Int. J. Production Economics 291 (2026) 109854

Contents lists available at ScienceDirect

International Journal of Production Economics

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

Impact of network nestedness on resistance and recovery of supply chain resilience

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ARTICLE INFO

Keywords:
Supply chain resilience
Network nestedness
Buyer-supplier networks
Resistance
Recovery

ABSTRACT

Network nestedness, which refers to the hierarchical structure of interconnections within a network, plays an important role in supply chain resilience but remains understudied. We use data from listed firms in China between 2002 and 2022 to construct buyer-supplier networks and measure nestedness using the SNODF metric. We validate SNODF's robustness across varying levels of network completeness. Listed firms are centrally positioned in our networks, making them crucial focal points for analysis. Our empirical results show that network nestedness has a dual effect on supply chain resilience: it weakens short-term resistance to disruptions but enhances long-term recovery. This trade-off arises because hierarchical structures concentrate vulnerability at hub nodes while enabling coordinated resource reallocation after a disruption. We examine two managerial levers that moderate these effects: (1) supplier concentration, an external strategy that attenuates the negative effect on resistance but dampens recovery gains; and (2) corporate digitalization, an internal strategy that mitigates initial losses and enhances recovery. These findings imply that firms should balance two approaches: (1) mitigating risk through supplier diversification to reduce dependence on dominant hubs, and (2) leveraging digital technologies to improve recovery capabilities, thus strengthening long-term resilience.

1. Introduction

1.1. Background and motivation

Modern supply chains face disruptions across multiple scales. High-frequency operational disturbances (e.g., supplier delays, quality defects, demand volatility) generate cumulative costs through cascading delays and inefficiencies (Hendricks and Singhal, 2014). In contrast, less frequent but high-impact operational disruptions impose severe and persistent losses, ranging from regional shocks such as floods and mergers & acquisitions (M&As) to systemic crises including the Ukraine-Russia war or global pandemics (Srai et al., 2023). These multi-scale vulnerabilities have intensified focus on supply chain resilience: the systems' capacity to resist and recover from disruptions regardless of their frequency or magnitude.

Prior risk-management approaches, such as stockpiling inventory (Liu et al., 2016), employing contingency planning (Pavlov et al., 2019), or relying on reactive responses (Faruquee et al., 2024), are increasingly inadequate in dealing with the complexity and interconnectivity of today's supply chains (Zheng et al., 2025). Effective resilience strategies require understanding the structural and systemic properties of the buyer-supplier network. As Complex Adaptive Systems (CAS), these networks emerge from decentralized firm decisions rather than top-down design (Brintrup et al., 2018). Firms' production and partnership choices generate self-organizing behaviors that transcend individual-level analysis, necessitating a multilevel approach that examines both firm-specific and collective network dynamics to identify resilience factors.

Network nestedness is a prominent topological feature in numerous real-world networks with distinct hierarchical structures. Although extensive research has examined small-world properties (Wiedmer and Griffis, 2021), scale-free patterns (Broido and Clauset, 2019), as well as other topological features and metrics of buyer-supplier networks (Jiang et al., 2023), less attention has been paid to how the hierarchical layering of ties (i.e., network nestedness) affects resilience. Originally studied in ecological systems (James et al., 2012), nestedness in

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https://doi.org/10.1016/j.ijpe.2025.109854
Received 21 April 2025; Received in revised form 21 August 2025; Accepted 9 November 2025
Available online 19 November 2025

buyer-supplier networks represents the degree to which smaller, specialized nodes form proper subsets of connections held by larger, diversified nodes (Chauhan et al., 2021). Recent evidence from the global automotive industry reveals that firms with narrow product ranges nest within portfolios of firms with extensive production capabilities (Olivares Aguila and ElMaraghy, 2018). This finding goes against the traditional expectation that small, "specialist" firms would handle rare or high-value components (Brintrup et al., 2018). Instead, large "generalist" suppliers dominate critical categories, maintaining numerous buyer relationships. This core-periphery pattern implies higher resilience to random disruptions through substitutability, yet increased vulnerability to targeted disruptions at high-degree hubs (Ledwoch et al., 2018).

Fig. 1 illustrates how network density and hierarchical ordering reveal nested, core-periphery structures. Subfigure (a) displays four synthetic networks ($n = 50$) with edge probabilities $\alpha \in \{0.1, 0.3, 0.5, 0.7\}$, transitioning from sparse to dense configurations. In nested architectures, high-degree core nodes connect extensively while periphery nodes link to subsets of core neighbors, creating hierarchical layering where peripheral suppliers experience hub disruptions indirectly through network paths. Subfigure (b) shows degree-sorted adjacency matrices (red cells indicate links). Weak nestedness yields scattered links; strong nestedness produces triangular bands indicating that lower-degree nodes' neighbor sets are subsets of those of higher-degree nodes. This pattern is a signature of core-periphery organization. For example, Tesla relies on Panasonic for batteries, while smaller suppliers depend on Panasonic's contracts; Tesla's partnership changes affect these suppliers through their Panasonic reliance, despite lacking direct Tesla connections. While immediate suppliers directly impact focal firms' performance (Lu and Shang, 2017), the nested perspective highlights the role of deeper-tier dependencies (see Fig. 3).

Nestedness in buyer-supplier networks can weaken short-term resistance to disruptions by concentrating dependence on a few highly connected hubs, yet it may strengthen long-term recovery. Although these hierarchical patterns can help firms weather sudden demand drops or supplier failures, they also intensify vulnerability when core hub firms are disrupted (Chauhan et al., 2021). This interplay between short-term weakness and long-term potential remains underexplored, leaving a gap in our understanding of how hierarchical structures shape both resistance and subsequent recovery. To fill this gap, we explore the role of network nestedness as a driver of resilience, focusing on the central question: *How does network nestedness impact the resistance and recovery dimensions of supply chain resilience?*

To systematically examine the impact of nestedness, we employ established metrics adapted from ecology for supply chain. NODF (Almeida-Neto et al., 2008) quantifies nestedness based on pairwise neighbor overlap under a decreasing-fill ordering. Stable-NODF (SNODF), which treats degree ties consistently and is less sensitive to small link perturbations (Bastolla et al., 2009). These properties are particularly desirable for supply-chain data with incompleteness and noise. We also report row scores (buyer perspective) and column scores (supplier perspective) separately to ensure observed nestedness isn't driven by one network side alone (Mariani et al., 2019).

Prior research has recognized the significance of tiered topology in nested buyer-supplier networks, where lower-degree suppliers tend to be incorporated into the partner sets of higher-degree, diversified firms (see Table 1). Ledwoch et al. (2018) demonstrate that both Supplier-Product and Supplier-Manufacturer networks exhibit nested patterns enhancing system-level robustness, though small suppliers face intensified competition in highly nested structures. Perera et al. (2020) reveal that hub-and-spoke topologies foster higher topological rationality than scale-free or random topologies, yet remain susceptible to disruptions affecting major hubs. Chauhan et al. (2021) highlight the fundamental trade-off: nested buyer-supplier networks are robust to random disruptions but vulnerable to targeted hub disruptions, creating tension between operational efficiency and systemic risk.

However, existing research faces critical limitations. First, studies predominantly examine single industrial sectors, limiting cross-sector generalizability to industries with different supply structures, competitive dynamics, or governance forms. Second, the literature relies heavily on simulation models or synthetic networks, which, although informative, lack extensive empirical verification. Third, most analyses focus on

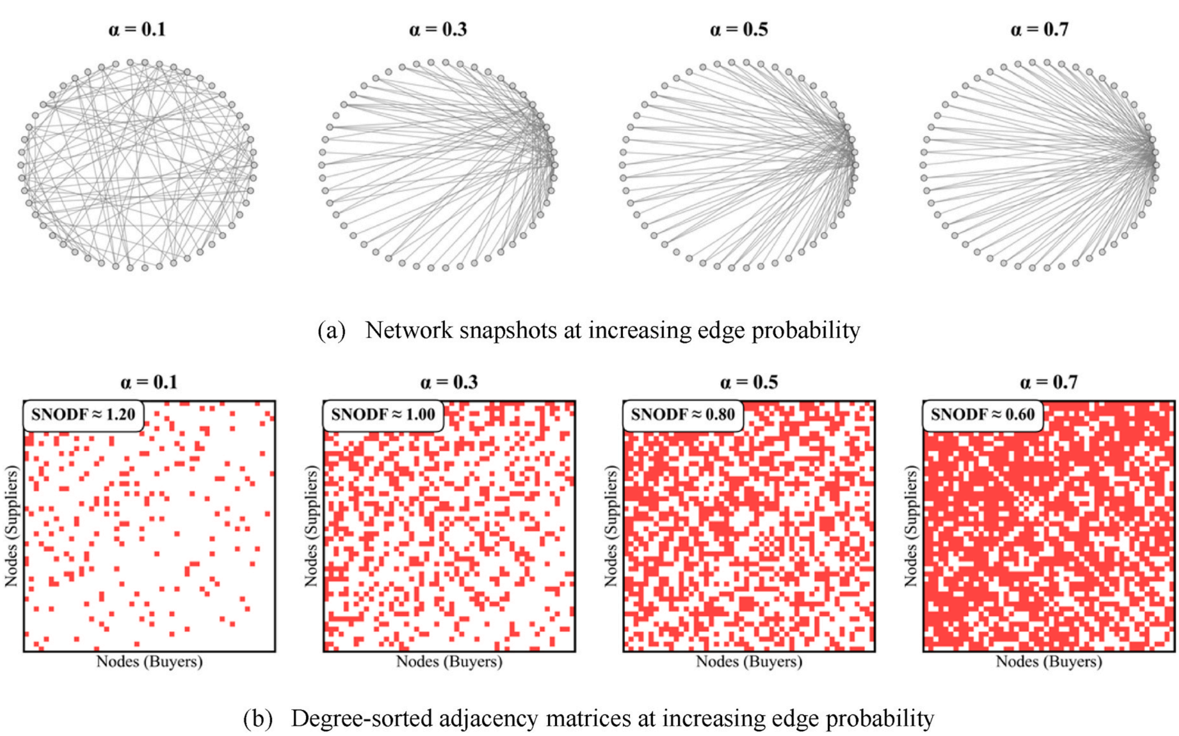

Fig. 1. Example networks with $n = 50$ nodes at increasing edge probabilities $\alpha \in \{0.1, 0.3, 0.5, 0.7\}$. As α rises, the graphs evolve from sparse, loosely connected structures (left) to dense, nearly complete configurations (right), reflecting a transition from lower to higher levels of network nestedness.

Table 1
Overview of research on the nestedness of buyer-supplier networks.

Literature	Dataset	Research Method	Key Insights
Ledwoch et al. (2018)	Global automotive network (over 18,000 firms)	Simulation on observed networks	• Supplier-product and supplier-manufacturer network are nested, which enhances system robustness •Small suppliers face intensified competition in highly nestedness
Perera et al. (2020)	Synthetic networks through log-normal fitness (1000 nodes)	Simulation on observed networks	•Node degree bounded rationality •Hub-and-spoke structures show high topological rationality but is fragile to hub failures
Chauhan et al. (2021)	A three-layer network: 928 products, 16,642 suppliers, 2470 buyers	Simulation on observed networks	•Nested networks are robust to random shocks but vulnerable to targeted hub attacks •Highlights cost-benefit trade-offs vs. more random designs

static network snapshots rather than dynamic resilience outcomes. We address these gaps by examining nested dimensions across multiple industries through comprehensive empirical data analysis, linking network structure to observed resistance and recovery performance.

1.2. Theory and hypotheses development

Resource Dependence Theory (RDT) argues that firms establish alliances or contracts to secure critical inputs and reduce external uncertainties (Hillman et al., 2009). In buyer-supplier networks, this dynamic often manifests in the formation of dominant hubs: large, diversified suppliers that consolidate technological expertise, production capacity, or logistical advantages (Sauer and Seuring, 2019; Tachizawa and Wong, 2014). By capturing key resources, these hubs gain leverage over numerous buyers and smaller suppliers, reshaping resource flows to reinforce their central position (Casciaro and Piskorski, 2005).

We distinguish resilience from robustness. Robustness is an ex-ante, design-oriented property: a supply chain's ability to maintain performance across a predefined uncertainty set of potential disruptions, often formalized through worst-case (robust) optimization models that guarantee service levels against anticipated shocks (Simchi-Levi et al., 2018). By contrast, resilience is a broader, dynamic capability rooted in the concept of "bouncing back" after a disruption. It encompasses not only the ability to withstand a shock but also the adaptive capacity to recover, return to a normal state, or even evolve to a better one post-disruption (Shishodia et al., 2021). We connect nestedness to resilience rather than robustness because we analyze the full disruption lifecycle, including both resistance and recovery. By contrast, robustness is an ex-ante design property focused on maintaining performance within specified bounds, without capturing post-disruption adaptation or recovery dynamics. Fig. 2 presents our conceptual framework illustrating these hypothesized relationships.

Consistent with RDT, buyer-supplier ties often concentrate around diversified hubs that control access to key inputs. The resulting nestedness reduces independent substitution paths and increases overlap in exposure (Baselga, 2012; Ledwoch et al., 2018). This overlap underpins our position on resistance. During the resistance phase, higher nestedness raises immediate exposure to hub shocks because many dependents share the same upstream gatekeepers. Thus, the expected effect on resistance is negative (Hosseini et al., 2016). Apparent buffering from widely shared parts is better viewed as a recovery-phase advantage.

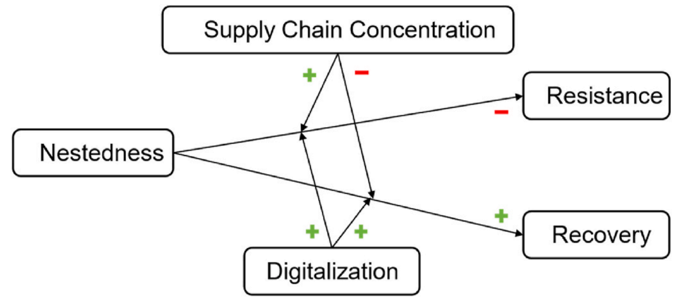

Fig. 2. The conceptual framework.

Hubs can coordinate rerouting and reconfiguration, but they do not insulate the network at the moment the disruption strikes. Such buffering depends on time-dependent reallocation, engineering and contractual changes, and logistics adjustments implemented after the initial impact (Ivanov, 2022; Shishodia et al., 2021). This interpretation aligns with evidence that nested buyer-supplier networks are robust to random failures yet highly sensitive to targeted hub disruptions—the scenarios that dominate early shock transmission (Chauhan et al., 2021). It also aligns with the phase distinction that substitutability effects materialize during restoration rather than at the initial shock. We therefore to propose.

Hypothesis 1. Higher degrees of nestedness in a buyer-supplier network are negatively associated with the resistance but positively associated with the recovery dimension of supply chain resilience.

Although network nestedness can both weaken resistance and facilitate recovery, its impact also depends on broader structural features of the supply base. One crucial factor is supplier concentration, defined as the extent to which a small number of suppliers exert disproportionate control over essential inputs (Choi and Krause, 2006). Firms facing nested buyer-supplier networks must choose between internal and external adaptive responses: they can either reduce dependence through supplier diversification (external restructuring) or enhance internal capabilities through digitalization to better coordinate with existing concentrated suppliers (internal adaptation).

From an RDT standpoint, high supplier concentration amplifies dependence on dominant hubs, intensifying immediate vulnerability if disruptions occur (Kleindorfer and Saad, 2005). In a nested network, this means that when one powerful supplier encounters a shock, numerous peripheral firms simultaneously lose critical resources. Supplier concentration may also constrain longer-term recovery. While a smaller set of key suppliers could theoretically accelerate knowledge transfer, dominant hubs often have strong bargaining power and limited capacity to prioritize all buyers during disruptions (Holcomb and Hitt, 2007). This power imbalance can slow realignment and reallocation processes, weakening the adaptive benefits of nestedness. Therefore.

Hypothesis 2. Supplier concentration positively moderates the relationship between network nestedness and supply chain resistance, but negatively moderates the relationship between network nestedness and supply chain recovery.

Following Information Processing Theory (IPT), firms in volatile environments use two approaches to manage complexity and uncertainty. First, they increase external visibility by building lateral ties with key partners (e.g., direct collaboration, connected information systems) (Barratt and Barratt, 2011). Visibility requires timely, accurate demand and supply data, as well as internal processes to organize and disseminate such data (Williams et al., 2013). These linkages expand information-processing capacity by supplying point-of-sale data, supplier inventory levels, and market signals, giving managers a clearer view of changing conditions. Second, organizational flexibility enables rapid action on new information (Flynn et al., 2016). Flexibility is the ability to reconfigure assets, decision rights, and routines with minimal time and cost. Vertical information systems and analytics convert real-time data into executable plans, enabling agile responses to demand shocks or supply disruptions. Together, enhanced visibility and flexibility provide the awareness and speed firms need to operate in volatile markets (Peng et al., 2014).

Building on insights from IPT, corporate digital activities can serve as a powerful enabler in handling the informational complexity inherent in highly nested supply structures. By enhancing a firm's lateral information flows, advanced analytics, and vertical decision-support systems (Peng et al., 2014), digitization can expand the scope and depth of visibility into upstream or downstream processes. In the short term, such technological platforms integrate real-time supplier data, demand signals, and market fluctuations, thereby reducing information lags or distortions that could otherwise intensify disruptions within a nested network (Williams et al., 2013). Thus, corporate digitalization complements network nestedness since it quickly identifies hub suppliers at risk and proactively isolates potential bottlenecks before they spread (Srinivasan and Swink, 2018). Further, digital tools and activities can enhance the recovery advantages of network nestedness: well-connected hubs can promptly reallocate resources or reconfigure production routes, especially when supported by agile information systems that coordinate decisions across multiple interdependent nodes (Tang and Nurmaya Musa, 2011). Although excessive reliance on digital infrastructure may introduce new vulnerabilities, such as cybersecurity threats or synchronization issues (Liu et al., 2024), the general expectation is that digital maturity magnifies the benefits of network nestedness for both short-term shock absorption and long-term recovery coordination. We propose.

Hypothesis 3. Corporate digitalization positively moderates both the relationship between network nestedness and supply chain resistance, and the relationship between network nestedness and supply chain recovery.

1.3. Key findings and contributions

We draw on a dataset of 3417 publicly listed Chinese firms from 2002 to 2022. We obtain firm-level supplier data from two authoritative sources: Tianyancha and CNRDS. Based on this information, we construct detailed buyer-supplier networks by mapping buyer-supplier relationships across firms. Then, we measure network nestedness using the SNODF metric (Bastolla et al., 2009; Mariani et al., 2019), which captures nested structure by normalizing pairwise neighbor overlap by the smaller degree.

Our results confirm the dual role of network nestedness and clarify measurement and design choices. We focus on publicly listed firms because they occupy structurally central positions in the buyer-supplier network, with markedly higher degree, betweenness, and closeness, so shocks and adjustments at these nodes propagate system-wide. In panel regressions, higher SNODF is associated with lower resistance (*Resis1* and *Resis2*) and higher recovery (*Recov1* and *Recov2*). These patterns hold across ownership and firm size. Nestedness more strongly weakens resistance in SOEs and large firms, strengthens operational recovery in non-SOEs and smaller firms, and concentrates performance-recovery gains in SOEs and large firms. Moderation tests show that supplier concentration attenuates the resistance penalty but mutes recovery gains, whereas corporate digitalization mitigates early-phase losses and amplifies longer-horizon recovery. The instrumental variable estimates using peer nestedness reproduce the same pattern, alleviating endogeneity concerns. Robustness checks with row-SNODF, column-SNODF, JNODF, and NODF yield consistent signs. SNODF remains our preferred metric because it is comparatively stable under disclosure-based incompleteness, as indicated by cross-network concordance, and the core results hold across alternative specifications and completeness tests.

This study makes three major contributions. First, we deepen understanding of supply chain resilience by breaking it into resistance and recovery. We emphasize the nested nature of relationships, particularly the role of hub suppliers deeper in the network on short-term stability and long-term recovery. Grounded in RDT, we explain that firms, seeking secure access to scarce yet critical inputs (Hillman et al., 2009), converge on resource-rich suppliers. This collective pursuit strengthens hierarchical structures and creates nested patterns that influence resilience. By integrating RDT with IPT, we clarify how network nestedness shapes resilience and how digitalization moderates these effects. Second, we translate these findings into two actionable strategies for managers who cannot redesign the entire network: an external strategy, which involves managing supplier concentration through diversification and allocation safeguards, and an internal strategy, which involves leveraging corporate digitalization to sense, coordinate, and reconfigure rapidly. This approach clarifies how to manage core-periphery relationships when multiple actors rely on a few suppliers. Third, we provide large-scale empirical evidence by constructing objective network measures and linking them to firm-level resistance and recovery outcomes.

This paper is structured as follows. Section 2 presents the methodology for measuring nestedness and resilience. Section 3 reports the empirical tests and results. Section 4 discusses theoretical contributions and managerial implications. Section 5 concludes with key findings, limitations, and directions for future research.

2. Methodology

2.1. Data sources and pre-processing

We construct buyer-supplier networks using two primary data sources: CNRDS and Tianyancha,[1] covering 3417 publicly listed firms on China's A-share main board and ChiNext from 2002 to 2022. Our focus on publicly listed firms is mainly driven by data requirements. Listed firms are subject to stringent regulatory disclosure requirements that provide the reliable, detailed financial and supplier data essential for network analysis and panel regressions. We begin in 2002, which represents the first reporting cycle following the China Securities Regulatory Commission's, 2001 revision of annual report disclosure guidelines.[2] While prior studies (Falcone et al., 2025) rely on official corporate disclosures, which yield 85,243 buyer-supplier relationships in our sample period, we leverage Tianyancha's comprehensive database to identify 473,930 relationships—a 5.6-fold increase. This expanded coverage identifies supply chain connections from two sources: voluntary public announcements on third-party tendering platforms and bidding records.

We implement rigorous filtering procedures using Python and Stata to ensure data validity.[3] For relationship construction, we drop bidder-only entries appearing in bidding data so that only confirmed supply ties remain, ensuring the network reflects actual business relationships. At the firm-year level, we apply the following exclusion criteria consistent with corporate finance research standards (Allen et al., 2024; Hirshleifer et al., 2013): (1) We remove financial sector firms due to their distinct accounting standards and regulatory requirements. (2) We exclude firms designated as "Special Treatment" (ST), as these companies face

[1] The reliability CNRDS (https://www.cnrds.com/) of and Tianyancha (https://www.tianyancha.com/) as data sources has been well recognized, as each platform compiles comprehensive, government-verified corporate records and financial disclosures, which are routinely used in empirical research on Chinese enterprises.

[2] Official text available at the State Council website: https://www.gov.cn/gongbao/content/2002/content_61795.htm.

[3] Code and supporting materials are available at: https://github.com/chensh236/Nestedness-and-Supply-Chain-Resilience.

delisting risk and exhibit abnormal operating characteristics. (3) We remove observations from firms' IPO years, addressing the post-IPO volatility driven by retail speculation rather than fundamentals. (4) We eliminate firm-years with significant trading suspensions or missing financial data essential for calculating our key variables. (5) All continuous variables are winsorized at the 1st and 99th percentiles.

2.2. Nestedness measurement

Network nestedness is prominent in buyer-supplier networks because specialist buyers often source from suppliers already used by generalist buyers. In other words, the supplier sets of specialist buyers are subsets of those of generalist buyers (Brintrup et al., 2018). This structure concentrates coordination and risk on high-degree buyers, constrains substitution options for specialists, and channels shock propagation along shared-supplier paths.

We quantify nestedness with SNODF, which captures set inclusion through neighbor overlap normalization (Bastolla et al., 2009). SNODF suits buyer-supplier networks better than NODF for two reasons. First, NODF exhibits mathematical discontinuity that makes it unsuitable for incomplete and noisy networks. Specifically, NODF considers node pairs where $k_i > k_j$ and assigns zero contribution to pairs with equal degrees, causing abrupt drops in nestedness values when minor link perturbations occur. By contrast, SNODF normalizes pairwise overlap using $min(k_i, k_j)$ for all node pairs regardless of degree ordering, ensuring continuous and stable measurements even with missing links common in supply chain data (Bastolla et al., 2009; Payrató-Borràs et al., 2019). Second, SNODF mitigates NODF's bias under heavy-tailed degree distributions, a hallmark of hub-dominated supply chains (Mariani et al., 2019). For robustness, we compute alternative metrics NODF and JNODF (Joint Degree Matrix Normalized Overlap and Decreasing Fill), which normalize overlap differently to address degree heterogeneity in buyer-supplier networks.

Network nestedness measures rely on two fundamental parameters: overlap O_{ij}, which counts common neighbors between nodes i and j, and degree (k_i or k_j), which represents each node's total connections. In our bipartite buyer-supplier matrix, rows represent buyers and columns represent suppliers. SNODF computes nestedness for both dimensions: row-based nestedness η_R measures how buyers' supplier sets overlap:

$$\eta_R = \sum_{(i,j)} \frac{O_{ij}}{\min\{k_i, k_j\}}, \tag{1}$$

where O_{ij} represents shared connections between nodes i and j. The denominator, $\min\{k_i, k_j\}$, normalizes the overlap by the smaller of the two degrees. Column-based nestedness η_C follows the identical formula, measuring how suppliers' buyer set overlap. The overall indicator η_{SNODF} averages η_R (row-SNODF) and η_C (column-SNODF):

$$\eta_{SNODF} = \frac{\eta_R + \eta_C}{2}. \tag{2}$$

This index ranges from 0 to 1, with larger values indicating higher level of nestedness of the buyer-supplier network.

On the other hand, JNODF introduces an alternative normalization particularly suited for unipartite or long-tailed networks, where a small number of hubs have disproportionately high degrees (Jonhson et al., 2013). Formally, the measure of η_{JNODF} is given as:

$$\eta_{JNODF} = \frac{1}{N^2} \sum_{i,j} \frac{O_{ij}}{k_i k_j}, \tag{3}$$

where N is the total number of nodes. By dividing overlap by the product rather than minimum of degrees, JNODF reduces bias from heterogeneous degree distributions, providing a more robust gauge of nestedness in buyer-supplier networks.

To address potential confounding from macroeconomic fluctuations and temporal trends, we de-trend the network nestedness variables before regression analysis (Broadberry et al., 2023). We apply a linear de-trending approach that regresses each nestedness metric against time while preserving cross-sectional variation across firms:

$$Metric_{it} = \alpha + \beta \cdot Year_t + \epsilon_{it}, \tag{4}$$

where $Metric_{it}$ represents the original nestedness value for firm i in year t, $Year_t$ captures the linear time trend, and ϵ_{it} denotes the residual. The de-trended nestedness measure equals the residual $\widehat{\epsilon}_{it}$, which removes common temporal patterns while retaining firm-specific structural variations.

We apply uniform de-trending across all firms rather than industry-specific de-trending based on the nature of the buyer-supplier network formation. Buyer-supplier networks form integrated systems where firms connect across traditional industry boundaries. In modern supply chains, firms increasingly establish cross-industry supplier relationships that blur traditional sectoral boundaries (Chauhan et al., 2021). For instance, a semiconductor manufacturer may supply to both automotive and consumer electronics industries, while logistics providers serve clients across all sectors. In this instance, industry-specific de-trending would incorrectly assume that automotive and electronics sectors experience independent temporal trends, when they share common suppliers and face synchronized shocks through these shared nodes. This would bias the comparability of nestedness series across industries by artificially creating divergent time paths for interconnected network segments. Instead, we remove system-wide drift through uniform de-trending and handle remaining heterogeneity with fixed effects in our regression specifications.

2.3. Supply chain resilience measurement

Supply chain resilience refers to the ability to maintain operations during disruptions and restore performance promptly. Supply chain disruptions fall into two categories (1) high-frequency operational disturbances (e.g., supplier delays, quality defects, demand volatility): that create persistent stress through backlogs, inventory imbalances, and cascading delays; and (2) low-frequency catastrophic events (e.g., natural disasters, pandemics, major M&As) that cause acute shocks to network structure. While catastrophic events capture attention, operational disturbances account for most supply chain costs through their cumulative impact. We employ panel regression to capture both types (Tang, 2006): operational disruptions appear as persistent variation in performance metrics, while catastrophic events manifest as period-specific shocks whose differential impacts depend on network structure. Panel regression models how these effects compound over time and controls for unobserved firm-level differences, helping isolate the association between network structure and resilience (Ivanov et al., 2019).

Supply chain resilience includes response, recovery, and continuous improvement but hinges on preparedness and responsiveness (Tukamuhabwa et al., 2015). As an adaptive capability, it requires proactive measures like risk mitigation and resource buffering to reduce disruption risks and impacts (Ponomarov and Holcomb, 2009). We measure resilience with four indicators to capture resistance and recovery from both operational and financial perspectives. Together, these indicators form a comprehensive framework of four measures summarized in Table 2.

2.3.1. Resistance

Resistance reflects a firm's ability to sustain operations during external disruptions, minimizing performance deviations and maintaining functional stability despite shocks to the supply chain.

Resis1. *Resis1* is defined as the proportion of a firm's year-end top-five suppliers that are retained from the prior year (Bernard et al., 2010). A higher *Resis1* indicates that a larger share of top suppliers remains

Table 2
Resilience measurement framework in empirical analysis.

Dimension	Name	Description/Rationale
Resistance	*Resis1*	Proportion of year-end top-five suppliers retained from the prior year. Greater stability secures inputs and buffers shocks.
	Resis2	Upstream capital occupancy. Higher value implies lower occupancy, easing financial strain and preserving ties.
Recovery	*Recov1*	Inflation-adjusted inventory turnover. Higher turnover signals faster operational realignment post-shock.
	Recov2	Performance deviation: residual from a baseline model of EBIT per employee. Higher positive deviation indicates stronger post-shock performance recovery.

consistent year-over-year. We use *Resis1* because stable supplier relationships fortify supply chain resistance in three ways. First, long-term partnerships encourage suppliers to invest in higher quality, more reliable delivery, and operational redundancies, enabling resilience against external shocks (Lai et al., 2005). Second, well-established ties help firms secure critical inputs promptly and reduce supply uncertainties, lowering both disruption risks and management costs (Hosseininasab and Ahmadi, 2015; Peng et al., 2020). Third, mutual trust fosters deeper coordination and collective risk-sharing, ultimately strengthening supply chain resistance (Song et al., 2019).

Resis2. *Resis2* captures the ratio of the sum of accounts payable to main business revenue, expressed in natural logarithms (Cull et al., 2009):

$$Resis2 = -ln\left(\frac{\text{Accounts Payable}}{\text{Main Business Revenue}}\right). \tag{5}$$

We apply a negative sign to ensure the directionality of *Resis2* aligns with *Resis1*, that is, a higher *Resis2* value implies lower capital occupancy from upstream partners, suggesting enhanced supply chain stability and greater resistance to external shocks (Mirzabeiki and Aitken, 2023). When buyers excessively tie up suppliers' working capital, the working-capital balance becomes imbalanced, increasing the vulnerability of buyer-supplier networks to external shocks. Moreover, such capital occupancy can erode relational capital, as mutual trust and credit deteriorate under heightened financial pressure (Autry and Griffis, 2008; Johnson et al., 2013). Additionally, from a buyer-supplier network perspective, a higher accounts payable ratio enhances connectedness in the short term; however, it simultaneously undermines the system's transformation capability by depleting the resource slack required to absorb fluctuations (Wieland, 2021). Thus, *Resis2* effectively encapsulates the capital occupancy aspect, where a higher value signifies lower capital encumbrance and, consequently, a greater capacity to resist external disturbances.

2.3.2. Recovery

Recovery reflects a firm's ability to resume normal operations after external disturbances. When a supply chain is subjected to external shocks, firm performance tends to deviate from its expected trajectory before gradually adjusting back to its pre-shock state.

Recov1. A key firm-year indicator for evaluating this recovery capacity is the inventory turnover ratio, calculated as the cost of goods sold (COGS) divided by the average inventory. Rooted in lean and agile principles, a higher turnover rate generally signifies greater operational efficiency, as it reflects a firm's ability to align production and logistics with market demand, thereby minimizing recovery time after a shock (Lücker and Seifert, 2017).

However, in the context of significant supply chain disruptions, the traditional inventory turnover ratio can be a misleading indicator of operational recovery. Such disruptions are often accompanied by significant price volatility, which can distort the nominal financial figures used in the ratio (Carvalho et al., 2021). Specifically, the numerator (COGS) can become artificially inflated due to rising input costs, while the denominator (average inventory) may simultaneously shrink due to supply shortages. This can create a mathematical artifact where the ratio improves, suggesting a recovery that is driven by price effects rather than by a genuine restoration of the firm's physical operations.

To isolate the true operational recovery, we construct an inflation-adjusted inventory turnover ratio. Following established practice for controlling for price-level changes in performance measurement, we deflate each firm's reported COGS using the national Producer Price Index (PPI), with 2002 serving as the base year. The real inventory turnover (RIT_{it}) for firm *i* in year *t* is:

$$RIT_{it} = COGS_{i,t} \times \left(\frac{PPI'}{PPI_t}\right) \Big/ AvgInv_{i,t}, \tag{6}$$

where PPI' is the PPI in the base year (2002) and PPI_t is the index in year *t*. $COGS_{i,t}$ is the annual COGS from the consolidated statements, $AvgInv_{i,t}$ is computed as the simple average of the beginning-of-year and end-of-year inventory balances (Robb et al., 2012). This adjustment converts the nominal COGS to a constant price level, ensuring our metric reflects changes in the physical volume of goods being sold relative to inventory. Finally, to reduce the skewness of the distribution and allow for a semi-elasticity interpretation of regression coefficients, we take the natural logarithm of this real turnover ratio. Our final recovery measure (*Recov1*) is:

$$Recov1_{it} = ln(RIT_{it}). \tag{7}$$

This refined metric captures the recovery of a firm's real operational efficiency while being robust to the confounding effects of price volatility.

Recov2. We define performance deviation, the gap between a firm's actual performance and its expected performance, as a critical firm-year level measure for assessing the recovery aspect of supply chain resilience (Chen et al., 2015). Precisely, we define *Recov2*as the residual (ε_{it}) from this regression:

$$Perform_{it} = \alpha + \beta_1 Size_{it} + \beta_2 Lev_{it} + \beta_3 Growth_{it} + \beta_4 Age_{it} + \beta_5 Board_{it} + \epsilon_{it}, \tag{8}$$

where Perform_{it} is measured as EBIT (Earnings Before Interest and Taxes) per employee for listed firm *i* at time *t*. The independent variables include firm size ($Size_{it}$), leverage (Lev_{it}), revenue growth ($Growth_{it}$), firm age (Age_{it}), and board size ($Board_{it}$). The residual $\widehat{\varepsilon}_{it}$ indicates the extent to which a firm's performance deviates from its predicted baseline. Such regression residual represents deviations from the baseline, capturing the firm's agility in recovering from adverse conditions. To address the wide range of residual values and normalize their distribution, we apply a logarithmic transformation to construct the measure:

$$Recov2_{it} = ln(\widehat{\varepsilon}_{it}). \tag{9}$$

This transformation compresses the scale of large residuals while preserving their relative magnitudes. A higher Recov2 indicates that the firm's performance surpasses the baseline prediction following an external shock, signaling stronger recovery capacity.

Drawing on behavioral theory and performance feedback mechanisms, the performance deviation serves as a key signal for managerial decision-making (Cyert and March 2015). When the gap between actual performance and expectations widens, it triggers a feedback tension that compels firms to reallocate resources, revise strategies, and implement transformative measures to restore balance (Greve, 1998, 2003). In other words, a higher performance deviation indicates that the firm is more urgently motivated to initiate recovery actions, such as reallocating resources, diversifying supply sources, or investing in digital upgrades, to close the performance gap and enhance supply chain resilience (Bode and Macdonald, 2017). Consequently, performance deviation not only reflects current operational shortcomings but also functions as a proxy for the intensity of recovery efforts undertaken in response to supply chain disruptions.

2.4. Control variables

We include several control variables to mitigate confounding in estimating the effect on supply chain resilience. Following prior studies (Basole et al., 2018; Jiang et al., 2023; Swift et al., 2019), we control for five factors that may influence supply chain resilience: *Size* is the logarithm of total assets, as larger firms typically have more resources to handle shocks. *Leverage*, the ratio of debt to assets, can limit financial flexibility during crises. *Tangibleness* measures tangible assets as a proportion of total assets, with higher levels enhancing liquidity and adaptability. *SOE* is a binary variable indicating state ownership, which may provide extra government support. *Size* is a standard corporate-governance variable that shapes how firms monitor risk, process information, and make timely operating decisions—all of which can affect our resilience outcomes. Board-structure variables are persistent and dynamically endogenous to performance, so omitting them can bias inference (Wintoki et al., 2012). Larger boards typically provide more expertise and oversight but also face higher coordination costs and slower decision cycles. By contrast, smaller boards tend to move faster but may monitor less intensively.

We also add two contextual controls to account for industry- and region-level differences. First, we include the Herfindahl-Hirschman Index (*HHI*) at the industry-year level to net out changes in market structure that co-move with profitability and supply chain choices, reducing sensitivity to industry boundary changes (Falcone et al., 2025). Second, we include the provincial Marketization Index (*MIndex*) to capture cross-regional variation in institutional quality and market development. China's provinces differ substantially in regulatory efficiency, financial market depth, and legal enforcement, creating heterogeneous operating environments that affect firms' crisis response capabilities (Liu, 2025). By controlling for MIndex, we help ensure that our nestedness effects are not confounded with regional institutional advantages, thereby improving comparability across regions.

2.5. Model specification

In panel regression analysis, we examine whether a firm's network nestedness in year t predicts its resistance and recovery dimensions of supply chain resilience. Specifically, we examine whether higher nestedness is associated with lower resistance and higher recovery. To estimate the dual effects of network nestedness, we estimate the following panel regression:

$$Resilience_{i,t} = \alpha + \beta_1\, SNODF_{i,t} + \gamma^{\top} \boldsymbol{X}_{i,t} + \alpha_{firm} + \alpha_{year} + \epsilon_{i,t}, \tag{10}$$

where $Resilience_{i,t}$ represents one of four resilience measures for firm i in year t. $SNODF_{i,t}$ captures the degree of network nestedness measured at the firm-year level. The vector $\boldsymbol{X}_{i,t}$ contains control variables that may confound the association between network structure and resilience. α_{firm} and α_{year} denote firm and year fixed effects, capturing unobserved time-invariant firm characteristics and common temporal shocks.

3. Results

3.1. Descriptive analysis and data validation

3.1.1. Summary statistics and network visualization

Table 3 presents descriptive statistics for our key variables across 12,482 firm-year observations. The sample exhibits moderate network nestedness, with *SNODF* averaging 0.3320. The interquartile range (0.1613–0.5140) indicates substantial variation in hierarchical patterns across firms. The resilience measures display distinct distributions. Resistance indicators show that *Resis1* averages 0.6811, reflecting moderate supplier stability, while *Resis2* averages 1.891, indicating working capital tied up with suppliers. Recovery measures reveal *Recov1* averaging 1.5015 ($Std = 1.3437$) with considerable dispersion, suggesting heterogeneous operational recovery capabilities, while *Recov2* has a mean of 10.6898 ($Std = 1.2567$), capturing deviations from baseline performance. This heterogeneity in firm characteristics provides sufficient variation for identifying the relationship between network structure and resilience outcomes.

Table 4 presents the correlation matrix among all variables. *SNODF* shows significant correlations with our resilience measures in the expected directions: negative correlations with resistance indicators and positive correlations with recovery measures, all significant at the 1 % level. These correlations provide preliminary evidence for the dual effect of network nestedness on supply chain resilience.

Fig. 3 provides illustrative examples of Buyer-supplier (BS) networks for four representative A-share listed firms, underscoring the contrast between low and high network nestedness. In this figure, the blue node denotes the focal listed firm; gray nodes represent suppliers; edges indicate supply relationships. Subfigures (a) and (b) display the BS networks of stock codes 002111. SZ and 300284. SZ, respectively. Both exemplify low network nestedness, as reflected by their relatively low *SNODF* scores. The supplier relationships appear scattered, with smaller suppliers not consistently grouped around a common set of major buyers. In contrast, subfigures (c) and (d) illustrate the BS networks of 600126. SH and 601008. SH, respectively, each exhibiting a high level of network nestedness. Even if the focal firm does not maintain direct relationships with certain hub suppliers or attempts to diversify its sourcing, the overall structure continues to be dominated by these pivotal nodes. This dependence remains undetected by conventional indicators such as supplier concentration, which cannot fully capture the strong reliance induced by the hub-centric architecture. In these configurations, a small number of hub suppliers anchor a significant proportion of buyer-supplier the network's connections, such that many specialist suppliers overlap in serving the same large buyers. Furthermore, Table 4 presents the correlation coefficients among *SNODF*, the resilience indicators, and the control variables. *SNODF* exhibits a significant negative correlation with *Resis1* and *Resis2*, but a modest positive correlation with *Recov1* and *Recov2*. Therefore, stronger network nestedness may coincide with somewhat weaker initial resistance yet slightly more robust recovery.

3.1.2. Network centrality of listed versus non-listed firms

Table 5 compares network centrality metrics between listed and non-listed firms in the buyer-supplier network, supporting our analytical focus on publicly listed entities. Listed firms demonstrate substantially higher centrality across all metrics, with differences ranging from about 9 to 10 % for closeness centrality to 1872.10 % for betweenness centrality. These disparities reveal three critical structural advantages of listed firms. First, their disproportionate connectivity (354.50 % higher degree centrality) can amplify disruption cascades throughout the network. Second, their hub positions anchor the network's hierarchical structure. Therefore, removing listed firms would likely reduce nestedness and change overall topology. Third, their exceptional betweenness centrality demonstrates that listed firms bridge otherwise disconnected network components. These structural properties underscore listed firms as critical nodes for understanding systemic supply chain resilience and interdependencies.

3.2. The effect of nestedness on supply chain resilience

Table 6 reveals that *SNODF* has opposite associations with the two resilience dimensions, supporting Hypothesis 1. *SNODF* is significantly negatively related to resistance: a one-point increase in *SNODF* is associated with a 0.1005-point decline in *Resis1* ($p < 0.01$) and a 0.1961 decline in *Resis2* ($p < 0.01$). These negative effects remain robust after controlling for firm characteristics, industry concentration, and regional marketization. By contrast, *SNODF* is positively related to recovery, with a one-point increase associated with a 0.2260-point increase in *Recov1* ($p < 0.01$) and a 0.2634-point increase in *Recov2* ($p < 0.01$). Nested

Table 3
Statistical description.

	Observations	Mean	Std	Min	25 %	50 %	75 %	Max
SNODF	12482	0.3320	0.2068	0.0000	0.1613	0.2471	0.5140	1.0000
Resis1	12482	0.6811	0.3703	0.0000	0.4000	0.8667	1.0000	1.0000
Resis2	12482	1.8906	0.8022	−1.9918	1.3708	1.8327	2.3195	11.6236
Recov1	12482	1.5015	1.3437	−5.3886	0.7740	1.3871	2.0683	15.7823
Recov2	12482	10.6898	1.2567	2.6329	9.9775	10.7603	11.5004	14.4012
Size	12482	22.7058	1.4241	18.3492	21.6844	22.5137	23.5326	28.6067
Lev	12482	0.4609	0.2021	0.0103	0.3067	0.4585	0.6083	1.9566
Tangibleness	12482	0.9275	0.0897	0.0636	0.9169	0.9562	0.9776	1.0000
SOE	12482	0.4938	0.4961	0.0000	0.0000	0.3333	1.0000	1.0000
BoardSize	12482	7.9924	2.9649	0.0000	7.0000	9.0000	9.0000	18.0000
HHI	12482	0.1268	0.1277	0.0142	0.0499	0.0863	0.1530	1.0000
MIndex	12482	9.8944	1.6677	0.6470	8.9905	10.1230	11.1370	12.8640

structures concentrate dependencies on hub suppliers, amplifying initial shock propagation and reducing resistance. However, these same hubs drive recovery through two advantages: extensive network connections that enable rapid supply chain reconfiguration, and resource slack that supports emergency response.

3.3. Heterogeneity analysis

3.3.1. Subperiod analysis

We examine whether network nestedness effects vary across economic conditions by dividing our sample into distinct periods based on NBER business cycle.[4] Specifically, we identify three periods: pre-financial crisis (2002–2007), financial crisis and recovery (2008–2019), and pandemic disruption (2020–2022). The pre-financial crisis period yields only 58 observations—insufficient for reliable statistical inference. We therefore focus on two periods with adequate sample sizes: Period 1 (2008–2019), encompassing both the financial crisis and subsequent recovery, and Period 2 (2020–2022), capturing COVID-19 disruptions.

Table 7 reveals distinct temporal patterns in how nestedness affects resilience. During Period 1, *SNODF* is significantly associated with both resistance measures (*Resis1*: -0.0893, $p < 0.05$; *Resis2*: -0.2616, $p < 0.01$). During the pandemic, the negative association with *Resis1* strengthens (-0.1250, $p < 0.05$), while the association with *Resis2* becomes statistically insignificant (-0.0843, $p > 0.10$). This divergence reflects the different mechanisms underlying each resistance measure. *Resis1* captures supplier relationship stability, a structural characteristic that becomes even more critical during systemic crises when finding alternative suppliers proves extremely difficult. The intensified negative effect during the pandemic confirms that nested structures' vulnerability to hub failures amplifies when replacement options are scarce. In contrast, *Resis2* measures capital occupation through accounts payable, reflecting financial interdependencies between buyers and suppliers. During the pandemic, repayment deferrals, credit guarantees, targeted liquidity facilities, tax rebates, and the expansion of supply-chain finance, together with relational forbearance (suppliers extending terms to preserve core accounts), partially decouple financial flows from network topology and compress cross-sectional variation in working-capital stress (Didier et al., 2021). These interventions partially decouple the usual relationship between network structure and financial stress propagation, and temporarily weakens the relationship between nestedness and *Resis2*.

Recovery effects remain positive in both periods but attenuate in magnitude: *Recov1* declines from 0.2467 ($p < 0.01$) to 0.1854 ($p < 0.01$), and *Recov2* from 0.2860 ($p < 0.01$) to 0.2396 ($p < 0.05$), suggesting that nestedness continues to support recovery under pandemic conditions, but the effect is weaker under systemic disruptions than under idiosyncratic shocks. Overall, nested structures perform better against localized shocks through hub coordination but prove less effective during systemic crises when multiple hubs fail simultaneously, and policy interventions alter normal market mechanisms.

3.3.2. Subgroup analysis

To examine whether the nestedness-resilience relationship varies across firm characteristics, we conduct subsample analyses along two critical dimensions: ownership structure and firm size. These heterogeneity tests provide insights into boundary conditions and enhance the generalizability of our findings. Our analysis focuses on network topology rather than product attributes. Product differentiation is a contract- and market-specific construct that requires feature-level data and industry-specific identification (e.g., non-standard mortgage features in Haslag et al., 2024). We therefore interpret our coefficients as average network effects and do not test heterogeneity by product differentiation or substitutability, which would call for a different research design and data.

State ownership heterogeneity. We partition the sample into SOEs and non-SOEs because ownership shapes financing frictions and contracting in China's bank-centric system. On the one hand, SOEs benefit from government connections and preferential credit, thereby loosening financing constraints relative to private firms (Cull et al., 2015). On the other hand, they often face greater operational rigidities due to bureaucratic governance, complex procurement protocols, and social welfare burdens, which can hinder agile responses to disruptions (Raynard et al., 2020). Private firms rely more on relationship-based and informal finance, including trade credit within supply chains (Didier et al., 2021). In this environment, downstream bargaining power (amplified by customer concentration) tightens suppliers' financing conditions by worsening trade terms and shifting risk upstream (Fabbri and Klapper, 2016). These contrasting characteristics suggest heterogeneous resilience mechanisms: SOEs combine superior financial resources with operational inflexibility, while non-SOEs pair financing vulnerability with adaptive capacity. Splitting by ownership mitigates pooling bias, isolates mechanism-consistent effects, and improves external validity for both state-dominated and market-oriented contexts (Cull et al., 2015).

Table 8 Panel A reveals nuanced heterogeneity. Nestedness is associated with weaker resistance in both groups, with larger negative coefficients for SOEs. For recovery, nestedness is positively related to operational recovery in both groups but more strongly for non-SOEs, whereas its association with performance recovery is concentrated in SOEs. These patterns align with ownership-driven frictions: SOEs'

[4] The National Bureau of Economic Research (NBER) Business Cycle Dating Committee identifies turning points in U.S. economic activity, marking peaks and troughs that define economic expansions and recessions. We use these official dates to delineate periods of distinct macroeconomic conditions. Although NBER dates reflect U.S. cycles, we use them to identify globally synchronized events (2008 crisis, COVID-19) that simultaneously affected Chinese firms through integrated supply chains and capital markets. See https://www.nber.org/research/business-cycle-dating for detailed methodology and historical dates.

Table 4
Correlation coefficient matrix.

	SNODF	Resis1	Resis2	Recov1	Recov2	Size	Lev	Tangibleness	SOE	BoardSize	HHI	MIndex
SNODF	1.0000***	−0.0649***	−0.0528***	0.0880***	0.0368***	−0.0162	0.0068	−0.0202**	0.1374***	0.0209**	0.0662***	−0.0978***
Resis1	−0.0649***	1.0000***	−0.0354***	−0.0556***	−0.0411***	−0.1038***	−0.0877***	0.0288***	−0.2230***	−0.0591***	−0.0717***	0.1391***
Resis2	−0.0528***	−0.0354***	1.0000***	−0.1279***	−0.0305***	0.0811***	0.2247***	0.0001	0.0415***	0.0109	0.0129	0.0074
Recov1	0.0880***	−0.0556***	−0.1279***	1.0000***	0.0667***	0.1752***	0.1068***	−0.0255***	0.1658***	0.0636***	0.1208***	−0.0121
Recov2	0.0368***	−0.0411***	−0.0305***	0.0667***	1.0000***	0.0713***	0.0276***	−0.0203**	0.0490***	−0.0171*	0.0008	−0.0201**
Size	−0.0162	−0.1038***	0.0811***	0.1752***	0.0713***	1.0000***	0.4832***	−0.0487***	0.3359***	0.2129***	0.1321***	−0.1077***
Lev	0.0068	−0.0877***	0.2247***	0.1068***	0.0276***	0.4832***	1.0000***	0.0271***	0.2478***	0.0237**	0.0190*	−0.1458***
Tangibleness	−0.0202**	0.0288***	0.0001	−0.0255***	−0.0203**	−0.0487***	0.0271***	1.0000***	0.0093	−0.0078	0.0182*	0.0324***
SOE	0.1374***	−0.2230***	0.0415***	0.1658***	0.0490***	0.3359***	0.2478***	0.0093	1.0000***	0.2270***	0.1218***	−0.2609***
BoardSize	0.0209**	−0.0591***	0.0109	0.0636***	−0.0171*	0.2129***	0.0237**	−0.0078	0.2270***	1.0000***	0.0857***	−0.1014***
HHI	0.0662***	−0.0717***	0.0129	0.1208***	0.0008	0.1321***	0.0190*	0.0182*	0.1218***	0.0857***	1.0000***	−0.0461***
MIndex	−0.0978***	0.1391***	0.0074	−0.0121	−0.0201**	−0.1077***	−0.1458***	0.0324***	−0.2609***	−0.1014***	−0.0461***	1.0000***

Note: The table presents the correlation coefficients among the variables. The symbols ***, **, and * denote significance at the 1 %, 5 %, and 10 % levels, respectively.

procurement and governance constraints make substitution harder, amplifying initial shock propagation, while private firms' greater operational flexibility supports faster reconfiguration; performance recovery benefits accrue primarily to SOEs, consistent with stronger financial and policy backstops.

Taken together, these patterns indicate that the underlying mechanism operates under both state-affiliated and private ownership regimes. Because many economies feature mixed-ownership structures, the consistency of signs across SOEs and non-SOEs increases external validity and suggests potential applicability beyond China.

Firm size heterogeneity. We split the sample by size because scale systematically shapes resilience mechanisms. Large firms command greater resource slack, formal risk-management infrastructure, and bargaining power, which support disruption preparedness and rapid performance recovery (Pettit et al., 2013). They also tend to occupy more central, hub-like positions, increasing exposure to topology-driven shock propagation (Ambulkar et al., 2015). In contrast, small firms possess fewer resources but often adjust faster through lean structures and dynamic reconfiguration (Wei and Wang, 2010). These structural and capability differences imply that the effect of network nestedness on resistance and recovery should vary across the size distribution.

Table 8 Panel B indicates that firm size conditions the nestedness-resilience relationship. On resistance, nestedness shows a more negative association for large firms, as the effect on *Resis1* is significant only for large firms and the negative impact on *Resis2* is larger for the large-firm group, consistent with hub-like positions and coordination rigidities that amplify shock propagation. On recovery, both groups exhibit positive operational recovery, with a stronger coefficient among smaller firms for the *Recov1* metric, aligning with greater agility and reconfiguration capacity. The concentration of performance recovery measured by *Recov2* among large firms is consistent with their scale-driven slack and financing access that convert operational stabilization into measured performance. These patterns imply that size acts as a boundary condition on the magnitude and channels of the nestedness effect, rather than on the validity of our measures: the indicators capture meaningful variation in both size groups, but the dominant mechanisms differ.

3.4. Moderating effects of the nestedness-resilience relationship

3.4.1. The moderating role of supplier concentration

We examine whether supplier concentration moderates the relationship between network nestedness and resilience. Supplier concentration captures the extent to which a firm depends on one or a few dominant upstream partners. We measure concentration with a Herfindahl index based on each firm's disclosed procurement shares of its top suppliers (Chen et al., 2023; Lin et al., 2021). Using purchasing percentages for up to the five largest suppliers reported in procurement notes, we compute:

$$CN_i = \sum_{j=1}^{J} \left(PurchasingRatio_{ij} \right)^2, \tag{11}$$

where $PurchasingRatio_{ij}$ is the proportion of listed firm i's total annual procurement drawn from each of its top J suppliers ($J \leq 5$). As a result, values closer to 1 indicate a heavier reliance on one or a few dominant suppliers, whereas values nearing 0 suggest that purchases are more evenly distributed among a larger set of suppliers.

Table 9 Panel A presents the regression results for the moderating effect of supplier concentration. The interaction terms reveal how concentration shapes the nestedness-resilience relationship. For resistance measures, the positive interaction coefficients indicate that supplier concentration attenuates the negative impact of nestedness on resistance. Firms with concentrated supplier bases experience less severe resistance deterioration from nested structures, possibly because established relationships with dominant suppliers provide stability during

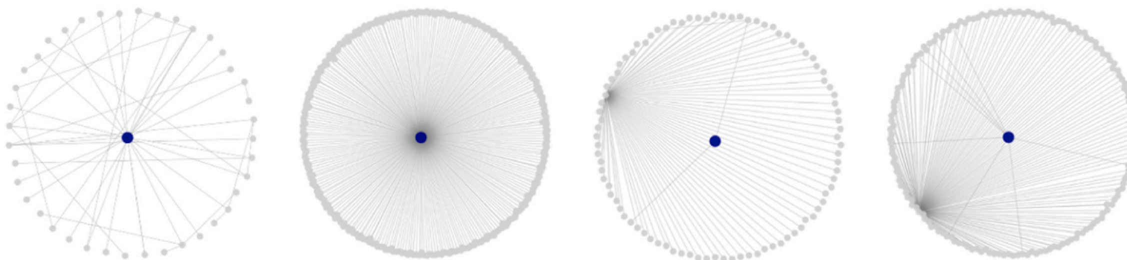

Fig. 3. Low vs. high level of buyer-supplier network nestedness of four listed firms in 2022.

Table 5
Network centrality comparison between listed and non-listed firms in buyer-supplier networks.

Centrality Metric	Avg. Listed Firm	Avg. Non-Listed Firm	Percent difference (Listed vs. Non-listed)
Degree	6.2982	1.3857	354.50 %
In Degree	1.6755	0.8658	93.50 %
Out Degree	4.6227	0.5199	789.10 %
Betweenness	105.9562	5.3727	1872.10 %
Closeness In	0.9401	0.8589	9.50 %
Closeness Out	0.9364	0.8591	9.00 %

Note: Degree measures total connections; in-degree captures the number of suppliers; out-degree represents the number of customers; betweenness indicates the frequency of appearing on shortest paths between other firms (brokerage position); closeness measures average distance to all other reachable firms in the network. All metrics are averaged across the 2002–2022 period.

initial shock exposure. However, for recovery measures, the negative interaction coefficients show that concentration weakens the recovery benefits of nestedness. While concentrated sourcing may buffer immediate disruptions, it constrains the flexibility needed to leverage nested networks' coordination advantages during recovery phases.

These findings support Hypothesis 2, indicating that a more concentrated supplier base attenuates the negative impact of network nestedness on near-term resistance yet constrains the beneficial effect on long-run recovery. Specifically, when firms concentrate their sourcing around a small set of core suppliers in an already nested network, they can maintain operational continuity through deep relationships and prioritized allocations. However, this same concentration limits substitution options during recovery: if key suppliers fail or face prolonged disruptions, the firm lacks alternative sourcing channels that nested networks typically provide through hub coordination. This trade-off underscores the need to balance concentrated relationships with contingency strategies so that short-term shock absorption does not come at the expense of long-term adaptability in nested buyer-supplier networks.

3.4.2. The moderating role of digitalization

We examine whether a firm's digital activities moderate the relationship between the network nestedness and the supply chain resilience. We measure firms' digital emphasis by counting MD&A sentences that contain terms from a curated digital dictionary (e.g., AI, big data, cloud, IoT). To reduce false positives, we exclude negated or dismissive mentions. This proxy usually captures disclosed managerial priority rather than installed technology. Critically, MD&A is forward-looking: it records planned initiatives and managerial priorities before they materialize in capitalized assets or standardized line items, whereas many digital investments are expensed and thus under-captured by financial statements (Thomas et al., 2024). Further, MD&A is a high-stakes, legally liable section, so misstatements are costly and subject to securities-law scrutiny (Muslu et al., 2014). Moreover, MD&A language operates as a widely used market signal, so the text metric captures information that is acted upon and priced even when physical adoption is

Table 6
Regression results for the effect of *SNODF* on supply chain resilience.

	Resis1		Resis2		Recov1		Recov2	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
SNODF	−0.2095***	−0.1005***	−0.1849***	−0.1961***	0.2957***	0.2260***	0.2795***	0.2634***
	(0.0381)	(0.0368)	(0.0495)	(0.0468)	(0.0466)	(0.0448)	(0.0751)	(0.0753)
Size		−0.0139		−0.0350***		0.0612***		0.0736***
		(0.0101)		(0.0128)		(0.0110)		(0.0189)
Lev		−0.0750		1.0703***		0.0619		−0.0288
		(0.0602)		(0.0806)		(0.0719)		(0.1169)
Tangibleness		0.0796		0.0367		−0.3093*		0.0047
		(0.1294)		(0.1547)		(0.1591)		(0.2322)
SOE		−0.2076***		0.0275		0.1403***		0.0768
		(0.0238)		(0.0302)		(0.0286)		(0.0481)
BoardSize		−0.0015		0.0021		0.0043		−0.0148**
		(0.0029)		(0.0042)		(0.0035)		(0.0061)
HHI		−0.1961**		0.0714		0.6038***		−0.1419
		(0.0899)		(0.1151)		(0.1204)		(0.1637)
MIndex		0.0269***		0.0214**		0.0160**		0.0013
		(0.0065)		(0.0087)		(0.0077)		(0.0124)
Constant	−0.2951***	−0.1826	−1.8242***	−1.8056***	0.1613***	−1.2849***	10.6025***	9.0305***
	(0.0158)	(0.2511)	(0.0222)	(0.3193)	(0.0203)	(0.2851)	(0.0324)	(0.4701)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	12,482	12,482	12,482	12,482	12,482	12,482	12,482	12,482
Adj. R^2	0.0051	0.0582	0.0025	0.0694	0.0069	0.0558	0.0022	0.0111

Notes: The symbols ***, **, and * denote significance at the 1 %, 5 %, and 10 % levels, respectively. Standard errors (in parentheses) are clustered at the firm level.

Table 7
Network nestedness and supply chain resilience across economic cycles.

	Resis1		Resis2		Recov1		Recov2	
	Period 1	*Period 2*	*Period 1*	*Period 2*	*Period 1*	*Period 2*	*Period 1*	*Period 2*
SNODF	−0.0893**	−0.1250**	−0.2616***	−0.0843	0.2467***	0.1854***	0.2860***	0.2396**
	(0.0430)	(0.0509)	(0.0571)	(0.0600)	(0.0539)	(0.0581)	(0.0927)	(0.1001)
Size	0.0045	−0.0456***	−0.0455***	−0.0227	0.0694***	0.0461***	0.0441**	0.1157***
	(0.0112)	(0.0116)	(0.0143)	(0.0141)	(0.0125)	(0.0136)	(0.0224)	(0.0222)
Lev	−0.1750**	0.1021	1.1485***	0.9593***	−0.0663	0.2796***	0.1855	−0.3355**
	(0.0699)	(0.0671)	(0.0920)	(0.0936)	(0.0841)	(0.0879)	(0.1359)	(0.1449)
Tangibleness	0.0838	0.1155	−0.0270	0.1819	−0.1256	−0.6229***	−0.1960	0.3178
	(0.1301)	(0.1810)	(0.1706)	(0.2101)	(0.1801)	(0.1887)	(0.2495)	(0.3235)
SOE	−0.1977***	−0.2171***	0.0224	0.0434	0.1336***	0.1404***	0.0702	0.0844
	(0.0252)	(0.0284)	(0.0335)	(0.0351)	(0.0332)	(0.0329)	(0.0536)	(0.0592)
BoardSize	−0.0017	0.0009	0.0024	0.0026	0.0031	0.0087	−0.0166***	−0.0093
	(0.0032)	(0.0045)	(0.0045)	(0.0057)	(0.0038)	(0.0056)	(0.0064)	(0.0094)
HHI	−0.1201	−0.3491***	0.1655	−0.0542	0.4910***	0.7636***	−0.1559	−0.0840
	(0.1001)	(0.1054)	(0.1325)	(0.1298)	(0.1357)	(0.1530)	(0.1907)	(0.2008)
MIndex	0.0354***	0.0147*	0.0178	0.0246**	0.0178*	0.0039	0.0207	−0.0326*
	(0.0078)	(0.0084)	(0.0110)	(0.0101)	(0.0098)	(0.0092)	(0.0156)	(0.0169)
Constant	−0.6508**	0.5696*	−1.4945***	−2.2400***	−1.5889***	−0.6405*	9.5973***	8.2455***
	(0.2812)	(0.3155)	(0.3718)	(0.3709)	(0.3295)	(0.3563)	(0.5677)	(0.5780)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7900	4524	7900	4524	7900	4524	7900	4524
Adj. R^2	0.0585	0.0673	0.0750	0.0629	0.0483	0.0725	0.0103	0.0206

Notes: The symbols ***, **, and * denote significance at the 1 %, 5 %, and 10 % levels, respectively. Standard errors (in parentheses) are clustered at the firm level.

still ramping up.

External validation shows that MD&A-based digital scores co-vary with hard adoption indicators (subsequent digital-related patents and IT hiring), predict higher valuation multiples and stronger pricing of fundamentals, and co-move with technology returns (Chen and Srinivasan, 2024). Related textual-measure evidence also supports reliability despite disclosure noise (e.g., text-based innovation measures predict performance even beyond patents; Bellstam et al., 2021). We acknowledge that keyword methods can misclassify hype, negative mentions, or quiet adopters. Such noise is classical measurement error that biases estimates toward zero, so our significant moderation effects are conservative lower bounds.

Initially, we compile a domain-specific dictionary of digital technology terms, including artificial intelligence, big data, cloud computing, blockchain, mobile internet, internet of things, from policy documents.[5] Through an iterative review process, we refine this dictionary to accurately capture references to advanced digital technologies. We then apply the dictionary to identify sentences in MD&A sections featuring at least one digital technology keyword. Let $S_{i,t}$ be all sentences in listed firm i's MD&A for year t, and let $D_{i,t}$ be the count of sentences referencing digital technologies. Hence,

$$Digital_{i,t} = \sum_{s \in S_{f,t}} 1(digital\ keyword\ in\ s), \tag{12}$$

where $1(\cdot)$ is an indicator function taking the value of 1 if the sentence s contains any digital keyword. This count $Digital_{i,t}$ offers a proxy for the firm's emphasis on digitalization, facilitating inter-firm and cross-time comparisons of how extensively each organization discusses digital activities.

Table 9 Panel B examines the moderating role of corporate digitalization. The interaction terms are the key result. For resistance, the coefficients on interaction terms are positive and significant for both measures. This indicates that digital engagement systematically attenuates the negative association between nestedness and resistance. For recovery, the interaction is insignificant for Recov1 but positive and significant for *Recov2*. Thus, digital capabilities do not materially alter the near-term bounce-back, but they amplify the longer-horizon recovery benefits of nested structures.

These patterns are broadly consistent with Hypothesis 3. Digital tools enable faster information sharing, tighter cross-firm coordination, and more flexible resource reallocation. During the shock period, these capabilities blunt the brittleness associated with nestedness, improving resistance. During the restoration phase, they help firms mobilize hub-based networks and exploit coordination advantages, strengthening long-run recovery.

We focus on China because it is a global digital leader, with about 788 million smartphone users, trillion-dollar digital transformation plans, and digitization projected to add 7–22 % to GDP growth by 2025 (Xu et al., 2024). However, the digitalization effects we study are not China-specific. They reflect technologies that improve information processing, coordination, and operational flexibility in any market (Akhtar et al., 2024). Our text-based measure captures disclosure-level managerial emphasis, not policy compliance, so it is not mechanically tied to China's regulatory regime. The same method yields validated results in U.S. data (Chen and Srinivasan, 2024). In China, annual reports also carry legal liability, and firms operate on globally standardized digital platforms within international supply chains; text-based technology measures there predict innovation-related outcomes (Chen et al., 2024). Empirically, firm and year fixed effects absorb unobserved, time-invariant firm traits and nationwide shocks to regulation or infrastructure, while *HHI* and the *MIndex* capture time-varying industry structure and regional institutional quality. Together, these design choices limit the risk that tight regulation or digital infrastructure idiosyncrasies drive our findings.

3.5. Robustness tests

3.5.1. Robustness of nestedness metrics to network incompleteness

To further validate the robustness of *SNODF* under buyer-supplier network incompleteness, we calculate nestedness metrics for two versions of our buyer-supplier networks: a disclosure-only (incomplete) network and a more complete network. We then correlate the year-level measures across the same set of years.

[5] We consider the definitions of digital technology keywords, text composition, and categorization as outlined by previous literatures and the "Digital Economy and its Core Industries Statistical Classification (2021)" issued by the National Bureau of Statistics of China. The dictionary is available from the authors upon request.

Table 8
Heterogeneous effects of network nestedness across firm characteristics.

Panel A: State ownership heterogeneity								
	Resis1		Resis2		Recov1		Recov2	
	SOE	*Non-SOE*	*SOE*	*Non-SOE*	*SOE*	*Non-SOE*	*SOE*	*Non-SOE*
SNODF	−0.1142** (0.0543)	−0.0803* (0.0445)	−0.2152*** (0.0679)	−0.1535*** (0.0593)	0.1832*** (0.0646)	0.2785*** (0.0586)	0.3984*** (0.1094)	0.0832 (0.0992)
Size	−0.0181 (0.0144)	−0.0064 (0.0135)	−0.0264 (0.0184)	−0.0513*** (0.0167)	0.0769*** (0.0160)	0.0365** (0.0142)	0.1172*** (0.0263)	0.0147 (0.0268)
Lev	−0.1480 (0.0997)	−0.0246 (0.0603)	1.1242*** (0.1290)	1.0672*** (0.0924)	−0.1410 (0.1132)	0.3075*** (0.0871)	−0.1262 (0.1829)	0.1148 (0.1415)
Tangibleness	0.3624 (0.2250)	−0.1182 (0.1273)	−0.1497 (0.2609)	0.2669 (0.1698)	−0.5862** (0.2673)	−0.0594 (0.1770)	−0.0707 (0.3804)	0.0845 (0.2778)
BoardSize	−0.0057 (0.0056)	−0.0013 (0.0030)	0.0034 (0.0070)	0.0048 (0.0058)	0.0107* (0.0062)	0.0005 (0.0045)	−0.0269** (0.0118)	−0.0031 (0.0079)
HHI	−0.1279 (0.1309)	−0.2951*** (0.0933)	0.1983 (0.1607)	−0.1330 (0.1460)	0.4792*** (0.1699)	0.7249*** (0.1417)	−0.3015 (0.2195)	0.1024 (0.2320)
MIndex	0.0354*** (0.0104)	0.0173*** (0.0066)	0.0257* (0.0133)	0.0150 (0.0104)	0.0080 (0.0111)	0.0176* (0.0098)	0.0211 (0.0185)	−0.0294* (0.0164)
const	−0.5667 (0.3673)	−0.0832 (0.3455)	−1.8954*** (0.4812)	−1.5999*** (0.4085)	−1.0946** (0.4406)	−1.0845*** (0.3438)	8.1065*** (0.6730)	10.4639*** (0.6636)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6056	6210	6056	6210	6056	6210	6056	6210
Adj. R^2	0.0191	0.0086	0.0734	0.0675	0.0410	0.0363	0.0205	0.0027
Panel B: Firm size heterogeneity								
	Resis1	Resis2	Recov1	Recov2				
	High Size	*Low Size*	*High Size*	*Low Size*	*High Size*	*Low Size*	*High Size*	*Low Size*
SNODF	−0.1500*** (0.0553)	−0.0572 (0.0440)	−0.2046*** (0.0685)	−0.1642*** (0.0567)	0.1977*** (0.0634)	0.2637*** (0.0597)	0.4137*** (0.1066)	0.1152 (0.0991)
Size	−0.0131 (0.0188)	0.0276 (0.0173)	−0.0267 (0.0232)	−0.0485** (0.0239)	0.0654*** (0.0185)	0.0064 (0.0237)	0.1525*** (0.0341)	−0.1481*** (0.0384)
Lev	−0.0439 (0.0983)	−0.1161* (0.0646)	1.2633*** (0.1303)	0.9261*** (0.0850)	−0.0202 (0.1152)	0.1439* (0.0845)	−0.5024*** (0.1816)	0.4615*** (0.1328)
Tangibleness	0.2466 (0.1875)	−0.1589 (0.1380)	−0.0412 (0.2224)	0.0655 (0.1852)	−0.5327** (0.2232)	−0.0157 (0.1956)	−0.1150 (0.3248)	0.0606 (0.2893)
BoardSize	−0.2552*** (0.0362)	−0.1571*** (0.0263)	0.0303 (0.0446)	0.0280 (0.0362)	0.1552*** (0.0392)	0.1248*** (0.0379)	0.0763 (0.0695)	0.0850 (0.0597)
HHI	−0.0051 (0.0045)	0.0033 (0.0033)	0.0040 (0.0061)	0.0002 (0.0055)	0.0060 (0.0052)	0.0010 (0.0045)	−0.0197** (0.0094)	−0.0110 (0.0072)
MIndex	−0.1176 (0.1337)	−0.2714*** (0.1049)	0.2294 (0.1757)	−0.1205 (0.1325)	0.5998*** (0.1742)	0.5701*** (0.1505)	−0.4656* (0.2389)	0.1414 (0.1895)
const	0.0246** (0.0105)	0.0296*** (0.0068)	0.0193 (0.0133)	0.0243** (0.0101)	0.0056 (0.0105)	0.0278*** (0.0106)	−0.0038 (0.0184)	0.0043 (0.0153)
Firm FE	−0.2901 (0.4443)	−0.9209** (0.4143)	−2.0584*** (0.5450)	−1.4814*** (0.5580)	−1.0369** (0.4608)	−0.5118 (0.5481)	7.6147*** (0.8218)	13.5345*** (0.8914)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6246	6236	6246	6236	6246	6236	6246	6236
Adj. R^2	0.0568	0.0407	0.0804	0.0552	0.0512	0.0266	0.0227	0.0108

Notes: The symbols ***, **, and * denote significance at the 1 %, 5 %, and 10 % levels, respectively. Standard errors (in parentheses) are clustered at the firm level.

Table 10 demonstrates that *SNODF* exhibits the highest cross-network agreement among the three metrics, with positive Pearson (0.264) and Spearman (0.294) correlations. These values suggest partial stability rather than equivalence across disclosure-only and enriched networks. In contrast, *NODF* shows weak positive Pearson correlation (0.123) and negative Spearman correlation (−0.245), indicating rank-order instability when only disclosure data are used. *JNODF* lies in between, with limited rank concordance.

While *SNODF* shows relatively greater robustness to missing data, the incomplete network still exhibits systematic biases. Fig. 4 reveals that the incomplete network displays a tall, narrow mode just above zero and a thinner right tail, indicating lower measured nestedness and compressed dispersion. By contrast, the more complete network is right-shifted with broader spread, revealing richer hierarchical structure. This contrast is consistent with attenuation to zero from edge censoring[6]: omitted ties reduce observed pairwise overlaps, push nestedness levels downward and dampen variance. *SNODF* appears relatively less sensitive to this censoring but cannot recover missing links. Accordingly, beyond adopting metrics less sensitive to incompleteness, analyses should also use a relatively complete buyer-supplier network to approximate the true architecture.

3.5.2. *Potential endogeneity concerns*

Endogeneity arises from unobserved variables and simultaneity bias. Network nestedness patterns likely reflect unmeasured factors like managerial competence that simultaneously affect resilience outcomes

[6] Edge censoring refers to partial observability of links: some true buyer-supplier ties exist but are unreported or absent from available sources. We use "censoring" in its statistical sense, meaning data are observed only on a subset.

Table 9
Regression results for the moderating role of supplier concentration and corporate digital emphasis.

Panel A: Moderating role of supplier concentration

	Resis1	Resis2	Recov1	Recov2
SNODF	−0.0862**	−0.2813***	0.2387***	0.2732***
	(0.0418)	(0.0530)	(0.0512)	(0.0871)
CN	−0.3688**	−1.5211***	1.0799***	0.8545**
	(0.1581)	(0.2104)	(0.1850)	(0.4350)
SNODF × *CN*	0.0383*	1.7609***	−0.6153***	−0.4835**
	(0.0220)	(0.4350)	(0.2100)	(0.2200)
Size	−0.0143	−0.0360***	0.0622***	0.0744***
	(0.0100)	(0.0126)	(0.0110)	(0.0189)
Lev	−0.0846	1.0426***	0.0854	−0.0101
	(0.0603)	(0.0799)	(0.0712)	(0.1158)
Tangibleness	0.0953	0.0760	−0.3457**	−0.0241
	(0.1296)	(0.1532)	(0.1569)	(0.2310)
SOE	−0.2011***	0.0419	0.1260***	0.0655
	(0.0239)	(0.0299)	(0.0283)	(0.0479)
BoardSize	−0.0021	0.0009	0.0056	−0.0138**
	(0.0029)	(0.0042)	(0.0035)	(0.0061)
HHI	−0.1943**	0.0771	0.5991***	−0.1457
	(0.0900)	(0.1125)	(0.1194)	(0.1626)
MIndex	0.0268***	0.0205**	0.0165**	0.0017
	(0.0065)	(0.0087)	(0.0076)	(0.0124)
Constant	−0.1632	−1.7143***	−1.3460***	8.9821***
	(0.2510)	(0.3143)	(0.2848)	(0.4703)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	12,482	12,482	12,482	12,482
Adj. R^2	0.0622	0.0844	0.0708	0.0155

Panel B: Moderating role of corporate digital emphasis

	Resis1	Resis2	Recov1	Recov2
SNODF	−0.0952**	−0.1165**	0.2156***	0.3047***
	(0.0441)	(0.0556)	(0.0538)	(0.0890)
Digital	0.0046	0.1228***	−0.0069	0.0165
	(0.0258)	(0.0329)	(0.0341)	(0.0556)
SNODF × *Digital*	0.0138**	0.1282***	0.0294	0.1322*
	(0.0065)	(0.0420)	(0.0814)	(0.0750)
Size	−0.0139	−0.0362***	0.0611***	0.0745***
	(0.0101)	(0.0127)	(0.0111)	(0.0190)
Lev	−0.0749	1.0801***	0.0620	−0.0308
	(0.0602)	(0.0807)	(0.0718)	(0.1170)
Tangibleness	0.0799	0.0834	−0.3084*	−0.0076
	(0.1305)	(0.1559)	(0.1597)	(0.2326)
SOE	−0.2076***	0.0338	0.1406***	0.0739
	(0.0238)	(0.0302)	(0.0286)	(0.0483)
BoardSize	−0.0015	0.0020	0.0043	−0.0149**
	(0.0029)	(0.0042)	(0.0035)	(0.0061)
HHI	−0.1957**	0.0829	0.6031***	−0.1402
	(0.0901)	(0.1138)	(0.1207)	(0.1637)
MIndex	0.0269***	0.0173**	0.0158**	0.0030
	(0.0066)	(0.0087)	(0.0077)	(0.0126)
Constant	−0.1859	−1.8512***	−1.2785***	9.0044***
	(0.2519)	(0.3172)	(0.2854)	(0.4718)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	12,482	12,482	12,482	12,482
Adj. R^2	0.0583	0.0736	0.0558	0.0114

Notes: The symbols ***, **, and * denote significance at the 1 %, 5 %, and 10 % levels, respectively. Standard errors (in parentheses) are clustered at the firm level.

Table 10
Stability of nestedness metrics under varying network completeness.

Metric	Pearson Correlation	Spearman Correlation
SNODF	0.2640	0.2945
NODF	0.1234	−0.2450
JNODF	0.2287	0.0936

(Eugster, 2020). Further, prior resilience performance could shape current network structure choices, generating reverse causality. Such concerns necessitate careful econometric treatment. Instrument-variable (IV) methods face implementation challenges in buyer-supplier network contexts because network structures emerge from complex, endogenous firm decisions rather than exogenous shocks. IV requires strong correlation with nestedness (relevance) while influencing resilience exclusively through nestedness (exclusion restriction) (Rossi, 2014). The specific challenge for nestedness arises from three reasons: First, network nestedness reflects accumulated strategic choices—which suppliers to engage, how deeply to integrate, whether to diversify or concentrate sourcing. These decisions stem from the same managerial capabilities and strategic vision that drive operational performance, violating the exclusion restriction (Yan et al., 2015). Second, unlike single-firm decisions, network structures involve bilateral relationships. A focal firm cannot unilaterally determine its position in a nested hierarchy—suppliers must agree to partnerships. This interdependence makes it nearly impossible to find instruments affecting one firm's network position without influencing connected firms' performance (Mitrega et al., 2017). Third, external shocks that could theoretically instrument network changes either affect too few firms for statistical power or impact so broadly they violate exclusion restrictions. While using external events, systematically identifying shocks that reshape network topology without directly affecting firm performance proves impractical in buyer-supplier networks (El Baz and Ruel, 2021).

To address endogeneity, we instrument firm-year nestedness with the leave-one-out industry peer average (*PeerSNODF*), an approach theoretically grounded in mimetic behavior theory (Campos-Alba et al., 2024) and consistent with established methodologies in supply chain research (Barker et al., 2024; Sharma et al., 2020). The instrument's validity rests on two mechanisms. The first mechanism is the relevance. Industry peers face similar external pressures that shape supply-chain architecture; under uncertainty, firms benchmark and imitate, converging toward standard network configurations. Consequently, peer nestedness predicts the focal firm's nestedness (Peng et al., 2022). The second is the exclusion. Peers' network structures affect the focal firm's resilience only through the focal firm's own network choices (Falcone et al., 2025). Competitor configurations do not directly determine the firm's capabilities, resources, or crisis response, which depend on internal factors. We compute a leave-one-out peer average to remove mechanical correlation with the focal firm's network. In markets with thousands of suppliers, direct constraints from peer nestedness on the focal firm's operations are unlikely.

We implement a two-stage least squares (2 S LS) approach. For each focal firm i in year t, we calculate:

$$PeerSNODF_{i,t} = \frac{1}{N_{j,t}-1}\sum_{k\in J, k\neq i} SNODF_{k,t}, \tag{13}$$

where J represents all firms in the same industry and $N_{j,t}$ is the number of firms in that industry-year. In the first stage, we regress:

$$SNODF_{i,t} = \gamma_0 + \gamma_1 PeerSNODF_{i,t} + \gamma_2' \boldsymbol{X}_{i,t} + \eta_{i,t}. \tag{14}$$

The fitted values $\widehat{SNODF}_{i,t}$ represent the exogenous component of nestedness driven by industry-wide patterns. In the second stage:

$$Resilience_{i,t} = \alpha + \beta\,\widehat{SNODF}_{i,t} + \gamma' \boldsymbol{X}_{i,t} + \epsilon_{i,t}. \tag{15}$$

We assess the strength of $PeerSNODF_{i,t}$ as an instrument using the partial F-statistic in the first stage (Andrews and Stock, 2005).

Table 11 presents the 2SLS estimation results addressing potential endogeneity concerns. First, the instrument meets the relevance condition. Panel A reports the two-stage regression outcomes. The first-stage results (column 1) confirm the instrument's relevance: *PeerSNODF* strongly predicts focal firm nestedness ($p < 0.01$) with a Cragg-Donald Wald F-statistic of 655.219, well above the conventional threshold of

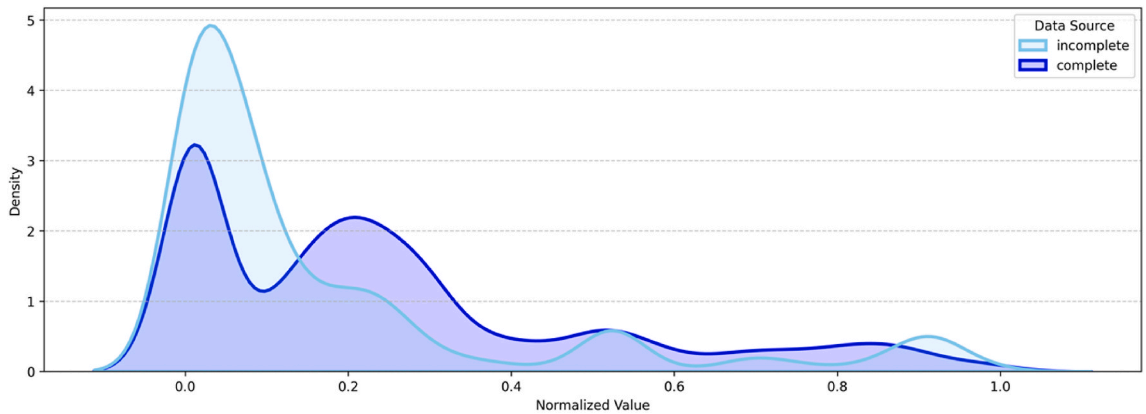

Fig. 4. Distributional stability of nestedness estimates under complete vs. incomplete networks.

10, confirming the instrument is strong and meets the requirements. The second-stage results (columns 2–5) reveal that the instrumented *SNODF* maintains its dual effect on resilience. For resistance measures, *SNODF* exhibits negative and significant coefficients for both *Resis1* ($p < 0.01$) and *Resis2* ($p < 0.01$), indicating that higher nestedness reduces short-term shock absorption. Conversely, for recovery measures, *SNODF* shows positive and significant effects on both *Recov1* ($p < 0.01$) and *Recov2* ($p < 0.01$), confirming enhanced post-disruption recovery.

Second, the instrument appears to satisfy the exclusion restriction. Table 11 Panel B validates the exclusion restriction through falsification tests. When we regress each resilience measure directly on PeerSNODF while controlling for firm characteristics, the instrument shows no significant direct effect on any resilience measure (all $p > 0.1$), confirming that peer nestedness affects focal firm resilience only through the focal firm's own network structure. These results demonstrate that after accounting for endogeneity, network nestedness undermines immediate resistance while enhancing subsequent recovery.

3.5.3. Alternative variable tests

We probe whether our findings depend on how nestedness is measured. Table 12 re-estimates the baseline specifications after replacing SNODF with four alternatives: *row-SNODF*, *column-SNODF*, *JNODF*, and *NODF*. The results are consistent across metrics. For resistance, nestedness loads negatively and significantly in every case. For recovery, coefficients are also positive and significant across all specifications. Coefficient magnitudes vary across metrics, with *NODF* producing larger but less precise estimates and *JNODF* yielding smaller but more precise estimates. These differences reflect variations in scale and sensitivity across indices.

Taken together, these patterns confirm that our key finding of nestedness undermining resistance while enhancing recovery is not an artifact of a particular index. The row and column decompositions indicate that both dimensions of the bipartite structure contribute to the relationship. The relatively noisier *NODF* estimates are consistent with its greater sensitivity to degree heterogeneity and missing links, whereas *SNODF* delivers stable, well-identified effects. For these reasons, we retain *SNODF* as the preferred measure and use the alternatives as robustness checks.

4. Discussions

4.1. Theoretical and methodological contributions

Our study makes two major theoretical contributions and an additional methodological contribution that together deepen the understanding of supply chain resilience under nested network structures. First, our findings show that network nestedness serves as a source of vulnerability and a means of enhancing resilience simultaneously. In accordance with RDT, firms seeking secure access to critical inputs (Hillman et al., 2009) cluster around a small number of resource-rich hub suppliers, giving rise to hierarchical, nested patterns (Chauhan et al., 2021). Although this arrangement may undermine short-term stability by concentrating disruptions in these hubs, thereby increasing vulnerability, our evidence indicates that it ultimately strengthens recovery. Specifically, the same hubs that heighten exposure in the short term also facilitate a faster reconfiguration of resources once bottlenecks ease, leading to more robust post-disruption rebounds. We contribute to the resilience literature (Brintrup et al., 2018; Payrató-Borràs et al., 2019) by clarifying the dual nature of nested networks, highlighting how short-term resistance and long-term recovery both stem from the same hierarchical structure.

Second, we shed new theoretical light on how supplier concentration and corporate digitalization influence these resilience outcomes by treating them as managerially actionable solutions rather than immutable contextual conditions. Prior research often examines concentrated supplier portfolios (Choi and Krause, 2006; Jiang et al., 2023) or digital technologies (Gonul Kochan et al., 2018) in isolation. We instead integrate these as two complementary levers for settings where firms cannot redesign the entire network. The first is an external portfolio lever that tunes supplier concentration through diversification, allocation caps, and contingency contracts. The second is an internal capability lever based on corporate digitalization, which enhances visibility and coordinated reconfiguration (Srinivasan and Swink, 2018; Williams et al., 2013). By integrating RDT and IPT, we explain how corporate digitalization influences resilience outcomes.

Finally, our study provides empirical evidence by using objective, large-scale data and systematically maps buyer-supplier linkages beyond immediate tiers, revealing deeper dependencies where data permit. Previous research has often relied on self-reported supplier data or focused on single-industry case analyses (Ledwoch et al., 2018; Olivares Aguila and ElMaraghy, 2018). In contrast, we track buyer-supplier relationships across multiple organizational levels, thereby capturing the deeper levels of nested connectivity. This multi-layer perspective extends beyond a firm's immediate partners and reveals more subtle forms of hierarchical dependence that might otherwise go unnoticed in traditional surveys. Moreover, comparing disclosure-only and enriched networks shows that SNODF exhibits modest, positive cross-network concordance and outperforms alternative metrics under incompleteness. Further, listed firms exhibit markedly higher degree, betweenness, and closeness, confirming their structurally pivotal role. Together, these checks enhance methodological rigor and provide clear justification for focusing on listed firms when analyzing complex, large-scale buyer-supplier networks.

Table 11
2SLS estimation for network nestedness and supply chain resilience.

Panel A: Two-Stage Least Squares (2 S LS) results for network nestedness and resilience

	(1)	(2)	(3)	(4)	(5)
	SNODF	*Resis1*	*Resis2*	*Recov1*	*Recov2*
PeerSNODF	0.7934***				
	(0.0310)				
SNODF		−0.5142***	−2.3400***	1.1261***	1.2438***
		(0.1825)	(0.2305)	(0.2285)	(0.3328)
Size	−0.0152***	−0.0170	−0.0544***	0.0693***	0.0841***
	(0.0022)	(0.0103)	(0.0128)	(0.0112)	(0.0190)
Lev	0.0052	−0.0782	1.0630***	0.0668	−0.0329
	(0.0147)	(0.0604)	(0.0785)	(0.0716)	(0.1168)
Tangibleness	−0.0145	0.0724	0.0108	−0.3017*	−0.0056
	(0.0264)	(0.1289)	(0.1532)	(0.1584)	(0.2285)
SOE	0.0495***	−0.1817***	0.1620***	0.0833***	0.0141
	(0.0056)	(0.0263)	(0.0315)	(0.0306)	(0.0511)
BoardSize	0.0001	−0.0018	0.0005	0.0052	−0.0142**
	(0.0008)	(0.0029)	(0.0043)	(0.0035)	(0.0061)
HHI	0.0776***	−0.1512	0.3292***	0.4985***	−0.2632
	(0.0211)	(0.0920)	(0.1100)	(0.1231)	(0.1684)
MIndex	−0.0061***	0.0237***	0.0026	0.0236***	0.0107
	(0.0015)	(0.0065)	(0.0088)	(0.0078)	(0.0127)
const	0.4491***	0.0480	−0.5236	−1.8168***	8.4233***
	(0.0549)	(0.2721)	(0.3404)	(0.3114)	(0.5012)
Firm FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
N	12,437	12,437	12,437	12,437	12,437
F-statistic	185.87	97.88	165.68	97.75	19.79
Adjusted R^2	0.1069	0.0593	0.0964	0.0592	0.0126

Panel B: Exogeneity check: Regressions of *PeerSNODF* on resilience measures

	(1)	(2)	(3)	(4)
	Resis1	*Resis2*	*Recov1*	*Recov2*
PeerSNODF	0.0732	−0.1187	−0.0918	0.1999
	(0.1366)	(0.1699)	(0.1751)	(0.2907)
Size	0.0377*	0.0164	−0.0091	0.0049
	(0.0206)	(0.0255)	(0.0263)	(0.0427)
Lev	0.0823	0.6050***	−0.1916**	−0.1025
	(0.0723)	(0.0876)	(0.0919)	(0.1700)
Tangibleness	−0.2007	0.0987	−0.2996	0.3235
	(0.1469)	(0.1725)	(0.2109)	(0.4336)
SOE	−0.0830	0.1179	−0.2670**	0.1339
	(0.1288)	(0.1572)	(0.1362)	(0.1818)
BoardSize	0.0095***	0.0001	−0.0045	−0.0073
	(0.0033)	(0.0033)	(0.0032)	(0.0056)
HHI	−0.0440	−0.1498	−0.0565	0.4191*
	(0.0965)	(0.1363)	(0.1546)	(0.2446)
MIndex	0.0033	−0.0003	−0.0002	0.0505*
	(0.0132)	(0.0138)	(0.0134)	(0.0272)
const	−1.1588**	−2.6238***	1.0376	9.7004***
	(0.5300)	(0.6340)	(0.6677)	(1.1400)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	12,437	12,437	12,437	12,437
F-statistic	6.06	30.13	4.50	3.36
Adjusted R^2	0.0054	0.0261	0.0040	0.0030

Notes: The symbols ***, **, and * denote significance at the 1 %, 5 %, and 10 % levels, respectively. Standard errors (in parentheses) are clustered at the firm level.

4.2. Managerial implications

Our study offers several insights for managers seeking to enhance supply chain resilience. First, our results emphasize that nested network structures are a double-edged sword. A high level of network nestedness may undermine short-term stability if a small number of core suppliers fail; conversely, it can significantly enhance long-term recovery by accelerating resource reallocation among interconnected partners. Therefore, managers should assess the extent to which their upstream relationships are centered on a small number of powerful hub suppliers and consider measures such as dual sourcing or more distributed contracting, even when ties are indirect through shared hub exposure. This can help mitigate potential vulnerability while retaining the recovery benefits of network nestedness.

Second, when firms cannot redesign the wider network, they should pull two levers: manage supplier concentration externally and strengthen digital capabilities internally. While concentration with critical suppliers may partially offset nestedness-induced vulnerabilities in the near term, persistent shocks make such concentration a constraint on recovery. Managers should adopt a tiered policy: keep targeted concentration for coordination efficiency while building redundancy through dual sourcing, allocation caps, and contingency contracts. Concentration lowers lead times and coordination costs but constrains access to alternatives during severe shocks. For strategic or complex items, balance concentration and diversity to preserve flexibility and mitigate the effect of a single hub. Corporate digitalization is a

Table 12
Comparative analysis of alternative nestedness metrics.

	Resis1				*Resis2*				*Recov1*				*Recov2*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
row-SNODF	−0.4827**				−0.4510**				1.1793***		0.2759***		0.9904***			
	(0.2140)				(0.2258)				(0.1856)		(0.0787)		(0.3512)			
column-SNODF		−0.4898**				−0.4824**				1.2665***				0.9992***		
		(0.2271)				(0.2396)				(0.1961)				(0.3746)		
JNODF			−0.1812***				−0.3565***				0.2759***				0.5188***	
			(0.0667)				(0.0838)				(0.0787)				(0.1265)	
NODF				−0.8089*				−0.6048*				2.1589***				1.8085**
				(0.4440)				(0.4925)				(0.4025)				(0.7617)
Size	−0.0103	−0.0104	−0.0147	−0.0110	−0.0307**	−0.0307**	−0.0365***	−0.0317**	0.0526***	0.0525***	0.0618***	0.0539***	0.0657***	0.0660***	0.0761***	0.0668***
	(0.0102)	(0.0102)	(0.0101)	(0.0101)	(0.0127)	(0.0127)	(0.0128)	(0.0127)	(0.0110)	(0.0110)	(0.0111)	(0.0109)	(0.0191)	(0.0192)	(0.0190)	(0.0191)
Lev	−0.0814	−0.0808	−0.0736	−0.0791	1.0648***	1.0651***	1.0732***	1.0678***	0.0776	0.0770	0.0593	0.0729	−0.0160	−0.0173	−0.0329	−0.0199
	(0.0603)	(0.0603)	(0.0602)	(0.0602)	(0.0803)	(0.0803)	(0.0805)	(0.0804)	(0.0720)	(0.0719)	(0.0720)	(0.0719)	(0.1174)	(0.1174)	(0.1170)	(0.1174)
Tangibleness	0.0816	0.0817	0.0775	0.0829	0.0387	0.0390	0.0326	0.0393	−0.3142**	−0.3148**	−0.3062*	−0.3181**	0.0005	0.0003	0.0108	−0.0027
	(0.1297)	(0.1297)	(0.1298)	(0.1298)	(0.1549)	(0.1549)	(0.1548)	(0.1547)	(0.1589)	(0.1589)	(0.1595)	(0.1589)	(0.2329)	(0.2330)	(0.2327)	(0.2329)
SOE	−0.2074***	−0.2079***	−0.2130***	−0.2100***	0.0214	0.0211	0.0171	0.0182	0.1385***	0.1391***	0.1530***	0.1441***	0.0799*	0.0812*	0.0907*	0.0846*
	(0.0237)	(0.0237)	(0.0237)	(0.0238)	(0.0303)	(0.0303)	(0.0302)	(0.0303)	(0.0287)	(0.0287)	(0.0287)	(0.0288)	(0.0482)	(0.0482)	(0.0479)	(0.0480)
BoardSize	−0.0013	−0.0013	−0.0017	−0.0014	0.0024	0.0024	0.0019	0.0023	0.0038	0.0038	0.0045	0.0040	−0.0153**	−0.0153**	−0.0144**	−0.0151**
	(0.0029)	(0.0029)	(0.0029)	(0.0029)	(0.0042)	(0.0042)	(0.0042)	(0.0042)	(0.0035)	(0.0035)	(0.0035)	(0.0035)	(0.0061)	(0.0061)	(0.0061)	(0.0061)
HHI	−0.2028**	−0.2034**	−0.1958**	−0.2043**	0.0531	0.0528	0.0721	0.0510	0.6179***	0.6186***	0.6120***	0.6208***	−0.1214	−0.1203	−0.1456	−0.1190
	(0.0888)	(0.0889)	(0.0897)	(0.0889)	(0.1164)	(0.1164)	(0.1153)	(0.1164)	(0.1198)	(0.1198)	(0.1208)	(0.1199)	(0.1646)	(0.1646)	(0.1643)	(0.1648)
MIndex	0.0275***	0.0275***	0.0277***	0.0274***	0.0228***	0.0228***	0.0229***	0.0228***	0.0149*	0.0149*	0.0142*	0.0152**	−0.0003	−0.0003	−0.0006	−0.0000
	(0.0066)	(0.0066)	(0.0065)	(0.0066)	(0.0087)	(0.0087)	(0.0087)	(0.0087)	(0.0077)	(0.0077)	(0.0077)	(0.0077)	(0.0124)	(0.0124)	(0.0124)	(0.0124)
Constant	−0.2894	−0.2873	−0.1706	−0.2757	−1.9649***	−1.9653***	−1.7810***	−1.9457***	−1.0354***	−1.0339***	−1.2607***	−1.0611***	9.2828***	9.2781***	8.9819***	9.2611***
	(0.2541)	(0.2541)	(0.2533)	(0.2530)	(0.3207)	(0.3207)	(0.3226)	(0.3206)	(0.2816)	(0.2816)	(0.2882)	(0.2817)	(0.4748)	(0.4750)	(0.4726)	(0.4743)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	12,482	12482	12,482	12,482	12,482	12,482	12,482	12,482	12,482	12,482	12,482	12,482	12,482	12,482	12,482	12,482
Adj. R^2	0.0582	0.0581	0.0581	0.0577	0.0673	0.0673	0.0692	0.0669	0.0563	0.0563	0.0535	0.0549	0.0103	0.0102	0.0112	0.0100

Notes: The symbols ***, **, and * denote significance at the 1 %, 5 %, and 10 % levels, respectively. Standard errors (in parentheses) are clustered at the firm level.

complementary internal lever. Real-time monitoring, analytics, and collaborative planning improve early warning and recovery coordination. This visibility matters most in nested networks, where indirect ties create hidden failure points and enable cascading disruptions. Managers should invest in systems that integrate supplier data, automate inventory analytics, and issue timely upstream-risk alerts.

Finally, we recommend that managers adopt a network perspective when evaluating their supply chain strategies. While immediate supplier relationships remain important, indirect connections, especially shared exposure to hub suppliers, often shape material flows and risks in nested architectures. Assessing exposure to common hubs and substitution paths not only reveals potential bottlenecks but also helps decision-makers predict where digital coordination or contingency sourcing arrangements can most effectively strengthen resilience. Managers who regularly review these indirect dependencies are more likely to anticipate systemic vulnerability and adjust their network configurations to ensure both immediate shock absorption and rapid post-disruption recovery.

5. Conclusions

This study examines how network nestedness shapes two dimensions of supply chain resilience (resistance and recovery) using a buyer-supplier network built around publicly listed firms as focal nodes. We operationalize nestedness with SNODF and show a clear dual effect: higher nestedness weakens near-term resistance but strengthens long-run recovery. We further find that supplier concentration attenuates the negative effect of nestedness on resistance yet dampens recovery gains, while corporate digitalization mitigates early losses and amplifies recovery. Together, these results explain why hierarchical, core-periphery structures simultaneously create fragility on impact and a capacity for rebound.

We acknowledge several limitations and their implications for inference. First, our sample covers publicly listed firms in one country. Listed entities are structurally central in our data, which supports system-level inference, but generalizability beyond China and listed firms remains untested. External validity may be limited, and effect sizes or mechanisms may differ for micro and small enterprises or in other institutional settings. Second, we estimate network measures from incomplete data. We mitigate censoring by comparing disclosure-only with enriched networks and by triangulating across nestedness metrics, yet the full buyer-supplier network is not observable. Missing links likely bias measured nestedness downward and attenuate estimated coefficients toward zero, so our estimates are conservative lower bounds. Third, our digitalization measure is a text-based proxy from annual reports. Dictionary methods may capture managerial "cheap talk," similar to greenwashing (Bingler et al., 2024). The approach is common used because financial statements lack standardized digital-asset accounts, and prior work links disclosure emphasis to subsequent implementation (Chen and Srinivasan, 2024). Even so, the proxy reflects disclosure emphasis rather than installed technology, may undercount quiet adopters or include rhetorical claims, and likely attenuates moderation estimates toward zero.

Future research can strengthen reliability and generalizability in the following ways: (1) Extend the design to micro and small enterprises and additional countries to test portability across institutional settings and governance forms. (2) Fuse disclosures with transactional and operational traces (e.g., EDI or ERP logs and shipment events) to reduce network censoring and observe deep-tier ties. (3) Develop multi-indicator measures of digitalization using IT capital, digital patents, job postings, and vendor deployments. Recruitment announcements offer detail but risk cheap-talk bias. Job postings provide harder evidence but offer limited granularity. Future work should use generative AI (e.g., ChatGPT, Llama) to separate substantive initiatives from rhetoric by assessing contextual specificity.

CRediT authorship contribution statement

Sihang Chen: Writing – original draft, Software, Methodology. **Junqin Lin:** Validation, Conceptualization. **Xiaopo Zhuo:** Writing – review & editing, Methodology, Conceptualization. **Libo Yin:** Validation, Conceptualization. **Jiaxin Shen:** Software, Investigation, Data curation.

Acknowledgments

The authors are grateful to the editor and the reviewers for their helpful comments. The work is partially supported by the National Natural Science Foundation of China (72371252 and 72471255), the Basic and Applied Basic Research Project of Guangzhou (Nos. SL2024A04J01795), the Guangdong University Young Innovative Talents Program (2025WQNCX017), the Guangdong Provincial University Innovation Team Project (2024WCXTD007), the Natural Science Foundation of Guangdong Province, China (2025A1515011150), and the STU Scientific Research Initiation Grant (STF23029T).

Data availability

Data will be made available on request.

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