Journal of Applied Economics and Policy Studies Vol.19 Issue 9 EWA Publishing
Available Online: 31 August 2026 DOI: 10.54254/2977-5701/2026.36430

# Research on measuring risks in digital service trade between China and OECD countries

***Ziyue Liu, Chuanrong Huang*, Yuyuan Liu, Ting Ren***

Wu Jinglian School of Economics, Changzhou University, Changzhou, China

*Corresponding Author. Email: hcr@cczu.edu.cn

**Abstract.** Against the backdrop of rapid global growth in digital service trade and complex international dynamics, risks associated with digital service trade have emerged as critical factors affecting industrial security and trade stability. This study examines China's trade with 32 OECD member states, utilizing digital service trade data from the UNCTAD database (2010~2024). Employing complex network analysis and kernel density estimation, it constructs a digital service trade network between China and OECD countries to reveal trade network characteristics, track the evolution of trade risks, and construct an early warning table. Findings indicate that while the density of China's digital service trade network with OECD countries continues to rise, reflecting increasingly close trade ties, a pronounced core-periphery structure persists. Kernel density estimation reveals that China's digital service trade competitiveness with OECD countries exhibits a fluctuating evolutionary feature, with some countries exhibiting clusters of heightened risk. Early warning system based on risk metrics identifies Greece, Hungary and others as orange-level high-alert countries, providing precise targets for the prevention and control of digital service trade risks. The findings of this study provide empirical support and policy references for China to address digital service trade risks and optimize its trade layout.

**Keywords:** digital service trade, trade risk, complex network analysis, kernel density estimation, risk early warning

## 1. Introduction

The rapid development of digital technology has driven the digital transformation of global trade. Digital services trade has become the core engine of global trade growth, with its share in total global trade in services continuing to climb [1]. In particular, the globalization trend of digital services trade has become more pronounced since the COVID-19 pandemic [2]. China's digital services trade exports grew from US$31.235 billion in 2010 to US$77.044 billion in 2024, representing a growth rate of up to 146.66% and demonstrating a strong development momentum. Organization for Economic Cooperation and Development (OECD) member countries are a major force in global digital trade, with advanced economies and the lowest level of digital trade restrictiveness [3]. As the major economy with the largest increase in global digital trade share, China and OECD member countries both occupy a pivotal position in global digital trade and are key interactive players in the field of digital services trade.

However, increasingly stringent global digital trade regulation, prominent barriers in infrastructure and connectivity, fragmented cross-border data flow rules coupled with intensifying data localization restrictions, and significant regional regulatory disparities have exposed digital services trade between China and OECD countries to multiple risks and challenges [4]. Factors including the rise of trade protectionism [5], growing non-tariff barriers, and government support for domestic industries may all trigger trade disruptions or competitiveness fluctuations, posing a threat to the sustainable development of China's digital services trade. Against this backdrop, systematically analyzing the structural characteristics of the digital services trade network between China and OECD countries and accurately monitoring the evolution trend of trade risks carries important theoretical and practical significance for safeguarding industrial security and enhancing trade resilience.

## 2. Literature review

The deep penetration of digital technologies has accelerated the restructuring of the global trade pattern. Digital service trade has become the core engine driving the growth of international trade. Its proportion in total global service trade continues to rise. Meanwhile, issues such as deglobalization sentiment, geopolitical conflicts and the fragmentation of digital trade rules have become increasingly prominent, and the barriers and risks confronting digital services trade keep amplifying, posing a significant challenge to trade stability [6]. Against this background, research on digital service trade risks has become a hot topic. Scholars at home and abroad have carried out a series of discussions on relevant dimensions. However, most existing studies suffer from insufficient scenario focus and single research methods. Based on the bilateral trade scenario between China and OECD countries, this paper integrates multiple methods to construct a risk measurement and early warning system. It provides theoretical support and empirical reference for risk prevention and control.

Research on digital trade has formed a multi-dimensional system. It mainly focuses on digital trade rules, digital trade barriers, influencing factors of digital trade and multi-dimensional economic effects of digital trade on carbon emissions, industrial development and corporate competitiveness. On digital trade rules, Suh et al. empirically found that bilateral trade agreements with digital trade provisions can significantly increase trade flows [7]. More specific rules produce stronger promotion effects. Restrictive domestic regulations of importing countries significantly inhibit digital trade. Jiang et al. confirmed that digital service level significantly promotes the export of digital service trade based on data from 71 countries around the world [8]. This effect shows obvious heterogeneity in low- and middle-income countries. Natanael emphasized the important role of institutional quality in digitally delivered service trade [9]. Corruption control and government effectiveness significantly promote the expansion of trade scale. Li et al. further revealed that the deepening of digital trade rules can reshape the international division of labor by enhancing the new comparative advantages of data factors [10]. It promotes the growth of bilateral trade flows and the improvement of product diversity. In the field of digital trade barriers, Ferracane et al. found that strict data policy restrictions have a significant negative impact on the productivity of enterprises in data-dependent industries [11]. Van Der Marel et al. confirmed that restrictive data policies are significantly negatively correlated with imports of data-intensive services [12]. The restrictive effect of cross-border data flow restrictions is particularly prominent. Zhang et al. pointed out that digital trade barriers significantly inhibit import trade by raising information costs [13]. They also affect both the intensive margin and extensive margin of imports. Ma et al. systematically sorted out the types of new digital trade barriers [14]. They clarified their multi-dimensional impacts on the high-quality development of China's digital trade. On the influencing factors of digital trade, Li et al. confirmed that economic scale, industrial structure, scientific and technological talents and other factors can significantly improve the resilience of China's digital trade under the background of trade frictions [15]. The level of resilience shows significant spatial differences among regions. In the research on economic effects of digital trade, Qiu et al. confirmed that digital service trade can promote the high-quality development of global manufacturing through technological innovation and industrial structure upgrading [16]. On carbon emissions, Chen et al. found an inverted U-shaped nonlinear relationship between digital service trade and carbon emissions [17]. Li et al. confirmed that digital trade has an overall significant low-carbon effect [18]. The effect shows heterogeneity at different national development levels. Ma et al. focused on regional trade agreements [19]. They pointed out that US-style digital trade rules positively promote trade between China and CPTPP member countries. Liu et al. pointed out that digital service trade in RCEP economies can achieve emission reduction through scale and technological effects [20]. In addition, Liu et al. found that digital service trade can significantly improve carbon total factor productivity through technological progress and industrial structure upgrading [21]. Tang et al. confirmed that digital trade can promote the rational upgrading of China's manufacturing structure through multiple channels [22]. It has regional heterogeneity and threshold effect. Wu et al. microscopically confirmed that digital trade can improve corporate competitiveness through three paths [23]. These paths are asset expansion, cost reduction and efficiency improvement. In summary, existing studies have achieved rich results on the rules, barriers, influencing factors and economic effects of digital trade. However, special research on digital trade risks is still rare. Existing discussions mostly stay at the theoretical level. Research on quantitative measurement, dynamic evolution and early warning system construction of digital trade risks needs to be further expanded.

On risk measurement methods, existing achievements have evolved from single indicators to multi-method integration. A mature measurement system for digital service trade has not yet been formed. Early studies mainly adopted the single-index method. Zeng et al. measured trade competitiveness risk by the change rate of net export revealed comparative advantage index [24]. They designed a risk monitoring system combined with kernel density estimation. Wang et al. constructed a multi-index evaluation system from the dimensions of import stability and resource availability [25]. They dynamically assessed copper trade risks. Xu et al. combined ARIMA algorithm and BP neural network [26]. They built a combined forecasting model for international trade risks. Wintle et al. optimized the transparency of risk assessment through Bayesian networks [27]. However, existing studies have obvious limitations. Most risk measurements focus on traditional industries such as copper resources and energy. They rarely involve digital service trade. At the same time, single methods are mostly used. There is a lack of multi-method cross-validation. The innovation of this paper lies in this. It integrates complex network analysis and kernel density estimation. It identifies risk transmission paths and structural vulnerabilities from the topological structure level. It quantifies the intensity of risk evolution from the perspective of competitiveness fluctuation. It realizes dual verification and accurate measurement of digital service trade risks. It fills the core gap of existing research.

In summary, scholars at home and abroad have built a relatively complete research system on digital trade rules, digital trade barriers, influencing factors, economic effects and risk measurement methods. It has laid a solid foundation for the development of this field. But there are still two core deficiencies. First, the research scenarios are generalized. There is a lack of risk research on bilateral digital service trade between China and OECD countries. Second, the risk measurement methods are single. There is a lack of multi-method cross-validation system for digital service trade. Based on this, this paper takes China and 32 OECD member countries as research objects. It systematically depicts the evolutionary characteristics of trade networks based on bilateral trade data from 2010 to 2024. It quantifies the dynamic fluctuation of competitiveness. It constructs a risk early warning system. It not only enriches the scenario and methodological connotation of digital service trade risk research. It also provides empirical support and policy reference for China to cope with bilateral trade risks and optimize trade layout.

# 3. Research design

## 3.1. Data sources

This study utilizes data from the UNCTAD database, selecting digital service trade figures between China and 32 OECD member states from 2010 to 2024. The data encompass trade volumes of fields including insurance services, personal services, telecommunications services, financial services, and other related services. As emphasized by Herman et al., Internet usage and bandwidth capacity serve as critical foundations for digital trade [28]. Future research could further incorporate network infrastructure indicators to more comprehensively capture the drivers of trade. During data processing, significant data gaps and numerous outliers were encountered in early years for some countries. Consequently, complex network analysis, kernel density estimation, and risk warning primarily utilize the 2010~2024 data as the core sample. This study takes the data covering the period from 2010 to 2024 between China and the 32 remaining OECD member states after excluding Chile, Colombia, Costa Rica, Mexico, Norway and Türkiye as the core of its research.

## 3.2. Digital service trade network model between China and OECD countries

### *3.2.1. Network construction and visualization*

Based on complex network theory, this research regards China and 32 OECD member countries as network nodes and uses bilateral digital service trade import and export volumes as edges to construct a digital service trade network between China and OECD countries. Following standardized processing, this network is denoted as $W^U = (V, E)$, where $V$ and $E$ represent the sets of network nodes and edges respectively. Network characteristic metrics and node characteristic metrics were subsequently calculated:

#### *3.2.1.1. Data processing*

Following the method of Ma et al., data from 2010 to 2024 were utilized. First, the average values of bilateral import and export data were calculated, then normalized by mapping all values to the [0,1] interval to eliminate magnitude differences [29]. Subsequently, symmetry tests were conducted on the symmetry index referenced in Fagiolo [30]. The symmetry index ranged from 0.00212 to 0.01716, confirming data symmetry. Consequently, the diagonal maximization symmetrical method was employed to transform the weighted directed trade network matrix $W^D$ into an undirected weighted trade network matrix $W^U$. Finally, using $W^U$ as the baseline, network characteristic metrics and node characteristic metrics were calculated respectively. Considering the inconsistency in statistical definitions between importing and exporting countries, data supplementation was performed by using the export value from $i$ to $j$ in the same year to adjust the import value from $j$ to $i$.

This study employs 2010, 2014, 2017, 2020, and 2024 as key reference points for analyzing China's digital service trade networks with OECD countries. The selection of these years not only encompasses important phases in the global development of digital service trade but also corresponds to critical nodes in the evolution of network structures. Consequently, these five years facilitate a systematic revelation of the dynamic evolution mechanism of network structure, providing a temporal framework for deepening our understanding of the formation and transmission of trade risks. Furthermore, Community modularity division is conducted based on import data in 2010, 2014, 2017, 2020 and 2024. Accordingly, trade relationship characteristics between China and 32 OECD countries are thoroughly analyzed from three dimensions: overall network structure, node centrality, and community modularity division.

*3.2.1.2. Complex network construction and modularity division*

Using initial import and export data from 2010, 2014, 2017, 2020, and 2024 as the foundation, with the 32 OECD countries and China as nodes, and bilateral trade volume as edge weights, the weighted network features node sizes positively correlated with node weighted degree (accounting for both the number of trading partners and trade volume), edge thickness positively correlated with trade volume and arrow direction preserving trade flow directionality, establishing directed trade networks for 2010, 2014, 2017, 2020, and 2024.

Modularity analysis of the import trade networks for 2010, 2014, 2017, 2020, and 2024 was performed using the *Gephi* software. The modularity metric was calculated via the *Louvain* algorithm, achieving node clustering by maximizing modularity.

*3.2.2. Overall network characteristics*

*3.2.2.1. Network density*

The network density formula is given in Equation (1):

$$D = \frac{2m}{n(n-1)} \tag{1}$$

where $n$ denotes network nodes, and $m$ represents the actual number of trade edges within the network. Higher density indicates tighter network connectivity and more alternative paths between nodes. When a trade relationship is interrupted, it can quickly switch to other paths, improving the network resilience.

*3.2.2.2. Average path length*

The average path length formula is given in Equation (2):

$$\bar{d} = \frac{2}{n(n-1)} \sum_{s<t\in V} d_G(s,t) \tag{2}$$

where $d_G(s,t)$ is the shortest path length from node $s$ to node $t$, and $V$ is the total number of nodes in the network. This metric reflects the ease of trade connections and the network's accessibility. Shorter paths indicate higher connectivity efficiency. When some nodes fail, the remaining nodes can still rapidly establish connections, reducing trade disruption losses and enhancing network stability.

*3.2.2.3. Average clustering coefficient*

This formula references memory triangle computation method for large scale sparse power law graphs, as proposed by Latapy [31]. The average clustering coefficient formula is given in Equation (3):

$$C(v) = \frac{2T(v)}{d(v)\times[d(v)-1]} \tag{3}$$

$T(v)$ is the number of triangles formed by vertex $v$ and its two neighbor nodes; $d(v)$ is the number of all possible edges among the neighbors of vertex $v$. The tighter the internal connections within China's trade community, the more robust the mutual assistance network becomes. When a node in the community fails, other nodes can substitute and supplement, thereby improving local robustness.

*3.2.3. Node individual characteristics*

*3.2.3.1. Node weighted degree*

The node weighted degree formula is given in Equation (4):

$$WD_i = \sum_{j=1,j\neq i}^{n} w_{ij} \tag{4}$$

$w_{ij}$ is the bilateral digital service trade volume between node $i$ and node $j$. A larger value indicates a larger trade scale of node $i$ and a closer connection with other nodes.

*3.2.3.2. Eigenvector centrality*

The eigenvector centrality formula is given in Equation (5):

$$EC_i = \frac{1}{\lambda} \sum_{j \in F} w_{ij} EC_j \tag{5}$$

$EC_j$ is the eigenvector centrality of node $j$, $\lambda$ is a constant, and $F$ is the set of digital service trade neighbors of node $i$. $w_{ij}$ is the bilateral digital service trade volume between node $i$ and node $j$. If the OECD countries connected to China are all core network nodes, a strong linkage is formed. Even if some peripheral nodes are disconnected, the core linkage network can still be maintained, resulting in better resilience. Conversely, if the network relies on peripheral nodes, it will be more vulnerable to shocks.

*3.2.3.3. Closeness centrality*

This formula references the research of Sabidussi [32]. The closeness centrality formula is based in Equation (6):

$$C_C(v) = \frac{1}{\sum_{t \in V} d_G(v,t)} \tag{6}$$

$C_C(v)$ is the closeness centrality of node $v$, and $d_G(v,t)$ is the shortest path length from node $v$ to node $t$. A higher centrality indicates that China occupies a more core position in the network and has stronger accessibility. Even if some peripheral nodes are disconnected, it can still maintain connections with core nodes and ensure trade continuity.

*3.2.3.4. Betweenness centrality*

This formula references the research of Freeman and Brandes. The betweenness centrality formula is given in Equation (7) [33, 34]:

$$C_B(v) = \sum_{s \neq v \neq t \in V} \frac{\sigma_{st}(v)}{\sigma_{st}} \tag{7}$$

$\sigma_{st}$ is the number of shortest paths from node $s$ to node $t$, and $\sigma_{st}(v)$ is the number of $s-t$ shortest paths passing through node $v$. The ratio of the two represents the proportion of $s-t$ shortest paths passing through node $v$; a higher value indicates a more prominent hub and intermediary role of the node. A higher betweenness centrality means that China is a key hub in the network. If the Chinese node is affected, it may cause the disruption of trade paths among some OECD countries, directly affecting the overall robustness of the network.

## 3.3. Modularity analysis

Drawing on the research methodology adopted by Yin Xiaoxiao et al., the *Louvain* algorithm is employed for community partitioning [35]. The core quality of community partitioning is measured via modularity $Q$, whilst local optimization of node movement is achieved through modularity gain $\Delta Q$, ultimately maximizing the modularity value. The cumulative effect of local gains drives the maximization of global modularity $Q$, forming the core mechanism by which the *Louvain* algorithm efficiently processes large scale weighted trade networks [36]. Furthermore, by integrating the temporal resolution concept proposed by Lambiotte et al., the optimization precision during iteration can be adjusted to accommodate community structure identification requirements at different hierarchical levels, thereby avoiding the inherent resolution limitations of modularity [37].

*3.3.1. Modularity Q*

The calculation of Modularity $Q$ constitutes the core formula of modularity analysis, as presented in Equation (8):

$$Q = \frac{1}{2m} \sum_{i,j} [A_{ij} - \frac{k_i k_j}{2m}] \delta(c_i, c_j) \tag{8}$$

$A_{ij}$ is the edge weight between nodes $i$ and $j$; $k_i$ represents the total weight for node $i$; $m$ denotes half of the total digital trade in service within the network; $c_i$ indicates the community to which node $i$ belongs; $\delta(u, v)$ is the Kronecker delta, equating to 1 when $u = v$, signifying that nodes $i$ and $j$ belong to the same community, and 0 otherwise. A higher modularity indicates a clearer community structure, with relatively independent functional communities. When a certain community fails, it is not easy to spread to the entire network, thus improving the overall robustness.

*3.3.2. Modularity gain ΔQ*

When node $i$ moves from its original community to target community $C$, the modularity gain is calculated as per formula (9):

$$\Delta Q = [\frac{\sum_{in} + k_{i,in}}{2m} - \frac{(\sum_{tot} + k_i)^2}{(2m)^2}] - [\frac{2m \cdot \sum_{in} - (\sum_{tot})^2}{(2m)^2} - (\frac{k_i}{2m})^2] \tag{9}$$

$\sum_{in}$ and $\sum_{tot}$ represent the sum of edge weights within the target community $C$ and the sum of all internal and external edge weights in the target community $C$; $k_i$ denotes the total weight of node $i$; $k_{i,in}$ represents the sum of edge weights between node $i$ and all nodes in the target community $C$; $m$ signifies the total network weight.

*3.3.3. Computational logic support of ΔQ for Q*

The core essence of modularity $Q$ lies in measuring the difference between the total edge weight within a community and the expected total edge weight in a random network. A greater difference indicates a clearer community structure. However, globally optimizing the community membership of all nodes across the entire network incurs extremely high computational complexity. $\Delta Q$ provides critical support for the efficient computation of $Q$ through local iterative optimization. Its computational logic is as follows.

*3.3.3.1. Local gain quantification*

$\Delta Q$ focusing on the community migration behaviour of a single node $i$, precisely calculates the magnitude of its impact on the overall modularity $Q$. The first half of the formula represents node $i$ 's local modularity contribution after migrating to target community $C$, while the latter half denotes its contribution prior to migration. The difference between these two values constitutes the change in $Q$ induced by the migration.

*3.3.3.2. Iterative optimization criteria*

If $\Delta Q > 0$, it indicates that migrating node $i$ to target community $C$ enhances overall modularity, thus retaining the migration. If $\Delta Q \leq 0$, node $i$ remains in its original community.

*3.3.3.3. Global optimal convergence*

The aforementioned migration-evaluation process is executed sequentially for all nodes in the network until no single migration can further lead to $\Delta Q > 0$ for any node's community affiliation, thus the first phase of optimization is completed. Subsequently, each community is treated as a supernode, and the node migration and $\Delta Q$ calculation processes are iterated until modularity $Q$ reaches its maximum value, which yields the optimal community partitioning result.

This logic circumvents the high complexity of global optimization while maximizing global modularity $Q$ through the accumulation of local gains. It constitutes the core mechanism enabling the $Louvain$ algorithm to efficiently process large scale weighted trade networks.

### 3.4. Kernel density estimation model

Kernel density estimation and the rate of change in the Net Export Revealed Comparative Advantage Index ($\Delta NXRCA$) are applicable to the risk research of digital service trade. Their core logic lies in that both methods precisely meet the requirements for risk quantification and distribution characterization. By calculating the rate of change in the Net Export Revealed Comparative Advantage Index among consecutive years, $\Delta NXRCA$ directly captures the dynamic fluctuations in China's and OECD countries' competitiveness within digital service trade. A significantly negative value indicates declining trade competitiveness, potentially triggering risks such as market share erosion and trade friction. Moreover, the magnitude of its fluctuations reflects the scale of risk exposure, which aligns closely with of digital service trade risk – namely, "competitiveness fluctuations leading to revenue losses". As a non-parametric fitting method, kernel density estimation requires no predefined data distribution. It intuitively presents the probabilistic distribution characteristics of $\Delta NXRCA$ across different countries and periods. Through peak positions, bandwidth sizes, and distribution patterns (uni-modal/bimodal), it clearly illustrating overall competitiveness trends, risk disparities between nations, and the differentiation of high risk clusters. This approach not only overcomes the limitations of traditional single metrics in balancing "overall trends" and "individual variations" but also provides visual support for risk identification and the identification and location of risk clusters. Complementing complex network analysis, it establishes a quantitative foundation for constructing risk early-warning mechanisms.

Drawing upon the methodology of Zeng Mengxia et al. [24], the rate of change in net export revealed comparative advantage ($\Delta NXRCA$) serves as the metric for change in trade competitiveness. The calculation formula is given in Equation (10):

$$\Delta NXRCA_{it} = \frac{NXRCA_{it} - NXRCA_{i(t-1)}}{|NXRCA_{i(t-1)}|} \qquad (10) \tag{10}$$

where, $NXRCA_{it}$ denotes the net export revealed comparative advantage index between China and OECD country $i$ in year $t$. Density estimation employs a normal kernel function, with optimal bandwidth determined via a two stage plug in method to fit the distribution characteristics of $\Delta NXRCA$ from 2010 to 2024.

Nations constitute the core analytical units within the international service trade landscape, and the precise measurement of trade data at the national level forms the foundation of research. Traditional trade statistics predominantly focus on aggregate performance, often overlooking the dynamic differences and distributional nuances of comparative advantages in digital service trade across nations. Building upon the calculation of $\Delta NXRCA$, this study integrates statistical distribution theory with research on comparative advantages in international service trade. Treating China and OECD countries as sample units within the population, it employs kernel density estimation—a non-parametric statistical method—to fit and smooth the distribution of $\Delta NXRCA$ across nations. This approach, preserves the informational detail of the original data while clearly revealing the dynamic evolution and distributional variations in each country's trade competitiveness, providing a more precise perspective for analyzing trade competitive patterns at the national level.

Employing the normal kernel function kernel density estimation method used by Zeng Mengxia et al. [24], a fitting analysis is conducted of the dynamic distribution characteristics of comparative advantage in digital service trade for China and OECD countries. The specific estimation formula is given in Equation (11):

$$f_h(x) = \frac{1}{\sqrt{2\pi}nh} \sum_{i=1}^{n} exp[-\frac{1}{2}(\frac{x-\Delta NXRCA_i}{h})^2] \tag{11}$$

where $n$ denotes the effective sample size, i.e., the total number of China and OECD countries participating in the kernel density estimation (excluding countries with missing or anomalous data from $\Delta NXRCA$), $\Delta NXRCA_i$ represents the change in digital service trade comparative advantage for the $i$ th country, reflecting its dynamic changes over time; $h$ denotes the optimal bandwidth, determined by minimizing the Mean Squared Error (MSE) criterion to balance the fitting bias and variance of kernel density estimation results; $exp\,()$ represents the natural exponential function, whose core employs normal distribution logic to smooth data processing, thereby more accurately depicting the continuous distribution pattern of comparative advantages across countries.

## 3.5. Early warning metrics and tier classification

Drawing upon the early warning framework proposed by Zeng Mengxia et al. [24] in 2014 and adapting it to the characteristics of digital service trade, a bidirectional early warning metrics system is constructed, the $EX$ calculation formula is given in Equation (12) and the $Cv$ calculation formula is given in Equation (13):

$$EX = \int_{-\infty}^{\infty} x f h(x) dx = \int_{-\infty}^{\infty} x \frac{1}{\sqrt{2\pi} nh} \sum_{i=1}^{n} exp[-\frac{1}{2}(\frac{x-xi}{h})^2] dx \tag{12}$$

$$= \frac{1}{n}\sum_{i=1}^{n} xi \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi}} exp(-\frac{t^2}{2}) dt + \frac{1}{n}\sum_{i=1}^{n} h \int_{-\infty}^{\infty} t \frac{1}{\sqrt{2\pi}} exp(-\frac{t^2}{2}) dt$$

$$= \frac{1}{n}\sum_{i=1}^{n} xi$$

$$Cv = \frac{SD}{mean} = \sqrt{\frac{\sum_{i=1}^{n}(x_i-\overline{x})^2}{n}} / \overline{x} \tag{13}$$

Here, $EX$ represents the mathematical expectation of the $\Delta NXRCA$ index for all sectors within the industry, obtained via kernel density estimation. This constitutes the average trade competitiveness index for the industry under study across nations, reflecting overall competitiveness trends. In its calculation formula, $n$ denotes the total valid sample size for China and OECD countries participating in the assessment; $x_i$ denotes the $\Delta NXRCA$ index for the digital service trade of the $i$-th country, indicating the direction of competitive shifts in that sector over time; $h$ represents the optimal bandwidth for kernel density estimation, determined by minimizing the mean squared error criterion to balance estimation accuracy with curve smoothness; $exp\,()$ is the natural exponential function, employed to achieve normalized data smoothing for a more precise characterization of the continuous distribution of national competitiveness. According to Zeng Mengxia et al. [24], when $EX > 0$, competitiveness is enhanced; $EX \in (-0.1, 0]$ indicates slight decline; $EX \in (-0.2, -0.1]$ signifies moderate decline; and $EX \leq -0.2$ denotes severe decline.

$Cv$ denotes the coefficient of variation, representing the relative dispersion of data obtained by dividing the standard deviation by the mean ($EX$). It eliminates dimensional differences across industries, measuring the divergence of $\Delta NXRCA$ indices among countries within the industry. Higher values indicate more pronounced competitiveness disparities and correspondingly elevated trade risks. In the coefficient of variation formula, the numerator $SD$ represents the sample standard deviation, characterizing the absolute fluctuation range of the trade competitiveness index $\Delta NXRCA$ for each country's industry. The denominator mean denotes the mean of $\Delta NXRCA$, i.e. $EX$, which neutralizes the effects of measurement scales and average levels. The ratio of these two values, $Cv$ reflects the relative dispersion of competitiveness among countries within the sample. A higher value indicates more pronounced competitiveness disparities within the industry and more prominent differentiation of trade risks. Similarly, by dividing the $|Cv|$ into two tiers and applying the proportional coefficient $a = 10$, values between 0 and 10 are classified as Tier I, while those above 10 constitute Tier II. A rising value indicates intensified disparities in competitiveness among nations.

In summary, early warning standards for industrial competitiveness divergence between China and OECD countries can be established, as shown in Table1.

**Table 1.** Early warning criteria for industrial trade competitiveness divergence risks between China and OECD countries

| *EX* | I | | II | | III | | IV | |
|---|---|---|---|---|---|---|---|---|
| \|*Cv*\| | I | II | I | II | I | II | I | II |
| Police Signal Light | Green | Blue | Blue | Yellow | Yellow | Orange | Orange | Red |

## 4. Analysis of topological characteristics in digital service trade networks between China and OECD countries

Based on China's digital service trade data with OECD countries from 2010 to 2024, the aforementioned network model and metric system, combined with visualization analysis using *Gephi* software, the following topological characteristics were yielded.

### 4.1. Network structural characteristics

As shown in Table 2, network density peaked at 0.97 between 2019 and 2021. During the 2010~2019 period, global digital technology proliferation and trade agreements synergistically enhanced connectivity. Breakthroughs in artificial intelligence and cross border digital delivery technologies reduced trade barriers, significantly boosting trade connectivity. Following 2019, connectivity declined steadily to 0.76 by 2024. Escalating geopolitical conflicts coupled with widening regulatory divergences among nations, particularly policies mandating localized data storage, directly increased institutional barriers to cross border data flows, causing trade connections between nodes to gradually weaken [38]. The average path length reached a low of 1.03 in 2019 but rising to 1.24 in 2024, indicating that the efficiency of trade transmission across nodes initially improved before declining. The average clustering coefficient peaked at 0.98 between 2019 and 2023, subsequently falling to 0.93 in 2024. According to data from the *China Trade in Services Development Report 2024*, travel imports and exports reached US$288.02 billion in 2024, representing a year on year increase of 36.6% and marking the fastest growth across all service trade sectors for two consecutive years [39]. It is therefore inferred that the robust recovery in tourism related trade in service during 2024 displaced digital service trade, leading to a marginal weakening of network clustering effects. Overall, the network's resilience to risks and the evolution of metrics proceeded in tandem, showing an enhancing trend prior to 2019 before, but declining steadily thereafter due to loosening connections, lengthening pathways, and weakened clustering.

**Table 2.** Digital service trade network topology metrics for China and OECD countries (2010~2024)

| | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 | 2019 | 2020 | 2021 | 2022 | 2023 | 2024 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Average Path Length | 1.17 | 1.16 | 1.13 | 1.07 | 1.05 | 1.05 | 1.04 | 1.04 | 1.04 | 1.03 | 1.03 | 1.03 | 1.07 | 1.08 | 1.24 |
| Average Clustering Coefficient | 0.78 | 0.81 | 0.84 | 0.85 | 0.96 | 0.96 | 0.97 | 0.97 | 0.97 | 0.98 | 0.98 | 0.98 | 0.98 | 0.98 | 0.93 |
| Network Density | 0.57 | 0.60 | 0.64 | 0.68 | 0.95 | 0.95 | 0.96 | 0.96 | 0.96 | 0.97 | 0.97 | 0.97 | 0.93 | 0.92 | 0.76 |

### 4.2. Node individual characteristics

The United States and the United Kingdom have consistently occupied core positions within the network, leveraging technological and market advantages. Their metrics have long maintained top two rankings with continuously strengthening dominance. As demonstrated in Tables 3 and Table 4, both nations consistently lead the network in weighted degree, eigenvector centrality, and closeness centrality. The United States has long held the top position in node strength, retaining its lead in 2024. As the primary load bearing entity and path hub within the network, the stability of its metrics directly underpins the network's fundamental resilience against shocks. The UK's closeness centrality has progressively risen from second place in 2017 to first in 2024, continuously enhancing its accessibility and influence over other nodes. Its stable performance in betweenness centrality positions it as a crucial bridge for cross regional trade. Germany, Ireland, and the Netherlands, as secondary cores, exhibit stable metrics with a steady upward trend, with Ireland's node strength ranking among the top three in 2024. Through policies such as its 2022 National Digital Strategy, Ireland has enhanced its digital infrastructure and institutional environment, establishing itself as a specialized trade hub. The stability and weight concentration of its metrics further solidify its role as a risk resilient pillar within the network, though this also heightens the network's dependency on core nodes.

Countries such as Greece, Hungary, Poland, and Slovakia remain on the periphery of the network due to insufficient technological innovation and the absence of targeted digital service trade strategies. Their metrics persistently rank low within the network and exhibit significant volatility, with closeness centrality and betweenness centrality approaching zero. Consequently, they exhibit high dependency on regional cores such as Germany and France. These nations exhibit uneven digital infrastructure development and lack alternative trade pathways, rendering them high risk clusters within the network. Localised disruptions can readily propagate through regional core nodes to broader areas, amplifying overall network risks.

**Table 3.** 2017 Digital service trade network node centrality rankings for China and OECD countries

| Rank | Node Weighted Degree | Closeness Centrality | Betweenness Centrality | Eigenvector Centrality |
|---|---|---|---|---|
| 1 | United States | United States | United States | United States |
| 2 | United Kingdom | United Kingdom | United Kingdom | United Kingdom |
| 3 | Germany | Germany | Germany | Germany |
| 4 | France | France | France | France |
| 5 | Ireland | Ireland | Ireland | Ireland |
| 6 | Netherlands | Netherlands | Netherlands | Netherlands |
| 7 | Switzerland | Japan | Japan | Japan |
| 8 | Japan | Belgium | Belgium | Belgium |
| 9 | Belgium | Luxembourg | Luxembourg | Luxembourg |
| 10 | Luxembourg | Canada | Canada | Canada |
| 11 | Canada | Italy | Italy | Italy |
| 12 | Italy | China | China | China |
| 13 | China | Sweden | Sweden | Sweden |
| 14 | Sweden | Spain | Spain | Spain |
| 15 | Spain | Austria | Austria | Austria |

**Table 4.** 2024 Digital service trade network node centrality rankings for China and OECD countries

| Rank | Node Weighted Degree | Closeness Centrality | Betweenness Bentrality | Eigenvector Centrality |
|---|---|---|---|---|
| 1 | United States | United Kingdom | United Kingdom | United Kingdom |
| 2 | United Kingdom | United States | United States | United States |
| 3 | Ireland | Ireland | Ireland | Ireland |
| 4 | Germany | France | France | France |
| 5 | France | Netherlands | Netherlands | Netherlands |
| 6 | Netherlands | Belgium | Belgium | Belgium |
| 7 | Switzerland | Italy | Italy | Italy |
| 8 | Belgium | Poland | Poland | Poland |
| 9 | Sweden | Finland | Finland | Finland |
| 10 | Italy | Czech Republic | Czech Republic | Czech Republic |
| 11 | Luxembourg | Hungary | Hungary | Hungary |
| 12 | Japan | Greece | Greece | Greece |
| 13 | Poland | Slovakia | Slovakia | Slovakia |
| 14 | Canada | Lithuania | Lithuania | Lithuania |
| 15 | Spain | Estonia | Estonia | Estonia |

As illustrated in Figures 1 to 4, the core metrics of China's nodes exhibit pronounced fluctuations, rising sharply before declining. Between 2010 and 2015, these metrics rose rapidly, driven by the widespread adoption of the internet in China and the rapid growth of cross border e-commerce. Following 2015, volatility diminished, reaching its lowest point in 2024, with betweenness centrality approaching zero levels after 2022. The *2022 Digital Trade in Services Restrictions Index* published by the OECD indicates that China's restriction index remains relatively high, ranking 71st among the 85 economies surveyed. This reflects insufficient openness in China's digital trade in service. This shift stems from China's insufficient core competitiveness in digital service trade, challenges in aligning with international rules, and regional competition diverting trade flows. Consequently, China has gradually transformed from a core enabler during 2010~2015 to an ordinary connecting node after 2015. The network has lost a crucial buffer layer, reducing cross community substitution pathways and indirectly exacerbating structural vulnerabilities.

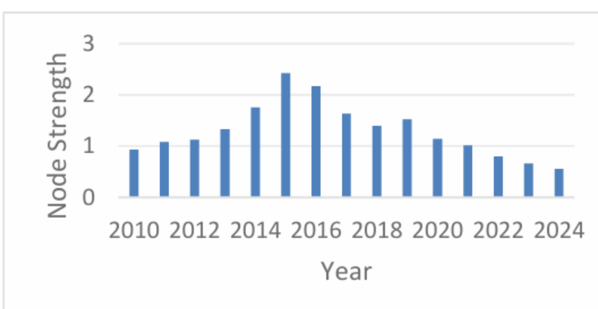


**Figure 1.** Trend in node strength of China's digital service trade network (2010~2024)

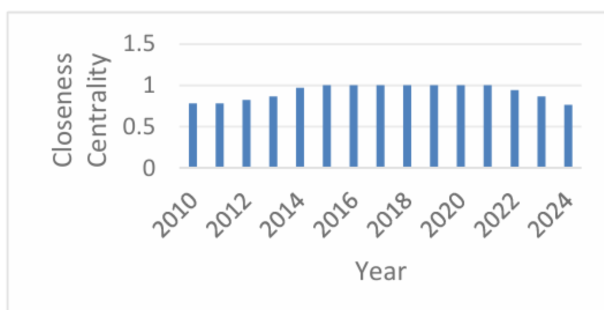


**Figure 2.** Trend in closeness centrality of China's digital service trade network (2010~2024)


**Figure 3.** Trend in betweenness centrality of China's digital service trade network (2010~2024)

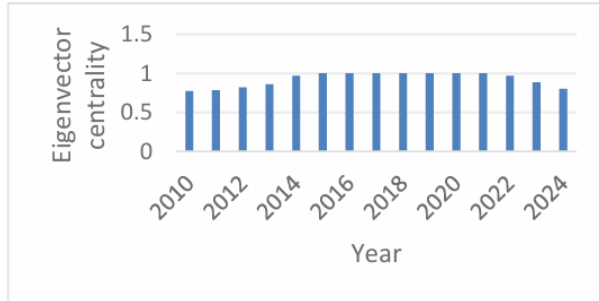


**Figure 4.** Trend in eigenvector centrality of China's digital service trade network (2010~2024)

## 4.3. Characteristics of import and export trade network diagrams for 2010, 2014, 2017, 2020 and 2024

Trade networks depicted by using *Gephi* software (Figures 5~14) reveal significant spatial evolution in China's digital service trade network structure with OECD countries between 2010 and 2024, accompanied by dynamic adjustments to China's role and status within these networks.

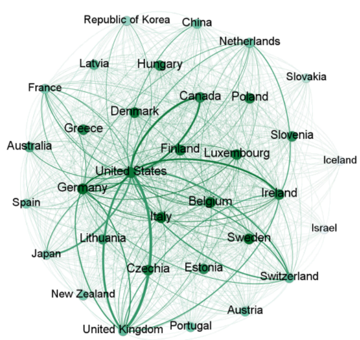


**Figure 5.** Export trade network, 2010

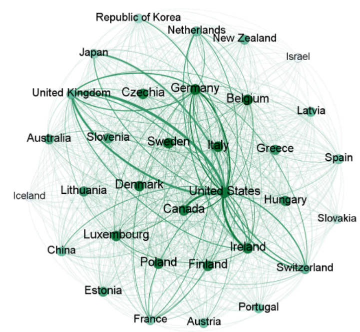


**Figure 6.** Import trade network, 2010

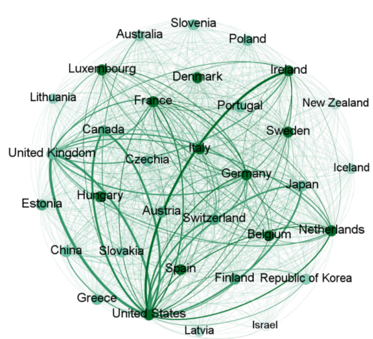


**Figure 7.** Export trade network in 2014

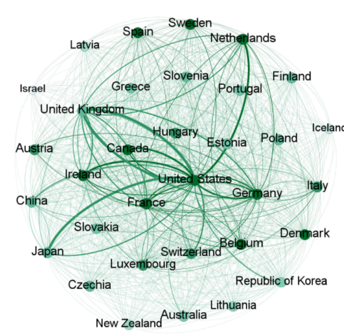


**Figure 8.** Import trade network, 2014

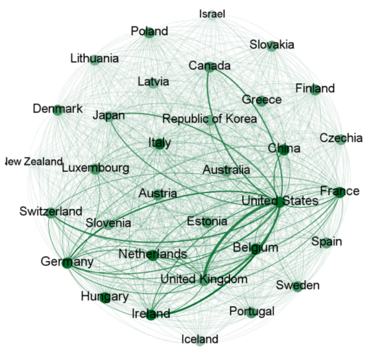


**Figure 9.** Export trade network in 2017

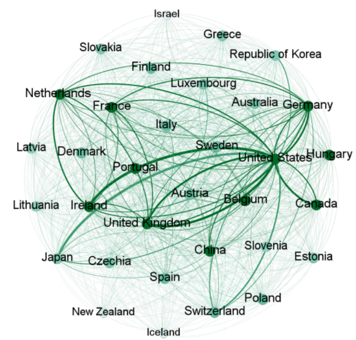


**Figure 10.** Import trade network, 2017

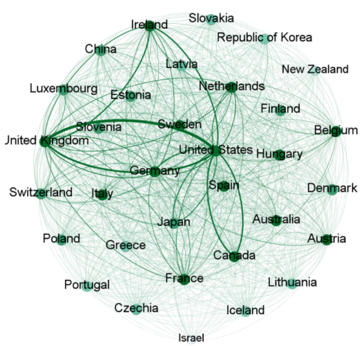


**Figure 11.** Export trade network, 2020

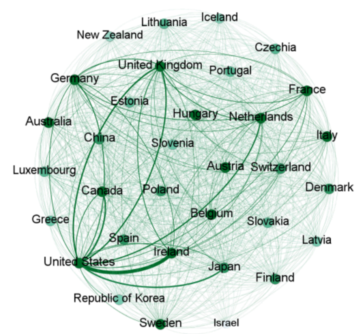


**Figure 12.** Import trade network, 2020

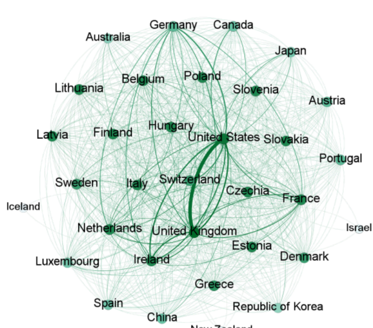


**Figure 13.** Export trade network in 2024

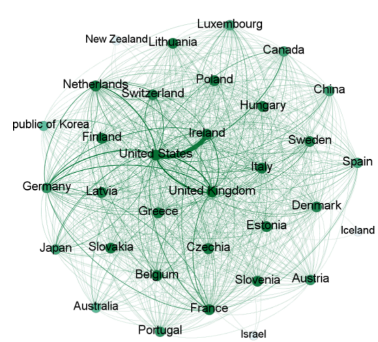


**Figure 14.** Import trade network in 2024

In 2010, the network was in an initial formative stage. The United States and the United Kingdom, leveraging technological first mover advantages and market scale, had already shown the embryonic form of core nodes, though their node size and edge weight dominance had yet to fully manifest. Continental European nations formed locally dense connections, while cross-regional trade corridors between East Asia, North America and Europe remained sparse. Edge weight distribution was relatively balanced, yet overall trade intensity remained low. China occupied a key connecting node position within the East Asian region, with a medium level of node weighted degree. Its initial connections were primarily formed through neighbouring trading partners, and yet it did not play a central hub role in cross-regional trade. The network density at this stage was only 0.83, reflecting the limited penetration of digital technologies and the immaturity of cross-border digital service delivery channels. Digital service trade among nations was predominantly intra-regional, with insufficient cross-regional coordination.

By 2014, the network had begun to establish a basic multi-regional linkage framework. Core nodes such as the United States, the United Kingdom, and Germany had started to demonstrate scale advantages, with relatively close trade ties among major economies in East Asia, North America, and Europe. This reflected the nascent collaborative phase of global digital economic development at that time. As a pivotal node in East Asia, China occupied a key position within the network, connecting trade flows between East Asia and Europe and North America. This demonstrated an active stance in early international cooperation on digital service trade. With digital infrastructure development progressing synchronously across nations and no systemic trade barriers yet established, the trade network exhibited a state of natural diffusion, consistent with a network density of 0.95.

In 2017, network connectivity further strengthened, with node size exhibiting a high positive correlation with weighted degree. Core nodes demonstrated significant scale, while edge weight distribution tended towards equilibrium, resulting in tighter connections between core and peripheral nodes. China maintained its pivotal position within the S-NT1 community, ranking 13th in node weighted degree and serving as a bridge connecting Asia-Pacific with Europe and America in digital service trade. This evolution stemmed primarily from the EU's deepening implementation of its Digital Single Market strategy and the OECD's initial coordination of digital service trade rules through its Base Erosion and Profit Shifting (BEPS) Action Plan, which reduced cross-border transaction costs [40]. Concurrently, accelerated global expansion by digital enterprises from China, the US, and Europe bolstered network connectivity density.

In 2020, the network underwent structural adjustments amid the COVID-19 pandemic. The dominance of core nodes further consolidated, yet connections among peripheral nodes began to show signs of disengagement. While network density remained at a high level of 0.97, a divergence in edge weights between core and peripheral nodes began to emerge. China's intermediary function within the network experienced fluctuations, with metrics such as betweenness centrality declining. This reflects that under external shocks, the connectivity efficiency of China's digital service trade faces temporary challenges. This shift stemmed partly from surging demand for remote working and online services, which reinforced the supply position of core economies. Concurrently, restrictions on cross-border personnel and logistics led to the contraction of non-core trade channels. Furthermore, the intensifying orientation driven by government and technology within digital service trade, coupled with barriers arising from divergent national regulations, further constrained the connectivity efficiency of peripheral nodes.

In 2024, the digital service trade network between China and OECD countries exhibited pronounced core "clustering-periphery marginalization" structural characteristics. Core nodes such as the United States, the United Kingdom, and Ireland continued to expand in scale, with a marked widening of the gap in edge weight distribution between nodes. Direct connections between core and peripheral nodes tended to decrease, while connections among peripheral nodes became even sparser. China remained within the S-NT1 global hub circle, but its node centrality ranking slipped compared to 2017, with eigenvector centrality falling to a relatively low level. This indicates that China faces adjustment pressures on its core influence during the global restructuring of digital service trade rules. This aligns closely with shifts in network morphology and topological metrics: network density has declined to 0.76, while average path length has risen to 1.24, collectively signalling reduced overall connectivity efficiency and weakened resilience.

Overall, China's role within the network's evolution from 2010 to 2024 has shifted from a critical bridge to a significant hub, and subsequently towards structural adjustment. This transformation is driven not only by changes in network structural metrics but also closely intertwined with China's competitiveness in digital service trade, its adaptability to international rules, and interactions with the external environment. The sustained strengthening of the dominant positions held by the United States and the United Kingdom, coupled with fluctuations in China's network role and the pronounced structural fragility of the peripheral nodes, collectively constitute key factors influencing the network's overall resilience performance. Therefore, enhancing network resilience necessitates a focus on three areas: the balanced distribution of nodes, the redundancy of cross-regional connections, and the stability of critical nodes. These approaches aim to build a more resilient and adaptive digital service trade system.

## 4.4. Clustering characteristics

Community modularity division was conducted on the digital service trade networks of 2010, 2014, 2017, 2020 and 2024 by using the Louvain algorithm (annual modularity $Q$ values of 0.121, 0.134, 0.165, 0.178 and 0.135). The distinct phased evolutionary characteristics in the community structure were revealed. Its partitioning logic exhibited strong correlations with network topology, trade patterns, and external environments, as illustrated in Table 5.

**Table 5.** Community partitioning results for 2010, 2014, 2017, 2020 and 2024

| Year | Community | Economy Name | Trade Volume (Billion USD) |
|---|---|---|---|
| 2010 | S-NT1 | AUS, CAN, CHN, IRL, ISR, JPN, NZL, KOR, GBR, USA | 4,429.26 (49.2%) |
| | S-NT2 | AUT, BEL, CZE, FRA, DEU, GRC, HUN, ITA, LUX, NLD, POL, PRT, SVK, SVN, ESP, CHE | 4,079.38 (45.3%) |
| | S-NT3 | DNK, EST, FIN, SWE, LVA, LTU, ISL | 493.38 (5.5%) |
| 2014 | S-NT1 | AUS, CAN, CHN, ISR, JPN, NZL, KOR, CHE, USA, ISL | 4,005.96 (31.63%) |
| | S-NT2 | BEL, FRA, IRL, ITA, LUX, NLD, PRT, ESP, GBR, AUT, CZE, DEU, GRC, HUN, POL, SVK, SVN | 7,982.65 (63.04%) |
| | S-NT3 | DNK, EST, FIN, SWE, LVA, LTU | 675.22 (5.33%) |
| 2017 | S-NT1 | AUS, CAN, CHN, ISR, JPN, NZL, KOR, CHE, GBR, USA, ISL | 5,706.57 (42.19%) |

**Table 5.** Continued

| | | | |
|---|---|---|---|
| 2017 | S-NT2 | AUT, BEL, CZE, FRA, DEU, GRC, HUN, IRL, ITA, LUX, NLD, POL, PRT, SVK, SVN, ESP | 7,116.97 (52.61%) |
| | S-NT3 | DNK, EST, FIN, LTU, SWE, LVA | 703.91 (5.2%) |
| 2020 | S-NT1 | AUS, CAN, CHN, ISL, ISR, JPN, NZL, KOR, GBR, USA | 5,793.60 (35.17%) |
| | S-NT2 | AUT, BEL, CZE, FRA, DEU, GRC, HUN, IRL, ITA, LUX, NLD, POL, PRT, SVK, SVN, ESP, CHE | 9,713.91 (58.97%) |
| | S-NT3 | DNK, EST, FIN, LVA, LTU, SWE | 964.43 (5.86%) |
| 2024 | S-NT1 | AUS, FIN, GBR, USA, CAN, CHN, DNK, JPN, SWE, CHE, KOR, ISL, ISR, NZL | 7,625.04 (38.36%) |
| | S-NT2 | BEL, CZE, EST, FRA, GRC, HUN, IRL, ITA, LVA, LTU, NLD, POL, SVK, SVN, AUT, PRT, DEU, LUX, ESP | 12,251.90 (61.64%) |

From the perspective of network composition, the 2010 network was divided into three major clusters, exhibiting an initial differentiation pattern of "core layer – regional clusters – distant nodes": S-NT1 centred on developed economies in Europe and America, aggregating nodes with substantial trade volumes such as the United States and the United Kingdom. Leveraging technological and market advantages, it formed the network's core layer, accounting for over 49.2% of total trade volume; S-NT2 encompassed regional nodes across France and Spain, forming a cluster primarily driven by intra-regional trade linkages, accounting for 45.3% of trade volume; S-NT3 constituted a relatively independent group of distant nodes, due to geographical distance and weaker trade ties. In 2014, the network was segmented into three major communities, reflecting an initial phase characterized by regional clustering: S-NT1 encompassed transcontinental core economies including China, the United States, and Japan; S-NT2 corresponded to southwestern and central-eastern European Union nations; while S-NT3 comprised Nordic and Baltic states. In terms of trade volume, the S-NT1 and S-NT2 communities collectively accounted for approximately 94.67% of total trade in 2014. The United Kingdom and the United States, with import trade volumes reaching US$337.357 billion, served as the core hubs of these communities. The 2017 network consolidation into three major communities reflects both enhanced intra-EU market coordination and the UK's dual role: as a participant in EU internal market integration while simultaneously occupying a pivotal position in cross-regional digital service trade, maintaining close ties with core economies across other continents. China is classified under S-NT1, ranking 13th in node weighted degree, demonstrating its early role as a regional connector. Its import trade value rose from US$45.004 billion in 2014 to US$58.584 billion in 2017. In 2020, amid the pandemic, regions such as Asia-Pacific, North America, and Western Europe, equipped with robust digital infrastructure including 5G and cloud computing, rapidly absorbed global demand for remote service. This fostered a hub-based community centred on Asia-Pacific, North America, and Western Europe. By 2024, this structure had further evolved into two major clusters: S-NT1 as a cross-regional global hub network, and S-NT2 as a regional cluster centred on the European Union. This demonstrates a parallel trend of global digital service trade forming alliances while simultaneously deepening internal regional integration. China remains within S-NT1, though its node weighted degree ranking and total trade volume have declined, signalizing a weakening of its core position. This reflects an adjustment in its role amid evolving rules and shifting external conditions.

Functionally, the divisions of labour among communities have become increasingly distinct and further deepened. Their evolution impacts the network's overall resilience primarily through two dimensions: local resilience and systemic stability. In 2010, functional exploration was in the initial exploration stage: S-NT1 focused on initial flows of high-end digital service (finance, telecommunications). S-NT2 centred on basic digital service trade, while S-NT3 featured modest scale, singular functions, and limited inter-cluster interaction. Overall network resilience depended on core-layer stability. In 2014, functional balance emerged across communities, characterized by intra-regional partial circulation, reflecting early stage synergistic and self-sufficient development. By 2017, S-NT1 progressively had assumed the role of a global hub for high-end service (e.g., finance, telecommunications), with China serving as a pivotal bridge connecting East Asia with the Europe and America bloc. By 2020, the COVID-19 pandemic had significantly altered the demand structure for digital service. Cross-regional communities further consolidated their global supply capabilities, with regional functional positioning becoming more clearly defined. By 2024, functional differentiation between the two communities had become more pronounced. The core circle of S-NT1, by virtue of the soundness and coordination of its digital trade rules, boasts stronger resilience of its digital services export network as well as greater risk resistance capacity [41], whereas S-NT2, due to uneven internal development levels, increasingly focused on regionally adapted sectors like telecommunications and personal service, with peripheral nations deepening their dependence on core nodes. China's relative weakening of its core position compared to the US and UK reflects both opportunities and challenges in China's digital service trade within the dynamics of global rule formulation. This functional divergence directly generates structural disparities in network resilience, enhancing local robustness while simultaneously concentrating systemic risks.

The community structure significantly influences network resilience. Between 2010 and 2014, the S-NT1 core cluster exhibited high trade concentration but limited inter-community connectivity. Consequently, fluctuations at core nodes could directly compromise overall network stability. S-NT3, being too small, lacked risk buffering capacity and thus became a weak link in the network. From 2014 to 2017, intra-community resilience was bolstered by regional coordination, yet inter-community connectivity relied heavily on a few core nodes, creating potential for cross-regional risk transmission. The emergence of cross-regional hub communities in 2020 enhanced the dispersion capacity of core flows, though dependency risks for peripheral communities increased. By 2024, S-NT1 had demonstrated greater resilience due to its multi-core, cross-regional structure. S-NT2, though internally more integrated, had remained vulnerable to single node failure due to its inclusion of high-risk peripheral nodes like Greece, Hungary, Poland, and Slovakia. These nodes had contributed little to total trade volume and exhibited high dependency on core nations such as Germany and France. Inter-cluster connections had remained concentrated among a few economies, with insufficient cross-regional channel redundancy, making the network susceptible to systemic risks during external shocks.

Thus, the evolution of network community structures reflects not only the combined effects of trade intensity and institutional coordination but also the global trends of functional differentiation and risk concentration within digital service trade. From the multi-regional clusters of 2010 to the dual-structure of 2024 featuring global hubs and regional clusters, functional specialization within clusters has intensified, yielding structural disparities in network resilience. The spatial configuration of core nodes, the redundancy of cross-community pathways, and intra-regional coordination efficiency collectively form the structural foundation underpinning network resilience. The clustering of high risk nations such as Greece and Hungary within the S-NT2 is particularly noteworthy. This phenomenon not only reveals potential pathways for regional risk transmission but also provides clear policy directions for China to implement precise risk management and differentiated trade policies. It holds significant practical guidance for constructing a robust and sustainable digital service trade network.

In summary, the characteristics of China's digital service trade network with OECD countries—including core-periphery differentiation, the strong dependency of peripheral nodes (such as Greece and Hungary), and fluctuating network connectivity efficiency, reveal structural drivers of trade risk. Peripheral nodes, lacking alternative trade pathways and possessing weak resilience, become potential risk hotspots. However, network analysis identifies risk carriers and transmission pathways solely at the topological level, without quantifying the dynamic fluctuations in trade competitiveness or the intensity of risk evolution at the node level. Therefore, the following section employs kernel density estimation with the rate of change in the net export revealed comparative advantage index as the core metric. This further delineates the distributional characteristics and evolutionary trends of digital service trade competitiveness across nations, precisely capturing competitiveness disparities between peripheral and core nodes. This provides quantitative support for subsequent risk early warning, achieving a logical closed loop of structural risk identification, quantification of competitiveness fluctuations, and risk level assessment.

## 5. Analysis of kernel density estimation results

Building upon the core conclusion of complex network analysis, which finds that trade networks exhibit a pronounced core-periphery structure and that peripheral nodes such as Greece, Hungary, and Poland representing structural vulnerabilities, this section employs kernel density estimation to conduct the dynamic quantitative analysis of OECD countries' digital service trade competitiveness by using the rate of change in the net export revealed comparative advantage index as the core metric. On one hand, it focuses on the divergent competitiveness characteristics between core and peripheral nodes to validate the structural inference that core nodes exhibit stable competitiveness while peripheral nodes demonstrate competitive weakness. On the other hand, by delineating the agglomeration and dispersion patterns of competitiveness distribution, it identifies high risk competitiveness fluctuation intervals. This provides crucial quantitative underpinnings for constructing subsequent risk warning tables, thereby addressing the shortfall in network analysis regarding quantification of risk intensity.

During the sample selection phase for this kernel density estimation, six countries—Chile, Colombia, Costa Rica, Mexico, Norway, and Turkey—were excluded from the final kernel density distribution analysis. This exclusion was due to their insufficient proportion of valid observations (below 50%) and persistent multi-year gaps in core trade metrics, conditions which rendered them unsuitable for the dynamic calculation requirements of the $\triangle NXRCA$ index. Consequently, the valid sample comprises the remaining 32 OECD countries. The kernel density analysis results obtained through using Equations (10) and (11) are presented in Figure 15.

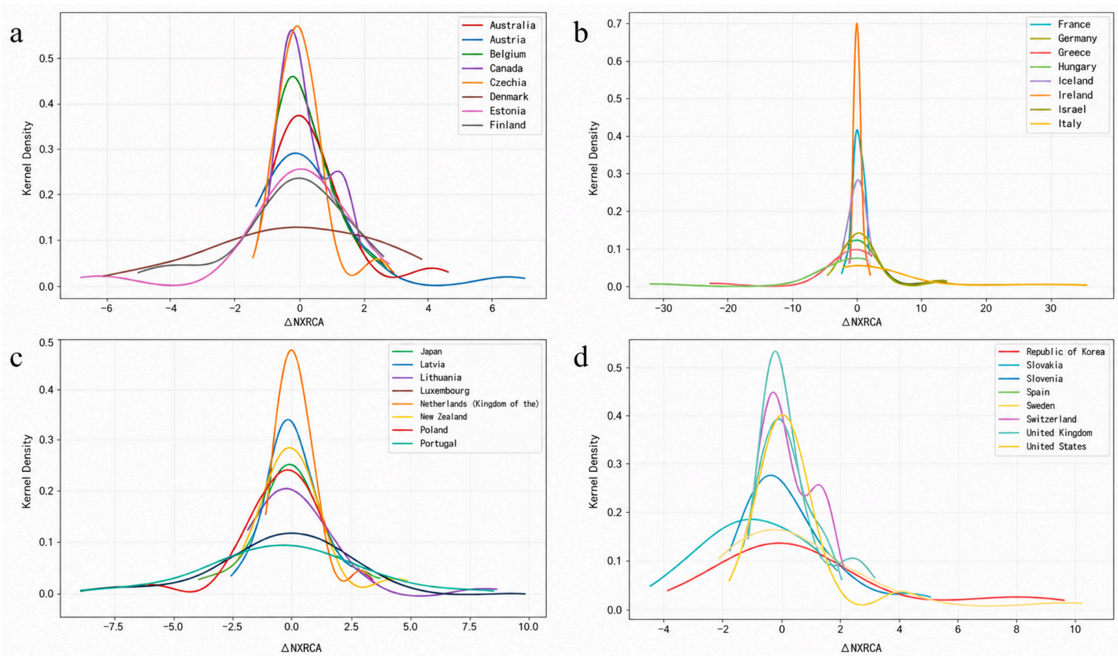


**Figure 15.** Comparison of kernel density distributions of *ΔNXRCA* between China and a subset of OECD countries

## 5.1. Analysis of distribution pattern evolution (2010~2024)

$\Delta NXRCA$ Trade competitiveness is assessed primarily based on the mean value from 2010 to 2024 ($\Delta NXRCA$). Drawing upon established research conventions for the Revealed Comparative Advantage Index ($\Delta NXRCA$), a mean value > 5 indicates high competitiveness with a relatively significant advantage. A mean value ∈[-5, 5] denotes moderate competitiveness with relatively stable performance, and a mean value < -5 signifies low competitiveness with a relative disadvantage. The kernel density distribution of the $\Delta NXRCA$ index across 32 OECD countries from 2010 to 2024 exhibits a pronounced "three-tier stratification" evolution trend, with characteristic differences among iers progressively crystallising over time.

The high-competitiveness tier, exemplified by Iceland, Japan, the United Kingdom, and South Korea, consistently exhibits peak values concentrated in the high range to the right of the $\Delta NXRCA$ index's zero point. The curve's steepness has progressively intensified. In 2010, Iceland's $\Delta NXRCA$ mean was 6.2 with a peak near $\Delta NXRCA = 5$. By 2024, the mean had risen to 8.3, with the peak shifting right to $\Delta NXRCA = 8$. Peak density increased from 0.5 to 0.7, while annual fluctuations narrowed from ± 1.1 to ± 0.3, reflecting both heightened competitiveness and markedly enhanced stability. Japan exhibited similar trends. In 2010, The mean was 7.1, With peak at $\Delta NXRCA = 6$; In 2024, The mean was 7.9, With peak shifted right to $\Delta NXRCA = 7.5$, with peak density rising from 0.45 to 0.6, indicating a more pronounced rise in the concentration of competitiveness. The United Kingdom and South Korea exhibit characteristics of "strength enhancement coupled with reduced volatility". Their respective 2010 averages were 5.8 and 5.5, rising to 6.9 and 6.7 by 2024, with peak density simultaneously increasing to 0.55 and 0.58, reflecting a sustained convergence of competitiveness within this tier.

The mid-competitiveness tier encompasses 20 nations including Germany, the United States, France, Italy, and Canada, forming the core sample group. Its kernel density curve exhibits "multiple peak concentration with internal stratification". Among these, Germany, the United States, and France—positioned within the mean range [2, 5]—showed averages of 3.2 for Germany, 2.8 for the United States, and 2.5 for France in 2010.

Their curve peaks clustered around $\Delta NXRCA$ = 3. By 2024, Germany's mean had slightly decreased to 2.4, the United States' rose marginally to 3.3, and France's remained at 2.7. Their curve peaks had narrowed to the $\Delta NXRCA$ = 2.5–3.5 range, with annual fluctuations consistently controlled within ± 0.8, maintaining stable positioning within the medium-to-high competitiveness bracket. Twelve nations including Italy, Canada, and Spain, situated within the mean range [-2, 2], exhibited mean values dispersed within ± 1.5 in 2010. By 2024, this dispersion had narrowed to ± 1.0, with curve peaks converging near $\Delta NXRCA$ = 0. Annual fluctuations had decreased from ± 1.5 to ± 0.7, demonstrating a trend towards convergence within the "competitiveness neutral zone", or the five countries within the mean range of [-5, -2], ncluding Poland and the Netherlands, ect. The mean stood at -3.1 in 2010, with curve peaks at $\Delta NXRCA$ = -3. By 2024, the mean had marginally decreased to -3.5, while peaks narrowed to $\Delta NXRCA$ = -3.2. Fluctuations had remained stable at ± 0.6, maintaining a position within the low-to-medium competitiveness range.

The low competitiveness tier comprises Greece, Sweden, Hungary, Austria, Portugal, Slovakia, Slovenia, and Finland. Their kernel density curves consistently exhibit peaks skewed towards the low range to the left of zero, with the shape progressively flattening. In 2010, Greece's average $\Delta NXRCA$ stood at -4.8, with the curve peak positioned at $\Delta NXRCA$ = -4.5. By 2024, the average had declined to -6.7, while the peak had shifted leftward to $\Delta NXRCA$ = -6.2. Peak density had decreased from 0.2 to 0.1, and annual fluctuation had widened from ± 1.8 to ± 2.1, revealing a pronounced trend of weakened competitiveness and heightened volatility. Sweden's changes were more pronounced. The mean in 2010 was -5.2 with a peak at $\Delta NXRCA$ = -5. By 2024, the mean had fallen to -7.1, and the peak had shifted left to $\Delta NXRCA$ = -6.8, The peak density had decreased from 0.18 to 0.12. Hungary converged with the other two, with a mean of -4.9 and peak at $\Delta NXRCA$ = -4.7 in 2010. By 2024, the mean had fallen to -6.5, the peak had shifted left to $\Delta NXRCA$ = -6.1, The peak density decreased from 0.21 to 0.13, indicating a persistent weakening of competitiveness among countries within this tier.

Regarding the overall convergence trend, the distribution of countries' kernel density curves has shifted from relatively loose patterns—where high, medium, and low tiers exhibited significant overlap—to a configuration characterized by "rightward movement of the high tier, leftward movement of the low tier, and concentration of the medium tier". The boundary between the high and low tiers has largely separated, while the middle tier has further converged towards the zero-value range. This indicates that the divergence in trade competitiveness among nations has persistently widened over the 15-year period.

## 5.2. Analysis of agglomeration characteristics

The kernel density distribution of the $\Delta NXRCA$ index for 32 OECD countries exhibits pronounced clustering characteristics, with significant variations in clustering intensity across different intervals. The core cluster zone is concentrated within the interval $\Delta NXRCA \in [-5,5]$, encompassing 20 moderately competitive nations including Germany, the United States, France, and Italy. These countries account for 62.5% of the total sample, forming the "core base" of OECD nations' trade competitiveness towards China. In 2010, the peak of the kernel density curve within this interval reached 0.35 near $\Delta NXRCA$ = 0, with a curve width spanning ± 6. By 2024, the peak had risen to 0.48, with the curve width narrowing to ± 4. Density increased by 37% compared to 2010, while the annual mean fluctuation within this group was only ± 1.2. Among them, fluctuations in the medium-high sub-tier (e.g., Germany, United States) were less than ± 1, and those in the neutral sub-tier (e.g., Italy, Canada) were less than ± 0.8. This reflects both enhanced concentration and strengthened competitiveness stability.

The high-value cluster zone lies within the range where $\Delta NXRCA > 5$, encompassing four highly competitive nations: Iceland, Japan, the United Kingdom, and South Korea. This zone exhibits characteristics of a "small leading cluster". In 2010, the curve peaked near $\Delta NXRCA$ = 6 within this zone, with a density of 0.4 and a group mean of 6.4. By 2024, the peak had risen to 0.65, with the interval narrowing to [6, 9] and the group mean increasing to 7.8 – a 22% rise from 2010. In terms of density disparity, the peak density within this interval was 1.35 times that of the core cluster zone and 6.5 times that of the low-value cluster zone, indicating significantly higher competitiveness concentration among high-competitiveness nations than in other groups. Concurrently. In 2024, the overlap between Iceland and Japan's curves reached 80%. Their respective $\Delta NXRCA$ mean values were 8.3 and 7.9, with annual fluctuations both below ± 0.5, demonstrating significant convergence in competitiveness levels and volatility characteristics. This feature aligns closely with the topological attributes of core nodes in network analysis—characterized by dense trade connections and strong resilience—validating the positive correlation between network centrality and trade competitiveness stability.

The low-value cluster is situated within the range where $\Delta NXRCA$ < -5, encompassing eight countries with low competitiveness such as Greece, Sweden, and Hungary, etc., exhibiting characteristics of a "tail-dispersed cluster". In 2010, the curve peaked near $\Delta NXRCA$ = -5, with a density of 0.1 and a group mean of -5.6. By 2024, the peak had declined to 0.08, the range expanded from [-10, -5] to [-12, -5], and the group mean fell to -7.2—a 28% decrease from 2010. The curve width in this interval was 2.5 times that of the core cluster zone, with annual fluctuations reaching ± 2.0—1.6 times that of the core cluster zone. Concurrently, Greece's curve peak in 2024 was located at $\Delta NXRCA$ = -6.7, while Sweden's peak was at $\Delta NXRCA$ = -7.1. The mean gap between these two widened from 0.3 in 2010 to 0.4, indicating a persistent intensification of internal differentiation among tail countries. This resonates with the structural weaknesses identified in complex network analysis, where peripheral nodes exhibit strong dependency and lack alternative trade pathways, further illustrating that weak network position is a significant driver of declining competitiveness.

# 6. Risk warning for digital service trade between China and OECD countries

## 6.1. Analysis of risk warning results

During the risk warning phase, Chile, Colombia, CostaRica, Mexico, Norway, and Turkey were excluded from risk warnings due to severe deficiencies in valid data, making precise forecasting unfeasible. By using Formulas (12) and (13), alongside the alert classification criteria (Table 1), and incorporating trade data between China and OECD countries from 2010 to 2024, EX and CV values were calculated to generate the trade risk warning table (As shown in Table 6).

**Table 6.** Digital service trade risk warning table for China and OECD countries

| Country | CV | EX | Sample Size | Alert |
|---|---|---|---|---|
| Sweden | 2.4316 | 0.903 | 14 | Green (No alerts) |
| Greece | 1.8474 | -1.9053 | 14 | Orange (High Alert) |
| Hungary | 3.0978 | -2.4944 | 14 | Orange (High Alert) |
| Austria | 0.9058 | 0.4872 | 14 | Green (No Alert) |
| Czech Republic | 2.4367 | 0.0795 | 14 | Green (No alerts) |
| Germany | 2.8249 | 0.9637 | 14 | Green (No warning) |
| Poland | 8.9495 | -0.3104 | 14 | Orange (High alert) |
| United States | 0.8279 | 0.3309 | 14 | Green (No Alert) |

**Table 6.** Continued

| | | | | |
|---|---|---|---|---|
| Finland | 2.1335 | -0.3596 | 14 | Orange (High alert) |
| Belgium | 1.5664 | 0.2158 | 14 | Green (No Alert) |
| Ireland | 5.6981 | 0.0388 | 14 | Green (No alerts) |
| Italy | 2.8751 | 4.2916 | 14 | Green (No alerts) |
| Luxembourg | 1.0993 | 0.3025 | 13 | Green (No alerts) |
| Slovenia | 3.0947 | 0.304 | 13 | Green (No alerts) |
| France | 3.0421 | 0.1264 | 13 | Green (No alerts) |
| Denmark | 9.3443 | -0.3206 | 13 | Orange (High alert) |
| Estonia | 3.1809 | -0.3154 | 13 | Orange (High Alert) |
| Lithuania | 1.1397 | 0.6185 | 12 | Green (No Alert) |
| Switzerland | 1.3402 | 0.2736 | 12 | Green (No alerts) |
| South Korea | 1.6849 | 1.1233 | 12 | Green (No alerts) |
| New Zealand | 1.4441 | -0.8128 | 12 | Orange (High Alert) |
| Australia | 1.2676 | 0.4659 | 12 | Green (No Alert) |
| Latvia | 5.0033 | 0.1051 | 11 | Green (No alerts) |
| Canada | 1.2877 | 0.2122 | 11 | Green (No alerts) |
| Iceland | 0.0181 | 1.1909 | 10 | Green (No alerts) |
| Spain | 0.7802 | 0.4188 | 10 | Green (No warning) |
| Netherlands | 2.9273 | 0.2484 | 10 | Green (No alerts) |
| Slovakia | 1.7957 | -0.9834 | 9 | Orange (High Alert) |
| Portugal | 9.8394 | -0.3457 | 9 | Orange (High Alert) |
| Israel | 0.7232 | 1.3648 | 9 | Green (No Alert) |
| Japan | 5.8894 | -0.0774 | 9 | Blue (Low Alert) |
| United Kingdom | 1.4344 | 0.1522 | 8 | Green (No Alert) |

Based on the alert results, nine countries are classified as orange high-alert countries, i.e., Greece, Hungary, Poland, Finland, Denmark, Estonia, New Zealand, Slovakia, and Portugal. These countries all exhibit negative EX values, indicating their digital service trade competitiveness is in a weak range. Furthermore, Poland, Denmark, and Portugal exhibit CV values of 8.9495, 9.3443, and 9.8394 respectively—significantly higher than other high-alert nations. This reflects not only their competitive weakness but also markedly greater volatility in trade development and heightened risk uncertainty. Greece and Hungary, with EX values of -1.9053 and -2.4944 respectively, represent the most competitively disadvantaged economies among high-alert nations.

Among the blue low-alert countries, only Japan stands alone with an EX value of -0.0774, approaching a neutral competitiveness level. While exhibiting a slight disadvantage, its weakness is substantially less pronounced than that of high-alert countries. Its CV value of 5.8894 indicates a degree of volatility in trade development, constituting a low-risk characteristic.

A total of 21 green no-alert countries form the core of the sample. These countries all achieve positive EX values, indicating a favourable foundation for digital service trade competitiveness. Moreover, the majority exhibit CV values below 3.0. For instance, Iceland's CV stands at merely 0.0181, demonstrating highly stable competitive performance. Italy, South Korea, and Iceland exhibit particularly strong competitive advantages among risk-free nations, with EX values of 4.2916, 1.1233, and 1.1909 respectively. Although Ireland and Latvia display relatively high CV values, their positive EX values maintain them within the risk-free range.

## 6.2. Analysis of risk causes

Integrating complex network topology features, kernel density estimation results, and early warning identification outcomes reveal that trade risk in high-risk nations arises not in isolation but from the interplay of three factors, i.e., network structural imbalance, competitive evolution imbalance, and external environmental shocks. This aligns closely with the core objective of the preceding complex network analysis (uncovering risk transmission pathways and structural vulnerabilities).

Firstly, the entrenched core-periphery structure of the network inherently undermines resilience. Complex network analysis indicates that nine high-alert nations, including Greece, Hungary, and Poland etc, have long occupied peripheral positions within the trade network. Their weighted degree, closeness centrality, and betweenness centrality all rank among the lowest in the network. Furthermore, many belong to the S-NT2 community, exhibiting high trade dependency on regional core nodes such as Germany and France. This "core clustering-periphery dependency" structural feature leaves peripheral nations without alternative trade routes. When core nodes adjust trade policies or experience demand fluctuations, it directly triggers severe oscillations in their own trade flows. This directly correlates with the generally high CV values observed in high-alert nations (particularly Poland, Denmark, and Portugal, where CV values approach 9), confirming that network structural imbalance is the core structural driver of risk concentration. Practical applications of regulatory technology in financial risk prevention further demonstrate that risk transmission within imbalanced network structures can be precisely identified through intelligent algorithms and complex network technologies.

Secondly, the competitiveness of digital service trade continues to decline with intensifying divergence. Kernel density estimation reveals that high-alert nations consistently rank within the low-competitiveness tier. Between 2010 and 2024, the mean $\Delta NXRCA$ value progressively decreased from -4.9 to -7.2, with the curve's peak persistently shifting leftwards and its bandwidth widening – indicating a solidifying pattern of competitive weakness. Further analysis of network characteristics reveals that these nations lag in digital infrastructure development (fixed broadband penetration rates are 30-40% lower than core nations) and lack targeted digital service trade strategies. Consequently, their trade shares in high-end sectors like finance and telecommunications are persistently squeezed by core nodes, while low-value-added sectors face homogenized competition. This ultimately creates a vicious cycle of "competitiveness erosion – network marginalization", explaining why High-Alert nations consistently exhibit negative EX values, mostly below -0.3.

Thirdly, functional differentiation among communities and institutional distance amplify risk exposure. Community evolution from 2014 to 2024 reveals that while the S-NT2 community—dominated by high-alert nations—shows enhanced internal integration, its functional focus remains confined to regionally adaptive domains. This lacks sufficient rule coherence with the S-NT1 global hub network. Suh et al. further found that the absence of unified digital trade provisions in bilateral trade agreements significantly amplified the trade costs arising from regulatory divergence, which also explained the policy origins of risk concentration among high-warning countries within the S-NT2 communit [7]. Concurrently, these nations exhibit pronounced institutional divergences with China regarding cross-border data flows and digital service regulation (generally recording a score above 0.6 on the OECD Digital Service Trade Restrictions Index). Compounded by geopolitical tensions, their incidence of trade frictions exceeds that of core nations by over twofold. The dual effects of institutional distance and functional barriers within communities render high-alert countries unable to integrate into global high-end trade networks or leverage regional coordination to buffer external shocks, further intensifying risk accumulation and transmission.

Fourthly, diminished network connectivity efficiency amplifies risk transmission effects. After 2019, network density declined from 0.97 to 0.76, while average path length increased from 1.03 to 1.24. Reduced direct connections between core and peripheral nodes led to diminished trade liquidity and elevated transaction costs for peripheral nations. This weakened network connectivity prevents high-alert countries from diversifying risks through multiple trade routes when facing external shocks, while also hindering their ability to mitigate pressures through intra-community coordination. Consequently, risks tend to concentrate and erupt at peripheral nodes, readily propagating through core nodes to broader regions. This pattern aligns closely with the expanded volatility observed in the low-competitiveness tier within kernel density estimation (annual fluctuations rising from ± 1.8 to ± 2.1).

# 7. Conclusion and policy recommendation

## 7.1. Conclusion

(1) The digital service trade network between China and OECD countries exhibits a dynamically evolving "core-periphery" dual structure, with the network's overall characteristics highly correlated with its resilience against risk. From 2010 to 2024, network density first increased then declined (peaking at 0.97 in 2019 and falling to 0.76 in 2024), while average path length exhibited an inverse trend. Core nodes (the United States, the United Kingdom, Ireland) continuously strengthened their dominance, whereas peripheral nodes (Greece, Hungary, etc.) exhibited heightened dependency. China's node centrality metrics initially rose before declining, with its eigenvector centrality falling to a decade low in 2024. It transitioned from a critical bridge node to an regular connecting node, with network resilience weakening as structural imbalances intensified. Complex network analysis provides core support for identifying risk transmission pathways and structural vulnerabilities.

(2) From 2010 to 2024, the kernel density curves of the $\Delta NXRCA$ for 32 OECD countries evolved from loose overlaps to a pattern characterized by "rightward shift of the high tier, leftward shift of the low tiers, and concentration of the middle tier". High-competitiveness countries (Iceland, Japan, etc.) saw their mean value rise to 7.8 with reduced volatility, while low-competitiveness countries (Greece, Sweden, etc.) saw their mean value drop to -7.2 with increased divergence. Overall risk trends upward, and the curve bandwidth of the low-competitiveness tier has widened since 2019, reflecting the simultaneous intensification of risk divergence and concentration.

(3) The risk early-warning system accurately identifies nine orange-level high-alert countries and one blue-level low-alert country, with risk sources exhibiting multidimensional correlations. High-alert countries concentrated in Central and Eastern Europe all display the characteristic of "negative EX + elevated CV", their risks stemming from the interplay of four factors, i.e., the solidification of network core-periphery structures, sustained competitiveness decline, functional differentiation within communities coupled with institutional distance, and diminished network connectivity efficiency. The warning results corroborate complex network analysis and kernel density estimation outcomes, forming a complete logical chain linking "structure-competitiveness-risk", providing quantitative evidence and targeted objectives for precise prevention and control.

(4) China's role and status within the digital service trade network undergo dynamic adjustments, confronting structural challenges. From 2010 to 2024, China's node centrality initially rose before declining, while its betweenness centrality fell to nearly-zero. This was primarily constrained by insufficient core

competitiveness in digital service trade, the need to enhance alignment with international rules, and regional competition diverting trade flows. Consequently, China lost its vital buffer layer function within the network, indirectly exacerbating the overall structural fragility of the network.

## 7.2. Policy recommendation

(1) Optimizing the network layout structure to resolve the core-periphery imbalance dilemma. In view of the dual structural characteristics of the network, cooperation on digital rules with peripheral countries such as Greece and Hungary should be strengthened [42]. Enhance their node weighted degree and connectivity through joint construction of cross-border digital corridors and shared digital technology standards, thereby reducing dependence on core nodes; Prioritize expanding trade cooperation with medium-centrality nodes like South Korea and Israel within the S-NT1 community, constructing a "core-medium-periphery" multi-tiered trade network. This enhances network resilience and redundancy while mitigating core dependency risks.

(2) Implementing differentiated competitiveness enhancement strategies to precisely counteract low-competitiveness risks. The decline in competitiveness of high-alert countries should be revolved in two ways: On one hand, enhancing competitiveness in specialized sectors such as finance and telecommunications through technology transfer and joint R&D can assist them to narrowing the gap with core countries. On the other hand, grounded in China's own competitive advantages, it should promote the high-quality development of trade in services through digital technologies [43], while strengthening cooperation with core node countries in the research and development of digital technologies and high-end trade in services sectors, optimizing the structure of China's digital services trade, enhancing its eigenvector centrality and bargaining power in trade, and breaking the vicious cycle of "weakening competitiveness—marginalization in the network".

(3) The study by Zhou Nianli et al. confirms that the more stringent a country's restrictions on cross-border data flows are, the less conducive they are to the country's digital services imports [44]. In response to the issues of functional differentiation of communities and institutional distance, it should promote the establishment of a dialogue mechanism on digital services trade rules between China and countries in the S-NT2 community. This would foster consensus on cross-border data flows and mutual regulatory recognition, thereby lowering institutional trade costs. Drawing on the research findings of Ferracane, in bilateral and multilateral trade agreements, it should prudently assess restrictive measures on cross-border data flows invoked on the grounds of national security, and give priority to addressing cyber threats through the implementation of sound security standards and encryption technologies [45]. This approach helps safeguard national security while avoiding unnecessary restrictions on digital services trade flows. Leveraging the cross-regional advantages of the S-NT1 community, a collaborative platform for digital service trade should be established to promote functional complementarity and rule alignment among different communities. This will reduce restrictions on risk dispersion caused by community barriers and enhance the network's overall coordinated risk resilience.

(4) Constructing a dynamic risk monitoring and emergency response system to strengthen targeted prevention and control capabilities. Based on the early warning results and the evolutionary characteristics of the network and competitiveness, the authors should establish a "one-to-one" monitoring mechanism for high-alert countries, with a focus on tracking the trade dynamics of countries with drastic fluctuations such as Poland, Denmark and Portugal whose CV value exceeds 8, and there are mature machine learning-based dynamic monitoring frameworks available for reference [46]. Through the real-time capture of trade data characteristics and automatic identification of abnormal fluctuation signals, early warning and rapid response to risks can be effectively realized. Addressing declining network connectivity efficiency, an emergency

reserve mechanism for trade disruptions is established, trade settlement and delivery channels are optimized, and path dependency risks are reduced. Simultaneously, differentiated trade strategies are formulated by referencing kernel density estimation competitiveness fluctuation ranges, quota management is implemented in highly sensitive sectors, and the precision and timeliness of risk responses are enhanced.

(5) China's network core capabilities are enhanced and buffer layer functions are reinforced. Addressing the weakening status of China's nodes, innovation in digital service trade is accelerated, advantages in high-end service exports are cultivated, and node weighted degree and betweenness centrality are elevated. Proactively participate in the formulation of global digital services trade rules, reduce the OECD Digital Services Trade Restrictiveness Index, and enhance the adaptability to international rules [47]. Strategic coordination with core nodes in the Asia-Pacific and European regions is strengthened to establish cross-regional trade hubs, China's buffer layer function within the network is restored, and the overall resilience of the network is bolstered.

## Fundings

The Great Project of Philosophy and Social Science Research in Jiangsu Province's Colleges &Universities, Project title: The Impact of Global Value Chain Reconstruction on the High-Quality Development of Reverse OFDI in Jiangsu Province (2023SJZD062) and the 2025 College Student Innovation and Entrepreneurship Training Program of Jiangsu Province, National-Level Project, Project Title: Research on the Risk Measurement of Digital Service Trade between China and OECD Countries (202510292057).

## References

[1] Zhao, X. Q., & Liu, Y. N. (2025). The conceptual evolution, measurement framework and international competitiveness comparison of digital trade. *International Trade*(4), 5–16.

[2] van der Marel, E. (2021). Digital-based services globalization and multilateral trade cooperation. *Global Policy, 12*(3), 392–398.

[3] López González, J., Sorescu, S., & Kaynak, P. (2023). Of bytes and trade: Quantifying the impact of digitalisation on trade. *Report*, Working Paper No.18166873.

[4] OECD. (2023). K*ey issues in digital trade review* (9789264518094).

[5] Gregori, T. (2021). Protectionism and international trade: A long-run view. *International Economics, 165*, 1–13.

[6] Kang, S. K., & Shang, Y. (2026). Exploring the sustainable development path of global digital service trade stability: A hybrid approach perspective. *Engineering Applications of Artificial Intelligence, 169*.

[7] Suh, J., & Roh, J. (2023). The effects of digital trade policies on digital trade. *The World Economy, 46*(8), 2383–2407.

[8] Jiang, M. D., & Jia, P. (2022). Does the level of digitalized service drive the global export of digital service trade? Evidence from global perspective. *Telematics and Informatic, 72*, 101853.

[9] Natanael, Y. (2025). Beyond borders and tangibility: Understanding trade restrictions, institutional quality and digital services trade. *International Journal of Development Issues, 24*(396-415), 396.

[10] Li, C. M., He, M. Y., & Dong, Z. Y. (2026). Digital trade rules, new comparative advantages and the reshaping of international division of labor: A dual test based on trade flow and category. *China Industrial Economics*(1), 123–145.

[11] Ferracane, M. F., Kren, J., & van der Marel, E. (2020). Do data policy restrictions impact the productivity performance of firms and industries? *Review of International Economics, 28*(3), 676–722.

[12] van der Marel, E., & Ferracane, M. (2021). Do data policy restrictions inhibit trade in services? *Review of World Economics, 157*(4), 727–776.

[13] Zhang, G. F., & Guo, B. L. (2025). The import-inhibiting effect of digital trade barriers. *Journal of International Trade*(11), 134–155.
[14] Ma, S. Z., & He, G. (2025). Digital trade barriers and the high-quality development of China's digital trade. *Reform*(3), 80–94.
[15] Li, C. L., Zhu, H. Y., Bao, W. P., & Qin, M. M. (2025). Spatial pattern and influencing factors of China's digital trade resilience under the impact of trade frictions. *Chinese Geographical Science, 35*(1), 203–216.
[16] Qiu, A. L., Yu, Y. C., & McCollough, J. (2023). Can digital service trade promote the high-quality development of global manufacturing? – existence and mechanism. *International Trade, Politics and Development, 7*(3), 191–213.
[17] Chen, F. Z., & Jiang, G. H. (2023). How does the digital service trade nonlinearly affect carbon emissions? Empirical evidence from G20 countries. *Environmental Science and Pollution Research, 30*(59), 123022–123038.
[18] Li, X. X., Hu, Y., Ding, L., Huang, Q. Y., & Jiang, Y. (2024). Impact of the digital trade on lowering carbon emissions in 46 countries. *Scientific Reports, 14*(1).
[19] Ma, H. L., & Kang, C. W. (2025). The impact of U.S.-style digital trade rules on digital services trade between China and CPTPP member countries. *Technology in Society, 83*, 103040.
[20] Liu, H., Liu, L., & Lin, L. (2025). Assessing the relationship between digital service trade and carbon emissions: Evidence from RCEP countries. *International Journal of Environmental Science and Technology, 22*(13), 12317–12330.
[21] Liu, Y., & Wang, X. L. (2024). Digital service trade and carbon total factor productivity: Empirical evidence from cross-country panel data. *Environment, Development and Sustainability*.
[22] Tang, W., & Lan, Q. X. (2024). Does digital trade promote China's manufacturing industry upgrading?—Based on structure rationalization perspective. *Economic Change and Restructuring, 57*(3).
[23] Wu, Q. Q., Bi, M. J., Siddiqui, F., & Tang, Y. (2023). Assessing the impact of digital trade on enterprise competitiveness: Evidence from Chinese A-share listed companies. *Journal of Industry, Competition and Trade, 23*(3-4), 329–362.
[24] Zeng, M. X., & Zhao, Y. Y. (2014). Industrial trade risk monitoring system: Design based on international competitiveness – A case study of the mechanical equipment manufacturing industry. *Journal of International Trade*, (8), 47–57.
[25] Wang, T. X., Wang, M. X., Kang, X. Y., Chen, L., & Li, X. (2023). Copper trade risk in China: A multidimensional dynamic evaluation. *Greenhouse Gases: Science and Technology, 13*(3), 379–395.
[26] Xu, L., Dong, G. C., & Li, Q. Y. (2022). Prediction model of international trade risk based on stochastic time-series neural network. *Computational Intelligence and Neuroscience, 2022*, 1–9.
[27] Wintle, B. C., & Nicholson, A. (2014). Exploring risk judgments in a trade dispute using Bayesian networks. *Risk Analysis, 34*(6), 1095–1111.
[28] Herman, P. R., & Oliver, S. (2023). Trade, policy, and economic development in the digital economy. *Journal of Development Economics, 164*, 103135.
[29] Ma, S. Z., Ren, W. W., & Wu, G. J. (2016). Characteristics of a country's agricultural product trade network and its impact on the division of labor in the global value chain: From the perspective of social network analysis. *Management World*, (3), 60–72.
[30] Fagiolo, G. (2006). Directed or undirected? A new index to check for directionality of relations in socio-economic networks. *Econ Bull, 3*(34), 1–12.
[31] Latapy, M. (2008). Main-memory triangle computations for very large (sparse (power-law)) graphs. *Theoretical Computer Science, 407*(1-3), 458–473.
[32] Sabidussi, G. (1966). The centrality index of a graph. *Psychometrika, 31*(4), 581–603.
[33] Freeman, L. C. (1977). A set of measures of centrality based on betweenness. *Sociometry, 40*(1), 35–41.

[34] Brandes, U. (2001). A faster algorithm for betweenness centrality. *Journal of Mathematical Sociology, 25*(2), 163–177.

[35] Yin, X. X., Tao, Y. W., & Zhao, X. Q. (2024). Research on crisis transmission effect of international trade network based on cascading failure model—Taking semiconductors as an example. *Journal of Systems Science and Mathematical Sciences, 44*(5), 1389–1411.

[36] Blondel, V. D., Guillaume, J. L., Lambiotte, R., & Lefebvre, E. (2008). Fast unfolding of communities in large networks. *Journal of Statistical Mechanics: Theory and Experiment*(10).

[37] Lambiotte, R., Delvenne, J. C., & Barahona, M. (2009). *Laplacian dynamics and multiscale modular structure in networks.*

[38] Hao, S., Chen, Z., Wang, C. C., & Hung, C. Y. (2023). Impact of digital service trade barriers and cross-border digital service inputs on economic growth. *Sustainability, 15*(19).

[39] Ministry of Commerce of the People's Republic of China. (2025). 2024 China digital service trade development report. *Report*, Department of Service Trade and Commercial Services, Ministry of Commerce of the People's Republic of China.

[40] Heidebrecht, S. (2023). From market liberalism to public intervention: Digital sovereignty and changing European Union digital single market governance. *JCMS: Journal of Common Market Studies, 62*(1), 205–223.

[41] Jing, S. W., Hu, C. H., & Guo, Y. T. (2025). Research on the impact of digital trade rules on the resilience of digital service export networks. *World Economy Studies*(08), 119–132.

[42] Fan, Y. L. (2025). Research on digital trade cooperation between China and Central and Eastern European countries. *Business Economy*(09), 88–91.

[43] Xia, J. C. (2023). Promoting the high-quality development of service trade with digital technology. *Red Flag Manuscript*, (19), 38–40.

[44] Zhou, N. L., & Yao, T. T. (2021). Measurement of the impact of cross-border data flow restrictions on digital service imports and heterogeneity analysis. *International Business (Journal of University of International Business and Economics)*, (2), 1–15.

[45] Ferracane, M. F. (2019). Data flows and national security: A conceptual framework to assess restrictions on data flows under GATS security exception. *Digital Policy, Regulation and Governance, 21*(1), 44–70.

[46] Liu, L. B., Chen, C., & Wang, B. (2021). Predicting financial crises with machine learning methods. *Journal of Forecasting, 41*(5), 871–910.

[47] Hu, M., & Zhao, Y. (2024). Digital service trade barriers and global value chain status. *Forum of World Economy & Politics*, (4), 122–137.