy designed to coordinate capabilities across the value chain, aiming for strategic autonomy (Zhou et al., 2016). In this environment, imperatives of security and supply chain resilience increasingly rival, if not supersede, pure economic efficiency as dominant logics influencing industrial organization (CSIS, 2025; Witt et al., 2023), leading to policy interventions with global spillover effects (Juhász et al., 2024). However, existing research provides a robust analysis of firm-level strategic choice and national-level industrial policy, yet it leaves a significant gap at the meso-level of the cluster ecosystem. It remains unclear how the diverse array of actors within a geographic cluster, including firms of various sizes, public research institutes, and universities, are collectively orchestrated into a coherent whole.

2.4. Cluster evolution and the foundations of innovation resources

Understanding why some clusters thrive while others decline requires examining their evolutionary dynamics and the composition of their innovation resource base. Lifecycle theory posits that clusters progress through predictable stages of emergence, growth, sustainment, and decline, driven by the demography of firms and the dynamics of local knowledge (Menzel & Fornahl, 2009). The initial capabilities and entry timing of firms can have long-lasting effects on a region's industrial trajectory (Klepper, 1996). The resource-based view complements this by emphasizing that clusters are not mere agglomerations but organized systems. Classic studies demonstrate how regional institutional configurations, such as the networked model of Silicon Valley versus the integrated corporations of Route 128, fundamentally shape innovation pathways (Saxenian, 1994). Empirical evidence confirms that strong cluster environments significantly enhance firm performance, entrepreneurship, and innovative output (Delgado et al., 2014). Recent synthesis work on technology clusters underscores how agglomeration benefits manifest through labor market pooling, input sharing, and knowledge spillovers, while also highlighting the growing spatial concentration of high-tech activity (Kerr & Robert-Nicoud, 2020).

The internal spatial and social organization of these resources is critical. High-technology clusters sustain innovation through processes of collective learning and networking, which facilitate the exchange of tacit knowledge (Keeble & Wilkinson, 2017). The quality of place itself, encompassing urban amenities, connectivity, and livability, has emerged as a key factor in attracting and retaining innovative talent within clusters (Esmaeilpoorarabi et al., 2018). Recent research reveals a nuanced micro-geography within clusters, where different value chain activities, such as R&D-intensive design versus capital-intensive fabrication, exhibit distinct locational preferences within a metropolitan area (Cui et al., 2024). Agglomeration effects, however, are not uniform across spatial contexts; research demonstrates that the benefits of clustering may differ substantially between urban and rural markets, and between different types of economic activities (Alfaro & Chen, 2019; Artz et al., 2016). Furthermore, the structure of collaboration networks, particularly between industry and universities, is a key determinant of knowledge flow efficiency (Etzkowitz & Leydesdorff, 2000). The presence of intermediary actors like public research institutes can be crucial in bridging structural holes within these networks. Recent trends point to increasing spatial concentration of innovation, with “superstar” clusters attracting a disproportionate share of talent and investment, which may challenge the development and sustainability of clusters in other locations (Chattergoon & Kerr, 2022; WIPO, 2024). However, innovation spillovers continue to connect geographically separate clusters, albeit with effects that diminish with distance (Giroud et al., 2024).

While existing research has effectively mapped cluster performance and analyzed the components of their resource base, it has not systematically connected these to a cluster's overall organizational form. A key unanswered question is whether a cluster's degree of integration across the semiconductor value chain, that is, its architectural configuration, has a bearing on its developmental trajectory and survival, independent of its foundational resources. This study directly addresses this gap by empirically examining the association between full-chain integration and cluster survival, while accounting for key resource connections.

3. Methodology

Innovation clusters refer to geographically proximate groups of actors, including firms, research universities, scientific institutions, and technology service providers, that are interlinked through collaborative innovation networks. Their core function is the sustained, high-intensity creation of knowledge, breakthrough of technologies, and commercialization of applications. The critical distinction from industrial clusters lies in their fundamental logic and output. While industrial clusters are primarily organized around production efficiency and cost reduction within established value chains, innovation clusters are architected for knowledge creation and reducing uncertainty in technological frontiers. The former thrives on stable, vertical supplier-buyer relationships and outputs standardized goods; the latter is characterized by fluid, horizontal networks for joint R&D, talent circulation, and venture capital, producing patents, prototypes, and spin-offs. Essentially, an industrial cluster optimizes the production of the known, whereas an innovation cluster explores the creation of the new.

To investigate the spatial and functional dynamics of semiconductor innovation clusters in China, this study relies on a combination of geocoded invention patent data and spatial analysis techniques. We construct a fine-grained dataset that captures the geographic distribution and technological composition of clusters across major Chinese cities over time. The methodological framework integrates spatial clustering, typological classification, and longitudinal analysis to comprehensively examine the evolution of semiconductor innovation networks. This study draws on the methodological framework of Zandiatashbar and Hamidi (2022) to identify semiconductor innovation clusters in China. Invention patent data were extracted from the database of China National Intellectual Property Administration (CNIPA). We use patent applications rather than grants to better capture the timing, location, and incremental character of semiconductor innovation activities, thereby improving the spatiotemporal accuracy of cluster identification. Applicants' addresses were geocoded using the Baidu Maps API to obtain precise latitude and longitude coordinates. Based on this geospatial information, Geographic Information System (GIS) techniques were applied to delineate the boundaries and spatial distribution of innovation clusters, enabling accurate mapping and analysis of their spatial patterns. We propose a set of methodological approaches to examine the spatiotemporal evolution and typology of semiconductor innovation clusters in China.

Step 1: Semiconductor Patent Screening.

Patents serve as a crucial indicator for measuring innovation, with their geographical distribution directly reflecting the intensity and characteristics of technological activities within regions. This study selected semiconductor patent application information from 2003 to 2022 as the initial sample. To ensure the accuracy and representativeness of the dataset, patents were screened using IPC codes and keyword filtering criteria related to semiconductor technologies. Based on the Wind Industry Research Report, the semiconductor industry chain can be broadly divided into upstream, midstream, and downstream segments (Fig. A.1 of Appendix A). The upstream sector includes wafer materials (such as silicon wafers, photoresists, and sputtering targets), wafer fabrication equipment (e.g., lithography and etching machines), and packaging materials and equipment, all of which provide essential technical and material support for chip production. The midstream segment constitutes the core of semiconductor manufacturing, encompassing chip design (from architectural planning to layout implementation), wafer fabrication (involving complex steps such as oxidation, lithography, etching, and ion implantation). The downstream segment refers to packaging and testing (ensuring chip functionality and reliability) and application of semiconductor products across a wide range of sectors, including computing, communications, consumer electronics, and automotive.

Semiconductor patents were further screened based on element keywords specific to subdivisions within each semiconductor patent classification. The classification of semiconductor innovation clusters and enterprise types was based on the characteristics of the technological domains along the semiconductor value chain, and the spatial organization features of innovation activities. At the cluster level, this research focuses on the core segments of the semiconductor technology chain, including wafer materials, wafer equipment, packaging and testing materials, packaging and testing equipment, design, wafer fabrication, packaging and testing and semiconductor product. This focus is justified because these segments exhibit significantly innovation-intensive characteristics, requiring substantial R&D investment and specialized talent support, thus making them more likely to form innovation agglomerations. Table A.1 of Appendix A presents examples of keywords for patents in various segments of the semiconductor production field. To focus the analysis on areas with substantive innovation activity, we first filtered the dataset by retaining only grid cells where the number of inner applicants exceeded the median value across all cells. This step ensured that subsequent clustering analysis was performed on units with a meaningful baseline of innovative actors.

Step 2: Identification of Semiconductor Innovation Clusters.

To identify semiconductor innovation clusters in China, this study integrates geocoded patent data with spatial statistical methods. Specifically, we first use the Baidu API to extract the geographic coordinates of applicants from semiconductor patent records. Based on this geospatial data, we apply hotspot analysis, a spatial statistical method commonly used to examine spatial clustering in urban and employment studies. The method assesses spatial autocorrelation by evaluating whether adjacent geographic units exhibit similarly high values. A unit and its neighboring cells are identified as part of a potential innovation cluster if they collectively show statistically significant intensity in the target variable.

$$G_i^* = \frac{\sum_{j=1}^{n} w_{ij} x_j - \overline{X} \sum_{j=1}^{n} w_{ij}}{S \sqrt{\frac{n \sum_{j=1}^{n} w_{ij}^2 - \left(\sum_{j=1}^{n} w_{ij}\right)^2}{n-1}}} \#(1)$$

where x_j denotes the observed value at location j, w_{ij} is the spatial weight between location i and j, n is the total number of observations, $\overline{X}$ and S are the global mean and standard deviation of all observations, respectively. The statistic G_i^* indicates the degree of spatial clustering between unit i and its neighbors. Hexagonal grid cells with significantly highG_i^* values are ultimately identified as candidate regions for innovation clusters.

A uniform hexagonal grid with a cell size of 3 km^2 is then overlaid on the national map, dividing the space into standardized analytical units. Each grid cell is assigned a count of semiconductor patents based on spatial joins conducted in ArcGIS. To ensure comparability and highlight regions with concentrated innovation activity, we retain only the top 30% of grid cells in each province by patent applications share, thereby filtering out low-density areas. Finally, we perform a hotspot analysis to detect statistically significant clusters, defined as areas where a cell and its neighboring cells exhibit consistently high patent intensity. This process allows us to identify core innovation zones in a spatially explicit and data-driven manner. The methodology is illustrated in Fig. 1.

The choice of $3km^2$ hexagonal grids as spatial analytical units is justified by three considerations specific to semiconductor innovation geography. First, this scale aligns with the typical spatial extent of innovation interactions in knowledge-intensive industries, consistent with recent evidence that localized knowledge spillovers and technological clustering operate primarily at the neighborhood scale of a few kilometers rather than at city or regional levels (Chen et al., 2026). Second, hexagonal tessellation eliminates the edge effects and orientation bias inherent in rectangular grids while maintaining computational efficiency for large-scale spatial analysis. Third, preliminary sensitivity analysis using alternative scales ($1km^2$, $5km^2$) confirmed that the $3km^2$ resolution optimally balances spatial detail with statistical reliability, capturing meaningful agglomeration patterns without excessive fragmentation.

Step 3: Measuring Innovation Intensity within Clusters.

To ensure temporal continuity, we define clusters for empirical analysis based on spatial overlap across consecutive years. In the baseline regression, a threshold of 80% overlap is used to identify the same

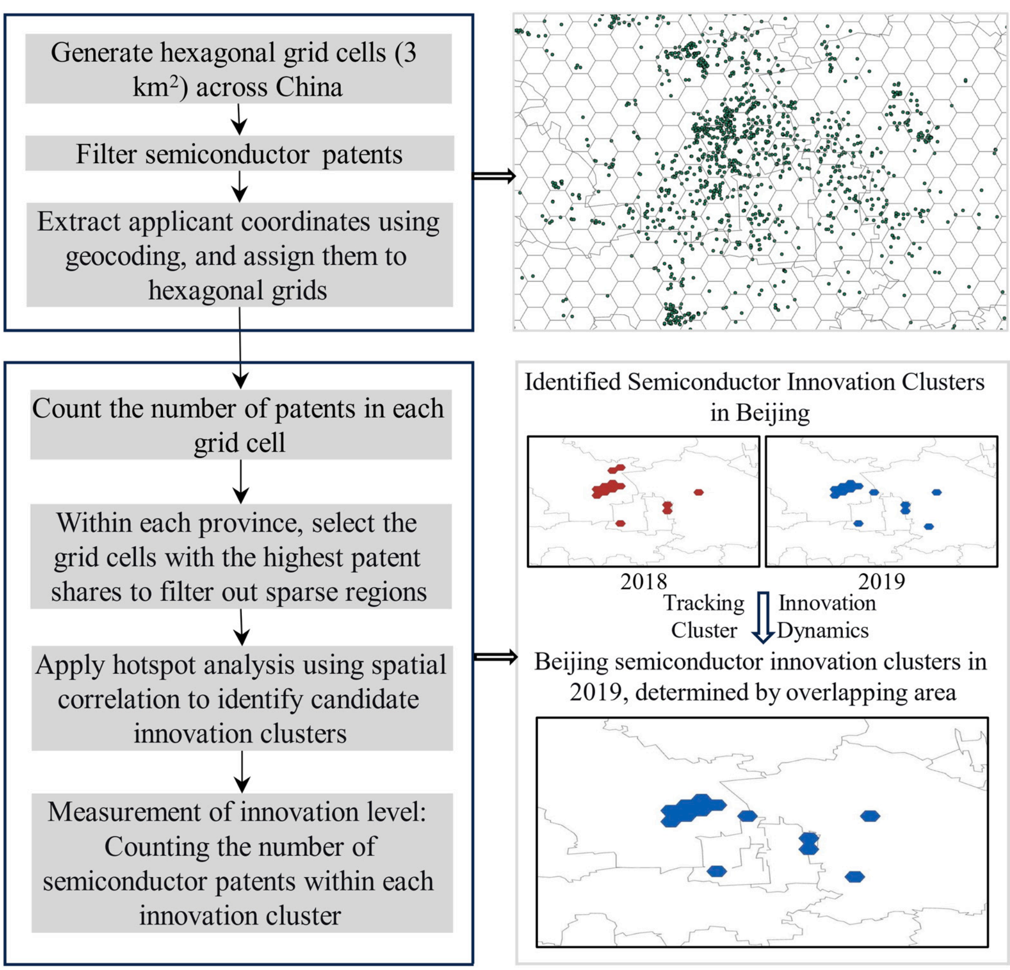


Fig. 1. Identification process of innovation cluster.

cluster over time, while alternative thresholds are tested in robustness checks. This process yields a clear spatial distribution of innovation clusters. Relying on the integration of semiconductor patent data and spatial grids, the method not only captures the spatial concentration of innovation activity but also provides a scientifically grounded tool for cluster identification and policy evaluation.

To ensure the reliability of results, several filtering steps are applied. First, clusters are dynamically tracked year by year; if two clusters have an area overlap above 80%, they are treated as the same cluster in different periods, otherwise as distinct clusters. This approach captures the spatiotemporal evolution of innovation clusters. Second, clusters with a duration of less than two years are excluded to improve stability. Third, to account for administrative boundaries, only one cluster is retained per county or district based on maximum area, avoiding statistical bias due to spatial overlap. Finally, the number of semiconductor patents within each identified cluster is counted to measure its innovation intensity.

Step 4: Cluster Typology Based on Specialization.

Based on agglomeration theory, this study constructs a dual-dimension analytical framework integrating specialization and regional competitiveness to identify and categorize distinct development models of innovation clusters in China. The classification system relies on two core metrics. First, the Herfindahl-Hirschman Index (HHI) is employed to measure the degree of industrial specialization within a cluster. The HHI is calculated as the sum of the squared shares of each industry segment within the cluster:

$$\mathrm{HHI} = \sum_{i=1}^{n} s_i^2 \#(2)$$

where s_i represents the share of the i-th segment, and n is the total patent number of segments. Second, the Location Quotient (LQ) is used to assess a cluster's relative competitiveness in specific sectors. It is formally defined as:

$$\mathrm{LQ} = \frac{s_{ic}}{s_{nc}} \#(3)$$

where s_{ic} denotes the patent share of industry i within cluster c, and s_{nc} represents the patent share of industry i at the national level. An LQ greater than 1.25 is considered indicative of significant competitive advantage in that industry.

For classification, strict thresholds are established based on the national distribution. Clusters with an HHI at or above the 90th percentile of the pooled national sample across all years (2003−2022) are defined as highly specialized. This time-invariant threshold ensures that observed changes in the share of specialized clusters reflect genuine distributional shifts rather than artifacts of a moving classification boundary, and clusters containing at least one industry with an LQ greater than 1.25 are deemed competitive. This yields a 2×2 typology: specialized-competitive, specialized-weak, diversified-competitive, and diversified-weak clusters.

To ensure the robustness and representativeness of the results, systematic data preprocessing was conducted. This included restricting the analysis to the period 2003–2022, retaining only clusters with patent counts above the 25th percentile to filter out negligible observations, and identifying the primary county for cross-administrative clusters by retaining the record with the largest overlapping area. Furthermore, clusters were required to have an observation period of at least 2 years to capture long-term dynamics, and those undergoing internal restructuring, identified by cases where the overlapping area decreased by more than 50% between consecutive years, were identified and recoded. Finally, for competitive specialized clusters, the core dominant industry was identified as the one exhibiting both the largest internal patent share and a significant LQ, thereby precisely delineating the source of competitive advantage.

To probe the heterogeneous innovation strategies within these structurally defined clusters, the analysis employs two metrics computed at the cluster level: the Chain Width Index (CWI) and the Critical Technology Ratio (CTR). For each cluster-year observation, all patents filed by innovation agents within the cluster boundary are pooled, and the CWI is calculated on this aggregated distribution to quantify the cluster's strategic breadth across the technology value chain. The CTR captures strategic depth by calculating the proportion of the cluster's total patents pertaining to foundational or core technological domains. We then employed K-Means clustering on the normalized cluster-level CWI and CTR values to identify natural groupings. The algorithm converged on three distinct clusters, the boundaries of which informed our classification of three strategic archetypes: "Deeply Integrated" ($\mathrm{CWI} > 4.0$ & $\mathrm{CTR} > 0.3$), indicating broad chain coverage with a focus on core technologies; "Broadly Integrated" ($\mathrm{CWI} > 3.5$ & $\mathrm{CTR} \leq 0.3$), indicating wide coverage with less strategic depth; and "Specialized" for all others. In clusters dominated by a single anchor firm, the aggregated metrics naturally reflect that firm's patent portfolio; we consider this appropriate, as anchor firms substantively define a cluster's technological character (see Section 4.7). This framework connects the structural patterns of patent-based agglomeration with the innovation strategies of their constituent agents, explaining how cluster-level competitive advantages emerge from collective technological positioning.

A methodological consideration concerns whether strategic patenting, meaning filing to meet policy KPIs rather than to protect genuine innovations, could inflate integration metrics. This risk is mitigated at three levels. First, our restriction to invention patents excludes the low-cost filing channels most susceptible to subsidy-driven inflation. Second, CWI measures cross-segment breadth; strategic inflation would require filing credible invention patents across unfamiliar technology domains, involving prohibitive technical barriers and high rejection risk under substantive examination. Third, CTR ensures that clusters broadening coverage through low-barrier segments without engaging critical technologies are classified as broadly rather than deeply integrated.

4. Results

4.1. The dominance of full-chain integration

Understanding the dominant organizational form of innovation clusters is a prerequisite for explaining their evolution and performance. We begin by documenting the prevalence of full-chain integration among Chinese semiconductor innovation clusters over the past two decades.

Fig. 2 (a) presents the annual composition of cluster types from 2003 to 2022. The results reveal a striking pattern of dominance by diversified-competitive clusters, which consistently account for over 80% of all clusters throughout most of the observation period. Specifically, this category represents 87.5% of clusters in 2009, rises to 96.4% in 2015, and stabilizes around 85% by 2022. In contrast, specialized-competitive clusters remain a persistent minority, fluctuating between 4% and 18% across years, while diversified-weak clusters appear only sporadically and never exceed 8% in any given year.

Fig. 2(b) further corroborates this finding using the CWI as a continuous measure of value chain coverage. The boxplots demonstrate that the median CWI consistently hovers around 4.5 throughout the observation period, well above the threshold of 3.0 that distinguishes diversified from specialized clusters. Notably, the interquartile range remains largely stable above the $\mathrm{CWI} = 3$ line, indicating that the majority of Chinese semiconductor clusters have maintained broad technological coverage as a baseline characteristic rather than an exceptional feature. The lower whiskers extending below $\mathrm{CWI} = 3$ in recent years suggest the emergence of new entrants that have not yet achieved full-chain integration, but these remain statistical outliers rather than a mainstream pattern.

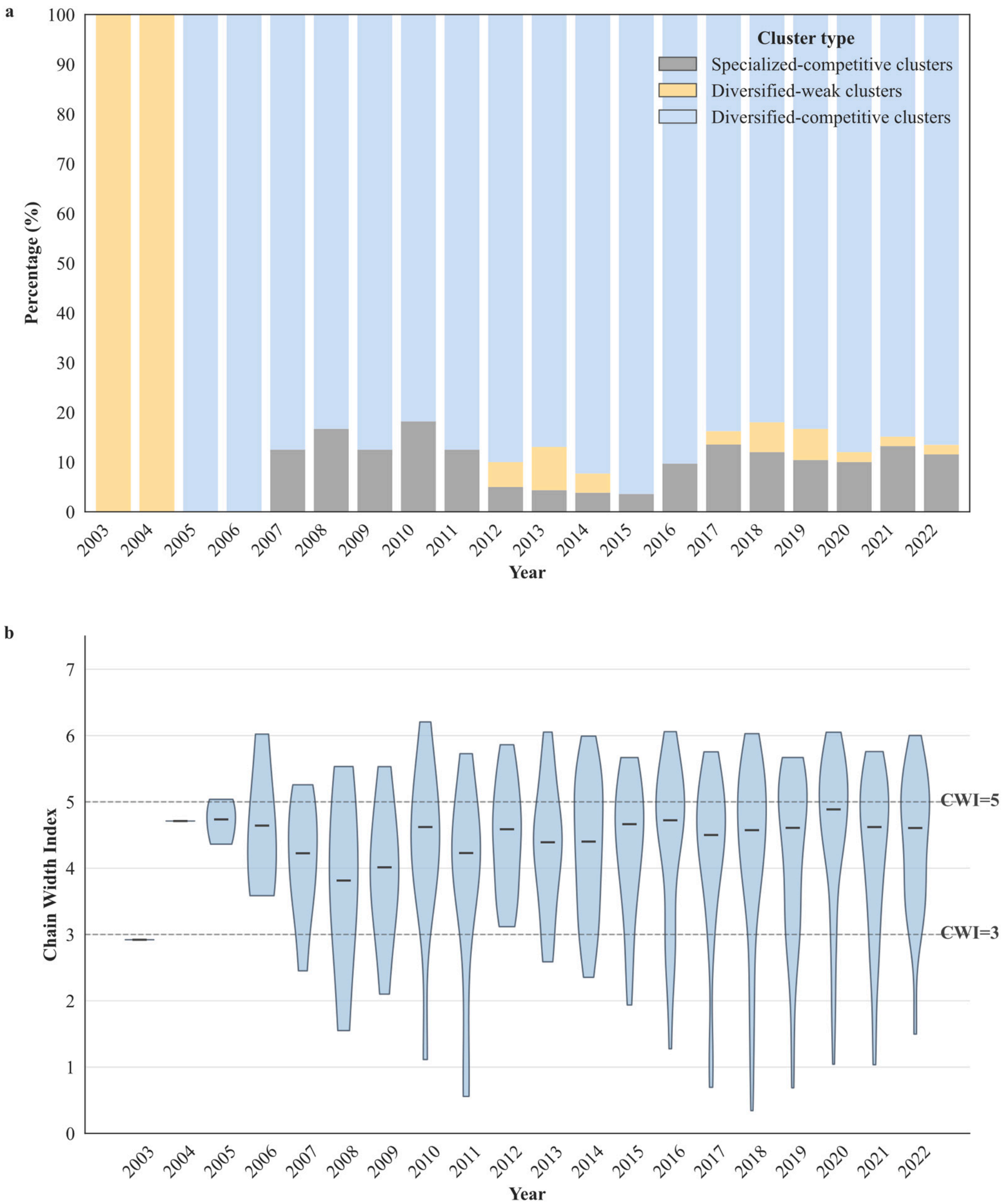


Fig. 2. The dominance of diversification and full-chain integration in semiconductor innovation clusters. (a) Annual composition of cluster types. Clusters are classified as diversified-competitive (light blue), diversified-weak (yellow), or specialized-competitive (gray) based on Chain Width Index (CWI) and location quotient thresholds. (b) Distribution of CWI by year. Boxes show the interquartile range with median (red line); whiskers extend to 1.5 IQR; dots are outliers. Dashed lines indicate CWI = 3 (red) and CWI = 5 (blue) thresholds. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

4.2. Quality heterogeneity within full-chain clusters

While the preceding analysis establishes full-chain integration as the dominant organizational form, it remains unclear whether all integrated clusters possess equivalent technological capabilities. This section examines quality heterogeneity within full-chain clusters by distinguishing between depth and breadth of integration. We divide the observation period into three phases based on major technological and geopolitical shifts in the global semiconductor industry. Phase I (2003–2009) corresponds to the PC Era, when personal computers dominated chip demand and China's semiconductor industry was in its nascent stage. Phase II (2010–2017) marks the Mobile Era, characterized by the explosive growth of smartphones and the deepening of global value chain integration. Phase III (2018–2022) represents the AI and Strategic Decoupling Era, shaped by two concurrent forces: the surge in demand for AI-oriented chips (GPUs, NPUs, and specialized accelerators) and the intensification of US-China technology decoupling through export restrictions and entity list designations. Fig. 3 presents scatter plots of cluster positioning across three developmental phases, with the CWI measuring breadth of value chain coverage and the CTR capturing depth of engagement in strategically important segments. The evolution from Phase I to Phase III reveals a pronounced pattern of directional selection toward deep integration. During the PC Era (2003–2009), the cluster population exhibited a bipolar structure, with deeply integrated and specialized clusters each accounting for 44.4%. The Mobile Era (2010–2017) witnessed dramatic reconfiguration, as deeply integrated clusters expanded to 69.0% while specialized clusters contracted to 25.9%. Notably, broadly integrated clusters remained marginal throughout, never exceeding 11.1%, indicating that breadth without depth constitutes an unstable intermediate state. By the AI and Strategic

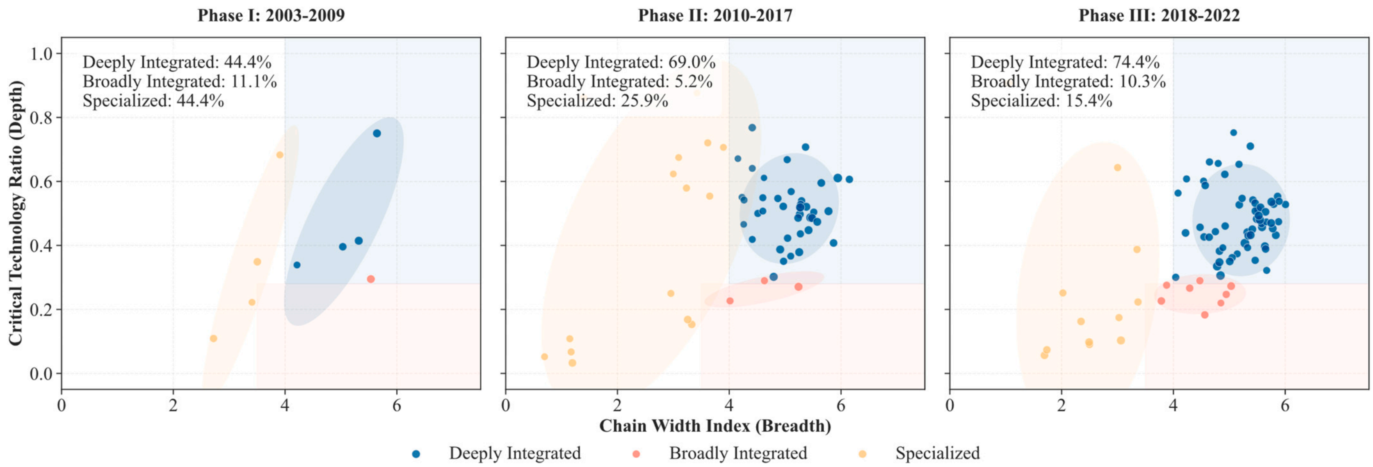


Fig. 3. Quality heterogeneity within full-chain clusters across three developmental phases. The horizontal axis represents CWI (breadth) and the vertical axis represents CTR (depth), calculated as the patent share in design, wafer fabrication, wafer equipment, and wafer materials. Bubble size is proportional to log of total patents. Shaded ellipses indicate approximate distribution ranges.

Decoupling Era (2018–2022), deeply integrated clusters achieved clear dominance at 74.4%, with their distribution concentrated in the upper-right quadrant. The mean CTR for deeply integrated clusters reached 0.48, substantially higher than 0.25 for broadly integrated clusters. The confidence ellipses further illustrate this structural divergence, with deeply integrated clusters exhibiting tight distribution at high values on both dimensions while specialized clusters remain confined to the lower-left region.

4.3. *Internal technological structure of integrated clusters*

The dominance of deeply integrated clusters in China's semiconductor innovation landscape, coupled with their demonstrated survival advantages, raises fundamental questions about what specific technological configurations underpin this integration advantage. While integration as an abstract concept suggests comprehensive value chain coverage, its substantive meaning emerges only through examining the actual technological choices and structural patterns within clusters. Analysis of functional orientation reveals that downstream-dominant clusters, characterized by concentration in semiconductor products and packaging, constitute the majority throughout all phases, accounting for approximately 60–70% of both cluster count and patent output (Fig. 4(a)). This pattern reflects the historical trajectory of China's semiconductor industry, which initially developed through downstream assembly and packaging before gradually moving upstream. Notably, the share of balanced clusters increases modestly over time, suggesting a gradual shift toward more evenly distributed value chain coverage, though downstream activities remain the foundational layer of China's semiconductor innovation system.

Technology co-occurrence patterns further illuminate the characteristic innovation pathways (Fig. 4(b)). The dominant two-technology combination is semiconductor products paired with wafer materials, appearing in 82.7% of all clusters. This is followed by semiconductor products plus wafer fabrication (56.1%) and wafer fabrication plus wafer materials (50.0%). The most frequent three-technology combination comprising semiconductor products, wafer fabrication, and wafer materials occurs in 49.0% of clusters. These patterns reveal a characteristic "core bundle" of technologies that Chinese semiconductor clusters tend to co-develop, centered on the production and fabrication segments rather than design or equipment, suggesting a manufacturing-centric innovation model.

The structural divergence between cluster types becomes particularly evident when comparing technology profiles (Fig. 4(c)). Deeply integrated clusters exhibit substantially higher shares in wafer materials (31.5% vs 9.2% in Phase III) and wafer fabrication technologies (12.9% vs 11.6%), while broadly integrated clusters concentrate disproportionately in semiconductor products (61.0% vs 40.6%). This contrast illuminates the substantive meaning of depth versus breadth: deeply integrated clusters achieve technological depth by penetrating upstream segments with higher technical barriers, whereas broadly integrated clusters spread across segments while remaining anchored in lower-barrier downstream activities. The evolution of these profiles across phases shows both types gradually diversifying, but deeply integrated clusters maintain their upstream focus while broadly integrated clusters expand their scope without fundamentally altering their downstream-heavy composition.

Fig. 5 visualizes the co-occurrence network of eight technology categories across the semiconductor technology chain, where node size represents patent volume and edge width indicates the strength of technological coupling between categories. The network topology reveals a persistent core-periphery structure centered on semiconductor products and wafer materials. Throughout all three phases, the strongest linkages connect these two nodes with wafer fabrication, forming a triangular backbone of the innovation network. The edge weight between semiconductor products and wafer materials increased from 1294 in Phase I to 18,563 in Phase III, reflecting the deepening technological interdependence as the industry matured. Critical technologies marked with dashed borders exhibit distinctive connectivity patterns. Wafer equipment and wafer materials maintain strong mutual connections (weight 4232 in Phase III) and serve as bridges linking upstream material science with midstream wafer fabrication. In contrast, design technologies remain relatively peripheral, with weaker connections to other nodes despite their strategic importance. This structural position suggests that design capabilities in Chinese semiconductor clusters have not yet achieved deep integration with wafer fabrication. The network densification from Phase I to Phase III demonstrates that technological coupling intensifies over time rather than fragmenting into specialized silos. The number of significant edges (relative strength above 0.10) expanded from 16 in Phase I to 21 in Phase III, indicating that successful clusters increasingly pursue multi-technology synergies rather than isolated specialization in single segments.

4.4. *Survival selection as the underlying mechanism*

Establishing the causal mechanism behind the dominance of deep integration requires distinguishing survival selection from strategic convergence. This section examines whether deeply integrated clusters exhibit systematically higher survival rates. Fig. 6(a) presents a scatter

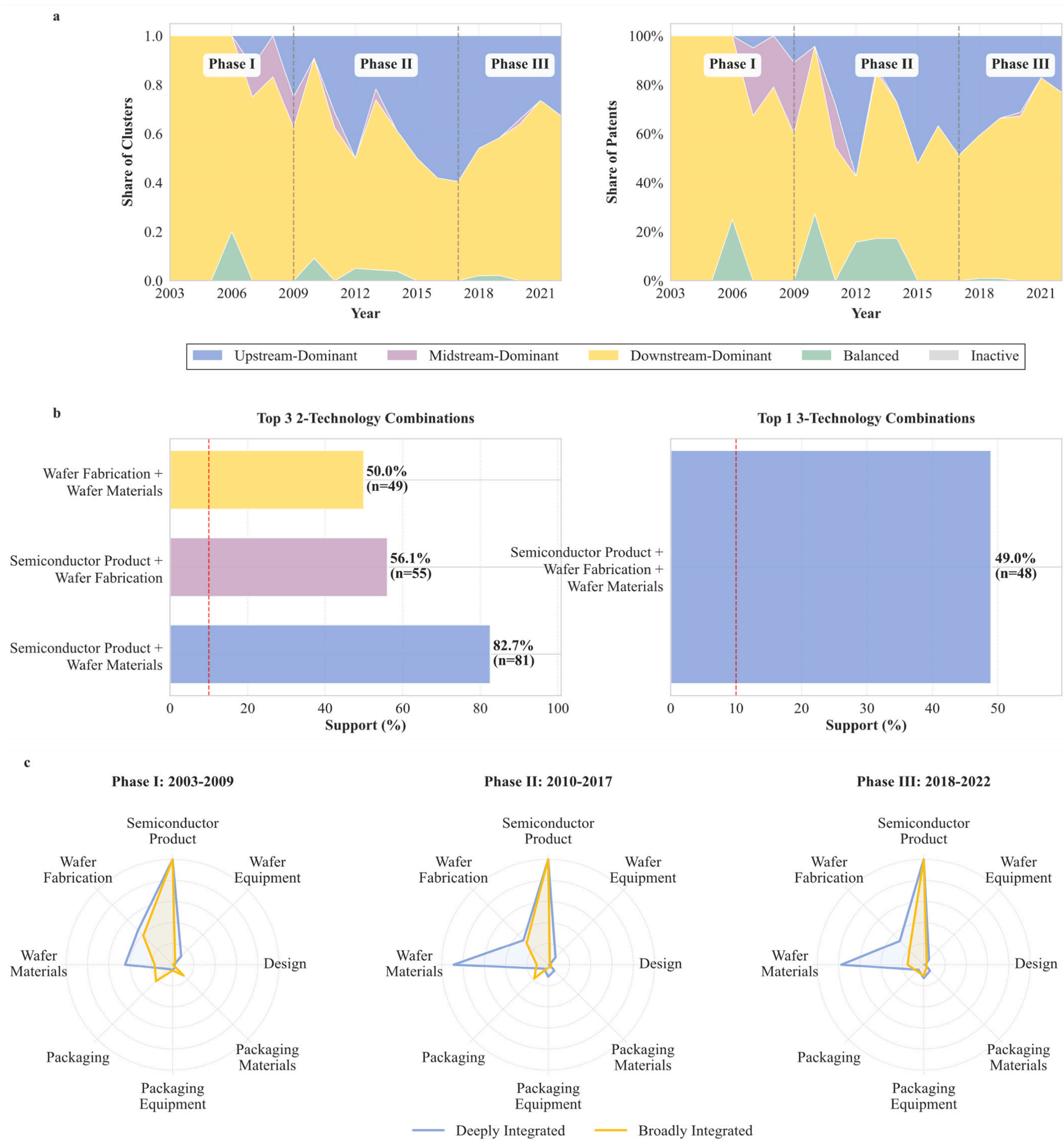


Fig. 4. Internal technological structure of integrated clusters. (a) shows stacked area charts of functional type distribution by cluster count share (left) and patent share (right). Clusters are classified as upstream-dominant, midstream-dominant, downstream-dominant, or balanced based on a 40% threshold for the largest segment. (b) displays the most frequent two-technology and three-technology combinations, with support indicating the percentage of clusters containing each combination. The red dashed line marks the 10% minimum support threshold. (c) presents radar charts comparing technology profiles between deeply integrated and broadly integrated clusters across three phases. Values are normalized to the maximum category within each cluster type for shape comparison. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

plot relating cluster survival duration to average CWI. A clear spatial segregation emerges between long-lived and short-lived clusters. Deeply integrated clusters concentrate in the upper-right quadrant, exhibiting both extended lifespans and high chain width values. In contrast, specialized clusters are concentrated in the lower-left region, with the majority surviving fewer than five years. The shaded rectangle demarcates a high exit rate zone where clusters with CWI below 3.5 and duration under five years are disproportionately represented, predominantly by specialized types. Fig. 6(b) displays Kaplan-Meier survival curves for the three cluster types. The curves diverge sharply from the

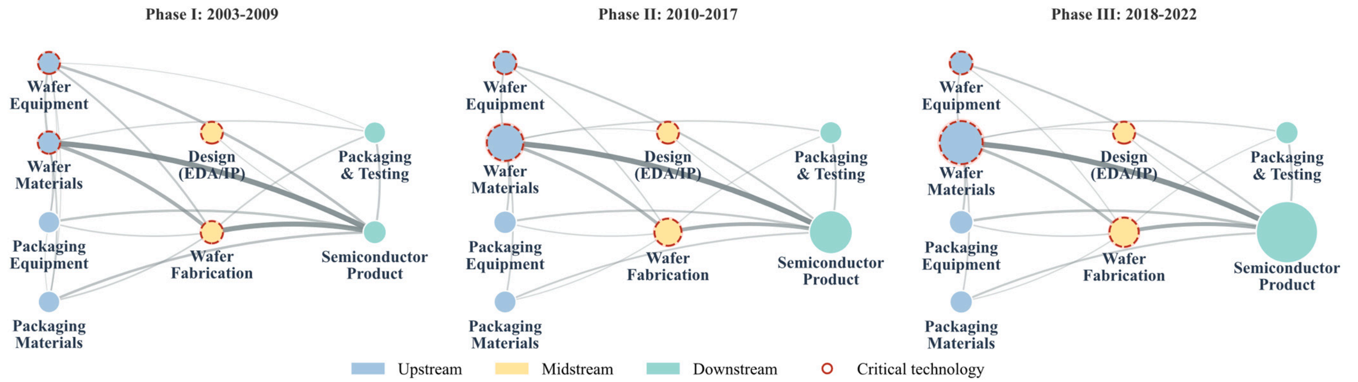


Fig. 5. Evolution of technology co-occurrence networks across the semiconductor technology chain. Nodes represent eight technology categories, with size proportional to total patent count (globally scaled across phases for comparability). Edge width indicates co-occurrence strength within each phase (locally scaled). Dashed red borders identify critical technologies (design, wafer fabrication, wafer equipment, wafer materials). Only edges exceeding 10% of each phase's maximum weight are displayed. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

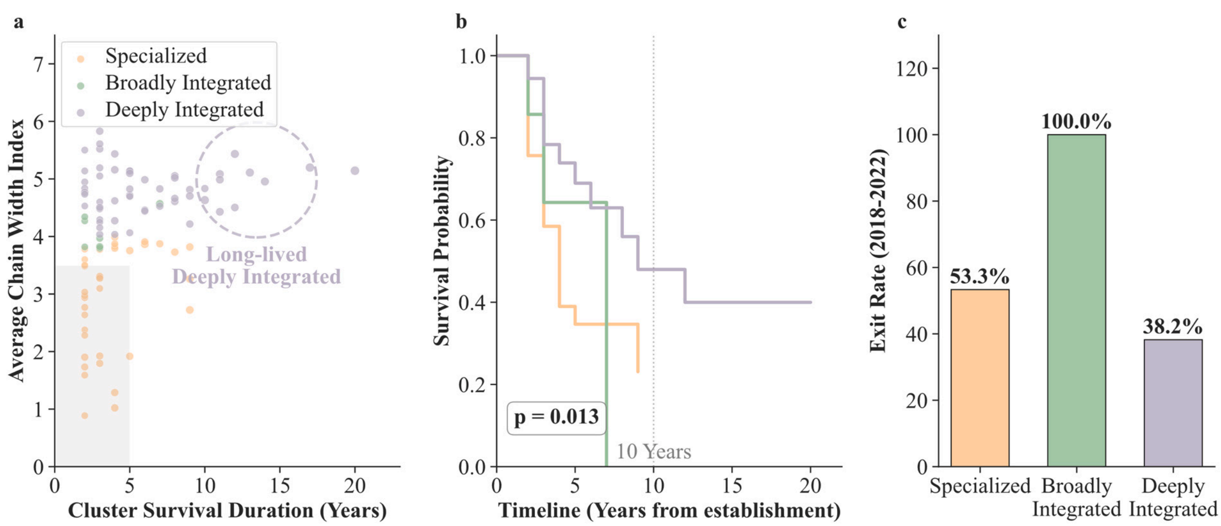


Fig. 6. Evidence of survival selection among semiconductor innovation clusters. (a) plots cluster survival duration against average CWI, with bubble size proportional to log of total patents. The shaded rectangle indicates high exit rate zone (duration <5 years, CWI <3.5). (b) shows Kaplan-Meier survival curves by cluster type, with the vertical dashed line marking 10 years. Clusters surviving until 2022 are treated as right censored. (c) displays exit rates during 2018–2022, calculated as the proportion of clusters active in 2018 that ceased patenting activity before 2022.

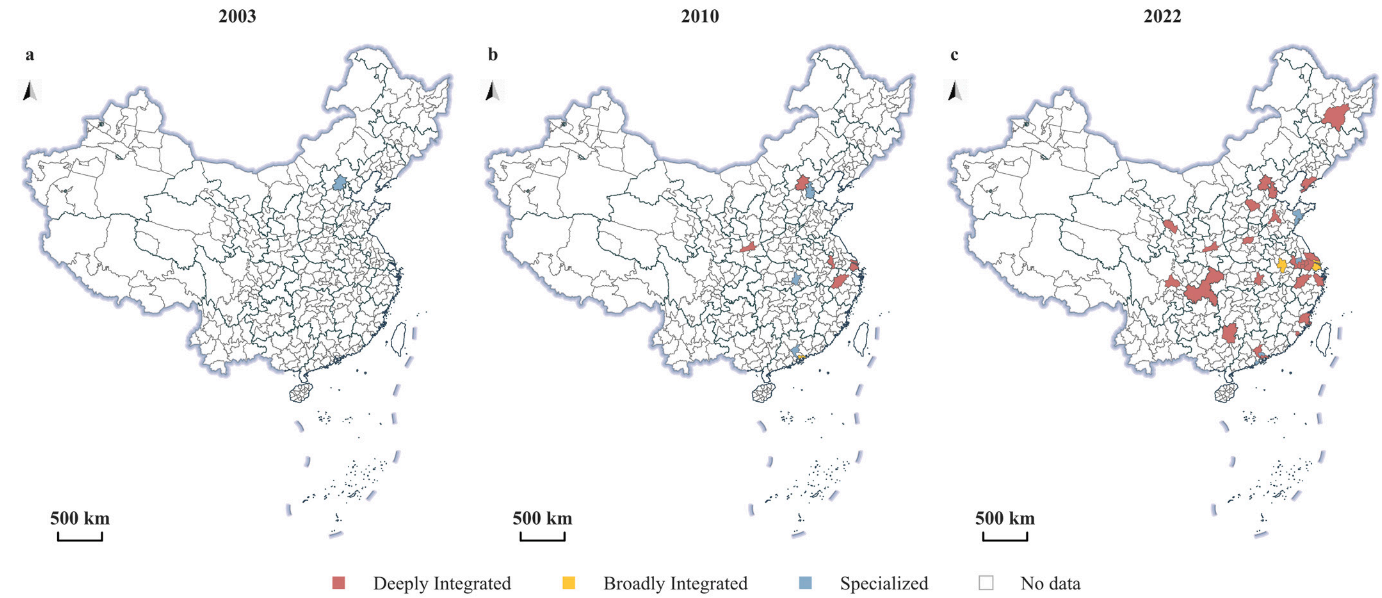
outset and maintain separation throughout the observation window. Deeply integrated clusters demonstrate substantially higher survival probabilities at all time points, while specialized clusters experience rapid attrition during the initial years. At the ten-year mark, deeply integrated clusters retain approximately 70% survival probability compared to roughly 30% for specialized clusters. The multivariate log-rank test confirms that these differences are statistically significant ($p < 0.001$), ruling out the possibility that the observed divergence results from sampling variation. Fig. 6(c) presents a natural experiment exploiting the dual pressures of AI-driven demand shifts and US-China trade frictions during 2018–2022 as an exogenous shock to the semiconductor innovation ecosystem. Exit rates during this period vary dramatically across cluster types. Specialized clusters exhibit the highest exit rate at approximately 25%, followed by broadly integrated clusters at around 14%, while deeply integrated clusters demonstrate remarkable resilience with an exit rate below 5%. This pattern suggests that deep integration provides a buffer against external technological and policy shocks, likely because diversified technological portfolios reduce dependence on any single supply chain segment vulnerable to export restrictions.

4.5. Spatial distribution and critical technology

4.5.1. Spatial evolution of innovation clusters

The spatial evolution analysis reveals a clear trajectory of semiconductor cluster development in China. From a single specialized cluster in Beijing (2003), the ecosystem rapidly diversified with Deeply integrated clusters dominating key cities by 2010. By 2022, Deeply integrated clusters expanded to 24 cities, accounting for 10,310 patents, demonstrating widespread adoption of full-chain integration strategies (Fig. 7).

The spatial expansion documented above raises a further question: does urban hierarchy constrain the type of clusters that can emerge in different cities? To examine whether urban hierarchy shapes cluster quality, Fig. 8 disaggregates cluster types by city tier across three phases. The results reveal a strong association between urban hierarchy and integration depth. Tier 1 and New Tier 1 cities account for 69% of deeply integrated clusters in Phase III, while Tier 2 cities host a growing but smaller share (22%). Notably, deeply integrated clusters expanded from exclusively top-tier cities in Phase I to penetrate Tier 2 cities by Phase III, suggesting gradual diffusion of advanced integration capabilities down the urban hierarchy.



Note: This map was produced using the standard base map (Map Approval No. GS(2020)4619) downloaded from the Standard Map Service of the Ministry of Natural Resources of China. The base map has not been modified.

Fig. 7. Spatial-temporal evolution of semiconductor innovation clusters in China.

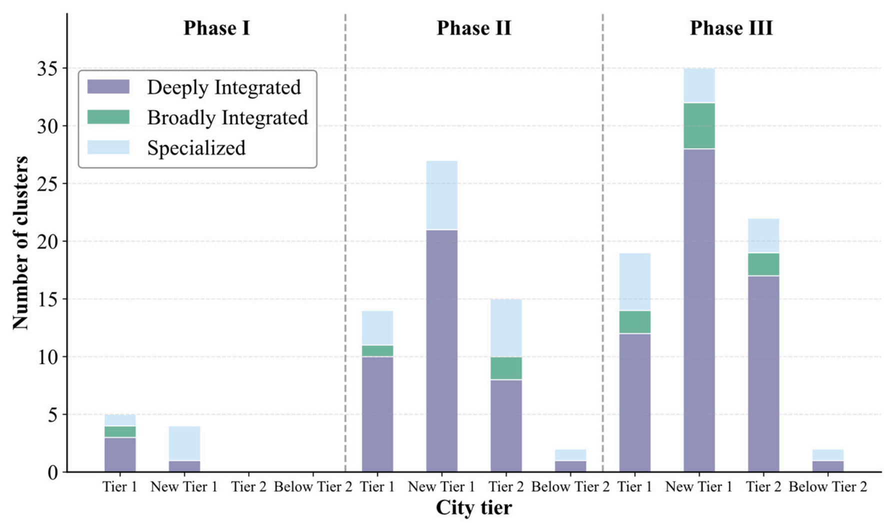


Fig. 8. Distribution of cluster types across urban hierarchy. Cities are classified as Tier 1 (Beijing, Shanghai, Guangzhou, Shenzhen), New Tier 1 (15 cities including Hangzhou, Suzhou, Nanjing), Tier 2 (30 cities), and Below Tier 2 (remaining cities).

4.5.2. Micro-location of typical clusters

While aggregate spatial analysis reveals macro-level distribution patterns, understanding how different cluster types position themselves within metropolitan areas requires micro-level investigation. This subsection examines the intra-urban location choices of semiconductor innovation clusters through representative cases from six cities, illustrating how integration strategies manifest in distinct spatial configurations (Fig. 9).

The deeply integrated cluster cases from Beijing and Shanghai demonstrate characteristic concentration in established high-tech zones with comprehensive infrastructure. In 2022, Beijing's singular deeply integrated cluster, anchored by semiconductor product innovation, was located within the Zhongguancun science corridor where dense research institutions and talent pools support cross-domain technological integration. Shanghai in 2022 presented a more diversified pattern, hosting multiple deeply integrated clusters with varying technological emphases including both semiconductor product-led and wafer materials-led configurations, distributed across Zhangjiang and adjacent innovation districts. This spatial co-location of technologically diverse yet deeply integrated clusters suggested agglomeration economies that facilitate knowledge spillovers across value chain segments.

The broadly integrated cases from Wuxi and Wuhan reveal a distinctive spatial pattern associated with rapid capacity expansion. These clusters exhibit extensive value chain coverage with CWI values approaching the maximum, yet concentrate patent output in non-critical downstream segments with CTR below 0.3. Their locations typically align with newly established industrial parks designed for manufacturing scale-up rather than research intensity, reflecting early-stage development strategies in emerging semiconductor regions pursuing breadth before depth.

The specialized cluster cases from Suzhou and Chengdu occupy niche positions within metropolitan innovation ecosystems. Suzhou's packaging equipment-focused cluster in 2011 exemplified single-segment specialization with extremely low CWI, serving targeted supply chain

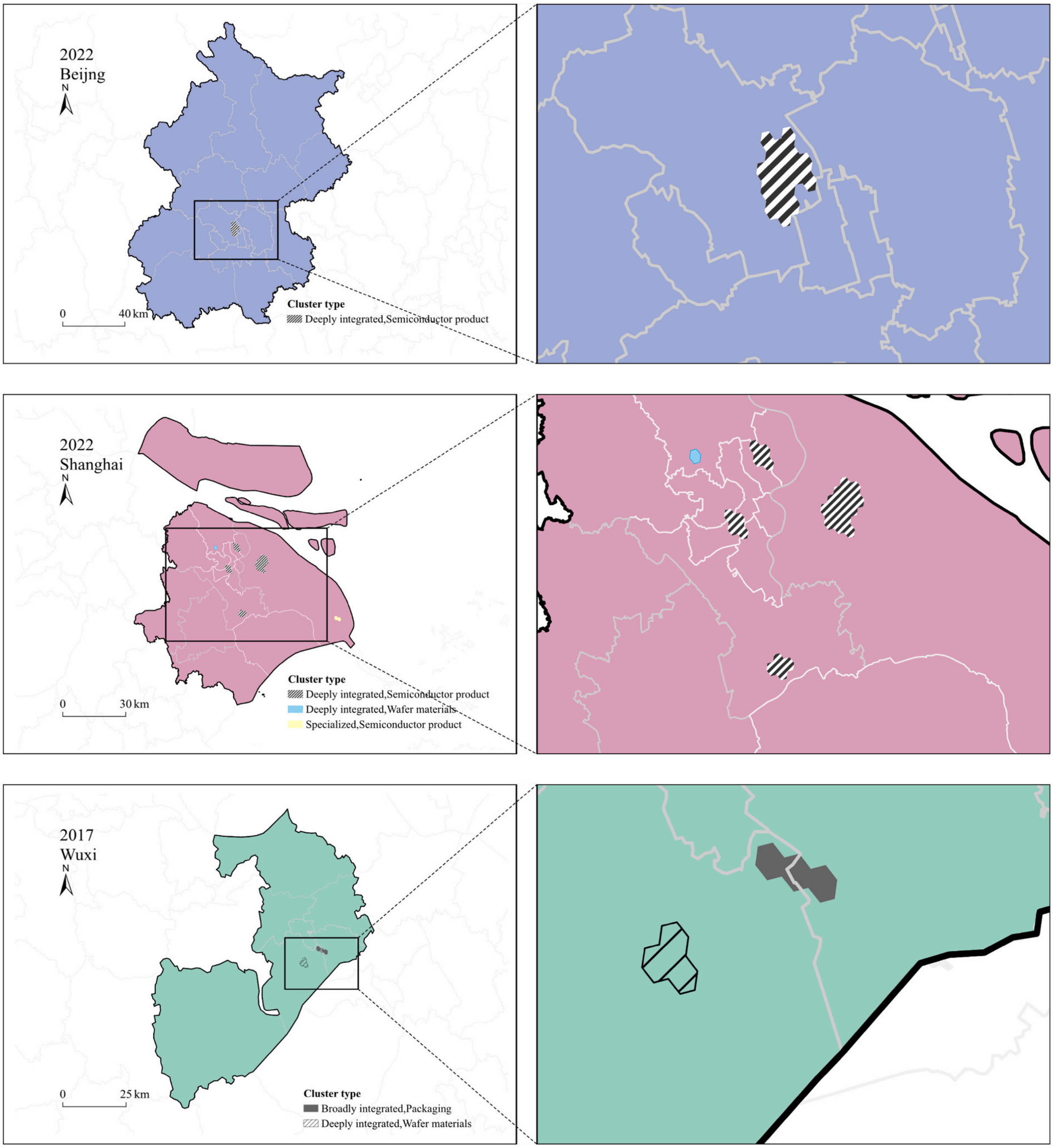


Fig. 9. Micro-location of representative semiconductor innovation clusters. Rows 1–2 present deeply integrated cluster cases from Beijing and Shanghai, rows 3–4 show broadly integrated cases from Wuxi and Wuhan, and rows 5–6 illustrate specialized cases from Suzhou and Chengdu.

functions. Chengdu's semiconductor product cluster in 2022 represented focused downstream development within a broader regional innovation system. These specialized clusters tend to locate in functional zones complementary to rather than competing with deeply integrated counterparts, suggesting an emergent spatial division of labor within and across metropolitan areas.

4.6. Characteristics of critical technologies

Critical technologies including design, wafer fabrication, wafer equipment, and wafer materials constitute the technological bottlenecks of the semiconductor technology chain, and a cluster's capacity in these domains largely determines its strategic position and long-term viability. Understanding the spatial distribution and concentration dynamics of these critical technologies is therefore essential for assessing China's semiconductor innovation landscape.

Fig. 10 presents bump charts tracking the ranking dynamics of the top five cities in each critical technology category from 2003 to 2022. The results reveal both persistent leadership and notable turbulence across different technological domains. In wafer materials, Beijing and Shanghai have maintained dominant positions throughout the observation period, consistently occupying the top two ranks with only occasional fluctuations. This stability suggests strong path dependence and cumulative advantage in upstream material innovation. In contrast, the design and wafer fabrication categories exhibit greater volatility in city rankings. For design technologies, Shenzhen rose rapidly from outside

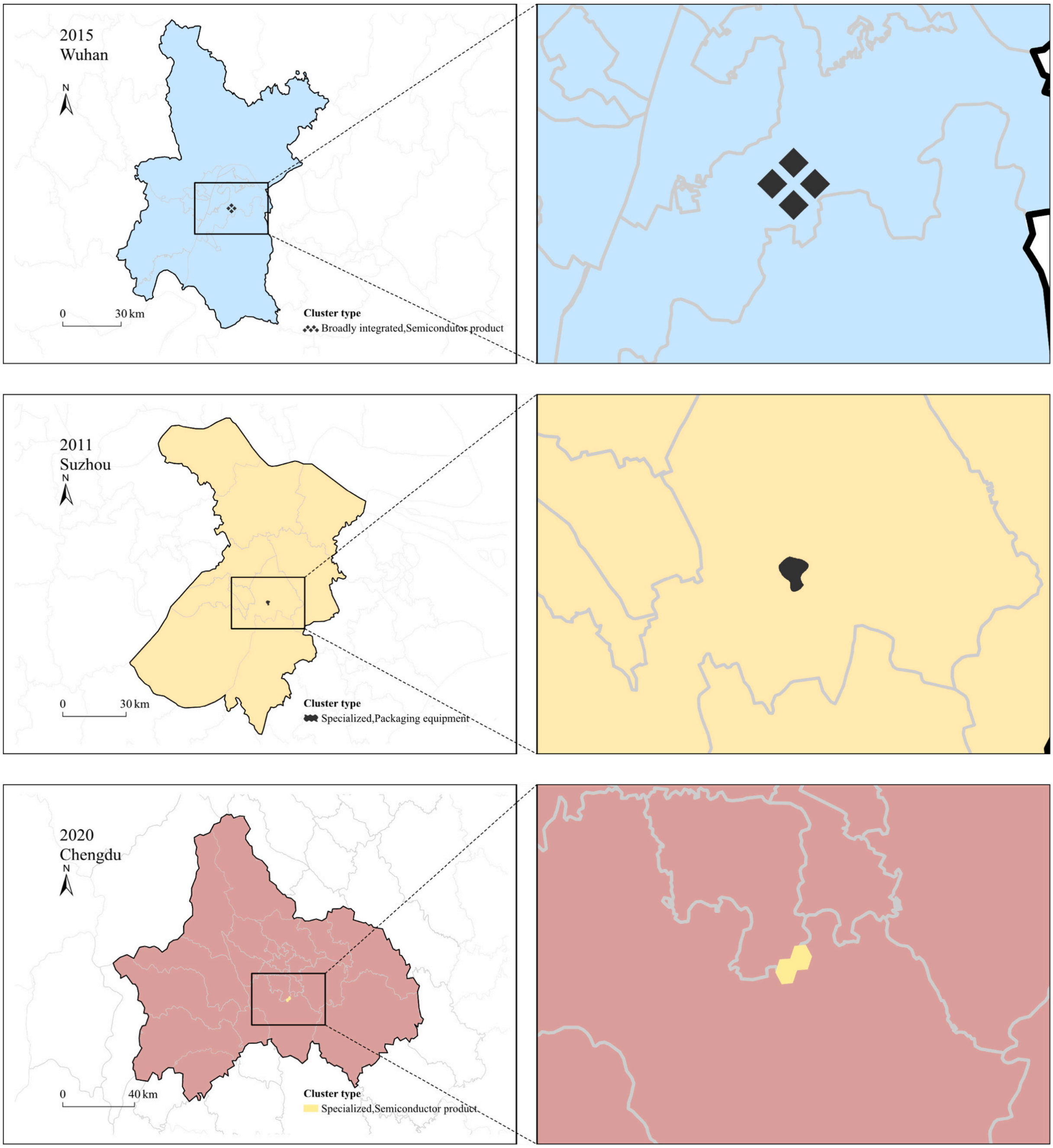


Fig. 9. (*continued*).

the top five in 2010 to claim the first position by 2016, before being overtaken by Nanjing in 2018. Similarly, the wafer fabrication technology rankings show frequent reshuffling, with cities such as Xi'an, Hefei, and Changsha emerging as significant players during the AI and Strategic Decoupling Era. This dynamism indicates that entry barriers in certain critical technology segments may be lower than commonly assumed, allowing latecomer cities to challenge established leaders. Wafer equipment displays an intermediate pattern, with Shanghai maintaining consistent leadership while Beijing serves as a stable second. The emergence of Wuxi and Shenzhen in recent years suggests gradual spatial diffusion of equipment-related innovation capabilities beyond the traditional core cities.

4.7. *Resource foundations of deep integration*

The survival advantage of deeply integrated clusters raises a critical question regarding the enabling conditions that support full-chain integration. Not all locations possess the resources necessary for clusters to achieve and sustain deep integration across the semiconductor value chain. This section examines whether deeply integrated clusters exhibit distinct spatial and organizational characteristics that differentiate them from other cluster types. Fig. 11(a) displays the distribution of distance to city center. Contrary to the expectation that semiconductor clusters might locate in suburban industrial zones, deeply integrated clusters consistently position themselves closer to urban cores. During Phase III, deeply integrated clusters average 8.0 km from city centers compared to 7.7 km for specialized clusters. While this difference appears modest, the distribution patterns reveal that deeply integrated

Fig. 10. Ranking dynamics of top five cities in critical technologies.

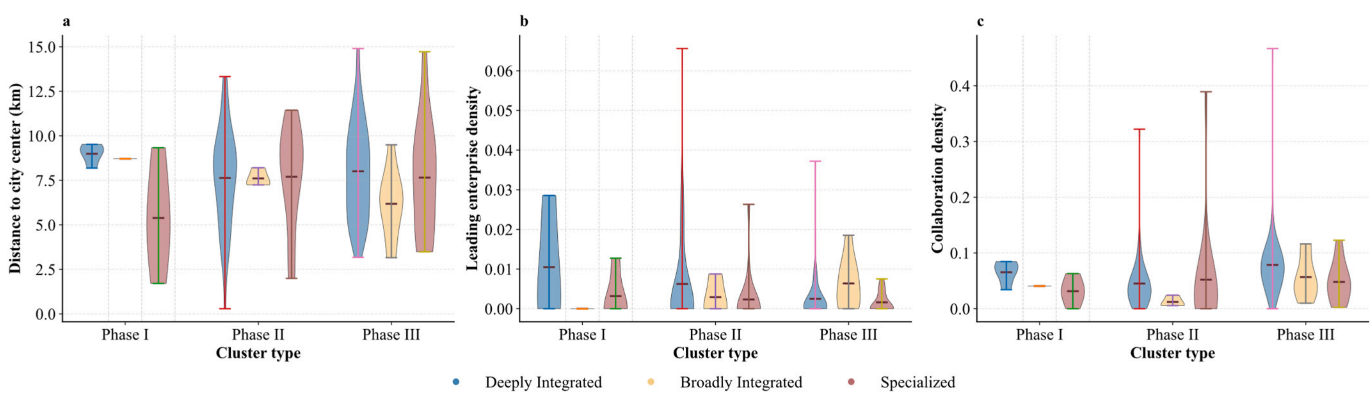


Fig. 11. Spatial and resource foundations of full-chain integration. Violin plots display the distribution of three resource indicators across cluster types and developmental phases. (a) shows distance to city center in kilometers. (b) shows leading enterprise density, calculated as leading firms divided by total firms. (c) shows collaboration density, calculated as jointly filed patents divided by total patents. The dark horizontal line within each violin indicates the mean. Outliers beyond the 99th percentile are excluded for visualization.

clusters exhibit less variance and avoid peripheral locations, suggesting deliberate selection of sites with superior access to urban amenities, diverse talent pools, and business services. Fig. 11(b) examines leading enterprise density, calculated as the ratio of anchor firms to total enterprises within each cluster. Deeply integrated clusters demonstrate higher concentrations of leading enterprises across all phases, with a mean density of 0.0025 in Phase III compared to 0.0016 for specialized clusters. This pattern suggests that anchor firms play a coordinating role in orchestrating vertical integration, leveraging their organizational capabilities and supply chain relationships to facilitate knowledge transfer and resource allocation across value chain segments. Fig. 11(c) displays collaboration density, measured as the share of jointly-filed patents relative to total patent output. Deeply integrated clusters exhibit substantially higher collaboration intensity, averaging 0.079 in Phase III compared to 0.048 for specialized clusters. This 64% difference indicates that deep integration is not achieved through isolated vertical expansion within single firms but rather emerges from dense inter-organizational cooperation. The elevated collaboration density likely reflects the technical complexity of coordinating across disparate technology domains, which necessitates pooling complementary capabilities through partnerships. Collectively, these findings reveal that full-chain integration is strongly associated with a constellation of enabling conditions including urban proximity, anchor firm presence, and collaborative networks.

5. Discussion

5.1. Theoretical implications for cluster development

This study contributes new evidence from a strategic high-technology industry to the longstanding debate on specialization versus diversification in regional innovation. Classical theory, grounded in Marshallian externalities and Porter's competitive advantage framework, posits that the geographic agglomeration of specialized industries drives regional growth through knowledge spillovers and factor sharing (Delgado et al., 2014). However, this logic is primarily derived from observations of traditional manufacturing clusters. In contrast, the core of an innovation cluster lies in the agglomeration of knowledge creation and diffusion (Audretsch & Feldman, 1996), suggesting that its organizational logic may fundamentally differ.

Our sector-specific analysis reveals a strikingly different pattern. In the semiconductor industry, innovation clusters exhibiting full-chain integration demonstrate overwhelming dominance and superior survival rates compared to specialized counterparts. This apparent contradiction demands explanation beyond simple empirical documentation. Why do Chinese semiconductor clusters follow this integration path rather than the modular specialization of Silicon Valley, the vertical integration of Korean chaebols, or Europe's niche expertise approach?

Three institutional and strategic factors systematically explain this divergence. First, China's state-led development model incentivizes comprehensive regional capability building, as local officials are evaluated on broad industrial upgrading rather than sectoral specialization, favoring integrated clusters over narrow specialization. Second, China's latecomer status creates fundamental uncertainty in global value chain positioning, forcing clusters to develop diversified local capabilities as strategic hedges against technological exclusion and supply chain disruptions. This logic has been intensified by recent export controls and geopolitical tensions. Third, China's indigenous innovation ideology prioritizes technological self-sufficiency over international specialization, with policies like Made in China 2025 systematically supporting clusters that reduce import dependencies across multiple value chain segments simultaneously. These factors explain why semiconductor innovation involves tightly coupled technological domains where fragmentation sacrifices critical synergies, and why geopolitical risks favor integration over external dependence. Comparative analysis highlights this distinctiveness: Silicon Valley's modular specialization thrives in open global networks; Korea's chaebol-level vertical integration operates within secure U.S. alliances; Europe's niche expertise depends on stable multilateral trade. China's integrated cluster model emerges from its unique institutional context of restricted technology access, export control vulnerabilities, indigenous innovation policies, and state-led governance, which makes deep specialization or external dependence riskier than in open or alliance-protected environments.

Our findings suggest that Chinese semiconductor innovation clusters exhibit distinctive organizational characteristics, but this conclusion requires careful qualification given analytical limitations. While we document cluster-level integration patterns differing from Taiwan's firm-level specialization and Korea's corporate integration, comprehensive international comparison remains constrained by data availability and methodological challenges. Patent data comparability across legal systems, innovation policy differences, and temporal misalignment limit direct cross-national cluster analysis. More precisely, our contribution lies in documenting that integration can outperform specialization under specific boundary conditions, namely geopolitical uncertainty, technology access restrictions, and state-led development priorities, rather than claiming Chinese exceptionalism. Whether similar patterns emerge in other latecomer economies facing comparable constraints requires future comparative research. The theoretical framework developed here, which emphasizes institutional context, sector characteristics, and geopolitical positioning as contingency factors, provides analytical tools for such comparisons while acknowledging the limitations of single-country analysis. This study thus identifies boundary conditions for specialization theory rather than refuting its general validity, contributing to contingency-based cluster theory that recognizes context-dependent optimal organizational forms.

5.2. Mechanisms underlying the dominance of deep integration

The survival differentials documented in Section 4.4 provide suggestive evidence consistent with selection-based explanations for the observed dominance of deep integration. Deeply integrated clusters exhibit approximately 70% survival probability at ten years compared to roughly 30% for specialized clusters, with the disparity widening during the external shock of US-China trade frictions when specialized clusters experienced exit rates five times higher than deeply integrated counterparts. These patterns are difficult to reconcile with pure policy convergence: if government guidance were the primary driver, broadly integrated clusters subject to similar policy environments should exhibit comparable longevity, yet they do not.

The selection mechanism operates through differential resilience to market and geopolitical shocks. From an evolutionary perspective, deeply integrated clusters possess higher ‘strategic redundancy.’ By maintaining capabilities across critical technology segments, they create a reservoir of alternative pathways that reduce dependence on any single supply chain node vulnerable to disruption. This internal variety functions as a shock absorber, allowing the cluster ecosystem to reconfigure its internal linkages when external connections are severed, a capacity largely absent in narrowly specialized clusters. When export restrictions target specific technologies, as occurred with advanced lithography equipment and EDA software, clusters with broader internal capabilities can substitute or work around constrained inputs more effectively than narrowly specialized clusters dependent on external provision. The survival advantage of deep integration thus reflects not merely scale or policy favor but substantive technological resilience.

A concurrent mechanism must be acknowledged: state-mediated exit barriers. Deeply integrated clusters encompass fabrication and materials segments with massive sunk costs and negligible redeployment value, while specialized design clusters are asset-light. China's state-led model amplifies this asymmetry. The Tsinghua Unigroup restructuring, state capital injections sustaining YMTC after Entity List designation, and counter-cyclical public co-investment in SMIC and Hua Hong all illustrate how strategic assets are shielded from market exit. However, this explanation is necessary but insufficient: the collapse of capital-intensive ventures like Wuhan Hongxin and Jinan Quanxin despite government backing shows that technological depth, not merely asset weight, conditions sustained state commitment. Furthermore, deeply integrated clusters continue expanding technology coverage rather than exhibiting the output stagnation expected of “zombie clusters.” We therefore reframe state-mediated exit barriers not as a confound but as a constitutive institutional feature of China's “Third Path,” distinguishing it from models where failure is normalized (U.S.) or where corporate balance sheets bear integration costs (Korea).

We therefore propose a multi-mechanism framework: state-mediated exit barriers prevent premature exit, strategic redundancy enables adaptive reconfiguration under shocks, and policy imitation accelerates convergence. These interact dynamically: state support buys time for capability accumulation, which justifies continued commitment and attracts imitation. Disentangling these mechanisms requires firm-level capital and subsidy data beyond our current dataset.

5.3. Unresolved challenges and structural limitations

Despite their survival advantage, deeply integrated clusters face structural limitations that our analysis reveals rather than resolves. A critical distinction must be drawn between coverage and co-occurrence connectivity. Our classification of “full-chain integration” is based on the former, specifically the breadth of technology categories in which a cluster is active. The network analysis in Section 4.3, by contrast, captures the latter, namely the intensity of co-innovative linkages between technology segments. The structural paradox identified below arises precisely from the divergence between these two dimensions. The resource foundations identified in Section 4.7, including urban proximity, anchor firm presence, and collaborative networks, are unevenly distributed across China's geography. Tier 1 and New Tier 1 cities host 69% of deeply integrated clusters, while lower-tier cities struggle to assemble the requisite conditions. This spatial concentration implies that the survival benefits of deep integration remain accessible primarily to clusters in privileged locations, potentially exacerbating regional innovation inequality rather than diffusing capabilities broadly.

More fundamentally, our technology network analysis reveals a persistent structural gap: design technologies remain peripheral in co-occurrence networks, exhibiting weak coupling with manufacturing and materials segments. This peripherality is consequential because design, particularly EDA tools and advanced chip architecture, constitutes precisely the chokepoint where China faces the most severe external constraints. The current integration model achieves breadth across fabrication-related segments and depth in wafer fabrication and materials, but it has not resolved the design deficit that underlies China's continued dependence on foreign intellectual property. Deeply integrated clusters, in other words, integrate around manufacturing rather than design, leaving the most critical vulnerability unaddressed. This structural paradox may reflect an inherent limitation of the state-led integration model itself. While government-coordinated resource mobilization is highly effective for capital-intensive, process-driven segments like fabrication and materials (like the Korean experience), it may be less conducive to the agile, modular, and risk-taking innovation required for chip design. Design innovation historically thrived in the vertically disintegrated, venture-capital-driven ecosystem of Silicon Valley, which relies on market flexibility rather than the heavy-asset integration currently prioritized by Chinese clusters. Therefore, the very organizational form that ensures survival in manufacturing may inadvertently constrain the breakthrough capabilities in design.

This structural limitation suggests that full-chain integration as currently practiced represents a partial rather than complete solution to technological self-sufficiency. Future evolution may require not merely broader integration but qualitative reorientation toward design-led rather than manufacturing-led cluster development, a transformation that would demand different resource foundations and potentially different spatial configurations than those supporting the current model.

5.4. Limitations and future research

Several limitations constrain the conclusions that can be drawn from this study. First, our reliance on patent data captures only codified innovation outputs, potentially overlooking tacit knowledge, process improvements, and organizational innovations that do not result in patent filings. The quality heterogeneity of patents, which ranges from incremental modifications to breakthrough inventions, is not fully addressed by our volume-based measures. Second, the observation window ends in 2022, precluding analysis of the most recent developments including intensified US export controls and China's accelerated indigenization efforts. Third, our survival analysis remains descriptive. The observed survival differentials likely reflect concurrent mechanisms, including evolutionary selection, state-mediated exit barriers, and imitation, that our dataset, lacking cluster-level capital intensity and subsidy measures, cannot disentangle.

Future research could address these limitations through several avenues. Firm-level analysis linking cluster membership to enterprise performance would illuminate how cluster-level integration translates into competitive advantage for constituent organizations. Cross-national comparison extending the framework to Taiwan, Korea, and emerging semiconductor regions such as India would test the generalizability of our findings beyond the mainland Chinese context. Cox proportional hazard models incorporating firm-level capital investment and subsidy data could formally test the exit barrier hypothesis against the selection hypothesis. Finally, exploiting policy discontinuities, such as the differential impact of specific export control announcements on clusters with varying critical technology exposure, could provide more rigorous causal identification of the selection mechanism we propose.

6. Conclusion

This study documents the organizational landscape of Chinese semiconductor innovation clusters from 2003 to 2022, revealing that full-chain integration overwhelmingly dominates over specialization. Within integrated clusters, substantial quality heterogeneity exists: deeply integrated clusters with strong critical technology engagement exhibit significantly higher survival rates than broadly integrated or specialized counterparts. These survival differentials, reaching 70% versus 30% ten-year survival probabilities respectively, reflect adaptive organizational responses to China's unique institutional constellation encompassing state-led development models, latecomer technological uncertainties, and indigenous innovation policy priorities.

The dominance of deep integration represents neither developmental inefficiency nor policy distortion but rather strategic adaptation to geopolitical constraints and supply chain vulnerabilities. However, this organizational model faces persistent structural limitations: spatial concentration in higher-tier cities constraining broad diffusion, and technological peripherality of design capabilities leaving critical chokepoint vulnerabilities unresolved. Our findings suggest that optimal cluster organization is fundamentally contingent on institutional context, sector characteristics, and geopolitical positioning, contributing to contingency-based cluster theory that recognizes context-dependent organizational forms. This challenges the universal applicability of specialization-driven development models while providing systematic evidence for understanding how latecomer economies organize innovation activities under technological and geopolitical constraints.

Based on our findings, three knowledge-focused interventions worth considering. First, establish inter-cluster innovation networks connecting specialized design clusters with deeply integrated clusters to facilitate cross-regional knowledge flows and compensate for spatial fragmentation of critical technologies. Second, create targeted fellowship programs enabling researcher mobility between design-focused institutions and integrated innovation environments, addressing the structural peripherality of design capabilities through human capital circulation. Third, develop innovation-specific metrics for cluster evaluation that reward breakthrough patent quality and cross-technology knowledge integration rather than conventional output volume measures. These interventions should enhance knowledge creation and technological learning processes within and across clusters while preserving the adaptive advantages of integration under geopolitical constraints.

CRediT authorship contribution statement

Yang Liu: Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Formal analysis, Data curation, Conceptualization. **Hao Yu:** Writing – original draft, Visualization, Validation, Software, Methodology, Formal analysis, Data curation. **Yuyuan Wen:** Writing – review & editing, Writing – original draft, Supervision, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Conceptualization.

Funding

This research was supported by National Natural Science Foundation of China (72373151,71773133) and Key Project of Beijing Social Sciences Fund (25BJ02015).

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.cities.2026.107361.

Data availability

Data will be made available on request.

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