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Structural Evolution and Robustness of the Digital Economy Industrial Network: An Empirical Analysis based on Beijing's Input-Output Tables

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Abstract

Scientific identification of the internal linkage structures and evolutionary stability of the digital economy is pivotal for fostering high-quality industrial development. Based on Beijing's input-output data from 2007 to 2020, this study reconstructs a longitudinal series of digital economy input-output sequences aligned with the Statistical Classification of the Digital Economy and Its Core Industries (2021). By integrating the IO-SNA approach with robustness simulation experiments, we systematically investigate the evolutionary trajectory of Beijing's digital economy industrial network. The findings reveal three critical insights: First, the network exhibits prominent "small-world" characteristics; while the scale of linkages remained stable, the system achieved a significant efficiency leap, with global efficiency surging by 92.7% to signal a transition from extensive connectivity to deep integration. Second, the network is characterized by a "stable core and viscous periphery" pattern. Within this structure, the driving momentum has undergone a structural shift from hardware support to service empowerment, with the financial and business service sectors emerging as pivotal hubs. Third, the system demonstrates a distinct "robust yet fragile" nature. While highly resilient to random shocks, it remains extremely sensitive to the failure of core hub nodes. Notably, as collaborative efficiency improves, systemic risks increasingly aggregate within these hub sectors, creating a precarious balance of "high efficiency and high sensitivity". These conclusions provide essential empirical evidence for identifying critical industrial risks and safeguarding the security of the digital economy industrial chain.

Keywords

Digital Economy; Industrial Network; Structural Evolution; Robustness; Input-output Analysis (IOA).

1. Introduction

Currently, against the backdrop of an intensifying new round of technological revolution and industrial transformation, the digital economy has emerged as a pivotal force reconfiguring global factor resources, reshaping global economic structures, and altering the landscape of international competition. The report of the 20th National Congress of the Communist Party of China explicitly proposed to "accelerate the development of the digital economy and promote its deep integration with the real economy," signaling that China's digital development has transitioned from a stage of mere quantitative expansion to a new phase of high-quality development centered on structural optimization and quality enhancement. As the "vanguard" of China's digital transformation, Beijing has taken the lead in proposing the construction of a "Global Digital Economy Benchmark City". In 2022, the added value of Beijing's digital economy accounted for over 40% of its regional GDP, ranking first nationwide. However, beneath the surface of rapid scale expansion, critical underlying structural issues remain to be elucidated:

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What specific input-output linkages have formed between the various sectors within the digital economy? How have these linkage structures evolved over time? More importantly, as a complex economic system, how does the digital economy industrial network exhibit robustness and structural stability when facing external shocks? Addressing these questions is of significant theoretical and practical importance for understanding the operational mechanisms of the digital economy and mitigating systemic risks arising from industrial transmission.

Existing research on the digital economy primarily revolves around two dimensions: scale measurement and empowerment effects. On one hand, scholars have utilized national accounting systems or satellite accounts to quantify the added value of the digital economy and its contribution to economic growth[1,2]. On the other hand, extensive empirical studies have explored the heterogeneous impacts of digitalization on total factor productivity, industrial structural upgrading, and the labor market[3~5]. Concurrently, with the rise of complex network theory, the integration of input-output techniques and social network analysis (IO-SNA) has emerged as a robust paradigm for analyzing industrial structural evolution. It has been widely established that economic systems are not uniformly distributed but instead exhibit significant “small-world” and “scale-free” characteristics, implying that a few critical hub sectors exert a decisive influence on the stability of the entire system[6,7]. For instance, micro-level shocks to specific sectors can propagate and amplify into macroeconomic fluctuations through the “star-shaped” structures of input-output networks-a phenomenon known as the “cascade effect”[8]. Furthermore, studies utilizing the World Input-Output Database (WIOD) have revealed typical “core-periphery” structures and identified super-nodes within global value chains[9,10] Additionally, some researchers have begun to investigate the robustness and vulnerability of industrial networks under external shocks. Despite these advancements, existing industrial network research predominantly focuses on traditional manufacturing or the aggregate national economic system, leaving the specific network structure of the “digital economy”- an emerging and highly integrated entity-largely unexplored. Due to its high permeability and cross-sectoral fusion, traditional linear regressions or aggregate measures fail to capture the complex web of dependencies and dynamic evolutionary paths between its sub-sectors. Moreover, due to the lag in statistical classification standards, many studies are restricted to cross-sectional data from a single year, which fails to capture the long-term dynamic patterns of the digital economy industrial network.

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To address these research gaps, this study focuses on Beijing-a city with a highly mature digital economy-as the empirical subject to investigate the evolutionary patterns and robustness of the digital economy's internal structures. To establish a data-driven foundation for long-term structural analysis, we first reconstruct a longitudinal series of input-output data for Beijing's digital economy spanning 2007 to 2020. Building upon this dataset, we utilize an IO-SNA framework to characterize the topological evolution of the sectoral linkage network and employ robustness simulation experiments to evaluate functional stability under diverse shock scenarios. By analyzing the relationship between sectoral linkage features and systemic robustness, this study aims to reveal the operational mechanisms and vulnerabilities of the digital economy, thereby providing strategic references for mitigating industrial risks and safeguarding supply chain security.

The marginal contributions of this study are primarily reflected in three aspects: First, the systematic and longitudinal nature of the data construction. Based on the Statistical Classification of the Digital Economy and Its Core Industries (2021), this paper constructs a 12-year series (2007-2020) of digital economy input-output tables for Beijing. Compared to existing cross-sectional studies, this research not only quantifies structural changes during the mobile internet explosion and the "13th Five-Year Plan" period but also provides solid empirical support for capturing the evolution of the digital economy from quantitative expansion to high-quality development. Second, the rigor and scientific logic of the methodology. Operating within the IO-SNA paradigm, this study develops a parameter optimization function based on the balance between "information retention" and "network redundancy," utilizing a hybrid row-column Top-k neighbor method to scientifically extract the optimal network skeleton. Furthermore, we introduce the Entropy Weight Method (EWM) to calculate comprehensive centrality, overcoming the limitations of single-indicator node identification and enhancing the reliability of the robustness simulation. Third, the in-depth identification of structural evolutionary patterns. From a systemic perspective, this paper quantitatively characterizes the intrinsic link between "efficiency enhancement" and "structural fluctuation" in Beijing's digital economy. Beyond identifying the shift of the network's driving force from hardware manufacturing to service empowerment, our simulation experiments reveal a critical structural feature: as collaborative efficiency improves, systemic risks increasingly aggregate within hub sectors, leading to a state of "high efficiency and high sensitivity". This discovery provides vital empirical evidence for ensuring the stability of the industrial chain.

2. Research Design

2.1. Construction of the Digital Economy IO Table

The core of constructing a digital economy IO table lies in disaggregating and reorganizing the traditional IO table to incorporate DEIs as independent sectors, thereby laying the foundation for subsequent analyses of inter-industry linkages. The construction process in this study follows a five-step procedure of "matching, decomposition, aggregation, re-decomposition, and re-aggregation."

Data accuracy serves as the fundamental prerequisite for robust network analysis. Given that current versions of the China Input-Output Tables do not explicitly list digital economy sectors, the original tables fail to capture the internal structure of the digital economy. To address this, we follow the Statistical Classification of the Digital Economy and Its Core Industries (2021)

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and employ the disaggregation coefficient method to reconstruct the input-output tables for Beijing for the years 2007, 2010, 2012, 2017, and 2020. Specifically, we isolate 4 core digital economy industries and identify 37 other sectors deeply integrated with digital technologies as "digital-fused sectors". The construction process involves the following steps:

Step 1: Sector Alignment and Mapping. In accordance with the Industrial Classification for National Economic Activities (GB/T 4754-2017), we first harmonize the sectors in the original input-output tables into a unified 39-sector framework. Subsequently, digital economy industries are mapped to these sectors based on four scenarios: (1) a sector contains a partial core digital component; (2) a sector is entirely comprised of a single core digital industry; (3) a sector spans across two core digital industries; and (4) a sector contains multiple distinct core digital sub-industries. The detailed correspondence is provided in Table 1.

Table 1. The core industries of the digital economy correspond to the input-output table

Digital Economy Core Industries	Classification	Input-Output Table Sector Code	Including Description of Digital Industry Segments
Digital Product Manufacturing	Computer Manufacturing	19	Manufacturing of computer complete machines, components, peripheral equipment, information security equipment, and other computer-related manufacturing
	Communication and Radar Equipment Manufacturing	19	Manufacturing of communication system equipment, communication terminal equipment, radar and supporting equipment
	Digital Media Equipment Manufacturing	19	Manufacturing of radio and television equipment, radar and supporting equipment
	Electronic Components and Equipment Manufacturing	16,18,19	Manufacturing of electronic components, semiconductors and related equipment
	Intelligent Equipment Manufacturing	16,18,19	Manufacturing of industrial and special operation robots, intelligent lighting, intelligent vehicles, and intelligent consumer equipment
	Other Digital Product Manufacturing	10,12,16 ,19,20	Reproduction of recording media, information chemicals, additive manufacturing equipment, optical fiber and cable manufacturing, and industrial automatic control system manufacturing, etc.
Digital Product Services	Digital Product Wholesale	26	Wholesale of computers, software and auxiliary equipment, communication equipment, and radio, film and television equipment
	Digital Product Retail	26	Retail of computers, software and auxiliary equipment, communication equipment, audio-visual products, electronic and digital publications
	Digital Product Leasing	32	Operating lease of computers and communication equipment, rental of audio-visual products

	Digital Product Maintenance	35	Repair of computers, auxiliary equipment and communication equipment
Digital Technology Application	Software Development	29	Development of basic software, support software, application software and other software
	Telecommunications, Radio, Television and Satellite, Transmission Services	29	Telecommunications, radio, television and satellite transmission services
	Internet-related Services	29	Internet access, search, games, information, security, data and other Internet-related services
	Information Technology Services	29,33	Information technology services such as integrated circuit design, information system integration, Internet of Things, geographic remote sensing, and other digital content services
	Other Digital Technology Applications	33	Promotion of 3D printing technology
Digital Factor-driven Industry	Internet Platforms	29	Internet platforms for production, daily life, and technological innovation
	Internet Wholesale and Retail	26	Internet wholesale and Internet retail
	Internet Finance	30	Online lending services, payment services by non-financial institutions, and financial information services
	Digital Content and Media	32,38	Radio, television and film production, film and television recording production, audio-visual products, electronic publications, and digital publishing
	Information Infrastructure Construction	25	Construction of networks, new technologies and other information infrastructure
	Other Digital Factor-driven Industries	33	Security system monitoring services, research and experimental development of digital technology

Step 2: Disaggregation of Core Digital Industries. We utilize the ratio of revenue from digital components to the total revenue of the corresponding sector as the disaggregation coefficient. The formula is expressed as follows:

$$s_{ij} = \frac{Revenue\ of\ digital\ sub - industry\ j\ within\ sector\ i}{Total\ revenue\ of\ sector\ i} \tag{1}$$

Where i represents the original input-output sector and j denotes the four core digital industries.

To ensure data consistency across years, we implement specific estimation strategies for missing data. For industrial sectors where sub-category (small-class) data is unavailable at the provincial level, we estimate Beijing's revenue based on national proportions:

$$\text{Estimated Sub} - \text{sector Revenue} = \frac{Mid - Sector\ Rvenue\ of\ Beijing}{Mid - Sector\ Rvenue\ of\ China} \tag{2}$$

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Where i represents the original input-output sector and j denotes the four core digital industries.

For service sectors (e.g., digital product maintenance) or emerging digital industries (e.g., internet platforms) with missing historical data, we apply a ratio-based interpolation method based on the assumption of structural stability:

$$s_{ij} = \frac{\text{Sub} - \text{sector Revenue}^{other\ years}}{\text{Mid} - \text{sector Revenue}^{other\ years}} \text{Mid} - \text{sector Revenue}^{target\ year} \tag{3}$$

Through these coefficients (detailed in Table 2), the original rows and columns are systematically decomposed and re-aggregated into 4 core digital industries and 37 digital-fused sectors. This results in a consolidated 41-sector Digital Economy Input-Output Table2 for Beijing.

Table 2. Input-output sector separation coefficient

IO sector	Digital Economy Core Industries	separation coefficient				
Number	Number	2008	2010	2013	2018	2020
10	01	0.032	0.021	0.014	0.009	0.007
12	01	0.006	0.008	0.009	0.005	0.001
16	01	0.025	0.025	0.025	0.030	0.033
18	01	0.156	0.202	0.233	0.316	0.367
19	01	1.000	1.000	1.000	1.000	1.000
20	01	0.291	0.376	0.432	0.416	0.382
25	04	0.083	0.072	0.064	0.062	0.064
26	02	0.081	0.082	0.083	0.097	0.107
	04	0.002	0.002	0.001	0.014	0.023
29	04	0.008	0.018	0.024	0.054	0.073
	03	0.992	0.982	0.976	0.946	0.927
30	04	0.005	0.004	0.003	0.013	0.022
32	02	0.001	0.001	0.001	0.001	0.001
	04	0.003	0.003	0.003	0.004	0.005
33	04	0.122	0.086	0.061	0.049	0.048
	03	0.002	0.002	0.002	0.003	0.003
35	02	0.152	0.130	0.114	0.136	0.157
38	04	0.232	0.269	0.294	0.364	0.406

Note：01,02,03 and 04 respectively represent the digital product manufacturing industry, the digital product service industry, the digital technology application industry and the digital Factor-driven Industry.

2.2. Construction of the Digital Economy Industrial Network

To accurately delineate the internal topological structure of the digital economy, this study follows a structured logical path: "Base Matrix Calculation-Parameter Optimization-Network Model Definition." This process is designed to extract a core network skeleton that represents the essential technical and economic linkages from the fully connected input-output data.

Step 1: Base Matrix Measurement. First, the total requirement coefficient matrix is calculated to measure the intensity of technical linkages between industries. Unlike direct consumption coefficients, the total requirement coefficient captures both direct technical-economic links and

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indirect dependencies propagated through the upstream and downstream industrial chains. The formula is as follows:

$$B = (I - A)^{-1} - I \tag{4}$$

where I is the identity matrix, A is the direct consumption coefficient matrix, and $(I - A)^{-1}$represents the Leontief inverse matrix. The element b_{ij} denotes the total output required from sector i to satisfy a unit increase in the final use of sector j .

Step 2: Network Sparsification and Parameter Optimization. The original matrix B is inherently dense, which may obscure key structural features due to a high volume of weak and redundant linkages. Consequently, a hybrid row-column Top-k neighbors method is employed for network sparsification. To determine the optimal number of neighbors k, a mathematical optimization function is developed based on the balance between "maximizing information retention" and "minimizing network redundancy."

The information retention rate ($I_t(k)$) for year t is defined as the ratio of the sum of edge weights retained (when each node keeps only its top k largest edges) to the total edge weights of the full network:

$$I_t(k) = \frac{\sum_{(i,j)\in B_t} b_{ij,t}}{\sum_{j=1}^{N}\sum_{i=1}^{N} b_{ij,t}} \tag{5}$$

The link set B_t is constructed through a three-step process: (1) column-wise filtering to retain the top k upstream input sources for each sector; (2) row-wise filtering to retain the top k downstream output destinations; and (3) taking the union of these two sets to form the final set of retained edges $B_t=B_1 \cup B_2$.

To find the optimal k we minimize the following Total Loss Function:

$$\min_{k\in[1,N-1]} L_t(k) = \left(1 - I_t(k)\right) + \frac{k}{N-1} \tag{6}$$

The first term $1 - I_t(k)$, represents the "information loss rate," while the second term $k/(N - 1)$, represents the "network redundancy rate." By seeking the minimum value of this function, we identify the optimal trade-off between architectural simplicity and information integrity.

Step 3: Network Model Definition. Based on the calculated results for the five selected years, the optimal values of k are determined to be 14, 13, 13, 10, and 10, respectively. To ensure strict comparability across time while maintaining inclusivity, the sparsification parameter is unified at $k=14$. Under this parameter, each year's network retains over 80% of technical-economic flows using only approximately 35% of the possible edges, successfully extracting the core industrial skeleton.

Building upon the optimized parameter k and the fixed number of nodes N, the Beijing Digital Economy Industrial Linkage Network is formally defined as $G=(V, E, N)$. The node set V=$\{v_1, v_2, v_3, \cdots, v_{41}\}$ encompasses the 41 industrial sectors integrated into the digital economy framework. The edge set E consists of directed links e_{ij} established via the hybrid row-column Top-14 filtering rule, where e_{ij} =1 if the connection exists within the optimized set B_t and e_{ij} =0 otherwise. Finally, the weight set W assigns specific values to these edges based on the corresponding coefficients within the total requirement matrix B_t, thereby reflecting the intensity of technical and economic interdependencies.

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2.3. Network Topological Features and Robustness Metrics

2.3.1. Aggregate Network Structure Indicators

To comprehensively evaluate the evolution and stability of the digital economy industrial network, this study constructs a multi-dimensional indicator system comprising overall structural metrics, individual sector characteristics, and systemic robustness measures.

Several indicators are employed to characterize the global properties of the network:

$$\mathrm{D}=\frac{M}{\mathrm{N(N-1)}} \tag{7}$$

Network Density (D): Measures the overall connectivity by calculating the ratio of actual edges (M) to the maximum possible edges.

$$\mathrm{E_g}=\frac{1}{\mathrm{N(N-1)}}\sum_{i\neq j}\frac{1}{d_{ij}^{w}} \tag{8}$$

Global Network Efficiency (E_g): Evaluates the parallel information transmission capacity. Given the weighted nature of the network, the "economic distance" between sectors is defined as the reciprocal of the linkage weight ($1/b_{ij}$); E_g is thus the average of the reciprocals of the shortest weighted path lengths (d_{ij}^{w}) between all node pairs.

$$\mathrm{L}=\frac{1}{\mathrm{N(N-1)}}\sum_{i\neq j}d_{ij} \tag{9}$$

Average Path Length (L): Represents the average number of steps required to connect any two sectors, reflecting the convenience of technical diffusion.

$$\mathrm{C_i}=\frac{E_i}{k_i(\mathrm{k_i}\text{-}1)} \tag{10}$$

$$\mathrm{C}=\frac{1}{N}\sum_{i\neq j}\frac{1}{\mathrm{C_i}} \tag{11}$$

Clustering Coefficient (C): Quantifies the local cohesiveness of the network. The global coefficient C is the average of local clustering coefficients (C_i), which measure the density of connections among a node's immediate neighbors.

2.3.2. Sector-Level Centrality Indicators

To identify the systemic importance of individual sectors, we employ a weighted centrality framework that accounts for the asymmetry of industrial linkages. As detailed in Table 3, five indicators are selected: Out-Strength and In-Strength (measuring supply-push and demand-pull effects), Out-Closeness and In-Closeness (measuring radiation and response efficiency), and Betweenness Centrality (measuring the sector's role as a bridging hub).

Table 3. Five bases for judging centrality and their formulas

Centrality	**Basis for judgment and economic implications**	**Calculation formula**
Out-degree Centrality	Measure the supply-driven capacity of an industry to downstream sectors. The larger the value, the stronger the radiation and driving effect of the industry as a power source.	$S_{out}(i) = \sum_{j} b_{ij}$
In-degree Centrality	Measure the demand-pulling capacity of an industry for upstream elements. The larger the value, the stronger the market driving effect of this industry as the consumer end.	$S_{in}(i) = \sum_{j} b_{ji}$
Out-closeness Centrality	Measure the efficiency of an industry in transmitting its influence across the entire network. The larger the value, the shorter the economic distance between the industry and its supply objects, and the faster the radiation speed.	$CC_{out}^{w}(i) = \frac{N-1}{\sum_{j\neq i} d_{ij}^{w}}$
In-closeness Centrality	Measure the efficiency of an industry in transmitting its influence across the entire network. The larger the value, the shorter the economic distance between the industry and its supply objects, and the faster the radiation speed.	$CC_{in}^{w}(i) = \frac{N-1}{\sum_{j\neq i} d_{ji}^{w}}$
Betweenness Centrality	Measure the intermediary capacity of industries as Bridges for resource circulation. The larger the value, the stronger the department is located at the core hub of more industrial paths and has a stronger regulatory power over network collaboration.	$BC_{i}^{w} = \sum_{s\neq i\neq t} \frac{\sigma_{st}^{\omega}(i)}{\sigma_{st}^{\omega}}$

Note: b_{ij},b_{ji}∈Bt;d_{ij}^{w} and d_{ji}^{w} is the shortest weighted path from node i to j (j to i); σ_{st}^{ω} is the total number of shortest weighted paths from node s to t ; $\sigma_{st}^{\omega}(i)$ is the number of shortest weighted paths passing through node i.

2.3.3. Network Robustness Measurement

Robustness is defined as the system's ability to maintain core functional stability under structural disruptions. Our simulation framework consists of three components:

Attack Strategies: We implement Random Attacks (simulating stochastic, non-specific failures) and Intentional Attacks (simulating targeted strikes on core hubs, such as critical technology supply chain disruptions).

Attack Sequences: To accurately identify critical nodes for intentional attacks, we apply the Entropy Weight Method (EWM) to calculate a comprehensive centrality score by normalizing and weighting the five centrality indicators.

Monitoring Metrics: Global network efficiency is utilized as the proxy for robustness. By constructing "node removal-efficiency" response curves, we analyze the rate of efficiency decline and the collapse threshold to evaluate systemic stability.

3. Results and Analysis

3.1. Evolutionary Trajectory of the Global Network Structure

Based on the measurement results presented in Table 4, Beijing's digital economy industrial network exhibited significant "small-world" characteristics throughout the observation period. The average path length consistently maintained a low level between 1.45 and 1.47. This suggests that establishing a technical-economic link between any two industrial sectors within the primary network requires, on average, only 1.5 intermediate steps, reflecting high global transmission efficiency and low industrial coordination costs. Concurrently, the clustering coefficient remained at a high value of approximately 0.82, which is significantly higher than

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that of a random network of the same scale. This indicates the formation of dense "industrial clusters" within Beijing's digital economy, where sectors tend to build stable ecosystems through close local reciprocity. This dual feature of “short paths and high clustering” provides a robust structural foundation for rapid technical spillovers and information diffusion.

From a dynamic perspective, the overall network structure followed a logic of optimizing from “scale stability” toward an “efficiency leap”. Regarding network density, the indicators fluctuated narrowly around 0.53, implying that the scale of core linkages within Beijing's digital economy has reached a relatively mature and stable plateau. However, the global network efficiency experienced a transformative surge, climbing from 0.124 in 2007 to 0.239 in 2020-a substantial growth of 92.7%. This efficiency leap, occurring while the network skeleton remained stable, reveals the profound nature of Beijing’s digital evolution: industrial interdependencies have shifted from the mere “existence of connections” to a structural reorganization characterized by “intensified linkage strength.” As the total requirement intensity between sectors increased, the technical support within core industrial chains was significantly bolstered, and barriers to factor mobility were substantially reduced. These trends signal that Beijing’s digital economy has successfully transitioned from “extensive connect” to “deep integration,” fundamentally enhancing the system’s collective operational capacity and resource allocation efficiency.

Table 4. Global Structural Indicators of the Digital Economy Industrial Network

Overall indicators	2007	2010	2013	2017	2020
Average path	1.472	1.459	1.461	1.468	1.469
Average path	0.818	0.829	0.821	0.827	0.821
Network density	0.528	0.541	0.539	0.532	0.531
Global efficiency of the network	0.124	0.196	0.182	0.226	0.239

3.2. Identification and Evolutionary Analysis of Key Industrial Nodes

Based on the Entropy Weight Method (EWM), comprehensive centrality scores were calculated for all 41 sectors across the five observation years to delineate the distributional landscape of industrial influence within Beijing’s digital economy. The resulting heat map (Figure 1) illustrates a hierarchical and multi-driven structural pattern. Throughout the study period, the network was characterized by a distinct integration of digital and real economies (digital-real integration). The first tier of comprehensive centrality includes not only core digital industries such as Digital Product Manufacturing (Sector 1) but also foundational industrial sectors like Chemical Products (16), Metal Smelting (18), and Electricity and Heat Supply (25), alongside modern service sectors such as Transportation (30), Financial Services (32), and Leasing and Business Services (34). This configuration demonstrates that Beijing’s digital economy is deeply embedded within an industrial base composed of high-end manufacturing and producer services.

Further examination of the dynamic migration paths of these sectors reveals a structural transition in the driving forces of Beijing's digital economy, despite the overall stability of the core configuration. Notably, the centrality of Digital Product Manufacturing (1) exhibited a fluctuating downward trend during the investigation period. This shift reflects the progression of the digital economy into a more mature stage: as foundational digital infrastructure was completed, the marginal impact of hardware manufacturing on the network diminished, allowing the driving momentum to shift toward digital applications and integration.

In contrast, the centrality of the Financial (32) and Leasing and Business Service sectors (34) rose significantly, as evidenced by the intensifying colors in the heat map over time. This ascent

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is largely attributable to Beijing's targeted policy support for digital finance and trade; these sectors successfully absorbed digital technology spillovers, thereby enhancing their resource allocation and intermediary support capabilities within the network. This trajectory signifies a logical pivot from "hardware support" to "service empowerment" and reflects the revitalized competitiveness of modern services in a digital environment. Furthermore, most peripheral traditional sectors experienced minimal changes in their centrality rankings, manifesting a "stable core and viscous periphery" distribution. This pattern suggests that while local momentum shifts are occurring, the diffusion of digital dividends remains constrained by existing industrial structures and path dependencies.

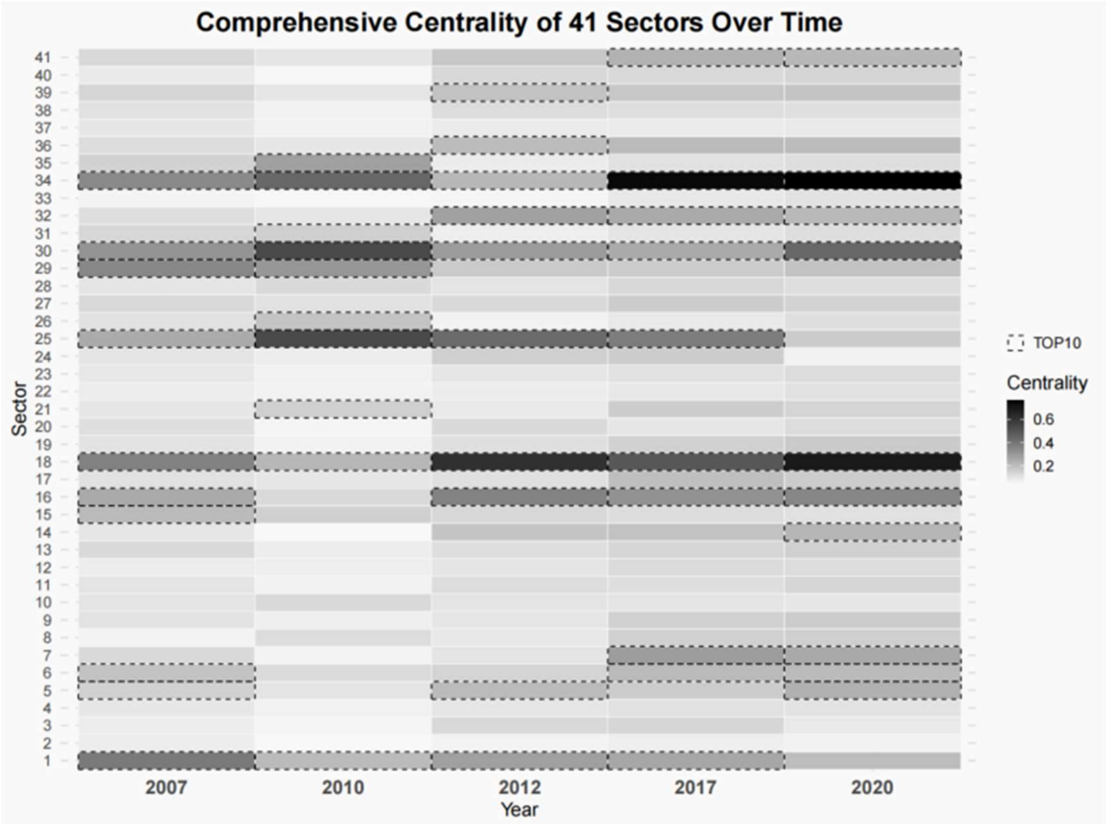

Figure 1. Heat map of the comprehensive centrality of the digital economy industry

3.3. Robustness Simulation and Structural Stability Analysis

This study quantitatively evaluates the survivability of Beijing's digital economy industrial network under various external shocks by simulating both Random Attacks and Intentional Attacks. The simulation results reveal a distinct "robust yet fragile" structural configuration within the system throughout the observation period. On one hand, the network exhibits significant robustness against random shocks, with the response curves for each year showing a slow and smooth decay. Taking 2020 as an example, even when 50% of the nodes are removed at random, global network efficiency remains above 0.15. This suggests that the network foundation, composed of a vast number of peripheral industries, provides ample buffer space, making it difficult for non-targeted, stochastic failures to trigger a systemic collapse.

On the other hand, the network demonstrates extreme sensitivity to intentional attacks, with efficiency curves exhibiting a precipitous, "cliff-like" decline at the early stages of node removal. In the 2020 simulation, removing only the top 10% of high-centrality nodes caused global efficiency to plummet from an initial 0.239 to approximately 0.10-a reduction of over 50%. This asymmetric response trajectory confirms that Beijing's digital economy relies heavily on a few

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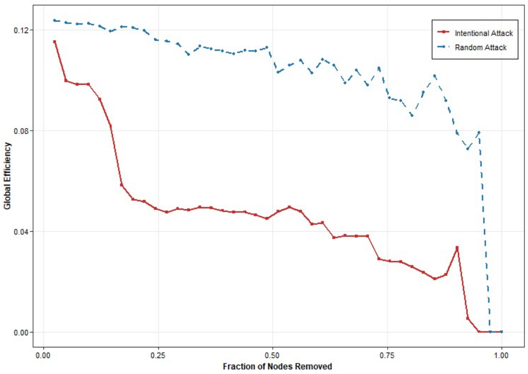
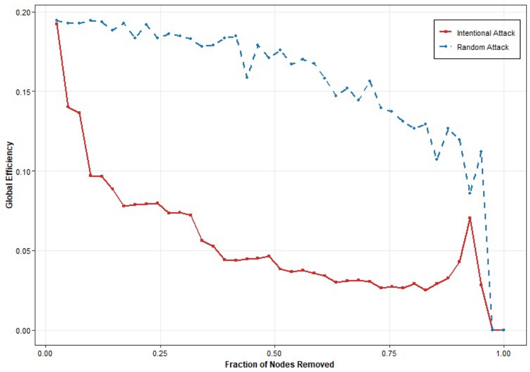
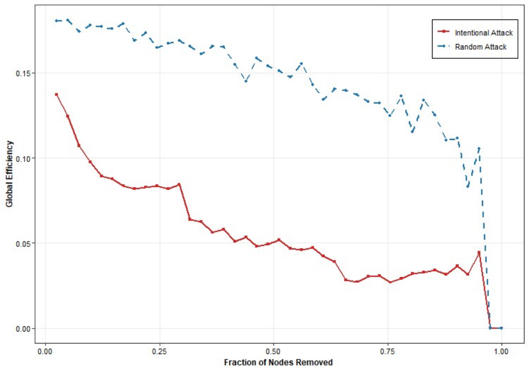
critical hub nodes; the failure of these core pathways can easily generate a cascade effect, leading to a rapid breakdown of overall systemic coordination.



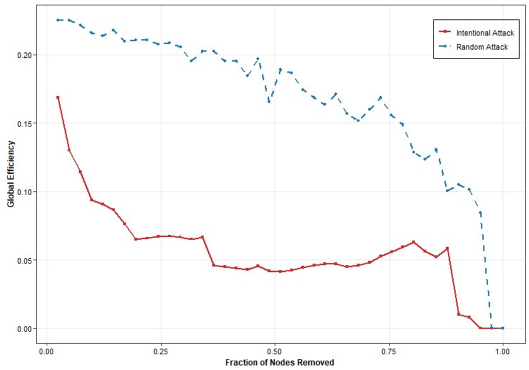
(a)2007



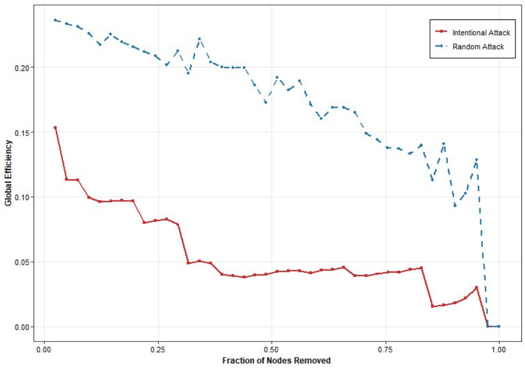
(b)2010



(c)2012



(d)2017



(e)2020

Figure 2. Robustness Simulation for Beijing's Digital Economy Industry Network

From an evolutionary perspective, the advancement in systemic efficiency has been accompanied by heightened structural stability risks. A comparison of the simulation curves between 2007 and 2020 shows that as global efficiency climbed from 0.124 to 0.239, the initial slope of the intentional attack curve became significantly steeper, and the time required to reach the collapse threshold was notably shortened. This shift highlights a fundamental "efficiency-robustness trade-off" in the evolution of Beijing's digital economy: as industrial linkages transition from "extensive connectivity" to "deep integration," technical support within core chains is strengthened, but systemic risks simultaneously aggregate within hub sectors such as Financial Services and Leasing and Business Services. Because these sectors perform vital resource allocation and intermediary functions, any targeted disruption to them propagates rapidly through the intensified input-output linkages. Consequently, while pursuing evolutionary efficiency, the system has partially sacrificed its structural interference resistance,

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resulting in a precarious balance of "high efficiency and high sensitivity". Thus, identifying and protecting core hub industries has become essential for mitigating systemic industrial risks and ensuring the security of the digital economy industrial chain.

4. Conclusion and Policy Implications

By utilizing longitudinal input-output data for Beijing from 2007 to 2020, this study systematically analyzes the structural patterns and stability of the digital economy industrial network through the IO-SNA paradigm. The primary findings are as follows:

First, the network has transitioned from linkage stability toward an efficiency leap. Throughout the study period, the network consistently maintained prominent "small-world" characteristics, with the average path length remaining at a low level of 1.45-1.47 and the clustering coefficient staying high at approximately 0.82. These features provide a solid topological foundation for technical spillovers and information diffusion. Notably, while the network density fluctuated narrowly around 0.53, global network efficiency surged by 92.7%-from 0.124 to 0.239. This trend reveals that Beijing's digital economy has achieved a qualitative leap from extensive connectivity to deep integration, shifting its logic from simple connection existence to a structural reorganization of linkage intensity.

Second, the industrial network exhibits a "stable core and viscous periphery" pattern, with driving momentum shifting from hardware to services. Analysis of comprehensive centrality shows that sectors such as Digital Product Manufacturing, Financial Services, and Leasing and Business Services remain the primary network hubs. Dynamically, as digital infrastructure construction reached maturity, the centrality of the hardware-focused Digital Product Manufacturing sector declined. In contrast, modern service sectors like Financial Services and Leasing and Business Services experienced a significant rise in status, driven by policy guidance and digital technology spillovers. This trajectory reflects a structural pivot from "hardware support" to "service empowerment" within Beijing's digital evolution.

Third, the network demonstrates a "robust yet fragile" nature, facing challenges from an efficiency-robustness trade-off. Robustness simulations prove that while the network is highly resilient to random shocks, it remains extremely sensitive to intentional attacks targeting core hubs. As systemic collaborative efficiency improves, risks increasingly aggregate within high-centrality hub sectors. This concentration leads to a steeper decline in efficiency and an earlier collapse threshold during targeted disruptions. These results suggest that in its pursuit of evolutionary efficiency, the system has partially sacrificed its structural resistance to extreme shocks, forming a precarious balance of "high efficiency and high sensitivity."

Based on the empirical findings, this study proposes the following policy recommendations:

Prioritize the protection of core hub sectors to safeguard industrial chain security. Given the system's heavy dependence on hubs like finance, business services, and digital manufacturing, authorities should establish risk early-warning mechanisms for these "lifeline" industries. This is crucial to prevent local shocks from escalating into systemic failures through intensified input-output linkages.

Balance evolutionary efficiency with structural stability during the integration of digital and real economies. Policymakers should focus not only on increasing linkage intensity but also on constructing diversified industrial pathways. By mitigating excessive risk concentration, the digital economy network can enhance its self-healing capacity and pressure resistance when facing extreme external shocks.

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