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Balancing risk and resilience: how network structures and firm strategies mitigate supply chain disruptions

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Abstract

Purpose – This study examines how network characteristics—specifically centrality and clustering—influence supply chain disruption risk in the context of the U.S. automotive sector. The paper investigates the moderating effects of firm-level risk management strategies—detection, mitigation, and recovery—on the relationship between network structure and disruption risk, addressing a critical gap in understanding the interplay between network position and risk management effectiveness.

Design/methodology/approach – A network model of automotive product flows was constructed using secondary data, and risk management strategies were stochastically integrated from a scenario-based vignette experiment. An agent-based contagion simulation modeled disruption propagation throughout the network. Generalized least squares regression with random effects was then employed to analyze how network characteristics and risk management strategies influence disruption risk.

Findings – The findings indicate a curvilinear relationship between network clustering and disruption risk, showing vulnerabilities at both extremely high and low levels of clustering. In contrast, centrality exhibited a predominantly linear relationship with disruption risk. Firm-level risk management strategies moderate these relationships differently, with detection and recovery strategies significantly attenuating the negative impacts of network vulnerabilities, while mitigation showed limited moderating effectiveness.

Originality/value – This research contributes to supply chain risk management literature by empirically exploring how firm-level strategies interact with network-level constructs to shape disruption risk. It challenges existing assumptions about linear relationships in network theory, providing nuanced insights for practitioners on tailoring risk management based on network position.

Keywords Risk management, Supply chain management, Supply chain risk, Supply chain risk management, Supply chain disruption, Supply chain complexity, Supply network structure

Paper type Research paper

1. Introduction

When a disruption occurs in a supply chain (e.g. the COVID-19 pandemic), widespread chaos frequently follows. International trade stalls, containers become stranded at ports, and inventory imbalances cascade through interconnected supply lines and production networks, propagating from upstream suppliers to downstream firms (Nikookar and Yanadori, 2022; Panwar *et al.*, 2022). Such disruptions often generate substantial bullwhip effects, causing severe shortages and significant price volatility in diverse products, from semiconductors to

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consumer staples like toilet paper, thereby exposing vulnerabilities inherent in globally integrated supply networks (Scarpini *et al.*, 2022). Recent high-profile disruptions provide further examples of these propagation effects. In March 2021, the Ever Given blocked the Suez Canal for six days, where it "*dammed up worldwide shipping and froze nearly $10 billion in trade a day*" [1]. Shortly thereafter, China's extensive lockdowns during the Omicron outbreak severely constrained global supply chains, disrupting manufacturing in a country that accounts for approximately one-third of worldwide production [2]. Furthermore, the ongoing war in Ukraine has significantly disrupted global fuel and agricultural markets, while geopolitical tensions around critical shipping lanes like the Red Sea have exacerbated existing pressures (Bednarski *et al.*, 2024). Together, these events highlight the interconnected and often chaotic nature of modern supply chains, highlighting how localized disruptions quickly escalate to network-wide impacts (Garcia *et al.*, 2024). Although these issues manifest at the macro-network level, their impacts are ultimately felt by individual firms within these networks.

Extant literature extensively documents the critical influence of network-level characteristics on firms' disruption risks and their ability to manage such risks (Azadegan *et al.*, 2020; Garvey and Steven, 2020; Son *et al.*, 2021). However, the precise interplay between network-level features and firm-level risk management strategies remains insufficiently understood. Disruptions, typically characterized as low-probability but high-impact events, can propagate widely through supply chains due to complex interdependencies (Kumar and Sharma, 2021).

Thus, the intersection of network structure—capturing a firm's exposure and susceptibility to disruptive events—and firm-specific risk management practices has significant implications for understanding and mitigating disruptions (Harland *et al.*, 2003; Craighead *et al.*, 2007; Azadegan and Dooley, 2021). Yet, prevailing risk management frameworks often emphasize sequential stages (detection, mitigation, and recovery) at the firm level, largely overlooking how network structures interact dynamically with these strategies (DuHadway *et al.*, 2019). Roshani *et al.* (2024, p. 1303) articulate this oversight explicitly, identifying that "*there is a knowledge gap related to capabilities that further improve resilience, such as SC node density, critically for suppliers . . . and complexity for transportation modes and routes*" (Roshani *et al.*, 2024, p. 1303).

Prior research has highlighted the critical role of firm-level risk management strategies and network structures in supply chain management (e.g. Wagner and Neshat, 2010; Blackhurst *et al.*, 2011; Craighead *et al.*, 2007; Azadegan and Dooley, 2021; Berger *et al.*, 2023; Guntuka *et al.*, 2024a, b). However, the dynamic interplay between network positions and firm-level risk management strategies has received limited attention, leaving a gap in the development of optimal strategies for managing disruption risk. This limitation partly arises from methodological challenges in obtaining robust empirical data that simultaneously captures firm-specific practices and network-wide disruption events (Garvey and Steven, 2020; Berger *et al.*, 2023). Moreover, existing frameworks often neglect potential non-linearities in how network positions—such as centrality (a firm's prominence relative to others within its supply network) and clustering (the extent of local interconnectedness)—influence firm vulnerability (Wagner and Neshat, 2010; Bode and Wagner, 2015; Dittfeld *et al.*, 2021). For instance, highly centralized firms may become more susceptible to cascading disruptions due to their numerous interconnections, whereas densely clustered networks can accelerate disruption propagation because of close inter-firm ties.

The absence of empirical studies integrating firm-level risk management strategies with structural network characteristics suggests that current approaches may be suboptimal, potentially leading to inadequate responses to disruptions (Fan and Stevenson, 2018). Understanding how network-level features influence disruption risks and how firm-level strategies might moderate these effects is crucial. Specifically, exploring whether centrality and clustering exhibit linear or curvilinear relationships with disruption risk, and clarifying the moderating roles of detection, mitigation, and recovery, can offer a more comprehensive approach to risk management.

To address these gaps, this study investigates two core structural characteristics of supply chain networks—centrality and clustering—and evaluates their direct impacts on disruption risk. It further explores how firm-level risk management strategies (detection, mitigation, and recovery) moderate these relationships. Specifically, the study addresses two research questions:

(1) How do a node's centrality and clustering characteristics affect its disruption risk? Is this relationship curvilinear?

(2) How do firm-level risk management strategies influence the relationship between network structure and disruption risk?

This research makes several contributions to the supply chain risk management literature. First, by integrating network theory (Fernández Campos *et al.*, 2024) with risk management strategy frameworks (e.g. Schoenherr *et al.*, 2023; Jazairy *et al.*, 2024; Friday *et al.*, 2024), this study provides empirical evidence on how centrality and clustering exhibit nonlinear relationships with disruption risk. These findings challenge traditional assumptions that network effects are primarily linear (Wagner and Neshat, 2010; Bode and Wagner, 2015). Second, by demonstrating that both excessive and insufficient connectivity can elevate risk, the study aligns with recent theoretical developments from complexity science, providing nuanced insights into network vulnerability (Haans *et al.*, 2016; Garcia *et al.*, 2024; Guntuka *et al.*, 2024a).

Methodologically, the study employs a robust, multi-method approach combining: (1) secondary data on U.S. domestic automotive shipping volumes to construct the network of connected freight nodes; (2) primary data from a scenario-based vignette experiment (DuHadway *et al.*, 2018), from which firm-specific risk management characteristics are assigned probabilistically; (3) agent-based contagion simulations to model disruption propagation dynamics (Macy and Willer, 2002), allowing agents to interact within the simulation (e.g. Chandrasekaran *et al.*, 2016; Hardcopf *et al.*, 2017); and (4) econometric analyses using generalized least squares regression with random effects to empirically assess the effects of network structure and risk management strategies on disruption risk. This integrative approach addresses the limitations of purely empirical studies (Davis *et al.*, 2007) and offers valuable insights into the relationship between firm-level strategies, network position, and disruption vulnerability.

2. Literature review

2.1 Supply chain risk and disruption management

Risk is an inherent component of supply chain management and is defined as the "*likelihood of an adverse and unexpected event that can occur and either directly or indirectly result in a supply chain disruption*" (Garvey *et al.*, 2015, p. 619). Firms operating within complex business environments, characterized by increasingly interconnected supply networks, face heightened vulnerability to supply chain disruptions. Disruptions are described as "*unplanned and unanticipated events that disrupt the normal flow of goods and materials within a supply chain*" (Craighead *et al.*, 2007, p. 132). To manage such disruption risks effectively and to enhance resilience, scholars stress the importance of thoroughly assessing existing risks, including their potential cascading effects within supply networks (Blackhurst *et al.*, 2008; Garvey *et al.*, 2015). Furthermore, network-level adjustment capabilities have been emphasized as critical for planning and responding to future risks (Guntuka *et al.*, 2024b).

This body of research broadly falls within the domain of supply chain risk management, defined as "*the identification, assessment, treatment, and monitoring of supply chain risks, with the aid of the internal implementation of tools, techniques, and strategies, and of external coordination and collaboration with supply chain members so as to reduce vulnerability and ensure continuity coupled with profitability, leading to competitive advantage*" (Fan and Stevenson, 2018, p. 201). Core risk management strategies to address disruption risk include detection, mitigation, and recovery, operating either independently or in sequential phases (DuHadway *et al.*, 2019). Detection emphasizes the early identification of potential risks; mitigation focuses on preemptive actions to minimize disruptions; and recovery pertains to restoring operations following a disruption. The growing complexity of global supply chains has led firms to integrate resilience-building practices, enhancing their ability to adapt to disruptions or to redesign network structures altogether (Pettit *et al.*, 2010; Guntuka *et al.*, 2024a; Nikookar *et al.*, 2024). Moreover, research underscores the role of collaboration between buyers and suppliers in reducing risks through coordinated responses (Zsidisin *et al.*, 2004; Mohammaddust *et al.*, 2017), further highlighting the necessity of robust strategic responses for disruption preparedness and recovery (Vega *et al.*, 2023; Nikookar *et al.*, 2024).

Supply chain research has progressively evolved from a linear perspective toward a network-based view, acknowledging interdependencies among organizations as both sources of strength and potential vulnerabilities (Choi and Hong, 2002; Choi and Kim, 2008; Kim *et al.*, 2011; Carnovale and Yeniyurt, 2014; Carter *et al.*, 2015; Wieland, 2021; Guntuka *et al.*, 2024a, b). A critical driver of this shift is the recognition that "*organizations are not autonomous, but rather are constrained by a network of interdependencies with other organizations*" (Pfeffer, 1987, pp. 26–27). Network theory provides a foundational framework emphasizing mechanisms and processes within network structures that yield outcomes for individual firms and the broader network (Borgatti and Halgin, 2011). Through graph theory, supply networks are modeled as nodes (firms) connected by edges (material or information flows) (Choi and Hong, 2002; Kim *et al.*, 2011). Additional types of relationships, such as competitive interactions (Skilton and Bernardes, 2015) and joint ventures (Carnovale *et al.*, 2016), have also been explored. Network theory abstracts from firm-specific details, highlighting instead the influence of interactions within a broader network context on firm behavior and performance.

This perspective often aligns with Complex Adaptive Systems (CAS) theory, which examines how network-level behaviors emerge from local interactions governed by simple rules (Holland, 1992). CAS theory implicitly stresses structural embeddedness, whereby a firm's actions are shaped significantly by connections to, and dependence upon, other entities within the network (Choi and Kim, 2008). These local interactions give rise to complex adaptive behaviors at the network level (Wycisk *et al.*, 2008; Nair *et al.*, 2009; Nair and Reed-Tsochas, 2019), frequently yielding critical insights into firm behavior and performance, particularly how network structure impacts firm outcomes.

The structure-performance relationship (Falcone *et al.*, 2023) requires an understanding of firm embeddedness, defined as "*the state of dependency of a company on its immediate as well as distant business partners in supply networks*" (Choi and Kim, 2008, p. 10). Structural embeddedness implies that a firm's behavior is shaped by its structural connections (i.e. direct and indirect linkages between firms) and embedded dependencies within its supply network (Kim, 2014). Consequently, network behavior arises from dynamic interactions between environmental pressures and the evolving behavior of system members (Choi *et al.*, 2001). Within supply networks, this perspective has been applied to various dimensions including efficiency (Kao *et al.*, 2017), strategic decision-making (Borgatti and Li, 2009), innovation performance (Carnovale and Yeniyurt, 2015), structural complexity (Choi and Krause, 2006), partnership formation and network expansion (Carnovale *et al.*, 2016, 2017), as well as competitive behavior and social capital development (Bernardes, 2010). Integrating network theory with CAS theory provides a robust framework for understanding both structural properties of supply chains and their adaptive responses to disruption events (Zhao *et al.*, 2019). Recent studies suggest that a firm's embeddedness within its supply chain network can either amplify or mitigate disruption risks, thus necessitating firms to align their risk management strategies explicitly with their network positions (Guntuka *et al.*, 2024a). These insights further motivate the need to explore these network and risk management interactions.

2.2 The intersection of network theory and risk management

Previous research has independently examined how firm-level risk management strategies and network characteristics influence disruption risk (Vanpoucke and Ellis, 2020; Chopra *et al.*, 2021). However, empirical studies that consider their interactions are scarce. Research on network complexity has shown how structural attributes like density and connectivity amplify the severity of disruptions (Craighead *et al.*, 2007), while graph-theoretic studies have highlighted network vulnerability from a structural standpoint (Wagner and Neshat, 2010).

Yet, the literature provides insufficient guidance on how firm-level risk strategies (e.g. detection, mitigation, recovery) should be adapted according to specific network positions, particularly in relation to centrality and clustering.

Empirical insights that can help firms strategically align their risk management practices with their network roles are particularly lacking. For example, firms with high network centrality may benefit significantly from early disruption detection capabilities due to their extensive connections (Chaudhuri *et al.*, 2020). In contrast, strategies emphasizing mitigation or recovery might have varied effects depending on local clustering patterns within the network. Although prior studies acknowledge the potential importance of these interactions (Berger *et al.*, 2023; Gholami-Zanjani *et al.*, 2021), direct empirical investigation remains limited, leaving this critical area inadequately understood.

Another notable gap involves assumptions about linear relationships between network characteristics and disruption risks. Most prior network-focused research assumes straightforward, linear impacts of attributes such as centrality and clustering on disruptions (Wagner and Neshat, 2010; Bode and Wagner, 2015). However, emerging perspectives from complexity science suggest these relationships might instead be nonlinear (Haans *et al.*, 2016; Guntuka *et al.*, 2024a). Such nonlinear dynamics could fundamentally alter the effectiveness of firm-level risk strategies depending on the structural attributes of their supply networks, yet this possibility has not been fully explored in existing empirical research.

Furthermore, while theoretical frameworks connecting network design and risk management have been proposed (Ho *et al.*, 2015; Garcia *et al.*, 2024), empirical validation remains limited. Evidence-based research that directly examines the interaction between structural network features and firm-specific risk strategies is notably sparse, underscoring the need for integrative empirical analysis.

To advance understanding at this intersection, our study focuses explicitly on two structural characteristics—centrality and clustering—and their interactions with core firm-level strategies of detection, mitigation, and recovery. We challenge the prevailing assumption of linear effects and consider the possibility of nonlinear relationships, which recent complexity theory suggests may exist but remain empirically unexplored in supply chain contexts (Haans *et al.*, 2016; Guntuka *et al.*, 2024a). This approach allows us to extend current theoretical insights into the interplay between structural network positions and firm risk strategies, providing nuanced guidance for managing disruption risks more effectively.

3. Hypothesis development

In this section, we develop hypotheses that address two related sets of relationships. The first set (Hypotheses 1 and 2) investigates how structural characteristics of supply chain networks—specifically centrality and clustering—directly influence disruption risk. The second set (Hypothesis 3) explores how firm-level risk management strategies moderate the effects of these network structures on disruption risk.

3.1 Network structure and disruption risk

Understanding a firm's centrality within a complex network is fundamental to assessing disruption risk. Craighead *et al.* (2007, p. 140) define complexity as "*the total number of nodes and the total number of forward . . . backward . . . and within-tier materials flows . . . within a given supply chain*." Building on this definition, we examine two critical structural dimensions of networks—centrality and clustering [3]—to explore their impact on disruption risk.

Centrality generally refers to a node's position within a network and its relationships with other nodes, both inbound and outbound. It captures "*a node's position in terms of features of their network environments*" (Friedkin, 1991, p. 1497). While various operationalizations of centrality exist, eigenvector centrality has emerged as particularly relevant in supply chain disruption studies due to its capacity to reflect the prominence of a node's first-tier connections, proportionally weighted by the centrality of those connections (e.g. Guntuka *et al.*, 2024b; Falcone *et al.*, 2023). Nodes with extensive, highly connected first-tier ties may face heightened exposure to disruptions originating from these directly connected network partners. Firms connected to highly prominent partners might experience amplified disruption risks because the advantages gained from these relationships (e.g. resource access) are accompanied by increased vulnerability.

For instance, consider the role of Chinese suppliers during the early phase of the COVID-19 pandemic. CNBC reported that "*every third company has major Chinese customers, and 81% of companies it surveyed rely on Chinese suppliers*"[4]. From a supply chain network perspective, these suppliers exhibited high levels of eigenvector centrality and embeddedness. Embeddedness, which denotes dependency on immediate and distant partners, significantly influences firm performance (Choi and Kim, 2008). Firms with high eigenvector centrality, particularly those spanning multiple regions within a network, become vulnerable to disruptions from diverse sources due to their extensive and prominent connections (Kim *et al.*, 2015; Son *et al.*, 2021). Simply put, as eigenvector centrality increases, so too does the risk of disruption and its associated cascading impacts.

Yet, high centrality also affords strategic advantages. Firms occupying central positions often enjoy access to diverse resources, enabling them to mitigate supply risks through strategies like multi-sourcing (e.g. Zsidisin *et al.*, 2004; Blackhurst *et al.*, 2011; Carnovale and Yeniyurt, 2014, 2015). Additionally, these firms can leverage extensive connections to detect disruptions early and implement proactive risk management actions, such as capacity adjustments or establishing supply redundancies (Elluru *et al.*, 2019). This duality suggests a non-monotonic relationship: disruption risk may initially escalate with increasing centrality, but at higher centrality levels, firms could utilize strategic benefits of their network positions to stabilize or even reduce disruption risk.

For example, Nokia successfully mitigated disruption risks through effective network design, thereby overcoming severe supplier disruptions. In contrast, Ericsson experienced substantial losses due to its relatively lower redundancy and flexibility (Chopra and Sodhi, 2004; Norman and Wieland, 2020). This contrasting example highlights how highly connected firms might exploit their network positions to manage disruptions effectively. Thus, we propose:

H1. There is a non-monotonic (curvilinear) relationship between a firm's centrality and its disruption risk, whereby disruption risk increases at lower levels of centrality, peaks at intermediate levels, and tapers off at higher levels of centrality.

The second dimension of network structure considered is clustering. Clustering refers to the extent to which nodes within a network are interconnected in their local neighborhood, forming tightly knit groups (Watts and Strogatz, 1998). It is operationalized as the ratio of the number of existing connections between a node's neighbors to the total possible connections within that neighborhood (Carnovale *et al.*, 2019). Clustering carries important implications for supply chain risk management, as it shapes a firm's local network structure, thereby influencing both resilience and vulnerability to disruptions (Guntuka *et al.*, 2024a).

We posit that clustering also exhibits a dual-faceted on disruption risk. On the one hand, clustering can be beneficial. High clustering may facilitate redundancy and alternative sourcing strategies, enabling firms to rapidly adapt to disruptions occurring within specific network segments. For instance, firms in highly clustered networks might reroute materials through alternative suppliers or redistribute production across interconnected nodes, thus reducing disruption impacts (Yang *et al.*, 2024). This perspective aligns with broader literature that associates clustering with enhanced resource access and flexibility (Brandon-Jones *et al.*, 2014). Additionally, clustering fosters trust and collaboration, which is critical for effective risk mitigation and information sharing in supply networks (Wiedmer and Griffis, 2021).

Conversely, clustering can also amplify disruption risks, especially in densely interconnected networks, where disruptions tend to cascade rapidly downstream (Kähkönen and Patrucco, 2022). Analogous to epidemiological models, where densely connected networks facilitate rapid disease transmission (Watts and Strogatz, 1998), dense interconnections in supply chains can accelerate disruption propagation. Heightened vulnerability arises from the proximity of a node to its first-tier connections and the concentrated material flows within clusters. For example, perishable goods supply chain studies illustrate how tightly clustered networks can exacerbate disruption propagation, especially in the absence of sufficient redundancy (Gholami-Zanjani *et al.*, 2021).

Moreover, while clustering initially provides redundancy-based protection, excessive clustering might create over-dependence within localized networks, restricting a firm's access to external alternative resources. This phenomenon parallels findings from innovation research, where moderate clustering facilitates collaboration, yet excessive clustering constrains diverse knowledge inputs (Schilling and Phelps, 2007; Wiedmer and Griffis, 2021; Jin *et al.*, 2022).

Such mixed outcomes imply that clustering's impact on disruption risk follows a curvilinear pattern rather than a strictly linear relationship. At low clustering levels, firms may have insufficient local connections to access alternative resources during disruptions, increasing vulnerability. Conversely, at high clustering levels, firms become more exposed to rapid cascading disruptions due to dense interconnections. However, moderate clustering levels may optimally balance redundancy and flexibility, thus mitigating disruption risk. Thus, we propose:

H2. There is a non-monotonic (curvilinear) relationship between a firm's clustering coefficient and its disruption risk, whereby disruption risk increases at lower clustering levels, peaks at intermediate levels, and decreases at higher levels of clustering.

3.2 Differential effects of risk management strategies

Three primary firm-level strategies for managing supply chain disruption risks are detection, mitigation, and recovery (DuHadway *et al.*, 2019). Although the literature extensively documents how network structure (e.g. centrality and clustering) influences disruption risk, fewer studies explicitly address how these firm-level risk management strategies interact with a firm's network position to shape its vulnerability.

Several authors advocate explicitly considering the interplay between risk management capabilities and the structural characteristics of supply networks. For example, Chaudhuri *et al.* (2020, p. 88) highlight the complex interplay between supply network structure and risk management, suggesting that "*for supply chains with moderate levels of complexity, moderate investment in supply chain visibility may be most appropriate*." Similarly, Berger *et al.* (2023) recommend closely monitoring specific nodes within networks based on their criticality to hedge against the negative impacts of risk. Other scholars emphasize the importance of carefully managing the cost–resilience trade-off to optimize disruption responses (Esmizadeh and Parast, 2021). Further research stresses the increased significance of visibility and proactive redesign of supply chains, particularly as supply networks become more digitalized (Saad and Ubeywarna, 2024).

Firms occupying high-risk positions in a network, such as those characterized by elevated centrality or dense clustering, may uniquely benefit from tailored investments in these strategies (Yu *et al.*, 2024). For example, detection capabilities can help highly central firms monitor disruptions across their extensive and diverse connections (Chaudhuri *et al.*, 2020). Mitigation strategies, such as maintaining redundancy or safety stocks, may particularly benefit firms embedded in tightly clustered networks by buffering the impacts of disruptions (Tomlin, 2006). Likewise, recovery capabilities could be essential for structurally embedded firms that must efficiently manage disruptions with prolonged impacts.

Given the distinct challenges posed by varying network structures, the effectiveness of these risk management strategies likely differs according to a firm's specific network position. Elevated levels of centrality and clustering in modern supply networks typically correspond to increased disruption risks. However, targeted firm-level investments in detection (Saad and Ubeywarna, 2024), mitigation (Duhadway *et al.*, 2018), and recovery (Ledwoch *et al.*, 2018) are expected to moderate and reduce these heightened disruption risks. Thus, to empirically assess this dynamic interplay, we propose:

> *H3*. Increased levels of (a) detection, (b) mitigation, and (c) recovery will dampen the positive relationship between network structure characteristics (centrality and clustering) and disruption risk. Specifically, as firm-level investments in these risk management strategies increase, the disruption risk associated with elevated levels of network structure characteristics will decrease.

4. Methodology: data generation, simulation, and measures

Following the recent call by Melnyk *et al.* (2024) to incorporate simulation approaches into supply chain research, we adopt an empirically grounded simulation procedure. Specifically, we adapt a viral contagion model (Stonedahl and Wilensky, 2008) to simulate network disruptions using NetLogo [5]. This methodological approach is especially suitable when empirical data collection faces significant challenges (Davis *et al.*, 2007). Our study, therefore, provides a unique, empirically grounded, multi-method analysis exploring the interplay between network positions, firm-level risk management strategies, and disruption risks.

The simulation procedure unfolds in several steps. First, we construct the network structure based on secondary data obtained from the US Government Center for Transportation Analysis [6]. Next, firm-level risk management strategies derived from a vignette-based experimental study (Duhadway *et al.*, 2018) are integrated into the simulation. The disruption simulation involves initializing a disruption at each of the 132 network nodes sequentially and allowing each disruption to propagate through the network using intervals of three months. To incorporate varying disruption magnitudes, disruptions are simulated at intervals ranging from a minimum of three months to a maximum of 24 months, increasing in three-month increments. Each node, therefore, serves as the source of eight disruptions, resulting in 1,056 simulated disruptions across the entire network after the initial simulation cycle (132 nodes × 8 disruptions each). These simulated disruptions are then analyzed at the firm level across all simulation runs. Additional methodological details and simulation procedures are provided in Online Supplementary Materials A.

4.1 Operationalization of main variables

The operationalization of the key variables in this research focuses on two primary network constructs—centrality and clustering—and three risk management strategies—detection, mitigation, and recovery. Our selection of centrality and clustering aligns with the logic of Peters *et al.* (2013), who identified three fundamental groupings of network structure: connections (e.g. structural holes), distributions (e.g. centrality), and segmentations (e.g. clustering). Given that their analysis focused primarily at the meso/micro level in social networks, and considering our macro-level supply chain context, we narrowed our scope to distributions and segmentations—represented by centrality and clustering, respectively.

Centrality is measured using eigenvector centrality, an extension of degree centrality (i.e. unweighted inbound and outbound connections) that proportionally captures the prominence of a firm's connections by weighting links to highly connected partners more heavily. Mathematically, eigenvector centrality is calculated using the largest eigenvalue of the binary adjacency matrix utilized to construct the network. *Clustering* is measured using the clustering coefficient, representing the extent to which nodes form tightly interconnected groups within the network. Specifically, it is computed as the ratio of the actual number of links among a node's neighbors to the total number of potential links among these neighbors. This measure provides insight into local cohesion (i.e. connectedness) and redundancy within the network, influencing both the propagation and containment of disruptions. After calculating these network variables and removing observations with missing or incorrectly computed values, the final usable dataset comprised 888 observations across 111 nodes.

The firm-level risk management strategies—detection, mitigation, and recovery—were collected through a vignette-based behavioral experiment conducted on the crowdsourcing platform Prolific [7]. Although derived from a previously conducted data collection effort (see Duhadway *et al.*, 2018), the dataset employed in this study was obtained prior to any experimental manipulations and remains unpublished (see Online Supplementary Materials A for detailed data collection procedures). This approach provides richer and more realistic data than random assignments, as it accounts for potential simultaneous adjustments among different risk management strategies. For instance, a firm choosing a high-risk strategy such as single sourcing might offset this risk by maintaining higher inventory levels.

1. *Detection*: Detection refers to a firm's capability to identify disruptions before they directly affect its operations. Operationally, detection is measured as the geodesic distance (number of linkages) at which a firm can identify a disruption occurring in another firm within the network. A detection value of 1 indicates the firm can detect disruptions among its immediate first-tier suppliers, while a detection value of 2 implies detection extends to second-tier suppliers (two links away).
2. *Mitigation*: Mitigation represents a firm's capacity to lessen the adverse effects of disruptions once they have occurred. It is operationalized as the number of months of inventory a firm maintains (e.g. Tomlin, 2006). Higher mitigation values imply the firm can sustain operations during disruptions for longer periods using its inventory, thus reducing the immediate operational impact.
3. *Recovery*: Recovery captures the firm's ability to quickly return to normal operational status after experiencing a disruption. It is operationalized as the firm's capacity to accelerate recovery compared to a baseline recovery rate. Firms with higher recovery values restore operations more rapidly, thus minimizing the overall disruption impact.

Finally, *disruption risk* is operationalized as the cumulative number of months a firm is affected by disruptions during the simulation. This variable captures the firm's overall exposure to network disruptions, reflecting the interplay between disruption propagation through the network and the firm's ability to detect, mitigate, and recover from these events. Table 1 summarizes the key variables used in the simulation and subsequent data analysis.

4.2 Data collection and integration

As previously described, this empirically grounded simulation incorporates two distinct data sources: secondary data from a U.S. Government database and primary data collected through a published behavioral experiment (DuHadway *et al.*, 2018) [8]. The integration process proceeded as follows. First, profiles representing the combined decisions from participants in the behavioral experiment—covering detection, mitigation, and recovery strategies—were assigned as node-level characteristics within the simulation. To facilitate integration, detection, and recovery variables were converted into quartiles, resulting in integer values of 0, 1, 2, or 3. Data on mitigation, originally measured as weeks of inventory ranging from 0 to 12, were similarly scaled to the 0 to 3 range by dividing the inventory values by four. This scaling ensured dimensional consistency and parameter coherence, essential for methodological rigor in simulation research (Senge and Forrester, 1980). Within the simulation, these three characteristics were operationalized differently from the data collected in the experiment. Detection was operationalized based on the geodesic distance—representing the number of network links—at which a firm could detect disruptions occurring at other firms. We recognize that geodesic distance captures only structural connectivity and does not explicitly account for geographic proximity or communication efficiency. However, given the novel nature of our methodological approach, this operationalization is sufficient for our study. A detection value

Table 1. Variable operationalization and data source

Variable	Operationalization	Data source
Eigenvector-centrality	$x_{it} = \frac{1}{\lambda}\sum_{j=1}^{n} a_{ijt}x_{jt}, i = 1, 2, \ldots, n$ *where x_{it} represents the eigenvector centrality of firm i in simulation period t, λ represents the largest eigenvalue of the binary adjacency matrix (used for network construction), n is the number of firms and a is a binary variable if firms i and j are connected in that period* (Falcone *et al.*, 2023; Guntuka *et al.*, 2024)	Calculated based on data gathered for this study (see supplementary materials for a detailed description)
Clustering coefficient	For a vertex u of a simple, finite, and undirected graph G, let the *clustering coefficient* of u in G be $C_u(G) = m(G[N_g(u)]) \Big/ \binom{d_{G(u)}}{2}$ if $d_{G(u)} \geq 2$, and 0 otherwise, where $N_g(u)$ represents the neighborhood $\{v \in V(G): uv \in E(G)\}$ of u in the graph G whose verted set is $V(G)$ and whose edge set is $E(G)$, $d_{G(u)}$ represents the degree $\lvert N_g(u) \rvert$ of u in G, $G[N_g(u)]$ denotes the subgraph of G induced by $N_g(u)$, and $m(G[N_g(u)])$ equals exactly the number of triangles of G that contain the vertex u." (Gentner *et al.*, 2018)	Calculated based on data gathered for this study (see supplementary materials for a detailed description)
Detection	The number of tiers away a firm can view a disruption to begin the recovery process	Values for these node characteristics were assigned stochastically from firm level risk management profiles that were previously gathered in DuHadway *et al.* (2018)
Mitigation	The number of months that a firm can withstand any impacts of a disruption, when such a disruption actualizes. This is equivalent to months of inventory a firm holds	
Recovery	The rate that a firm recovers from a disruption. Each unit represents how many months a current disruption is reduced in each month	
Disruption risk	Log (Total disruption experienced by the focal firm, when disruptions originate in each of the remaining firms in the network, over all simulation iterations)	Simulation outcome, captured for this study

Source(s): Authors' creation

of 1 indicates that a firm can detect disruptions at first-tier suppliers, while a value of 2 implies detection capability extends to second-tier suppliers. Mitigation was operationalized as the number of months of inventory maintained by a firm. Specifically, a mitigation value of X months signifies that the firm can reduce the duration of disruption impacts by X months, effectively buffering against operational disruptions. Recovery was defined as the firm's ability to return to pre-disruption operational performance, measured as the number of months by which the firm can reduce the magnitude of ongoing disruptions. Each unit indicates how many months of disruption a firm can eliminate from its current disruption profile per month.

Table 2 provides the summary statistics and correlations of the main variables derived from these integrated data sources.

4.3 Econometric analysis

Upon completing the simulation and data integration process, we proceeded to test our hypotheses. The simulation was conducted eight times, each iteration initiating different disruption magnitudes and stochastically assigning varying firm characteristics across the network. Throughout each simulation run, the network structure remained static, yielding a

Table 2. Pairwise (Pearson) correlation coefficients and summary statistics

Variable	1	2	3	4	5	6	7	8	9
1. Disruption risk (log)	–								
2. Eigenvector centrality	0.0744*	–							
3. Clustering coefficient	0.0192	−0.4547*	–						
4. Eigenvector centrality^2	0.0605	0.9542*	−0.5232*	–					
5. Clustering coefficient^2	0.0002	−0.6033*	0.9580*	−0.6158*	–				
6. Detection	−0.5110*	0.0077	0.0147	0.0040	0.0067	–			
7. Mitigation	−0.2498*	−0.0157	0.0344	−0.0202	0.0288	0.2392*	–		
8. Recovery	−0.4190*	0.0331	−0.0608	0.0376	−0.0683*	0.2912*	0.2518*	–	
9. Initial disruption	0.6554*	0.0000	0.0000	0.0000	0.0000	0.0316	0.0209	0.0276	–
Summary statistics									
Mean	5.6024	0.3423	0.6625	0.1655	0.4825	1.4887	1.1912	1.3070	13.5000
Standard deviation	2.3440	0.2198	0.2090	0.1894	0.2421	1.1216	0.5728	0.5963	6.8777
Minimum value	1.0986	0.0016	0.0000	0.0000	0.0000	0.0000	0.0000	0.5000	3.0000
Maximum value	11.1095	1.0000	1.0000	1.0000	1.0000	3.0000	3.0000	3.0000	24.0000
Sample size	888.0	888.0	888.0	888.0	888.0	888.0	888.0	888.0	888.0

Note(s): *$p < 0.05$
Source(s): Authors' creation

pooled panel dataset comprising 111 nodes [9], each with eight observations corresponding to the different disruption scenarios.

Given the nested structure of the data, we applied a random-effects generalized least squares (GLS) regression approach suitable for our pooled panel design. This technique effectively addresses unobserved individual heterogeneity that could correlate with regressors by incorporating firm-specific heterogeneity alongside the conventional random error term (Cameron and Trivedi, 2005).

To confirm the appropriateness of our model specification, we conducted a Hausman test, comparing the random-effects and fixed-effects models. Results from the Hausman test supported the selection of the random-effects model. Furthermore, the final models were estimated using the Huber/White robust sandwich estimator, correcting for potential heteroskedasticity and autocorrelation within panel data (Arellano, 1987, 2003). We also employed the Swamy–Arora method (Swamy and Arora, 1972) to estimate variance components, accounting for the relatively small number of observations per panel unit.

We specified the following models in our analyses:

$$\begin{aligned} Disruption\,Risk_n = {} & \beta_0 + \beta_1 Eigenvector\,Centrality + \beta_2 Eigenvector\,Centrality^2 \\ & + \beta_3 Detection + \beta_4 Mitigation + \beta_5 Recovery + \beta_6 Initial\,Disruption \\ & + c_n + e_n \end{aligned} \tag{1}$$

$$\begin{aligned} Disruption\,Risk_n = {} & \beta_0 + \beta_1 Clustering\ Coefficient + \beta_2 Clustering\ Coefficient^2 \\ & + \beta_3 Detection + \beta_4 Mitigation + \beta_5 Recovery + \beta_6 Initial\,Disruption \\ & + c_n + e_n \end{aligned} \tag{2}$$

Equations (1) and (2). RE-GLS Specifications for Main & Curvilinear Effects of Eigenvector Centrality and Clustering Coefficient

$$\begin{aligned} Disruption\,Risk_n = {} & \beta_0 + \beta_1 Eigenvector\,Centrality + \beta_2 Clustering\ Coefficient \\ & + \beta_3 Eigenvector\,Centrality * Detection + \beta_4 Clustering * Detection \\ & + \beta_5 Detection + \beta_6 Mitigation + \beta_7 Recovery + \beta_8 Initial\,Disruption \\ & + c_n + e_n \end{aligned} \tag{3}$$

$$\begin{aligned} Disruption\,Risk_n = {} & \beta_0 + \beta_1 Eigenvector\,Centrality + \beta_2 Clustering\ Coefficient \\ & + \beta_3 Eigenvector\,Centrality * Mitigation + \beta_4 Clustering * Mitigation \\ & + \beta_5 Detection + \beta_6 Mitigation + \beta_7 Recovery + \beta_8 Initial\,Disruption \\ & + c_n + e_n \end{aligned} \tag{4}$$

$$\begin{aligned} \mathit{Disruption\,Risk}_n = {} & \beta_0 + \beta_1 \mathit{Eigenvector\,Centrality} + \beta_2 \mathit{Clustering\,Coefficient} \\ & + \beta_3 \mathit{Eigenvector\,Centrality} * \mathit{Recovery} + \beta_4 \mathit{Clustering} * \mathit{Recovery} \\ & + \beta_5 \mathit{Detection} + \beta_6 \mathit{Mitigation} + \beta_7 \mathit{Recovery} + \beta_8 \mathit{Initial\,Disruption} \\ & + c_n + e_n \end{aligned} \tag{5}$$

$$\begin{aligned} \mathit{Disruption\,Risk}_n = {} & \beta_0 + \beta_1 \mathit{Eigenvector\,Centrality} + \beta_2 \mathit{Clustering\,Coefficient} \\ & + \beta_3 \mathit{Eigenvector\,Centrality} * \mathit{Detection} + \beta_4 \mathit{Clustering} * \mathit{Detection} \\ & + + \beta_5 \mathit{Eigenvector\,Centrality} * \mathit{Mitigation} + \beta_6 \mathit{Clustering} * \mathit{Mitigation} \\ & + \beta_7 \mathit{Eigenvector\,Centrality} * \mathit{Recovery} \\ & + \beta_8 \mathit{Clustering} * \mathit{Recovery} + \beta_9 \mathit{Detection} + \beta_{10} \mathit{Mitigation} \\ & + \beta_{11} \mathit{Recovery} + \beta_{12} \mathit{Initial\,Disruption} + c_n + e_n \end{aligned} \tag{6}$$

Equations (3)–(6). RE-GLS Specifications for Differential (i.e. Interaction) Effects of Risk Management Strategies.

Equations (1) and (2) separately test eigenvector centrality and clustering coefficient effects, including their linear and quadratic terms individually, to prevent potential multicollinearity. Equations (3) through 5 examine the interaction effects of eigenvector centrality and clustering coefficient independently with each risk management strategy (detection, mitigation, and recovery). Equation (6) simultaneously tests these interaction effects.

In Equations (1) and (2), a negative coefficient for the quadratic terms of eigenvector centrality or clustering coefficient indicates an inverted U-shaped relationship, while a positive coefficient signifies a traditional U-shaped curve (Cohen and Cohen, 1983). Additionally, all models include the firm's risk management strategies (detection, mitigation, and recovery) and the initial disruption size as control variables to facilitate comparisons with moderation effects explicitly tested in Hypothesis 3.

5. Results

First, we assessed the overall model fit for the specifications testing eigenvector centrality and clustering coefficient separately (Equations (1)–(2)). For eigenvector centrality, the Wald χ^2 was 3,447.88 (df = 6), and for clustering coefficient, it was 3,392.74 (df = 6). Both Wald values were statistically significant at the $p < 0.001$ level, indicating strong model fit. The R^2 values further supported this assessment, with values of 0.8155 for the eigenvector centrality model and 0.8144 for the clustering coefficient model.

We also assessed multicollinearity among the first-order terms using Variance Inflation Factors (VIFs). For the eigenvector centrality model, the VIFs were: Eigenvector Centrality (1.00), Detection (1.13), Mitigation (1.10), Recovery (1.14), and Initial Disruption (1.00), yielding a mean VIF of 1.07. For the clustering coefficient model, the VIFs were: Clustering Coefficient (1.01), Detection (1.13), Mitigation (1.11), Recovery (1.14), and Initial Disruption (1.00). All VIF values were low, indicating multicollinearity was not a concern and confirming that the independent variables were not excessively correlated. This strengthens confidence in the stability and interpretability of our regression coefficients.

Next, we evaluated the overall fit of models examining interaction effects between risk management strategies and eigenvector centrality/clustering (Equations (3)–(6)). The Wald χ^2 values for these interaction models with eigenvector centrality were 3,776.76, 3,672.10, and 3,917.22 (each with 8 degrees of freedom), and 4,406.22 (12 degrees of freedom) for the combined model. All Wald statistics were statistically significant at $p < 0.001$, confirming good model fit to the data.

Table 3 presents the regression results for both linear and quadratic model specifications, providing empirical tests of Hypotheses 1 and 2. Given that the dependent variable is log-transformed, the interpretation of coefficients requires exponentiation (e^{β}). Specifically, for each one-unit increase in an independent variable, the expected change in the dependent variable is given by the exponentiated coefficient. Exponentiated coefficients greater than 1 indicate a percentage increase in disruption risk, while those less than 1 indicate a percentage decrease.

To enhance interpretability, Table 4 displays the exponentiated coefficients (e^β) for each independent variable. For example, when the original coefficient is positive, subtracting 1 from the exponentiated value gives the percentage increase in disruption risk associated with a one-unit increase in the predictor. Conversely, a negative original coefficient corresponds to an exponentiated coefficient less than 1, and subtracting 1 provides the percentage decrease in disruption risk.

Finally, Table 5 presents the regression results for interaction effects to test Hypotheses 3(a, b, c).

5.1 Centrality: main effects and diminishing returns

Hypothesis 1 proposed a curvilinear relationship, suggesting that disruption risk would initially rise with higher eigenvector centrality, eventually peak, and then taper off at high levels of centrality. The results provided mixed evidence for this hypothesis. In the model for Eigenvector Centrality (Table 3), the linear coefficient for eigenvector centrality was positive (2.116) and statistically significant ($p < 0.05$), indicating a substantial 729% increase in disruption risk per one-unit increase in eigenvector centrality. However, the quadratic term was not statistically significant ($p > 0.1$). Therefore, these findings do not support Hypothesis 1. Although we find evidence of a significant linear relationship (suggesting disruption risk increases with rising eigenvector centrality), the absence of significance for the quadratic term means we cannot conclusively confirm the hypothesized curvilinear effect.

To provide additional insights, we visualized this relationship by plotting the predicted functional form of disruption risk based on the quadratic model for eigenvector centrality, holding all other variables constant. The empirical function derived from the model is:

$$\text{Disruption Risk} = 5.258 + [2.116 * \text{Eigenvector Centrality}] - \left[1.458 * \text{Eigenvector Centrality}^2\right]$$

In this equation, the intercept is estimated at 5.258, the linear coefficient for eigenvector centrality is 2.116, and the quadratic coefficient is -1.458. To generate a detailed visualization,

Table 3. Model results of random effects regression estimates

Models	Eigenvector			Clustering		
Independent variable	β		Robust S.E	β		Robust S.E
Detection	−0.8927	***	0.0330	−0.8947	***	0.0332
Mitigation	−0.3568	***	0.0588	−0.3662	***	0.0589
Recovery	−1.1536	***	0.0628	−1.1512	***	0.0639
Eigenvector centrality	2.1159	**	0.7498	–	–	–
Eigenvector centrality^2	−1.4581	N.S.`	0.9973	–	–	–
Clustering coefficient	–	–	–	3.3501	***	0.4968
Clustering coefficient^2	–	–	–	−2.9093	***	0.3986
Initial disruption	0.2313	***	0.0049	0.2314	***	0.0049
Intercept	5.2580	***	0.1739	4.9362	***	0.2067
Model fit						
R^2 (overall)	0.8155			0.8144		
Wald χ^2 (DF)	3447.88***(6)			3392.74***(6)		
Number of nodes	111			111		
Observations	888			888		

Note(s): ***$p < 0.001$, **$p < 0.05$, *$p < 0.1$, N.S.-Not Statistically Significant

Table 4. Exponential values and percentage increases

Exponentiated Effect		*Variable*	*Percentage Increase (Decrease)*	
Eigenvector	Clustering		Eigenvector	Clustering
e^{β}	e^{β}		%	%
0.4095	0.4087	Detection	–59.05%	–59.13%
0.6999	0.6933	Mitigation	–30.01%	–30.66%
0.3154	0.3162	Recovery	–68.45%	–68.38%
8.2972	-	Eigenvector Centrality	729.73%	-
0.2326	-	Eigenvector Centrality^2	–76.73%	-
-	28.5058	Clustering Coefficient	-	2750.58%
-	0.0545	Clustering Coefficient^2	-	-94.55%
1.2602	1.2603	Initial Disruption	26.03%	26.03%

Source(s): Authors’ creation

the range of eigenvector centrality values observed in the dataset [0.0016, 1] was divided into 50 intervals. The domain of the function was incremented along the range of the variable in the study. The resulting graph (Figure 1) clearly illustrates the predicted functional relationship between eigenvector centrality and disruption risk, based on our quadratic model.

5.2 Clustering coefficient: linear and diminishing returns

Hypothesis 2 proposed a curvilinear relationship between a firm’s clustering coefficient and disruption risk. Specifically, it suggested that disruption risk would initially rise with higher clustering levels, eventually peak, and subsequently decline, reflecting diminishing returns. The results provide strong empirical support for this hypothesis.

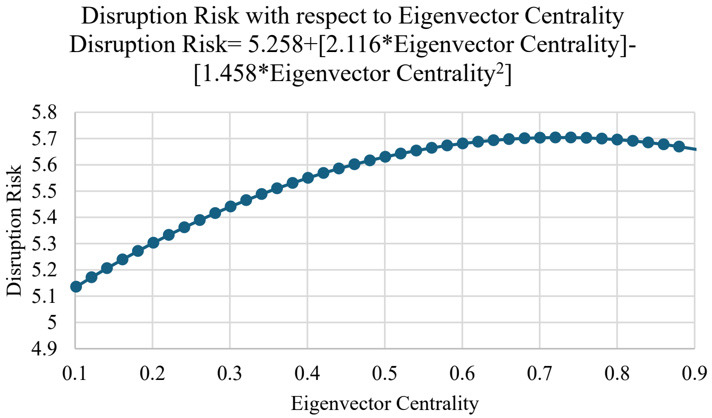

Figure 1. Non-monotonic effect of eigenvector centrality on disruption risk. Source: Authors’ creation based on model results

In the regression model (Table 3), the linear coefficient for the clustering coefficient was positive (3.350) and highly significant ($p < 0.001$), indicating a substantial 2,750% increase in disruption risk as the clustering coefficient hits its maximum value of 1. The quadratic term was negative (−2.909) and statistically significant ($p < 0.001$), clearly suggesting an inverted U-shaped relationship. This result confirms that clustering initially exacerbates disruption risk, but beyond a certain point, further increases in clustering actually reduce disruption risk, holding all other variables constant.

To rigorously validate the curvilinear relationship, we applied the three criteria described by Haans *et al*. (2016): (1) the statistical significance of both linear and quadratic terms; (2) a statistically significant slope (curvilinear coefficient); and (3) the vertex (peak) of the curve situated within the observed data range. Our results satisfied all three conditions.

1. Both linear and quadratic coefficients were statistically significant ($p < 0.001$).
2. The slope associated with the quadratic term was negative and statistically significant ($p < 0.001$).
3. The vertex of the curve occurred at a disruption risk value of approximately 5.7, comfortably within the ranges of both the dependent variable (Disruption Risk) and the independent variable (Clustering Coefficient: [0, 1]). This vertex corresponds to a clustering coefficient value of approximately 0.58.

Together, these conditions provide robust empirical validation of Hypothesis 2.

For clearer interpretation, we plotted the predicted relationship between clustering coefficient and disruption risk, holding all other variables constant. The empirical function representing this relationship is:

$$\text{Disruption Risk} = 4.936 + [3.350 * \text{Clustering Coefficient}] - \left[2.903 * \text{Clustering Coefficient}^2\right]$$

Given that the clustering coefficient ranged from [0, 1], we divided this interval into 50 increments, consistent with the eigenvector centrality visualization. The resulting graph (Figure 2) clearly illustrates the inverted U-shaped relationship between clustering coefficient and disruption risk, supporting our empirical findings.

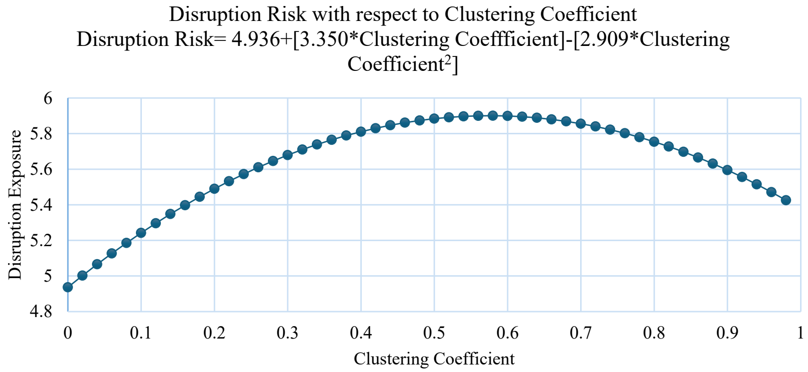

Figure 2. Non-monotonic effect of clustering coefficient on disruption risk. Source: Authors' creation based on model results

5.3 Differential effects of risk management on disruption risk

Hypothesis 3 examined how the three categories of risk management strategies—detection, mitigation, and recovery—moderate the relationship between network structure (eigenvector centrality and clustering coefficient) and disruption risk. Table 5 summarizes these interaction results.

Table 5. Interaction effects regression estimates (eigenvector centrality)

Models	Detection			Mitigation			Recovery			Full model		
Independent variable	β		Robust S.E	β		Robust S.E	β		Robust S.E	β		Robust S.E
Detection	−0.324	**	0.102	−0.895	***	0.033	−0.899	***	0.033	−0.457	***	0.100
Mitigation	−0.363	***	0.060	0.013	N.S.	0.240	−0.353	***	0.060	−0.363	**	0.186
Recovery	−1.150	***	0.063	−1.139	***	0.064	−0.171	N.S.	0.218	−0.485	**	0.182
Eigenvector centrality	2.071	***	0.321	1.620	***	0.487	2.371	***	0.393	2.597	***	0.574
Clustering coefficient	1.423	***	0.294	1.153	***	0.340	2.070	***	0.385	2.214	***	0.451
Eigenvector*detection	−0.613	***	0.131							−0.511	***	0.136
Clustering*detection	−0.542	***	0.130							−0.399	***	0.123
Eigenvector*mitigation				−0.349	N.S.	0.360				0.023	N.S.	0.350
Clustering*mitigation				−0.392	N.S.	0.279				−0.002	N.S.	0.242
Eigenvector*recovery							−0.858	***	0.260	−0.515	*	0.274
Clustering*recovery							−1.032	***	0.266	−0.743	***	0.233
Initial disruption	0.231	***	0.005	0.231		0.005	0.230	***	0.005	0.230	***	0.005
Intercept	4.102	***	0.260	4.423		0.301	3.563	***	0.328	3.400	***	0.387
Model fit												
R^2 (overall)	0.82			0.82			0.82			0.82		
Wald χ^2 (DF)	3776.76***(8)			3672.10***(8)			3917.22***(8)			4406.22***(12)		
Number of nodes	111			111			111			111		
Observations	888			888			888			888		

Note(s): ***$p < 0.001$, **$p < 0.05$, *$p < 0.1$, N.S.-Not Statistically Significant | All estimates are unstandardized
Source(s): Authors' creation

Detection. The interaction terms between detection and both eigenvector centrality and clustering coefficient yielded negative and statistically significant coefficients across both the individual and combined interaction models ($p < 0.001$). These findings strongly indicate that increased detection capabilities significantly attenuate the positive relationship between network structure and disruption risk, supporting detection as a critical moderating factor in limiting the propagation of disruptions through the network.

Mitigation. Although the interaction terms involving mitigation and both eigenvector centrality and clustering coefficient were negative, these coefficients did not reach statistical significance in either the individual or combined interaction models ($p > 0.1$). The absence of significant results implies that mitigation strategies, such as maintaining safety stocks, might not directly moderate the effects of network structure on disruption risk. A plausible explanation is that mitigation primarily serves as a proactive measure that may not dynamically interact with network structural characteristics during actual disruptions.

Recovery. Interaction terms involving recovery and eigenvector centrality, as well as recovery and clustering coefficient, were negative and statistically significant ($p < 0.001$) in the individual interaction models. In the combined interaction model, the interaction between clustering coefficient and recovery remained highly significant ($p < 0.001$), whereas the interaction between eigenvector centrality and recovery reduced in significance ($p < 0.1$). These results highlight recovery strategies as critical for reducing disruption risk, particularly within highly clustered networks. Recovery capabilities enable firms to swiftly resume normal operations, thereby significantly mitigating cascading disruption effects in tightly interconnected networks.

5.4 Post hoc robustness testing

To further assess the external validity of our findings, we conducted two post-hoc robustness tests. First, we repeated the main effects and interaction analyses using closeness centrality as an alternative operationalization of centrality. Second, we utilized relational data from joint ventures within the automotive manufacturing industry, sourced from Thomson Financial Security's SDC Platinum database. This second analysis spanned 19 years, creating a cumulative network structure. We applied the same variables and regression models from the primary analysis to these alternative datasets.

The results of both post-hoc analyses largely supported our initial findings, confirming the robustness and validity of our model. Detailed methodologies and results from these additional datasets and analyses are available in Online Supplementary Materials B and C.

6. Discussion

Building upon foundational research on risk propagation within supply networks (e.g. Garvey *et al*., 2015; Snoeck *et al*., 2019), methodologies and insights from Snoeck *et al*. (2019) and extending recent network-based analyses (Kao *et al*., 2017; Klibi and Martel, 2012; Berger *et al*., 2023), this study investigates how structural network characteristics—specifically eigenvector centrality and clustering—interact with firm-level risk management strategies to influence disruption risk. The empirical findings presented above provide detailed insights into the relationships between network positions, disruption vulnerabilities, and the moderating roles of detection, mitigation, and recovery strategies. Table 6 summarizes the outcomes of our hypotheses and their theoretical and practical implications, which we discuss in detail below.

6.1 Key findings and their implications

The central insight from this study confirms the principle that network structural characteristics have nuanced implications for disruption risk, reinforcing the idea that more

Table 6. Summary of study results and hypotheses

Hypothesis	Result	Explanation
H1: There is a non-monotonic (curvilinear) relationship between a firm's centrality and its disruption risk, whereby disruption risk increases at lower levels of centrality, peaks at intermediate levels, and tapers off at higher levels of centrality	Not supported	*Linear model*: Eigenvector centrality positively and significantly increases disruption risk in the main effects model. Thus, as firms' network structure becomes increasingly central their disruption risk increases *Quadratic model*: The introduction of the quadratic term renders the linear term insignificant, indicating no clear statistical evidence of diminishing returns. The data suggest that increased centrality consistently heightens risk, with no observable stabilization effect This lack of statistical significance likely is the result of contextual factors, where in some industries connecting to powerful suppliers has an incremental benefit to performance (Falcone *et al.*, 2023), whereas in others the effect is not demonstrable. Also of note, is that the post-hoc analysis of closeness centrality as an alternate operationalization of centrality did show a much stronger ($p = 0.106$) diminishing return effect, although marginally statistically significant, further emphasizing the likely context driven nature of the effect shown. Additional analyses on other network contexts is required
H2: There is a non-monotonic (curvilinear) relationship between a firm's clustering coefficient and its disruption risk, whereby disruption risk increases at lower clustering levels, peaks at intermediate levels, and decreases at higher levels of clustering	Supported	*Linear model*: Clustering coefficient significantly increases disruption risk across all models *Quadratic model*: The quadratic coefficient for clustering is negative and statistically significant, confirming an inverted "U"-shaped relationship. Disruption risk peaks at a clustering coefficient of approximately 0.6, with redundancy and local connectivity mitigating risk at higher levels This result suggests that in the case of a disruption initially high levels of clustering will increase disruption risk, but that at a certain point redundant network connections can provide for mitigatory and recovery benefits
H3a: Increased levels of detection dampen the positive impact of network structure on disruption risk	Supported	Detection significantly moderates the relationship between both eigenvector centrality and clustering coefficient and disruption risk. Detection's ability to identify disruptions early reduces the cascading effects of disruptions, especially in highly central or clustered networks
H3b: Increased levels of mitigation dampen the positive impact of network structure on disruption risk	Not supported	Mitigation showed no significant interaction effects with centrality or clustering. This suggests while mitigation strategies can clearly impact disruption risk, their effects get ameliorated in the presence of highly connected networks

(*continued*)

Table 6. Continued

Hypothesis	Result	Explanation
H3c: Increased levels of recovery dampen the positive impact of network structure on disruption risk	Supported	Recovery significantly moderates the relationship between clustering coefficient and disruption risk and partially moderates the relationship with eigenvector centrality. Recovery enables firms to rebound more quickly from disruptions, mitigating cascading effects in both highly central and clustered networks

Source(s): Authors' creation

connectivity is not always better. Specifically, the robust empirical support for a curvilinear relationship between clustering and disruption risk (Hypothesis 2) underscores this complexity. Our results demonstrate an inverted U-shaped pattern: initial increases in clustering amplify disruption risk by raising connectivity and vulnerability to cascading disruptions (Chaudhuri *et al.*, 2020), whereas further increases ultimately reduce risk through redundancy and the presence of alternative network pathways. These findings align with previous research highlighting the dual nature of clustering, where tightly connected groups can simultaneously facilitate rapid risk propagation (Dolgui and Ivanov, 2021) and act as buffers by providing redundancy (Schilling and Phelps, 2007; Carnovale and Yeniyurt, 2015; DuHadway *et al.*, 2018). Moreover, while existing studies on centrality emphasize how critical nodes in supply networks typically face heightened susceptibility to disruptions (Berger *et al.*, 2023), our work advances this understanding by explicitly examining and empirically testing the nonlinear dynamics underlying these relationships. Thus, we contribute to the literature by demonstrating the empirical thresholds at which clustering transitions from being a disruption amplifier to serving as a risk mitigator.

Additionally, our findings provide empirical validation for the moderating roles of firm-level risk management strategies, notably detection and recovery, in influencing disruption risk relative to network structure. Prior literature underscores intersections between network design and risk (Kao *et al.*, 2017; Ezmizadeh and Parast, 2023), suggesting that enhanced visibility through improved detection can significantly boost risk management efficacy (Saad and Ubeywarna, 2024). Our study corroborates these claims, confirming that detection capabilities significantly reduce disruption propagation, especially in tightly clustered supply networks where disruptions spread swiftly (Garvey *et al.*, 2015; Craighead *et al.*, 2007; Berger *et al.*, 2023; Dolgui and Ivanov, 2021). Likewise, recovery strategies moderate disruption risks by enabling firms to restore operations rapidly after disturbances (Ledwoch *et al.*, 2018), effectively dampening the risks inherent to clustered networks. These insights advance the understanding of how targeted firm-level strategies can interact effectively with structural network properties to mitigate disruption outcomes, emphasizing the critical importance of aligning risk management efforts with specific network contexts.

Overall, the demonstrated curvilinear relationship of clustering, alongside the significant moderating roles of detection and recovery, highlights a dynamic interplay between structural network characteristics and firm-level risk management practices. Firms operating within highly clustered networks should strategically invest in robust detection and recovery capabilities, enabling them to leverage clustering's beneficial redundancy while simultaneously reducing its potential risks. This refined understanding extends prior literature by illustrating how network theory can inform more tailored and effective supply chain risk management strategies, moving beyond industry-specific contexts to structural insights applicable across broader supply network settings.

6.2 Revisiting assumptions: insights from unsupported hypotheses

The results related to eigenvector centrality yielded mixed findings, presenting a challenge to prevailing perspectives within the literature. Although the linear effects model demonstrated that higher eigenvector centrality significantly increases disruption risk, aligning with earlier studies indicating that centrality can expose firms to disruptions through numerous and highly interconnected relationships (Kim *et al.*, 2015), the quadratic result did not support the anticipated diminishing returns effect. This finding suggests that the relationship between eigenvector centrality and disruption risk may be more complex and context-dependent than previously acknowledged. One plausible explanation is that the benefits typically attributed to centrality, such as greater resource access and diverse information flows (Carnovale and Yeniyurt, 2015), may not sufficiently offset or stabilize risk at higher levels of centrality. Consequently, centrality-driven risks may remain consistently elevated even for firms occupying highly prominent network positions.

Additionally, our analysis did not support the hypothesized moderating role of mitigation strategies on the relationship between network structure and disruption risk. This result contrasts with prior literature emphasizing mitigation strategies—such as maintaining safety stocks—as critical measures for reducing disruption exposure (Zsidisin *et al.*, 2004; Tomlin, 2006). A likely explanation for this divergence is that mitigation strategies, being inherently preparatory measures, might not dynamically interact with structural network characteristics during disruption events. Unlike detection and recovery, which actively respond to disruption propagation and restoration, mitigation tends to be less responsive in real-time scenarios, and thus may be limited in directly counterbalancing the risks embedded in network positions.

These unsupported hypotheses provide significant theoretical and practical implications. The persistent disruption risk linked to high eigenvector centrality questions the assumption that centrally positioned firms can (eventually) leverage their prominence to effectively reduce risk exposure. This finding emphasizes the need for a deeper exploration of context-specific factors influencing centrality's effects (Chaudhuri *et al.*, 2020). Furthermore, the absence of significant interaction effects involving mitigation suggests a reconsideration of its standalone efficacy within network-driven risk management frameworks. Practitioners may need to couple mitigation strategies with more dynamic and reactive measures, such as detection and recovery, to comprehensively address network-induced vulnerabilities.

7. Conclusions: main contributions and future developments

This research provides several important theoretical contributions, deepening our understanding of the intersection between network theory and supply chain risk management. Primarily, our findings reveal a nuanced, curvilinear relationship between network clustering and disruption risk, enriching the debate on network complexity and vulnerability. Contrary to simplistic assumptions that greater connectivity inherently amplifies risk, this study empirically demonstrates that network clustering initially increases disruption susceptibility but eventually promotes resilience through redundancy. Thus, our findings extend prior literature (e.g. Guntuka *et al.*, 2024a; Jin *et al.*, 2022), reinforcing the idea that tightly connected network clusters, traditionally perceived as vulnerabilities, can simultaneously enhance resilience when facing extensive disruptions.

A second key theoretical contribution emerges from the moderating roles of detection and recovery capabilities. By empirically validating how these firm-level strategies interact with network structure to shape disruption outcomes, this study offers insights beyond existing frameworks (e.g. Snoeck *et al.*, 2019). Specifically, detection capabilities that facilitate early disruption identification and recovery strategies that expedite post-disruption responses significantly mitigate disruption propagation in highly interconnected networks. These results underline the critical importance of aligning risk management strategies with firms' structural positions to effectively reduce network-driven disruption risks.

Furthermore, our findings regarding eigenvector centrality add complexity to previous linear conceptualizations (Craighead *et al*., 2007; Kim *et al*., 2015). While our data confirm that high centrality consistently increases disruption vulnerability, the absence of empirical support for diminishing returns indicates a context-dependent nature of centrality's impact. This challenges the conventional view that central firms eventually benefit from their position by stabilizing or reducing risk. The implication is clear: future research must investigate the specific industry or contextual boundary conditions under which centrality transitions from an asset to a liability.

Lastly, the limited moderating effects of mitigation strategies (e.g. safety stocks) provide another critical theoretical insight. Although widely endorsed as essential in the literature (Zsidisin *et al*., 2004; Tomlin, 2006), our findings suggest that mitigation alone does not effectively address structural network risks. This result emphasizes the necessity of integrating dynamic and adaptive approaches, like detection and recovery, within comprehensive risk management frameworks, setting the stage for future research to explore more sophisticated, context-responsive risk management strategies.

7.1 Managerial contributions

The findings from this study offer several valuable managerial implications, particularly relevant in industries characterized by complex, interconnected networks (e.g. automotive, electronics, pharmaceuticals, consumer goods). Managers must strategically align risk management investments with their firms' network positions. Specifically, the empirical evidence underscores detection capabilities as essential for firms occupying highly central or clustered positions. Investing in advanced monitoring and detection technologies can empower firms with the foresight needed to mitigate disruption impacts proactively, especially in environments where disruptions propagate rapidly and intensively.

Additionally, the critical role of recovery capabilities highlights the practical necessity for firms to develop robust operational resilience. Managers should prioritize building agile recovery frameworks that enable quick restoration of operations after disruptions, thereby minimizing cascading impacts within the supply network.

Insights from the curvilinear relationship of clustering further suggest managers should strategically balance network connectivity and redundancy. While initial clustering increases risk, firms can ultimately benefit from redundancy and alternative supply paths provided by highly clustered structures. Managers should leverage this duality by deliberately designing supply networks that combine sufficient redundancy with targeted detection and recovery investments, enhancing overall resilience.

The mixed outcomes associated with eigenvector centrality underscore the need for a nuanced evaluation of network prominence. Managers must recognize that centrality presents a risk-return trade-off, providing critical resources but simultaneously increasing vulnerability to cascading disruptions. Risk management strategies for highly central firms must therefore include targeted detection and agile recovery mechanisms to mitigate inherent structural risks.

Finally, the limited effectiveness of traditional mitigation measures such as inventory buffers indicates that firms must move beyond static, standalone strategies. Instead, managers should integrate dynamic, real-time capabilities like detection and recovery into their supply chain risk management portfolios. Such integrated approaches can better accommodate the complex, dynamic nature of contemporary supply networks.

7.2 Limitations and future developments

Despite the robust multi-method approach adopted, several limitations present opportunities for future research. The largest overarching need for improvement is to further address the knowledge gap between academia and industry (e.g. van Hoek and Wong, 2025), particularly during a time wrought with geopolitical challenges and increased regionalization of supply chains. While this work provides guidance for management to implement cutting-edge best practices for risk management in regional locations of supply chains, future research should heed the call to explore strategies that avoid “reverting back to pre-pandemic strategies and not seeing structural changes” in supply networks that mitigate such disruptions. Also noted are the following. First, disruptions in our simulations were assigned uniformly across nodes, implicitly assuming equal disruption probabilities. Future studies could refine this approach by incorporating node-specific disruption probabilities influenced by location, industry characteristics, or past disruption history.

Second, our simulation relied on a static network structure, limiting insights into dynamic changes that naturally occur in real-world supply networks. Although firm characteristics and risk management strategies varied across scenarios, future research should explore dynamically evolving network structures to capture longitudinal changes in supply chain resilience and disruption risk.

Third, our data constraints precluded the inclusion of certain critical variables that may influence network dynamics and disruption outcomes. Factors such as relational dynamics (e.g. collaboration, power, trust), firm size, financial dependencies, and transaction frequency likely moderate disruption risks and response capabilities. Future research should endeavor to integrate these control variables to more comprehensively capture how relational and transactional factors intersect with network structures.

Fourth, our operationalization of detection based on geodesic distance represents structural connectivity effectively but does not incorporate alternative measures such as weighted distances or technology-enabled visibility. Future studies could integrate hybrid metrics capturing both structural and technological aspects of detection capability, providing richer insights into how firms perceive and react to disruptions.

Methodologically, integrating structural network data directly with firm-level risk management strategies, rather than combining separate datasets, could further enhance the validity and depth of findings. Additionally, exploring diverse network types and structural configurations could yield valuable comparative insights that are generalizable across different supply chain contexts.

Future research could also extend our findings by applying insights from centrality and clustering to broader supply chain issues such as cybersecurity (Friday *et al.*, 2024), facility location optimization, offshoring decisions, and critical-path mapping of supply flows, in addition to digital transformation and sustainability-related work (van Hoek and Wong, 2025). Examining how network measures intersect with strategies to reduce supply chain complexity, enhance resilient ecosystems, and foster collaboration represents another promising research direction.

Finally, validating simulation findings through empirical analysis of actual supply chain disruptions over time would enhance methodological rigor and generalizability. Collecting real-world disruption data would enable researchers to confirm the relationships uncovered in simulations, enriching theoretical development and providing practical benchmarks for supply chain risk management and resilience.

Addressing these limitations and exploring these future directions will continue to refine network theory applications within supply chain management, contributing valuable theoretical insights and practical strategies for navigating increasingly complex, interconnected supply networks.

Notes

1. https://www.nytimes.com/2021/07/17/world/middleeast/suez-canal-stuck-ship-ever-given.html
2. https://www.nytimes.com/2022/01/16/business/economy/china-supply-chain-covid-lockdowns.html#
3. While there are several other network related variables that were available, a full review of these is outside the scope of this manuscript. We refer readers to Borgatti, Stephen P., and Xun Li. “On social network analysis in a supply chain context.” *Journal of supply chain management* 45.2 (2009): 5–22

or Galaskiewicz, Joseph. “Studying supply chains from a social network perspective.” *Journal of Supply Chain Management* 47.1 (2011): 4–8, for a detailed review.

4. https://www.cnbc.com/2020/03/20/coronavirus-shocks-will-lead-to-massive-global-supply-chain-shuffle.html
5. https://ccl.northwestern.edu/netlogo/
6. Available at https://faf.ornl.gov/fafweb/Extraction1.aspx
7. Prolific.com
8. Note that the data utilized from DuHadway *et al.*, (2018) in this paper are the pre-manipulation, baseline, data.
9. Note that the size of the number of nodes reduced from the original sample size due to eliminating observations with incomplete data for all network variables used in this study.

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Further reading

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Supplementary material

The supplementary material for this article can be found online.

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