Global Supply Chain Resilience and the Trump Election

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Abstract

Recent economic shocks have profoundly disrupted global supply chains — linkages in the production process that facilitate the transformation of raw materials into finished goods and services. In this paper, we focus on local network structures to examine the resilience of global supply chains to attacks. We first document the network properties of modern supply chains and show that, despite their seeming complexity, they are organized into regularly occurring common configurations, or "motifs". We then study how different types of disruptions affect the reliability of global supply chains and motifs and find that the prevalence of simple motifs, "outsourcing chain" and "hub-spoke" play vital roles in impacting the resilience of global supply chains. These findings serve to provide an easily interpretable view of the entire inter-firm network and strategies to improve the resilience of global supply chains.

Key words: Global supply chains, network resilience, network motifs

Contents

1 Introduction

The emergence of complex networks of producers, transport companies, and distribution centers to develop and move products and services has been a feature of the increasing globalization of international trade since the 1970s (The White House, 2022). But while the greater connectivity of supply chain resilience has fostered greater economic efficiency, it has also created challenges. In recent years, shocks to supply chains have commanded attention on a global scale. For example, disruptions such as the Great East Japan Earthquake in Tōhoku (Carvalho et al., 2021) and the US-China trade war (Fajgelbaum and Khandelwal, 2022) have cascaded through the supply chain network with significant micro- and macroeconomic consequences, destabilizing the global economy. And the global-scale lockdown during the COVID-19 pandemic created severe delays and bottlenecks in shipping industries, driving up import prices to unprecedented levels in most countries (The White House, 2022). The resilience of global supply chains to disruptions, and the roles played by underlying production structures in shaping the outcome, is therefore a fertile area of research.

In this paper, we offer a new perspective on this debate. Drawing on new tools from the interdisciplinary field of network analysis, we study how network resilience is intrinsically linked to local geometric topologies within the global supply chain. We follow Dey et al. (2019) to classify the global supply chain network based on "motifs" — the frequently recurring underlying building block structures that comprise a complex network (Milo et al., 2002). These motifs tend not to form by mere chance, instead, they serve crucial functions within complex networks by interacting with each other (Mangan and Alon, 2003). Dey et al. (2019) assess how long a network can preserve its geometry and present a motif-based analysis of network resilience under different attack strategies. In the context of an application to power-grid networks in four European countries respectively, they identify 4-order connected motifs as the underlying components of the system and assess the reliability of the network on the basis of the lifetimes of these motifs under failures from attacks (Dey et al., 2019). Their findings suggest that motifs may characterize network resilience, potentially serving as early warning indicators of system failure.

We first establish some stylized facts about global supply chains. We use firm-level data on the "supplier-customer" of more than 30,000 firms as of July 2024 to map out two types of supply chain networks – the first focuses on the cross-country linkages of firms, while the second considers firm linkages across industries. We present standard measures used in network theory – density, degree, and centrality – to characterize these networks and how the global supply chain exhibits several properties. First, the distribution of international connections between firms is "scale-free", i.e., exhibits fat-tails; secondly, the network is relatively sparse. This means that the global supply chain is exposed to concentration risk and resilience may be hindered; thirdly, there are clear local network structures – "motifs" that typify supply chains. The prevalence of 4-order motifs, "outsourcing chain" and "hub-spoke", suggests that firms always prefer simplicity and local proximity in terms of how they participate in supply chains. And these motifs play a key role in determining the resilience of global supply chains.

Second, we move to answer the question of what different roles local structures, i.e. motifs, are playing in impacting the global supply chains under adverse disruptions. We simulate random failures and targeted failures to represent shocks in the global supply chain, where random failures denote natural disasters and other unexpected events such as lost vessels, and targeted failures highlight scenarios when some important firms are attacked intentionally, such as cyberattacks on major intermediary Internet servers. We examine the motif lifetimes, – the waiting time until the death of a motif (Dey et al., 2019) – under failures to analyze the robustness of the entire supply chain.

While both networks are resilient under random failures, their reliability varies under targeted failures. The network decays faster under degree-based shocks – specifically, attacks on companies with higher cross-border transactions. This finding helps to prove the fact that many influential firms are controlling the development as well as the vulnerability of global supply chains. Moreover, comparing the performance of cross-country and cross-industry linkages, we find that cross-industry supply chains show longer lifetimes, i.e., higher resilience under failures, suggesting that supply chain structures spanning countries' borders are relatively more prone to collapse in the face of disruptions we consider.

Focusing on the performance of motifs under stress, we find that both "outsourcing chain" and "hub-spoke" survive longer than other complex structures, though decaying faster, too. Regarding their prevalence in global supply chains, we consider these two local patterns to have significant roles in shaping resilience, as well as serving as early warning indicators for the decay of entire networks.

To test our findings regarding the differing performance of networks under various failure scenarios, we introduce a non-parametric data depth approach to study characteristics of the multivariate motif concentrations and motif lifetimes distribution. Both findings support the importance of decentralized, and straightforward patterns of connections in enhancing the resilience of global supply chains. Finally, we discuss how our findings align with real-world facts and what strategies can be implemented to support resilient global supply chains. We believe that the findings from our analysis may provide more ideas for building a resilient supply chain network.

2 Literature Review

Our paper contributes to the literature on the fragility of supply chain networks. The strong interdependence and extensive interconnectedness of these networks make them highly vulnerable to various shocks, irrespective of their localized nature or magnitude. In the short run, these shocks are closely linked to the total value of the final products produced using the affected inputs, directly impacting efficiency throughout the production process. Conversely, in the long run, the effects of shocks tend to be more indirect, amplifying through changes in costs. The deeper the supply network is, the more risks emerge from increased levels of indirect links, leading to a higher level of fragility (Elliott and Golub, 2022). Elliott and Jackson (2024) also emphasize similar long-run effects through the propagation of shocks within global supply chains. They consider the fragility and resilience of the network as endogenous, incorporating the processes of adaptation. The ability of firms to adjust their decision-making to mitigate the fragility of structures is a key feature of their analysis. Rather than concentrating solely on the volatility or recovery of the system under stress, we highlight the importance of understanding the resilience of the network in terms of topological robustness. Supply chain resilience is then defined as the ability of the supply chain to maintain its functions under various scenarios.

This paper also contributes to the literature on international trade networks by exploring how the intricate relationships between firms across various countries and industries influence supply chain resilience. The increasing complexity of these network configurations has created pathways for disruptions to propagate and cascade across both regions and industries, exacerbating the fragility of global supply chains (Baqaee, 2018; Carvalho et al., 2021; Elliott and Golub, 2022). In particular, vertical configurations that link upstream and downstream firms are especially prone to fragility due to their streamlined, direct connections. Any shock affecting a firm within this vertical chain can transmit its impact sequentially to other interconnected firms and may halt the entire production process, undermining the overall resilience of the network (Grossman et al., 2023). Furthermore, Elliott and Jackson (2024) highlights the role of hub firms in amplifying disruptions. Similarly, Ganapati et al. (2024) emphasize the concentration of shipping activities at entrepots or trading hubs with 90% of indirect trade channeled through. These hubs, acting as central nodes in global supply chains, not only facilitate resource flows but also serve as centers for aggregating disruptions, rippling the effects throughout the network structure. While these works shed light on understanding the structural components within global supply chains by focusing on specific structures, our paper provides a comprehensive analysis of more possible connected structures of international trade, considering both vertical, hub-spoke, and other patterns, to examine the resilience of global supply chains.

The macroeconomics literature on production networks examines the intricate relationship between firms' decisions and social welfare. Elliott and Golub (2022) emphasize that firms' reallocating resource flows for diversification and redundancy in global supply chains can significantly impact social optimality, revealing a conflict between efficiency and adverse externalities in trade configurations. Similarly, Grossman et al. (2023) investigate inefficiencies in vertical supply chains through a market equilibrium framework, noting that private incentives often do not align with social efficiency. They argue that optimal policies for resilience networks should balance externalities and private profitability, ensuring that investments contribute positively to the broader economy while addressing the complexities of global supply chains. Our research builds on traditional approaches by shifting the focus from individual behaviors to the structural dynamics within global supply chains, treating their relationships as "clubs". By emphasizing the aggregated efficiency and resilience of these specific structures, our findings contribute to an understanding of the design of macroeconomic policies. Such policies may bridge the gap between private considerations and social efficiency, ultimately enhancing resilience and efficiency in production networks.

Finally, our focus on network motifs builds on important work in network analysis. The concept of motifs was first introduced by Milo et al. (2002) in their study of the Escherichia coli network and has since garnered considerable attention from researchers across multiple fields, aiming to unveil the underlying architectural patterns of various complex systems (Bedru et al., 2020). Dey et al. (2019) apply motifs to analyze the resilience of power grid supply chains in four different countries, clearly decomposing power grid networks by detecting the distribution of six types of four-order motifs. By simulating two types of targeted failures based on betweenness centrality and degree, and analyzing the survival time of these networks, they explored how different motifs interact to influence network resilience. Our research builds on their insights. Specifically, we identify and analyze 4-order motifs within our sample of global supply chains and interpret these topological structures in the context of supply relationships between firms. We then explore how different structures impact the resilience – defined as the ability to maintain its functions – of the global supply chain networks.

3 Global Supplier-Customer Networks — some stylized facts

3.1 Data

The global supply chain is an interconnected and intricate web of relationships between firms, composed of firm-level linkages across countries and industries. This web connects suppliers and customers from the world around to boost the production of goods, and the transaction of resources. Our goal is to figure out compelling evidence of how geographical and industrial relationships influence the resilience of global supply chains. Furthermore, this analysis aims to offer deeper insights into firms' strategic decision-making processes when establishing cross-border relationships within global supply chains. Although the comprehensive trade metrics at the firm level and global scale are not available until now, we follow Qiu et al. (2023) and use the firm-level business relationships on "supplier-customer" from the Capital IQ database [1] to construct global supply chains.

Since historical data is unavailable, we rely on a snapshot taken in July 2024, which includes information disclosed within the previous two years. More than 390,000 pieces of "supplier-customer" information of firms are observed from the database, including their industry classifications and geographical locations. To avoid intersectional effects, we split the data into two groups: cross-national

[1] Capital IQ: The dataset collects more than 1,800,000 pieces of inter-firm relationship data based on their financial accounts and declared business relationships from multiple sources (annual reports, new prospectus from the U.S. Securities and Exchange Commission (SEC), company websites, and other resources) For more details, check at https://www.capitaliq.com/CIQDotNet/my/dashboard.aspx.

and cross-industrial. This approach enables a comprehensive understanding of global supply chains, focusing on the influence of political alignments and vertical dependencies in upstream and downstream operations, respectively. Firms with fewer than 10 partnerships are excluded from this study to reduce noise and focus on meaningful interactions at a global scale. Consequently, the cross-national global supply chain that contains 7143 relationships and the cross-industrial group that contains 23852 relationships are established to analyze the intricate interdependencies present within the global outsourcing system (see Table 1). [2]

	Firms	Relationships	Average Relationships	Countries	Industries
Cross-national	2309	7143	3.094	181	160
Cross-industrial	6086	23852	3.919	190	164
Entire dataset	188584	392105	2.079	210	173

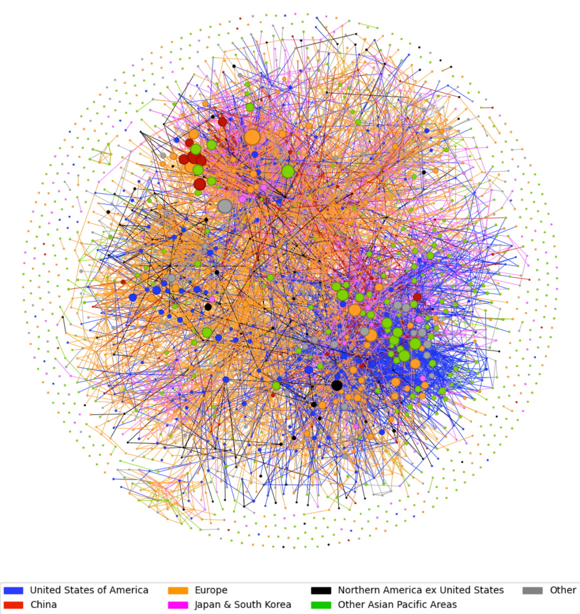
Tab. 1. Summary of Global Supply Chain Data

Following Khadka et al. (2025), Acemoglu and Tahbaz-Salehi (2024), Elliott and Jackson (2023), and Karakoc and Konar (2021), we model the global supply chain data as a network $G = (V, E)$, where V and E are two ordered disjoint sets denoting the firms and the their connections respectively. A directed link $e_{uv} \in E$ represents a piece of resource flow from supplier v to customer u in the network, where $u, v \in V$ and $u \neq v$. The matrix representation of the global supply chain network is illustrated in Figure 1 as "adjacency matrix" $\mathbf{A}$, where elements within the matrix represent cross-boundary interconnections between firms, and "$N = |V|$" denotes the number of firms that have cross-national or cross-industry connections in the dataset. In our case, it can reflect cross-country and cross-industry connections. In what follows, we refer to these as networks "A" and "B" respectively. Figure 2 depicts two supply chain network graphs, within which the colors of nodes correspond to firms' geographical or industrial classifications, the size of nodes represents firms' importance (measured by Eigenvector centrality), and the colors of edges correspond to classifications of suppliers.

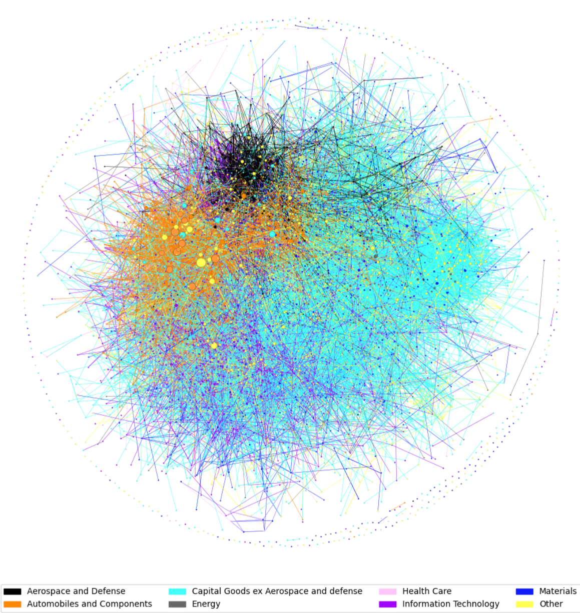
[2] For the cross-national group, we filter all firm-to-firm relationships and categorize firms by their country classifications. To better represent the geographical locations, we divide the countries into 7 regions, namely the United States, Northern America ex the United States, China, Europe, Japan & Korea, Other Asia-Pacific areas, and other regions. For the cross-industry group, we categorize the firms by their industries, following industry classifications of Capital IQ, and further classify them into 8 main industries, namely Automobile and Components, Health Care, Energy, Information Technology, Material, Aerospace and Defense, Capital Goods ex Aerospace and defense, and other industries.

$$
\mathbf{A} = \begin{bmatrix} 0 & e_{12} & \cdots & e_{1N} \\ e_{21} & 0 & \cdots & e_{2N} \\ \vdots & \vdots & \ddots & \vdots \\ e_{N1} & e_{N2} & \cdots & 0 \end{bmatrix}
$$

Fig. 1. Adjacency Matrix of Global Supply Chain Network



(a): Network A: Cross-National Network



(b): Network B: Cross-Industrial Network

Fig. 2. Network A & B
Source: S&P Capital IQ; manual calculations.
Layout algorithm: "Fruchterman-Reingol".

3.2 Network Properties

Beyond the uni-dimensional understanding of global supply chains, network approaches enable a structural analysis by offering detailed insights into how firms position themselves and collaborate with other trading counterparts within the international market. Three measures are to be used in this study to reveal the properties of global supply chain networks: density, degree, and centrality (see results in Table 2 and Figure **??** & **??**).

"Density" is a global measure reflecting the overall connectivity of the network, and can be mathematically represented as $\rho_G = \frac{|E|}{(|V|)(|V|-1))}$. By comparing the actual number of connections ("$|E|$") in the global supply chain network with the total possible number of connections if all pairs of firms are connected symmetrically ("$(|V|)(|V|-1))$"), the density measures the concentration of connections between firms (Bedru et al., 2020), indicating the global structural performance of networks.

"Degree" is one of the most intensively applied metrics in network analysis across various disciplines, such as food economics (Khadka et al., 2025), transportation (Dui et al., 2021), and biology (Dubitzky et al., 2013). In our study, the "degree" measures the sum of all business relationships directly connected to a firm v, denoting how strongly connected the firm is (Jackson et al., 2008) in global supply chains. The calculation of degree can be represented as $k_v = \sum_{u=1}(e_{uv}) + \sum_{w=1}(e_{vw})$, $(u \neq v, v \neq w)$, meaning all direct connections associated with firm v, regardless of their directions, contribute to its degree level. Specifically, the out-degree measures the number of firms that source resources from firm v, and the in-degree measures the number of firms that act as suppliers of firm v.

The importance of firms in the market can also be captured by "centrality". "Centrality" is another widely used metric to identify influential firms based on their positions within the network. Khadka et al.(2025), Gómez(2019) and Freeman et al.(2019) have used centrality measures in network analysis to find the most important nodes. In our case, the following centrality measures are used to describe the characteristics of global supply chains:

Degree Centrality:

$$C_v{}^k = \frac{k_v}{N-1}$$

The degree centrality measures the number of connections firm v has ("k_v") to other participants in the network ("$N-1$") (Freeman et al., 2002). Degree centrality is closely related to degree but offers a relative measure of a node's prominence within supply chains for further comparison across different scales of networks.

Closeness Centrality:

$$C_v{}^c = \frac{1}{\sum_{v \neq v} d(v,u)}$$

The closeness centrality measures the closeness between a specific firm v and other firms participating in global supply chains, where the sum of shortest path distances between firms v and u ("$d(v,u)$") calculates the closeness.

Betweenness Centrality:

$$C_v^{bw} = \frac{1}{(N-1)(N-2)N} \sum_{s,d=1, s \neq d \neq i} \frac{\sigma_{sd}(v)}{\sigma_{sd}}$$

The betweenness centrality measures the importance of firm v acting as an intermediary between other firms, indicating how often it lies on the shortest paths connecting pairs of firms ("$\frac{\sigma_{sd}(v)}{\sigma_{sd}}$") (Gómez, 2019).

Eigenvector Centrality:

$$C_v{}^e = \frac{1}{\lambda} \sum_{u \in N_v} C_u{}^e$$

The eigenvector centrality measures the importance of a firm on both the number and quality of business connections, where N_v denotes the set of neighbors of firm v, and λ represents the largest eigenvalue of the adjacency matrix of A.

	Network A	**Network B**
Nodes	2309	6086
Edges	7143	23852
Density	0.001	0.001
Average Degree	3.094	3.919
Average Degree Centrality	0.004	0.002
Average Closeness Centrality	0.028	0.024
Average Betweenness Centrality	0.001	0.000
Average Eigenvector Centrality	0.008	0.002

Tab. 2. Network Properties of Global Supply Chains

Property 1 (Sparsity) Sparsity is remarkably exhibited by the density measure and average degree measure in both groups of global supply chains. As the density measure shows, the cross-national

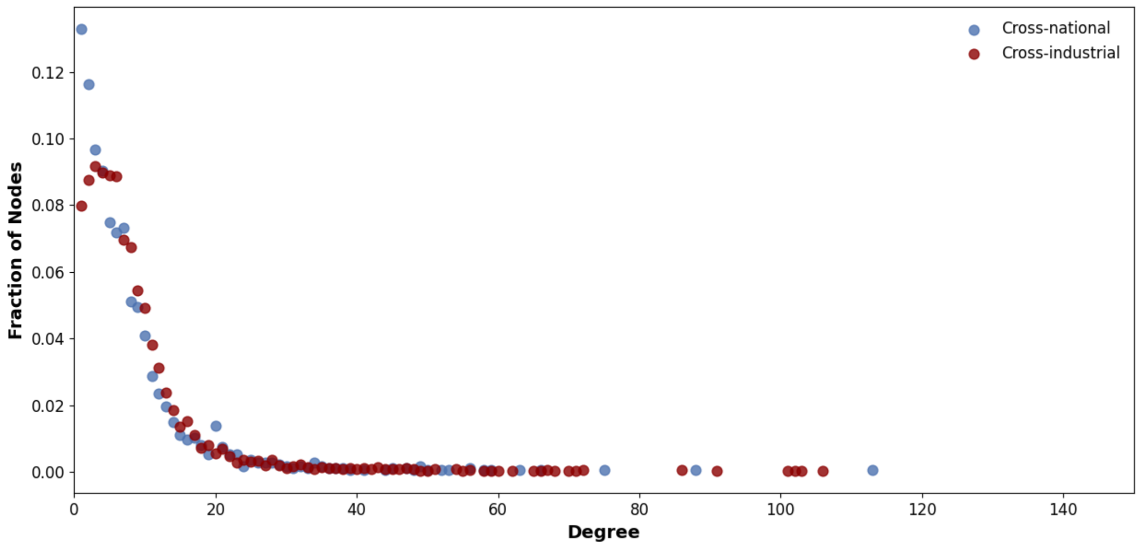


Fig. 3. Network A-Degree
Source: S&P Capital IQ; manual calculations.

and cross-industrial relationships between firms account for only 0.01% of all potential connections between firms in the set. Compared to other social networks including the intra-firm network (0.5) (Swaminathan and Moorman, 2009), the international commodity exchange network (0.55) (Bonaccorsi, 2020), and the international service exchange network(0.115) (Bonaccorsi, 2020), two global supply chain networks in our study are relatively sparse. As indicated by the average degree at 3.094 and 3.919 in both networks, most firms are not so interconnected by direct transactions, despite the vast number of firms operating across international boundaries in today's globalized economy (Though the connectivity in the cross-industrial network is stronger than that in the cross-national network). Take the example of Samsung, the multinational company headquartered in Korea, it maintains direct relationships with only 95 suppliers abroad for its diverse range of products. This local network of Samsung is relatively sparse given that there are over 1,000 potential suppliers in the global market that could serve its production needs. Similar results are shown by Ohnishi et al. (2010) in their study about inter-firm relationships in Japan (Density = 0.004).

Given the recent uncertainties arising from the US-China disputes and Russia-Ukraine tensions over the past two years, it is not surprising that cross-border transactions between firms have remained sparse. In light of the increased costs associated with outsourcing raised from geopolitical risks and import and export restrictions for specific industries, many firms are opting to reduce reliance on outsourced operations. The strategies include reshoring production or sourcing materials from home or allied regions to mitigate risks that could disrupt production continuity. The trend of industry integration is also widely seen across the world (Antras and Helpman, 2004).

Property 2 (Disparity) Disparity is significant in firms' connectivity, as suggested by degree and centrality measures in global supply chains. Degree distributions in both groups exhibit obvious power-law distributions with fat-tailed structures, suggesting that a majority of firms pushed to peripheries in global supply chains due to their lower level of connections (degree), and a minority accounting for a disproportionately high number of supply chain relationships (see Figure **??**).

Definition 1 ("Scale-free") *(Barabási and Albert, 1999)*

"Scale-free" describes the scenario when vertices' numbers of edges (degrees) are power-law distributed, resulting in few vertices having many edges and many vertices having few edges.

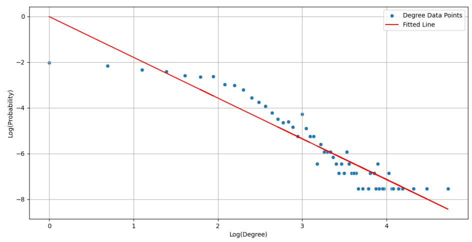
$$p_k \sim ck^{-\gamma}$$

$$\log f(k) = \log(c) - \gamma \log(k)$$

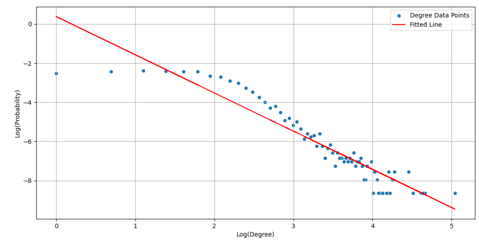
In the mathematical calculation, c denotes the scalar to normalize the support of the distribution to sum to 1, k is the degree measure we have mentioned above, and γ is the parameter of power function, which indicates the extent of "scale-free".

Degree distributions in our study approximately follow a "scale-free" style, aligned with findings in Ohnishi et al. (2010) and Saito et al. (2007) (see Figure 4). Blue points in the graphs represent different degree levels, and the red line is the fit line. Seen from the results, both groups are approximate "scale-free" networks. More specifically, the higher level of γ (1.952) in the cross-industrial group suggests that inter-firm relationships are more concentrated on a small number of firms that are regarded as hubs in supply chains. These findings suggest the existence of an uneven "core-periphery" structure in global supply chain networks.

The centrality measure shows similar results with some firms occupying a significant number of connections than other participants in the market, suggesting a limited number of firms act as hubs or important intermediaries in the network (see Figure **??**). More specifically, the average level of



(a) Network A



(b) Network B

Fig. 4. "Scale-free" Analysis

degree centrality, betweenness centrality, and eigenvector centrality measures—each below 0.01 — demonstrate that there are few firms within supply chains serving as bridges or hubs that facilitate resource flows globally (see Table 2). In contrast, the relatively higher closeness centrality values (0.028 in Network A and 0.024 in Network B) indicate the presence of small firms that cluster together for integration benefits. This disparity in centrality positions highlights the uneven nature of global supply chains, where a few dominant players control substantial connections, while many others are pushed to the periphery.

In light of recent disruptions to global supply chains, the increased cost of international trade has prompted firms to adopt a more strategic and prudent approach to cross-border sourcing decisions. This shift has not only resulted in sparse international connections but has also underscored the highly concentrated structure of global supply chains. This means that firms tend to choose outsourcing partners from large multinational companies or important suppliers of key materials, which aligns with the "preferential attachment" in network theory (Jackson et al., 2008). Firms intend to collaborate with these "star" firms for cost-effective considerations and their strong capability in mitigating supply chain risks. In contrast, firms with fewer partnerships (lower degree) are naturally distanced in the global inter-firm network. The distance hinders the possibility of mutual growth and innovation of firms. Such concentration can foster efficiency by allowing connectivity to central firms but allows for the fast diffusion of risks through those central hubs more possible. Consequently, this disparity further isolates smaller firms while increasing the prevalence of hub firms, making global supply chains uneven and brittle under stress.

In summary, the global supply chain is a brittle structure with few firms holding central roles. This suggests the strong concentration and dependence on some economies within global supply chains

(Jusoh and Razak, 2020). These players, often multinational corporations or strategically positioned entities, occupy critical hubs in the network, controlling large volumes of trade and resource flows. Such supply chain configuration implies a higher level of fragility within the systems – a disruption to any of these key players could lead to cascading effects, impacting the resilience of the entire supply chain system. In addition, the lack of enough intermediaries makes the network more fragmented and dispersed. This configuration is crucial for understanding resilience and vulnerability. Despite being sparse, the presence of a few hubs can make the network more robust in certain aspects but also more fragile if those hubs are disrupted.

3.3 Distances Between Firms

The proliferation of applying traditional measurements in network analysis has provided a profound understanding of how individual firms perform in global supply chains. However, efforts focused on the structural problem of how they are connected are still limited. In this section, we introduce the concept of "network distance", the metric widely used in network analysis to measure the network structure from the overall scale (Qiu et al., 2023, 2024), to depict structural interactions between firms that shape the complex supply chain network and its functionality.

Definition 2 *(Network Distance) (Qiu et al., 2023)*

Network distance is the length of shortest path (ℓ^s_{ij}) from node i to node j, $i, j \in V, i \neq j$.

Definition 3 *(Shortest Path)*

A path ℓ_{1m} in G is a sequence of nodes $P = (v_1, v_2, \dots, v_m) \in V$ such that v_i is adjacent to v_{i+1} for $i \in [1, m)$, the length of the path is then $m - 1$. Let $E = e_{ij}$, the shortest path from v to v' is the path $P = (v_1, v_2, \dots, v_m)$, where $v_1 = v, v_m = v'$, that over all possible m minimizes $|E|$.

Extending from the traditional focus on individual performance, network distance helps to map out how network effects bridge participants that may seem strange to each other from a bilateral perspective. In global supply chains, distance between firms can represent the most efficient route for market interactions that minimize costs while maximizing benefits. A highly connected network with shorter distances can lead to stronger spillover effects with improved coordination and greater resilience to shocks. Conversely, longer distances may indicate inefficiencies or fragmentation in the supply chain network. The longer average distance of the cross-industrial network (9.25) than that of the cross-national network (6.95) indicates the more dispersed structure and fragmented configuration in cross-industrial collaborations (see Figure 5).

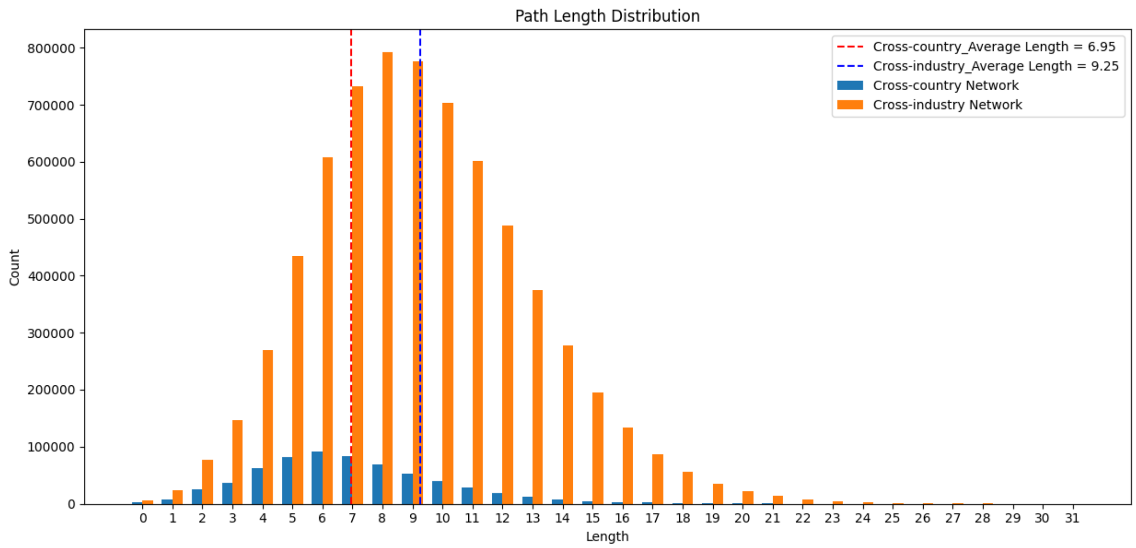


Fig. 5. Network Distance

3.4 Network Motifs

The discussion above has focused on the global topological properties of two supply chain networks. The performance of individual firms and their connections has represented the basic elements of the network, suggesting the overall sparse and imbalanced supply connections. However, they often fail to capture the network's specific relational forms and local structures. For example, while degree can indicate the number of connections a node has, it does not reveal the intricate patterns of interactions or the context of those connections. Therefore, although fundamental network metrics are important analytical tools, a deeper understanding of the economic underpinnings of a network's complex structure and functionality requires an examination of high-order properties.

Going beyond dyadic relations, high-order structures focus on features of coalitions formed from nonlinear interactions of multiple ($\geq$ 3) vertices. The high-order configuration works to elucidate complex interdependency within the network to provide clues for collective network dynamics (Bick et al., 2023). Considering the supply chain network is always formed and enforced to function by more than two participants (Galeotti and Goyal, 2010, Ding et al., 2024), high-order representations may provide more topological information about how firms interact with alliances, as well as how value flows within a suppliers-customers club, mapping local idiosyncracies with the aggregated measures used in previous studies (Xu et al., 2023). Beyond bilateral supply-demand analyses, high-order structures are set in our case to explore their joint actions that may contribute to the dynamics of supply chain resilience and robustness.

Motifs, one type of high-order structures, are foundational configurations of firms and connections, essential for understanding the local connecting mechanisms that shape supply chain behaviors in complex networks. Motifs allow us to pinpoint the most common connection patterns that link raw material suppliers, manufacturers, and distributors, indicating the usual way that firms collaborate or compete and leading to valuable insights into the overall network dynamics. In addition, we consider that networks with similar global properties, such as our two networks of global supply chains, may have distinct practical structural characteristics that serve different functions within the system (Liu et al., 2019), in other words, while the loose and skewed connections are ubiquitous, the mechanisms that give rise to such features can differ significantly. Therefore, further analysis of motifs, the basic unit of complex networks, is necessary.

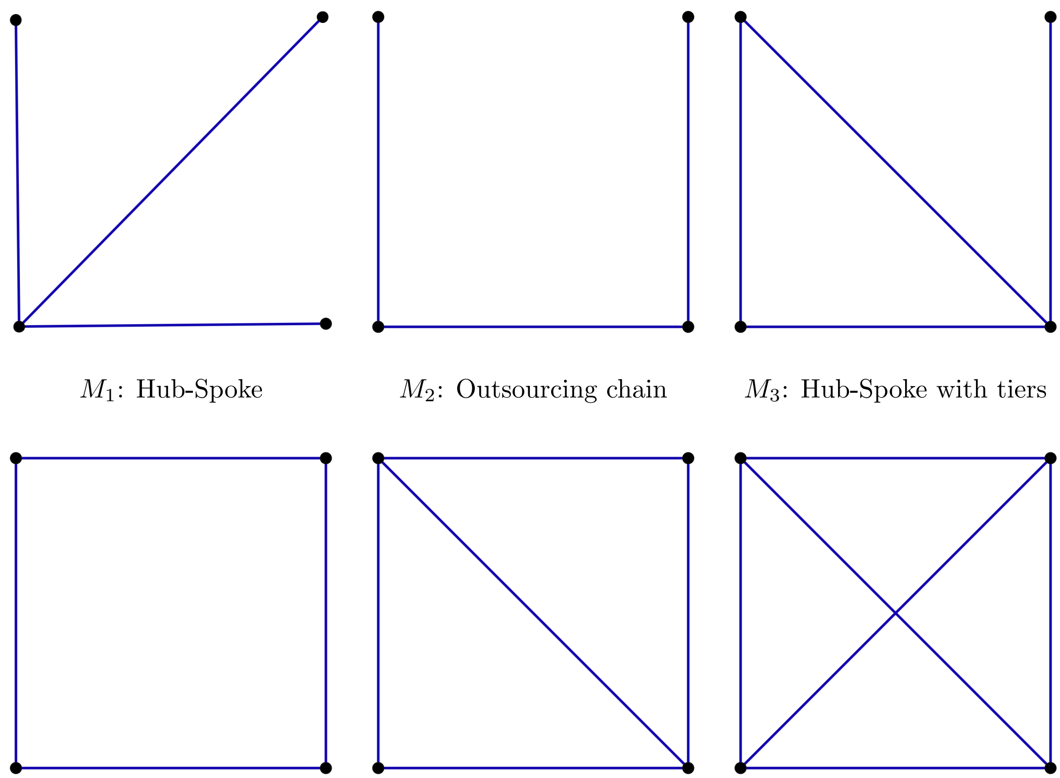
Definition 4 (Motif) *(Milo et al., 2002)*

A network motif is a recurrent and statistically significant sub-graph, or "signature" of a large network.

Undirected, 4-Order Motifs in Global Supply Chains Our identification methodology applies to n-order motifs. However, due to computational complexity (see Appendix) and as is convention in the motif literature (Dey et al., 2019; Xu et al., 2023; Ye et al., 2023), our focus will be on undirected 4-order motif units.[3] Our focus on low-order motif structures is further justified by the sparse nature of inter-firm relationships (see Section 3) and economic literature on clubs (Ding et al., 2024; Galeotti and Goyal, 2010). In this chapter, we focus on undirected motifs due to their relative ease of identification. This analysis could be extended to consider directed motifs, which would expand the number of distinct motif patterns from 6 to 64.

[3] Our research serves as an expansion of the 3-order motifs that Ohnishi et al. (2010) has studied to give more focus on structures in supply chain networks.

Figure 6 shows all possible undirected, connected 4-order motifs, each of which performs a different function in networks (Dey et al., 2019; Shoval and Alon, 2010), especially in risk propagation mechanisms (Carvalho, 2014). Motifs from M_1 to M_6 exhibit a clear ascending order regarding the density of interconnections, while simultaneously demonstrating an ascending order in the number of links, positioning the nodes at different levels of roles.



M_1: Hub-Spoke M_2: Outsourcing chain M_3: Hub-Spoke with tiers

M_4: Circular economy M_5: Hub Collaborations M_6: Tightly-knit clusters

Fig. 6. All 4-Order Connected Motifs

These distinct structures can be understood as relationships between firms in our supply chain networks. The "Hub-Spoke" relationship forms when a firm with general-purpose technology acts as a hub in the production process (Carvalho, 2014), and all other firms choose to outsource with it for intermediate input or final good demand (The White House, 2022). The "Outsourcing chain" structure represents the simplest linear economy where resources travel "one-to-one". The firms in between act as the important intermediaries that guarantee the operation and continuation of this supply chain structure. M_3 extends the outsourcing "chain" with an additional chord linked to the central firm. The "Circular economy" is interpreted as a feedback loop where members share equal importance while no one is dominant, which means that collaboration is welcomed and essential. Motifs M_5 and M_6 are two more complex patterns that require a strong interdependence between every two firms during international trade.

To illustrate the prevalence of these motifs, consider a sub-graph of network A that includes companies connected to "SAMSUNG Electronics Co., Ltd.".[4] The small world of "Samsung Electronics Co., Ltd." exhibits some salient motif patterns we have defined above, among which the "Hub-Spoke" and "Outsourcing Chain" types are easiest to find. We also identify M_3 and M_4 in the Samsung supply chain network.[5] Another finding is that many motifs share common edges even in the local network. That means that motifs are mutually dependent within the network, which means that small clubs of collaboration are always interdependent on other linking structures. This suggests that firms form different functions in different global sourcing arrangements and has implications for the structural robustness, i.e. resilience we conduct in section 5.

While the Samsung example helps to shed light on possible economic incentives for the various motif structures we see, it does not guarantee that such patterns carry over into our global-scale supply chain networks across industries or geographical locations. In the next section, we introduce a formal motif detection algorithm to identify the motifs and their occurrences across the global supply chain networks we consider.

Motif Identification and Concentration Motif discovery has always been a challenging task due to the exponential computational complexity of the identification of high-order sub-graphs (Patra and Mohapatra, 2020). To investigate the motif distribution within the two networks, we apply the "FANMOD" algorithm to detect 4-order motifs based on their balanced performance considering scalability, accuracy, and runtime efficiency (Wernicke and Rasche, 2006) (see Appendix for comparison of different algorithms).

Motif concentration is the simple distribution measurement to analyze the performance of high-order structures in a network at the local level, revealing essential network functionality and organizational mechanisms beyond global metrics. This metric was first introduced by Milo et al. (2002) in

[4] "Samsung Electronics Co., Ltd." is the firm with the highest degree of connections within network A with the degree of 246 (95 suppliers and 151 customers).

[5] M_1corresponds to green, M_2corresponds to red, M_3 corresponds to pink, and M_4 corresponds to blue.

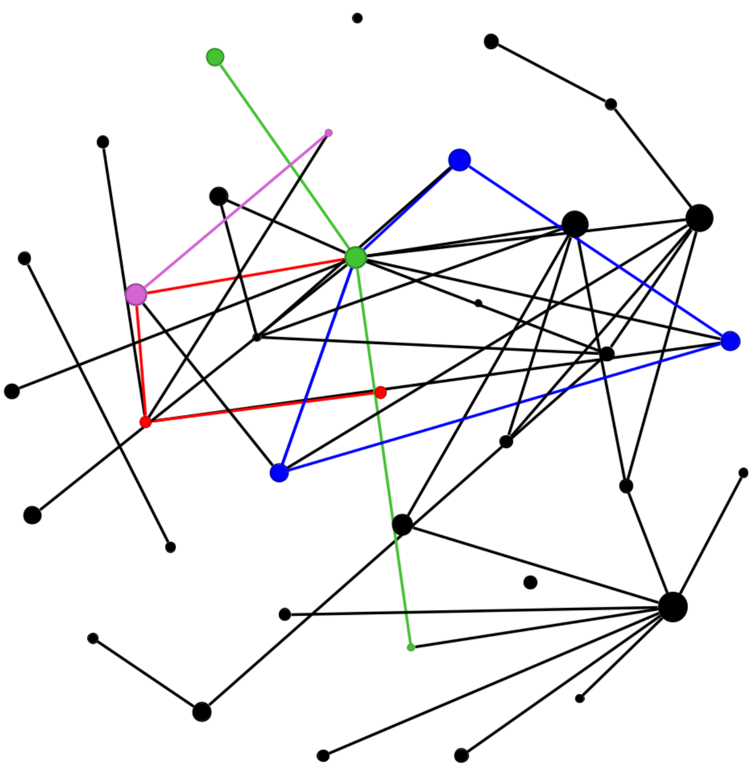


Fig. 7. The Local Network of "Samsung Electronics Co., Ltd."
This local network was generated by remaining the induced sub-graphs that contain "Samsung Electronics Co., Ltd.". Considering the small-world network is still complex, only part of the small world is shown in the figure to make it more readable (degree:15-49).

Algorithm 1 "FANMOD" Algorithm for Undirected Motif Identification

```
Input:
   G: Undirected graph
   k: Motif size
Output:
   M: Frequency of detected motifs
Initialize M ← ∅
function GenerateInducedSubgraphs(G, k)
    induced_subgraphs ← ∅                                   ▷ Store all induced subgraphs
    for each combination of k nodes in G do            ▷ Loop through all possible sets of k nodes
        Add the induced subgraph of these nodes to induced_subgraphs ▷ Create the subgraph for the selected nodes
    end forreturn induced_subgraphs
end function
function FindIsomorphicPattern(subgraph) return the canonical form of subgraph ▷ Convert the subgraph to a standard form for comparison, considering undirected edges
end function
function CountMotifs(induced_subgraphs)
    for each subgraph in induced_subgraphs do            ▷ Iterate through each induced subgraph
        pattern ← FindIsomorphicPattern(subgraph) ▷ Find the canonical form of the subgraph
        if pattern ∉ M then                              ▷ Check if this pattern is already counted
            M[pattern] ← 0
        end if
        M[pattern] ← M[pattern] + 1
    end for
end function
function Run
    induced_subgraphs ← GenerateInducedSubgraphs(G, k) ▷ Generate all induced subgraphs of size k
    CountMotifs(induced_subgraphs)   ▷ Count the frequency of each motif return M   ▷ Return the final motif frequency map
end function
```

the analysis of "feedforward" loop motifs in the subnetworks of the E. coli transcription network.

Definition 5 (Motif Concentration) *(Dey et al., 2019)*

The ratio of the occurrence of certain k-order patterns to the total number of all the k-order induced subgraphs in a network.

$$C(M_i) = \frac{|M_i|}{\sum_{i=1}^{m} |M_i|} \tag{1}$$

$|M_i|$: *the number of* M_i *in* G

m : *the number of motifs in* G

Figure 8 illustrates the concentration of each 4-order supply chain motif. Considering the sparse connections within global supply chains, it is unsurprising that M_6, the tightly-knit cluster is non-existent in both kinds of supply chain networks. The three simpler structures, M_1, M_2, and M_3 consistently dominate the motif distributions, while the relatively more complex structure, M_4 and M_5, which requires a higher degree of interconnectedness, are less prevalent.

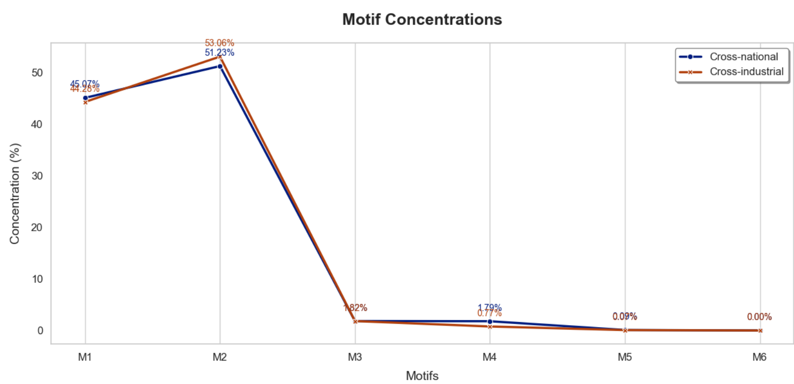


Fig. 8. Motif Concentrations in Network A & B

The prevalence of three kinds of motifs suggests the economic relationships that are central to supply chain networks. The "Outsourcing chain" and "Hub-Spoke" patterns always dominate in both networks with a combined concentration greater than 90%. These two patterns are suggestive of the highest cost-efficiencies with the least number of supply links which still ensure connectivity through structures. Their predominance is aligned with our findings in degree distributions which are always skewed and imbalanced. Combining our findings in network density, there are a small fraction of direct links in global supply chains, within which firms tend to form the least number of links for cost-efficiencies and share the externality from indirect connections (Ding et al., 2024). Moreover, the “Outsourcing chain” is more prevalent than “Hub-Spoke”, suggesting global dominance of sequential, production-line arrangements spanning different industries and geographical locations. We consider the reason lies in that there are only a small fraction of hub firms that control most linkages, i.e., owning “Hub-Spoke” pattern in their local networks, which makes the vertical chain, with lower coordination complexity (Grossman et al., 2023), more prevalent in global supply chains. Taking the example of Samsung and Toyota, Samsung develops its local network as a typical “Hub-Spoke” pattern to ensure its powerful position over suppliers and customers across the countries and industries. In contrast, Toyota is famous for its Just-In-Time (JIT) production, which is a perfect example of vertical configurations. It relies on hierarchical supplier coordination and integration for resource and information flows to minimize costs through the production processes. Overall, the dominance of these two simple structures unveils their important roles in facilitating resource flows through global supply chains, offering efficiency with the least number of links.

Detailed comparison reveals that network A exhibits a slightly higher proportion of “Hub-Spoke” structures (45.07%) than network B (44.28%). This observation aligns with our earlier findings regarding the degree distribution, which underscores the centralized characteristics of network A. The dominance of “Hub-Spoke” structures suggests that a few important firms serve as central hubs, facilitating the connectivity of resources within global supply chains. This centralization may lead to vulnerabilities, as disruptions to these hubs could disproportionately impact the overall network functionality. In contrast, the more distributed architecture of network B may offer greater resilience against targeted shocks, as it relies on a broader array of connections and does not depend heavily on any single firm's performance. We consider the reason why cross-industry networks tend to have a more uniform distribution compared to cross-country networks due to their diverse connections across various sectors and economies. In cross-industry interactions, firms engage in global trade, fostering collaborations that are less concentrated within specific industries or regions.

4 The Resilience of Global Value Chain Networks

Observations above about motifs have shown us some significant linking structures in supply chains. The edge-sharing features make motifs not independent but strongly interdependent, which mirrors the mechanisms of risk propagation in networks. For example, if a proportion of firms are hit by an attack, their direct suppliers or customers will also feel the effects, leading to a cascading collapse. It is in this light that we consider the resilience of global supply chains. Our measurement of resilience is distinct from what Elliott and Golub (2022) and Grossman et al. (2023) have applied. They consider resilience from a time-series view as the ability of the system to "bounce back" after disturbances, focusing on recoverability. In contrast, our focus lies on the fundamental structural characteristics within networks, defining resilience in terms of structural robustness — the inherent strength and stability of network configurations under shocks.

Definition 6 (Resilience) *(Dey et al., 2019)*

The resilience of a network is its tolerance to perturbations, in other words, the ability to keep its structural properties under exogenous failures.

The measurements of resilience are mostly lower-order and connectivity-based, e.g., giant component (Artime et al., 2024; Holme et al., 2002; Xu et al., 2023), degree distribution (Dekker and Colbert, 2004), average shortest path length (Karakoc and Konar, 2021; Shannon and Moore, 2004), and betweenness centrality (Ellens and Kooij, 2013; Sajedianfard et al., 2021). In this chapter, we apply motif metrics in the analysis of resilience in global supply chains, focusing on how overall stability arises from structural resilience.[6] Our motif-based resilience analysis measures the probability that the motifs in global supply chains remain functional after iterations of firm-level failures, be they random failures or targeted attacks on highly central firms. Applying the survival function helps to better explain the lifetime, i.e., network robustness before finally corrupts.

Definition 7 (Survival Function) *The resilience of the entire global supply chain network can be combined as a configuration of different motifs (Dey et al., 2019), which means that the entire network will lose its resilience, i.e. structural robustness, if and only if all the motif structures fail to remain*

[6] Motif metrics have been applied in shipping networks (Xu et al., 2023), inter-firm networks (Ohnishi et al., 2010) and power-grid networks (Abedijaberi and Leopold, 2018; Dey et al., 2019) to analyze network resilience.

functional. In our survival analysis of global supply chains, "lifetime" refers to the proportion of firms removed before the network reaches a critical point of failure. For instance, if the network experiences a breakdown after the removal of 90% of firms, then the network's lifetime is defined as 90%.

$$R_i(t) = \Pr(A_i) = \Pr(T_i > t), i = 1, \ldots, 6 \tag{2}$$

$R_i(t)$: *the survival function of motif* M_i

A_i : *the event when the motif* M_i *survives till* t *under shocks*

T_i : *the lifetime of motif* M_i

t : *the number of occurrences of disruptions to* M_i *(removal of firms)*

$\Pr(T_i > t)$: *the cumulative survival function of motif* M_i*, i.e., motifs still function after shocks.*

$$R_s(t) = \Pr(T_s > t) = 1 - \Pr\left(\bigcap_{i=1}^{6} A_i^c\right) \tag{3}$$

$R_s(t)$: *the survival function of entire network* G

T_s : *the lifetime of the entire network* G

$\Pr(T_s > t)$: *the cumulative survival function of entire network* G*, i.e., the network* G *still function after shocks.*

In network analysis, the survival function $S(t)$ typically represents the proportion of the network's original connectivity or functionality that persists beyond a certain threshold t, such as the fraction of nodes or edges removed. For instance, in a network that simulates a supply chain, $S(t)$ could track the fraction of firms (nodes) or supplier relationships (edges) still intact as disruptions increase.

4.1 Firm Failures in Supply Chains

In global supply chains, cascading failures may explode due to corruption of related firms or connections (Chen et al., 2022). For example, during the Great East Japan Earthquake, the shutdown of several Toyota and Honda plants—two of the world's leading automakers—triggered a ripple effect that even reached the United States, causing large-scale production halts due to supply shortages from Japan (Carvalho et al., 2021). A similar impact was observed during the COVID-19 pandemic when lockdowns in China triggered cascading effects across several countries heavily reliant on China's exports. The US-China trade war is an evident example of connection failure, which led to large-scale trade redistribution. This shift was marked by increased cross-country links between the US and other Asia-Pacific economies and a reduction in US-China linkages (Qiu et al., 2023). We find that while node failures consistently cascade through the network, influenced by the specific supply chain structures connected to each firm, the severing of specific trade connections is more likely to prompt rearrangements in trade flows between firms.

We consider the cascading effects from node failures to make a network approach well suited to the study of the resilience of global supply chains.[7] Firm-level failure in global supply chains means a firm exits the global network or is unable to operate productions. Failures come from different sources: natural disasters such as earthquakes and tsunamis (Carvalho et al., 2021) and other intentional attacks such as cyberattacks, tariffs (Grossman et al., 2024), and logistical failures (Chen et al., 2022). Once a firm fails as a result of disturbances, the related downstream nodes may not operate normally due to the shortage of supply, and the related upstream nodes may end their operations due to inventory backlogs, causing efficiency within supply chains to decline. They are then forced to seek partnerships with other companies to restore efficiency and reduce uncertainty. This cascading effect can be translated into the severing of previous links with the attacked firm.[8]

4.1.1 Simulation Process and Algorithm

In network theory, the failure of one firm can be expressed as the removal of one node and all the links connected to it, as well as those nodes isolated from the network after removal. Based on the discussion above, we consider three kinds of failures, namely random failure, and targeted failure based on degree and betweenness centrality respectively. Random failure selects nodes randomly, and targeted failures represent disturbances that will attack those important nodes in the network. The importance of nodes follows the descending order of degree and betweenness centrality respectively.[9]

- Random Failures

[7] Node-failure has been applied in resilience analysis in the maritime industry (Dui et al., 2021; Xu et al., 2023), logistics (Chen et al., 2022), and power-grid networks (Abedijaberi and Leopold, 2018; Dey et al., 2019).

[8] The addition of new links with other alternative firms is not counted in our study, as the database is not a dynamic one. Further study will focus on the dynamics of combining severing and adding new links.

[9] What we conduct is the non-adaptive failure, so both the information of degree and betweenness centrality order are based on their distributions in initial networks (Holme et al., 2002).

Random failures are unexpected untargeted events, namely natural disasters such as earthquakes and tsunamis, labor disruptions such as strikes, operational failures due to technical malfunctions, etc. To simulate the random failures in global supply chains, we conduct 100 rounds of iterations for the robustness of studying network resilience under random failures.

- Targeted Failures Based on Degree

  In global supply chains, numerous examples illustrate targeted failures based on degree. A notable example is the antitrust case against Google by the European Union. The multinational corporation faced a record fine of €2.42 billion (approximately $2.7 billion) in 2017 for unfairly prioritizing its own services over those rivals, which violated EU's competition laws. Such a significant penalty compelled Google to revise its policies and global strategies regarding fair competition, which is costly. Moreover, this ruling prompted other countries and regions to consider implementing similar antitrust measures, thereby amplifying the cascading effects of the case across the global landscape.

- Targeted Failures Based on Betweenness Centrality

  Cyberattacks on Dyn, an Internet intermediary, serve as a good example of targeted failures based on betweenness centrality. In 2016, Dyn experienced widespread outages that affected numerous high-profile websites, including Twitter, Netflix, and Reddit, affecting tens of millions of users worldwide. This disruption resulted in significant economic losses, with estimates indicating millions of dollars in lost revenue for businesses dependent on online services.

Algorithm 2, 3 and 4 show the realization of three different firm-level failures in networks:

Algorithm 2 Random Failure

```
Input: Network G = (V, E)
Output: Motif concentrations C_i under random node removals
for each motif type i = 1, ..., m_n do                ▷ m_n is the number of distinct n-order motifs
    N_i ← count of n-order motifs of type i in G
end for
Compute initial concentration: C_i ← N_i / Σ_i N_i for each motif type i
for t = 1 to |V| do                                   ▷ Iterate until all nodes are removed
    Randomly select a node v_r ∈ V
    V^f ← V \ {v_r}                                   ▷ Remove selected node
    E^f ← E \ {(x, y) ∈ E : x = v_r or y = v_r}       ▷ Remove related edges
    Remove isolated nodes:
    while true do
        I ← {v_j ∈ V^f : (v_j, v_k) ∉ E^f for any v_k ∈ V^f}   ▷ Identify isolated nodes
        V^f ← V^f \ I                                 ▷ Remove isolated nodes
        if I = ∅ then
            break
        end if
    end while
    for each motif type i = 1, ..., m_n do
        Recompute N_i for the modified network (V^f, E^f)
    end for
    Update concentration: C_i[t] ← N_i / Σ_i N_i
end for
```

Algorithm 3 Targeted Failure (Degree)

```
Input: Network G = (V, E)
Output: Motif concentrations C_i under targeted attacks
for each motif type i = 1, ..., m_n do                ▷ m_n is the number of distinct n-order motifs
    N_i ← count of n-order motifs of type i in G
end for
Compute initial concentration: C_i ← N_i / Σ_i N_i for each motif type i
Calculate degree k_v for each node v ∈ V
H(G) ← sorted V by k_v in descending order            ▷ Sort nodes by degree
for t = 1 to |H(G)| do                                ▷ Iterate over sorted nodes
    V^f ← V \ {H(t)}                                  ▷ Remove attacked node
    E^f ← E \ {(x, y) ∈ E : x = H(t) or y = H(t)}     ▷ Remove associated edges
    Remove isolated nodes:
    while true do
        I ← {v_j ∈ V^f : (v_j, v_k) ∉ E^f for any v_k ∈ V^f}   ▷ Identify isolated nodes
        V^f ← V^f \ I                                 ▷ Remove isolated nodes
        if I = ∅ then
            break
        end if
    end while
    for each motif type i = 1, ..., m_n do
        Recompute N_i for the modified network (V^f, E^f)
    end for
    Update concentration: C_i[t] ← N_i / Σ_i N_i
end for
```

Algorithm 4 Targeted Failure (Betweenness Centrality)

Input: Network $G = (V, E)$
Output: Motif concentrations C_i under targeted attacks
for each motif type $i = 1, \ldots, m_n$ **do** ▷ m_n is the number of distinct n-order motifs
  $N_i \leftarrow$ count of n-order motifs of type i in G
end for
Compute initial concentration: $C_i \leftarrow \frac{N_i}{\sum_i N_i}$ for each motif type i
Calculate betweenness centrality C_{bw} for each node $v \in V$
$H(G) \leftarrow$ sorted V by C_{bw} in descending order ▷ Sort nodes by betweenness centrality
for $t = 1$ to $|H(G)|$ **do** ▷ Iterate over sorted nodes
  $V^f \leftarrow V \setminus \{H(t)\}$ ▷ Remove attacked node
  $E^f \leftarrow E \setminus \{(x, y) \in E : x = H(t) \text{ or } y = H(t)\}$ ▷ Remove associated edges
  Remove isolated nodes:
  while true **do**
    $I \leftarrow \{v_j \in V^f : (v_j, v_k) \notin E^f \text{ for any } v_k \in V^f\}$ ▷ Identify isolated nodes
    $V^f \leftarrow V^f \setminus I$ ▷ Remove isolated nodes
    if $I = \emptyset$ **then**
      break
    end if
  end while
  for each motif type $i = 1, \ldots, m_n$ **do**
    Recompute N_i for the modified network (V^f, E^f)
  end for
  Update concentration: $C_i[t] \leftarrow \frac{N_i}{\sum_i N_i}$
end for

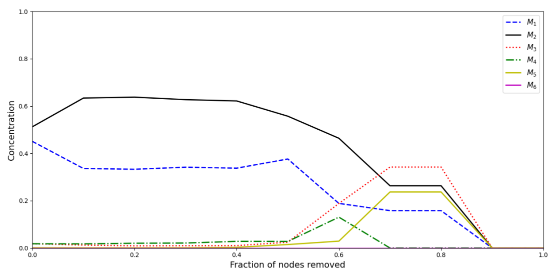
4.2 Resilience Analysis In Global Value Chain Network

4.2.1 Motif Concentration

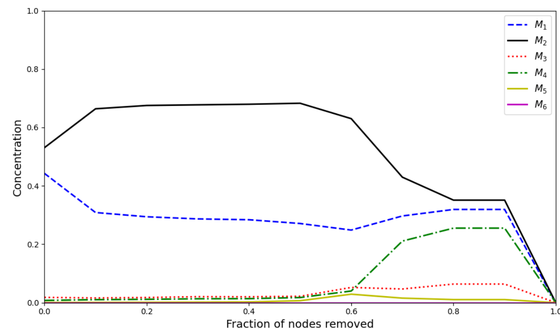
By conducting failure simulations, we compare the profile of motifs (motif concentrations) as a function of the fraction of firms attacked to assess the resilience, i.e. the survival threshold (survival subject to varying severity of attacks). Observing the change of motif distribution upon removal, we can gain insight into the resilience of different motif structures by their persistence relative to other structures. Furthermore, we expand to the resilience analysis of the entire network by combining the resilience analysis of different motifs.[10]

Figure 9 shows the results after simulating failures. Random failures have a limited impact on supply chains unless all the firms are excluded from participating in the global trade market: both networks fail when the removal fraction approaches 1. The betweenness centrality-based failures feature more volatile fluctuations in terms of motif concentrations than random attacks. We consider firms with higher betweenness centrality are structural bottlenecks facilitating transactions by bridging resource flows, such as “Microsoft” and “Maersk” in our global supply chains. Attacks on these firms may

[10] Given computational complexity, we calculate disruption in 10% increments.

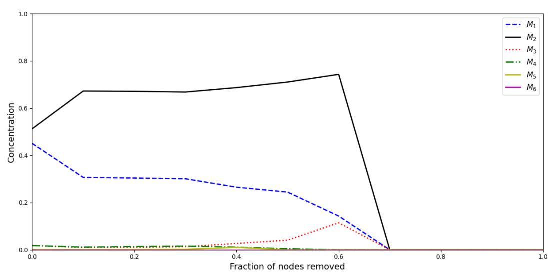


Network A

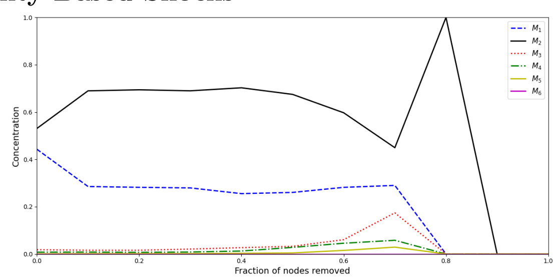


Network B

Betweenness-Centrality-Based Shocks

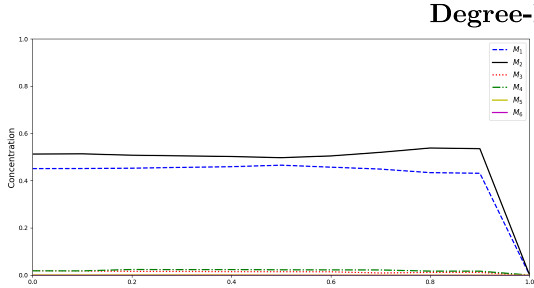


Network A

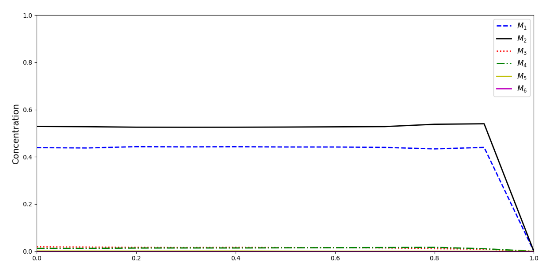


Network B

Degree-Based Shocks



Network A



Network B

Random Shocks (Average of 100 Simulations)

Fig. 9. Motif Concentrations in Networks A and B under Different Failures

sever the most critical supply links between suppliers and customers, leading to much sparser and more disconnected networks, triggering widespread and cascading disruptions in global supply chains. Focusing on degree-based failures, the results exhibit more pronounced volatility compared to both networks under betweenness centrality-based shocks. This heightened volatility likely stems from the unique structure of our network: it is notably sparse and skewed, with a small subset of companies functioning as critical bottlenecks, while a group of firms serve as essential hubs, holding the highest degree levels. In other words, degree-based shocks can lead to more significant disruptions than betweenness centrality-based shocks in our global supply chains. There is also a marked distance between the two motifs under different shocks, and the distance gets larger when supply chains are hit by degree-based shocks, suggesting the higher decaying rate of global supply chain networks under degree-based failures.

Moreover, network B always survives longer than network A under different severities of targeted attacks, considering the distance always shows a larger gap between Network B and the overall longer lifetimes, which means that Network A vanishes faster than Network B in every scenario, which is consistent with our initial finding in degree distribution that Network B is more robust and resilient than Network A. For example, under betweenness centrality failures, all the structures corrupt when 90% firms are excluded in the international trade in network B while the time is when 80% of node removal happens in network A. Similar results can be seen under degree-based attacks. The reason may lie in that network B has more decentralized distribution than network B. The more evenly distributed connections across network B allow the entire network to maintain its functionality under node removal since there are less critically important firms that control the trade connections in network B. Conversely, the cross-country links that strongly rely on central hubs are more fragile if those central firms are impacted because they control a large volume of trade links, providing paths for many resource flows.

4.2.2 Mahalanobis Depth

To further assess the resilience of distinct motifs in two networks of global supply chains under various disruptions, we employ Mahalanobis Depth. This method analyzes the relative depth of a specific point within a distribution of points in a multidimensional space. In our analysis, we use Mahalanobis

Depth to measure how the performance of a motif compares to the distribution of other motifs under different attacks. The point of interest is represented by motif lifetimes $T = (T_1, T_2, \ldots, T_6)$, where each T_i reflects the fraction of firms that have been removed under the previously mentioned shocks. The Mahalanobis Depth is calculated based on the proximity of the motif lifetime to the overall set of motif lifetimes derived from our failure simulations. Motifs with higher Mahalanobis Depths are considered more central to the distribution of motif lifetimes, indicating that these motifs are more resilient and better at maintaining their functions in the face of various shocks. Conversely, motifs with lower depths are typically more peripheral and vulnerable to disruptions, as they exhibit greater deviations from the distribution of motif lifetimes.

Definition 8 (Mahalanobis Depth) *Given the concentration dataset of motifs under different attacks, Mahalanobis Depth measures how deep or central an observed point is relative to a certain finite data cloud $S \in \mathbb{R}^p$. In our study, the point can be translated into motif lifetimes $T = (T_1, T_2, \ldots, T_6,)$.*

$$MhD(x|S) = \left[1 + (x - \mu)'\Sigma^{-1}(x - \mu)\right]^{-1} \tag{4}$$

μ : *the sample mean vector of S*

Σ : *the covariance matrix of S*

S : *a set of motif lifetimes in $\mathbb{R}^p$, where p is the number of dimensions. S represents the distribution of the motif lifetimes.*

We draw the DD plot (depth vs. depth plot) to investigate the motif lifetime performances in different networks under various scenarios (see Figure 11).

Overall, the Mahalanobis Depth in network B tends to exceed that of network A, indicating that network B exhibits greater resilience under various shocks. This finding aligns with our observations regarding motif concentrations. When comparing the motif lifetime performance in network A under targeted shocks, we observe that more points fall below the 45-degree line, suggesting that motifs demonstrate increased stability in response to betweenness centrality shocks. Focusing on Networks A and B under two types of targeted failures, we find that the cross-industry connections within global supply chains consistently exhibit higher Mahalanobis Depth than cross-country links. The higher

Mahalanobis Depth in network B indicates that the lifetimes of motifs in this network are more closely aligned with the average motif lifetimes, reflecting a relatively consistent and standardized performance of supply chain structures. This suggests that motif structures within industry-based global supply chains are more predictable, further indicating a higher level of resilience within cross-industry global supply chains.

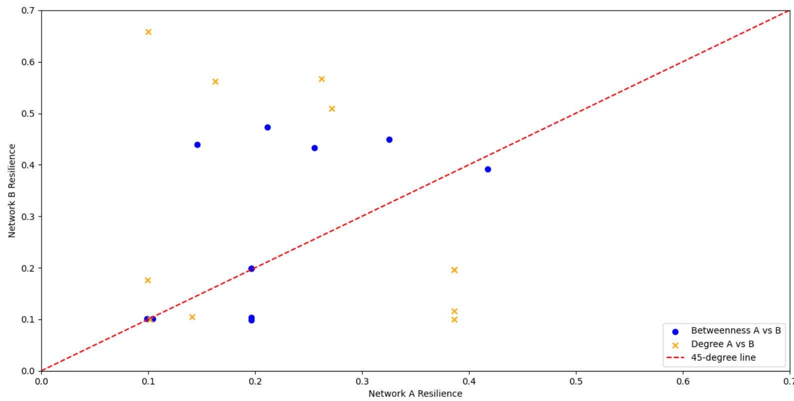
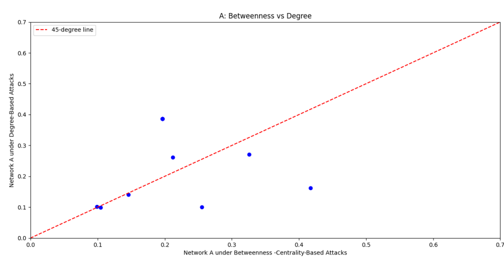
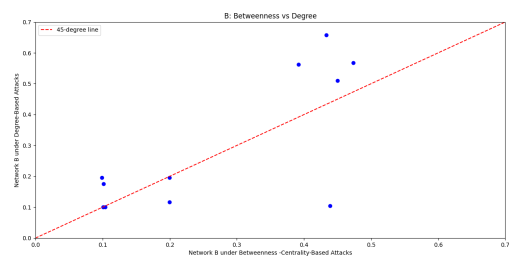


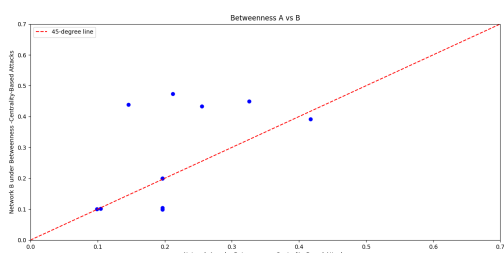
Fig. 10. DD Plot-Mahalanobis Depth



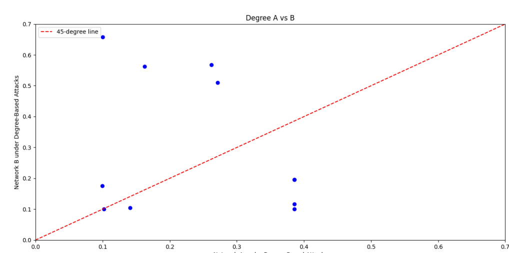
(a) Network A (Betweenness Vs Degree)



(b) Network B (Betweenness Vs Degree)



(c) Network A Vs Network B (Betweenness-Centrality-Based Attacks)



(d) Network A Vs Network B (Degree-Based Attacks)

Fig. 11. Mahalanobis Depth Comparison

5 Discussion

Global supply chain connections are sparse and skewed, but generally resilient under different disruptions. Starting from traditional measures, we find imbalanced degree distributions of connections with a few large enterprises holding a disproportionate share of connections. The small and medium firms which are less connected are located at peripheries within the supply chain network. This finding aligns with Ohnishi et al. (2010), who have studied interrelationships among firms in Japan. Such skewed distribution has made the entire supply chain sparser than we expected, leaving clues for further resilience analysis. A possible explanation for the extreme skewness is preferential attachment in network theory, which emphasizes that large enterprises that already enjoy a large number of partners tend to expand more relationships (Saito et al., 2007), consistent with the "Matthew Effect" in economics. Another reason may lie in that trade dynamics are always related to geopolitical fragmentation (Qiu et al., 2024). Firms located in those less geopolitically aligned countries may suffer from continuous trade barriers that hinder their global connections, paving the way for those companies located in countries with higher geopolitical stability.

The motif study in global supply chains has provided us with basic components of it by focusing on 6 types of 4-order motifs. The prevalence of "outsourcing chain" and "Hub-Spoke" patterns implies the important functions these simple connections play within global supply chains. Combining the results from failure simulations, we find that these two patterns always survive longer than other structures, though they also decay faster, revealing their functions in determining the resilience of the network. In the motif "outsourcing chain", M_2, there are no hub firms that dominate the trade flows, while bilaterally dependent on each other, are especially vulnerable to disruptions (Grossman et al., 2023). The failure of any firm lying on the chain will directly transmit itself through the linear and sequential linkages to other firms, influencing their normal operations and destroying this specific motif pattern.

In the "Hub-Spoke", M_1, there always exists a central hub that controls most linkages, such as Samsung in our global supply chains. While the central hub firms can act as important information centers for firms to interact, offering an externality of connectivity (Ding et al., 2024), the targeted failure of these important firms may also trigger cascading effects through this strongly centralized structure, diffusing risks to every branch that relies on the operation of central hub firms.

The significant degree of dependency within global supply chains, suggests the vulnerabilities that can compromise the overall resilience of supply chains through ripple effects (Katsaliaki et al., 2022). Focusing on other structures' performance, we find the relative stability of M_3, M_4, and M_5 with the lower decaying rates in the global supply chain when facing attacks. Considering the cost of building more links between firms for redundancy (e.g. legal, administrative, and fixed costs), firms have other choices to strengthen the stability of "Outsourcing chain" by investing it for higher stability of these structures (Grossman et al., 2023). In terms of different networks' performances under failures, our results show overall higher resilience in the industry-classified supply chains. Its more evenly distributed structures allow it to maintain efficiency in retaining its operational capabilities under various disruptions. In balanced networks, the distribution of connections among firms is relatively even, minimizing the risk associated with any single node failure.

6 Conclusion

In our paper, we study the resilience of global supply chains from a structural perspective. Analyzing the traditional properties of the system, we identify the sparse and imbalanced characteristics of a supply chain network, which mitigate, in the case of sparsity, and amplify, in the case of imbalance, the overall fragility of supply chains to certain disruptions. Moreover, we introduced the concept of "motif" to analyze the resilience of structures within supply chains. By applying three kinds of failure simulations, we found that firms always choose to form simpler connecting patterns, resulting in the scale-free distribution of degrees. Furthermore, we performed a non-parametric data-depth approach to evaluate the various features of motif lifetime distributions. All findings support that the "Outsourcing chain" is the most widely existent and most resilient to different attack strategies.

We believe our work will enhance the structural understanding of global supply chains. Analyzing the resilience of these supply chains from a local topological perspective can provide valuable insights for developing robust strategies from both firm and government perspectives. Our concept of resilience is limited to the retention of structural integrity in the face of disruptions, and we do not consider the intense margin (Fernández-Cerezo et al., 2023) or how firms adapt to disruption over time (Elliott and Golub, 2022). The ability of global supply chains to withstand shocks is always a global imperative.

Future work could usefully explore the extent to which firms' private incentives to source globally align with socially optimal supply chain linkages that support sustained economic growth and prosperity.

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