ESSAYS ON MANAGING SUPPLY NETWORKS

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ABSTRACT

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This dissertation studies the impact of different network structures and the structural positions of supply chain entities on their performance. The first essay focuses on the performance of buyers by examining the relationship between buyers' supply network structures and their performance. We use two network-level measures (network density and network centralization) as indicators of different supply network structures to study this relationship. We investigate how the interplay between network structure and firm performance differs in various industry settings. Our ego-centric network panel dataset from 2015 to 2018 included the focal companies from three industries: automotive (n = 76), pharmaceutical (n = 66), and food & beverage (n = 105). Our results suggest that supply network structures have differential effects on buyer performance contingent upon industry context. We provide specific recommendations to focal companies' managers on what specific network structures would enhance their operational performance under various business environments.

The second essay investigates what specific aspects of first-tier suppliers drive their performance. We consider two multi-factor efficiency measures: operational efficiency and structural efficiency. We investigate the direct effects of operational and structural efficiencies on first-tier supplier's performance as well as the moderating role of structural efficiency in the relationship between operational efficiency and supplier performance. We test these relationships using a panel dataset of 278 observations obtained from 75 first-tier suppliers in the global

automotive supply network over four years from 2015 to 2018. Our findings demonstrate synergies between suppliers' internal resources and external relationships in enhancing their performance.

Building on the first two essays, the third essay investigates the supply network structures that are robust to disruptions from the focal company's standpoint. By considering network density and network centralization, and modeling supply chain disruptions using simulations, we assess the impact of disruptions by investigating changes in the structural efficiency of the focal company. Our findings suggest that dense and decentralized supply networks are more robust to disruptions than sparse and centralized supply networks. We also find that this result becomes more evident as the magnitude of the disruption increases. Our findings have important implications for resource allocation and fortification strategies to design and operate robust and resilient networks.

This dissertation is dedicated to my wife Sujung Lim and my parents.

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CHAPTER 1 - Introduction

1.1. Introduction

In this three-essay format dissertation, we study different research questions related to supply chain entities' network structures and structural positions. The first essay focuses on buyers (i.e., focal companies) by examining the relationship between a buyer's supply network structure and its performance. We used two network-level measures (density and centralization) as the indicators of different supply network structures to study this relationship. Each buyer's supply network was treated as an individual ego-network, and network-level metrics were calculated for each focal firm. We investigated how the interplay between network structure and firm performance differs in various industry settings. Our ego-centric network panel dataset from 2015 to 2018 included focal companies from three industries: automotive (n = 76), pharmaceutical (n = 66), and food & beverage (n = 105). We suggest that it is critical to analyze the relationship between supply network structures and buyer performance by specific industry context. We found a negative interaction effect between density and centralization on buyers' profitability in the automotive industry. In the pharmaceutical industry, we showed a positive interaction effect between density and centralization on the focal companies' profitability. Finally, we found negative direct and interaction effects of density and centralization on the focal firms' performance in the food & beverage industry. Our results suggest that supply network structures have differential effects on buyer performance contingent upon industry context. From a practical standpoint, we provide specific recommendations to focal companies' managers on what specific network structures would enhance their operational performance under various business environments.

In the second essay, we hypothesize that a supplier’s structural position in a supply network plays a significant role in understanding its performance. More specifically, we investigate the impact of the structural positions of the first-tier suppliers on their performance. Focal firms often depend heavily on their first-tier suppliers to effectively meet downstream customer demand. This can cause the performance of focal firms to be impacted by their first-tier suppliers. Given this, it is important to understand what specific aspects of first-tier suppliers drive performance. We consider two multi-factor efficiency measures associated with suppliers, operational efficiency and structural efficiency, as well as their interactions. The operational efficiency measure reflects a supplier's internal resource utilization and is derived from the established literature. The structural efficiency measure is based on a supplier's positional attributes within a supply network. Both efficiency measures are operationalized via data envelopment analysis (DEA). We investigate the direct effects of structural and operational efficiencies on first-tier supplier performance and the moderating role of structural efficiency in the relationship between operational efficiency and supplier performance. In terms of improving performance, our work underscores the importance of a supplier's structural position in a network and the efficacy with which it can leverage its relationships with other entities in the network. We test these relationships using a panel dataset of 278 observations obtained from 75 first-tier suppliers in the global automotive supply network over four years regarding supplier's firm profitability, cost performance, inventory performance, and intangible value. We provide managerial implications related to how suppliers should manage synergies between their internal resources and external relationships and thus enhance their performance.

Building on the first two essays, the third essay aims to identify supply network structures that are robust to disruptions from the focal company's standpoint. In this study, we investigate supply network structures that are robust to disruptions from the focal company's standpoint. We consider two specific dimensions related to supply chain networks in this context: network density

and network centralization. We model supply chain disruptions using simulations, specifically by randomly disrupting entities in the global automotive supply network. We then assess the impact of the disruptions by investigating changes in the structural efficiency of the focal company. Based on the results, the stability of the focal company's structural efficiency in the presence of random supplier disruptions provides an effective measure for the robustness of the supply network. Our findings suggest that dense and decentralized supply networks are more robust to disruption than sparse and centralized supply networks. We also find that this result becomes more evident as the magnitude of the disruption increases (i.e., stronger in severe disruptions). Our findings have important implications for resource allocation and fortification strategies to design and operate robust and resilient networks.

CHAPTER 2 - Investigating the Relationship between Supply Network Structures and Buyer Performance: A Cross-Industry Examination

2.1. Introduction

Designing an effective supply network involves managerial decisions about building the supply base for the focal companies to improve their performance and gain competitive advantages. Traditional supply network design literature has focused on total-cost minimization or profit maximization (Meixell and Gargeya 2005; Melo et al. 2009; Nagureny 2010; Govindan et al. 2017). With the changing business environment, recent optimization models in the literature have focused on different organizational objectives (Farahani 2014) such as service level (Sabri and Beamon 2000; Nozick and Turnquist 2001; Shen and Daskin 2005) and sustainability (Wang et al. 2011; Elhedhli and Merrick 2012; Nurjanni et al. 2017; Waltho et al. 2019).

Designing an optimal supply chain requires managerial decisions based on a variety of factors. Fisher (1997) underscored the importance of matching a company's supply chain to the product and market characteristics, introducing a cost-focused, efficient supply chain and a customer-focused, responsive supply chain (Fisher 1997; Selldin and Olhager 2007). Companies design their supply chains to better satisfy customer needs and market demands (Mckinsey & Company 2016). Therefore, supply network design decisions are aligned with focal company's strategic priorities and surrounding business environment and, consequently, have differential performance implications. However, existing studies have rarely conducted an industry-specific investigation on the performance implications of supply network structure. This study aims to fill that gap.

We suggest that the performance implications of supply network structures of the focal company will vary under different industry settings. For example, focal companies in the food and agriculture business tend to have a focused and vertically integrated supply chain to reduce costs and manage suppliers (Ernst & Young 2020). On the other hand, Inditex, the fast-fashion industry leader, is known for its highly responsive supply chain that has a minimal dependency on particular suppliers (Ferdows et al. 2003; 2004; Aftab et al. 2018), influencing the choice of network structure. If innovation is critical to a firm's success, the interconnected supply network structure will facilitate the flow of knowledge and information within the network. For instance, Toyota is known to cultivate collaborative and interdependent relationships with suppliers (Dyer and Hatch 2004) in its interconnected supply chain. In a recent study, Potter and Wilhelm (2020) also empirically investigated how Toyota's supply network structure positively influenced supplier-supplier innovations within the supply network.

In the current business environment, as the global supply chains are becoming more complex, an increasing number of researchers are utilizing the concepts and tools of network analysis to better explain the complex nature of supply chains (Kim et al. 2011; Wichmann and Kaufmann 2016; Kumar et al. 2020). Borgatti and Li (2009) provided an overview of how social network analysis (SNA) could be applied in supply chain research. They suggested possible interpretations of key concepts in SNA from a supply chain perspective, such as network structures, node-centralities, and equivalence. To this end, they highlighted the potential of SNA to bring together supply chain research and other streams of management research. Still, only a limited number of studies have focused on the structures of supply networks due to the difficulties of obtaining large-scale supply chain data. A few studies have explored the relationship between network structure and innovation-oriented outcomes (Bellamy et al. 2014; Carnovale and Yeniyurt 2015; Sharma et al. 2020).

However, research on the attributes of a firm's supply network structure and its influence on the operational performance that account for industry structure is still nascent. To this end, we investigate the relationship between buyers' supply network structures and their profitability. We focused on two important network measures (network density and network centralization) to characterize a focal firm's supply network structure. We chose three industries – automotive, pharmaceutical, and food & beverage – to explore the differences in the relationships between network structure and financial performance outcomes. The industries chosen satisfied the following criterion: First, each industry requires a sufficient number of focal companies for empirical analysis. Second, each focal company's supply network should be large enough to be studied via network analysis. Third, and most importantly, each industry has distinct product and market characteristics.

The automotive industry reflects a dynamic and fast-changing environment, while the food & beverage industry represents a stable and conventional setting with functional products. Lastly, the pharmaceutical industry is selected to describe a context with mixed market characteristics, where both innovative practices and centralized decisions are important. Given our study's interest in enhancing the understanding of the relationship between supply network structure and firm performance across different environments, examining multiple industries is appropriate to answer the research question. Our approach is also aligned with the mirroring hypothesis, which claims the correspondence between organizational structure and technical architecture (Colfer and Baldwin 2016). The mirroring hypothesis predicts that organizational ties within a firm correspond to the technical dependencies in the work or product (Colfer and Baldwin 2016). We show that the mirroring hypothesis is likely to operate in the supply network context.

We contribute to the supply network literature in two important aspects. First, our study bridges an existing research gap on supply networks by focusing on the focal companies' network structures based on two network-level measures. Since most of the current research in supply networks has focused on the firm-level rather than the network-level, we contribute to the literature by investigating the relationship between the supply network structure and the focal company's performance. Second, we conducted a cross-industry investigation of network structures' impact on the focal company's performance by testing the relationships in three different industries. Our results suggested that supply network structures, represented by network density and network centralization, had differential effects on buyer performance based on the industry environment. We conclude that the impact of supply network structures was driven by the industry context. Our results have important implications for managers in designing and operating large, complex supply chain networks.

The rest of the paper is organized as follows. In Section 2, we review the related literature on supply network structures and firm performance. Section 3 provides the rationalization for selecting the three industries considered in this study. In Section 4, we present the operationalization of variables and detailed information about the study's data. Subsequently, we present our empirical results from the panel regression models in Section 5. Finally, we conclude the paper by presenting theoretical and managerial insights and offering avenues for future research.

2.2. Literature Review

2.2.1. Network Structures and Social Network Analysis

Social Network Analysis has been used extensively to study the structure of social environments (Lin and Marsden 1982). It explains the mechanisms that interact with network structures to yield certain outcomes for individual entities (Borgatti and Halgin 2011). It also describes how different companies are embedded within an interorganizational network (Phelps 2010; Rowley et al. 2000). Phelps (2010) suggested that a firm's alliance network density strengthens the impact of technological diversity on innovation, based on the claim that dense networks facilitate trust and reciprocity among connected firms. Rowley et al. (2000) used data of strategic-alliance networks in the semiconductor and steel industries to investigate the impact of relational and structural embeddedness on firm behavior and performance, highlighting the importance of network structures in inter-organizational research.

Because social capital theory (SCT) focuses on the value gained from social relations, it has been often used in conjunction with network analysis (Kwon and Adler 2014; Moran 2005). Lin (1999) established a network theory of social capital, suggesting that social capital is derived from embedded resources and relationships in the network structure. Borgatti et al. (1998) summarized how different network-level measures such as density and centralization could measure the degree of social capital in the network.

Different network-level measures have been used to describe and compare alternative structures of a network. Among them, network density and network centralization are commonly used metrics (Tichy et al. 1979; Borgatti et al. 2009; Kim et al. 2011; Wichmaan and Kaufmann 2016). Contractor et al. (2006) summarized potential applications of other network-level measures, such as mutuality, transitivity, and cyclicality, in organizational research. However, only a few studies have utilized such measures in related areas (Panitz and Gluckler 2020; Peng et al. 2020). First, network-level measures such as reciprocity and connectivity have only been defined for directed graphs, where each edge has an associated direction. We did not consider those measures because our dataset was based on indirect edges. Second, other measures, such as weak components, two-step reach efficiency, and assortativity, have rarely been studied, probably due to the challenges of relating the mathematical definitions associated with the measures to empirical research.

To this end, we utilized these two established network-level measures to demonstrate the impact of different structures of focal firms' supply networks on their firm performance. Conceptually, network density reflects cohesiveness and interconnectedness among entities in the network. Therefore, dense networks are more likely to have a higher potential to build knowledge, cooperation, and trust through the interactions among the supply chain partners (Ahuja 2000; Obstfeld 2005; Reagans and McEvily 2003; Rowley et al. 2000; Basole et al. 2018). Network centralization describes the extent to which connections are concentrated around particular entities (Freeman 1978). It is related to the concentration or distribution of authority, power, and control (Ahuja and Carley 1999; Kenis and Knoke 2002; Provan and Milward, 1995) among the entities in the network. The following section develops the arguments for the impact of network measures on firm performance.

2.2.1. Network Density and Firm Performance

We first focus on the relationship between network density and a focal firm's performance. Prior literature has associated higher network density with higher inter-firm collaboration and cooperation. Reagans and Zuckerman (2001) suggested that network density increases team-level R&D productivity based on the idea that density is positively related to a team's coordination capacity. A dense network facilitates information and knowledge sharing among the members of a network. Inkpen and Tsang (2005) distinguished three common organizational networks (i.e., intra-corporate networks, strategic alliances, and industrial districts) and noted that network interconnectedness enabled knowledge transfer and information sharing among network members.

Supply chain research has also suggested that network density positively drives firm performance. Bellamy et al. (2014) showed that supply network accessibility had a significant association with a firm's innovation output through higher collaboration, cooperation, and knowledge sharing. They also suggested that network interconnectedness positively moderated the focal relationship. Basole et al. (2018) proposed that network interconnectedness among firms in a supply network could enable the strategic alignment of supply chain entities. They suggested that higher network density leads to improved asset utilization, cost performance, and operational efficiency. These findings from past research may not hold in certain contexts.

Few studies have examined the negative performance consequences of a very high level of network density. Borgatti et al. (1998) pointed out that if the network entities are extensively tied to each other, the redundant relationships may limit the relational focus and decrease social capital in the network. Wise (2014) found an inverted-*U* relationship between team performance and group cohesion, as measured by network density. The study highlighted the negative aspect of network density, such that too much cohesion could lead to unfavorable outcomes.

In supply chain research, the negative side of network density has been conceptualized as supply chain complexity (Choi and Krause 2006; Lu and Shang 2017; Sharma et al. 2020). Choi and Krause (2006) suggested that supply-base complexity can increase the focal company's transaction cost because a complex supply base likely has a higher cost of coordination and negotiation. Further, it is likely that these networks also have higher conflicts within the supply base. Lu and Shang (2017) discussed the impact of supply-base complexity on the focal company's financial performance. They found that complexity has a mixed impact on performance depending on different complexity dimensions. For example, they showed that eliminative complexity (i.e., connections between the first-tier suppliers and the focal firm's customers) had a negative effect on performance, while cooperative complexity (connections between the first-tier suppliers within the supply base) had a positive impact on the relationship. Sharma et al. (2020) investigated the impact of three different supply network complexity dimensions (horizontal, vertical, and spatial) on the innovation performance of the focal companies. They found that the impact of horizontal and vertical complexity on innovation was nonlinear with diminishing growth, while spatial complexity was negatively related to firms' innovation performance. To this end, we conclude that the relationship between network density and firm performance might not always be strictly positive or negative.

2.2.2. Network Centralization and Firm Performance

Centralization is a measure of the distribution of connections among network members (Wasserman and Faust 1994). Higher centralization represents networks in which a few members have many connections, while the remaining members have considerably fewer ties. In contrast, in a network with lower centralization, all the members have a similar number of connections.

In an interorganizational setting, centralization indicates the network's power and control structure, demonstrating how many network relationships and activities are established around particular entities (Provan and Milward 1995). Supply chain literature suggests that a centralized supply chain performs more efficiently than a decentralized one because the focal firm has more control over said supply chain (Kouvelis and Gutierrez 1997; Lee and Whang 1999). Centralization reflects how much power or control the focal firm exercises over other suppliers in the network (Choi and Hong 2002). If centralization is high, few suppliers account for the majority of the connections within the network. The focal firm will find it easier to control a centralized network than a dispersed one as they can concentrate on the relationships with these key suppliers for efficient supply chain management. In contrast, if centralization is low, many suppliers will have an equal (or similar) degree of connection to each other in the network. Thus, the supplier will take advantage of the (almost) symmetric distribution of power and control to the detriment of the focal company.

A decentralized network will lead to better performance if the focal firm is in a dynamic organizational environment. In such an environment, organizations tend to adopt a decentralized, team-based, and distributed organizational structure for flexible and prompt responses to rapidly changing business needs (DeSanctis and Jackson 1994; Drucker 1988). A decentralized network is also effective when the spread of knowledge and information is crucial within the network and when innovation output is the key indicator of the focal company's success.

In summary, a centralized supply network structure is helpful when the focal company's objective is to take power and influence its suppliers. This objective is most likely in a relatively stable business environment where the focal firms compete against each other in terms of efficient management and control of their business (e.g., cost minimization). In contrast, when the business environment changes dynamically, a decentralized supply network structure is expected to generate more value by facilitating knowledge and information diffusion and responding to the market change. In the following section, we will discuss how we selected three industries to demonstrate the differential impact of supply network structures on a focal company's performance.

2.3. Industry Selection

This study considers multiple supply networks across different industries to understand the business environment's contingent effect in a more nuanced manner. For instance, we expect that firms operating in a stable market (e.g., basic consumer goods) will behave differently from firms in a dynamic industry (e.g., high-tech electronics; Eisenhardt 1989; Eisenhardt and Martin 2000). Fisher (1997) has also suggested that it is crucial to design a supply chain that matches the surrounding industry environment in order to gain superior outcomes. For effective supply chain management, Fisher (1997) recommended an efficient supply chain for functional products but a responsive supply chain for innovative products.

To this end, we explore how the relationships between network structures and buyer performance vary in different settings. We expect the focal firms to utilize the supply network structure differently according to the business context. For example, we expect focal firms with sparse and centralized network structures to perform better in a stable market in which cost-cutting strategies are prominent. On the other hand, we anticipate that focal firms with dense and decentralized supply network structures will show superior performance in the industries where interfirm collaboration and cooperation are strong predictors of success.

In this study, we chose three different industries (automotive, pharmaceutical, and food & beverage) from the Standard Industrial Classification (SIC) based on the following conditions: First, we limited the selection to the manufacturing sector, with two-digit SIC codes ranging from 20 to 39. Because existing supply chain relationship data are more clearly defined in the manufacturing industries, we did not analyze the supply network structures of the focal companies in the retail (SIC 52-59) or service (SIC 70-89) sectors. Second, each industry should have a sufficient number of focal companies required for statistical analyses. Industries such as tobacco

(SIC 21) or lumber and wood (SIC 24) did not have enough focal companies. Therefore, we excluded them from the selection process. Third, each focal company should have a sizable supply network, with enough suppliers (nodes) and supply chain relationships (edges) within its network, to be analyzed via network analytics. Otherwise, focal companies with small supply networks would demonstrate extreme SNA scores, which may lead to the misinterpretation of the results.

Each selected industry has distinct product and market characteristics. First, we selected the food & beverage industry to represent a market that primarily produces functional products. Functional products are known to have stable and predictable demand (Fisher 1997). Therefore, the focal companies in this business generally focus on efficiency to minimize the total cost of managing their supply chains. To this end, the food supply chain generally has a push-oriented and inflexible structure (Van der Vorst et al. 2001). The focal companies in this area often have an integrated supply chain structure for efficient management of their suppliers (Ernst & Young 2020). This is motivated by the importance attributed to safety and quality in the industry. Production and consumption of food are directly related to public health and societal wellbeing (Aung and Chang 2014). To secure their food supply chains, leading companies in this area invest in compliance systems to follow the regulations and enhance product traceability (Deloitte 2015). Zhong et al. (2017) summarized the dominant research topics in food supply chain literature, which also provides a basis for the selection of the industry. Given the previous discussion, we anticipate that the focal companies in this industry would prefer a centralized supply chain structure for effective business control.

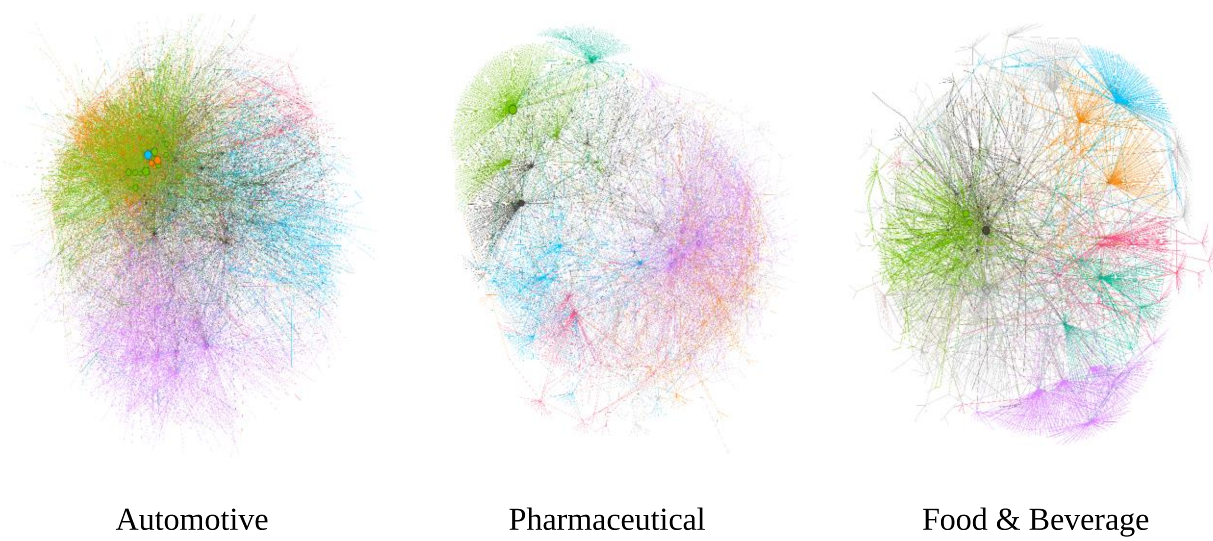
Second, we chose the automotive industry to reflect a relatively dynamic and fast-changing business environment. Global automakers make huge R&D investments to cope with rapidly changing market trends such as autonomous, connected, and electric vehicles (Mckinsey

& Company 2019). With a growing demand for new and enhanced technologies in vehicle production, automotive manufacturers are increasingly seeking innovations from the supply base (Wilhelm and Dolfsma 2018; Chae et al. 2020). In other words, cooperation among the partners and suppliers is becoming more critical in the automotive industry (KPMG 2018) than ever. Accordingly, we predict that focal firms with dense and decentralized supply networks would show greater performance in the automotive industry, benefiting from a network structure that facilitates collaboration and innovation.

Lastly, we chose the pharmaceutical industry. Traditionally, the pharmaceutical supply chain has been designed to focus on maximizing service levels in a stable business environment with fairly predictable demand patterns (BCG 2013). However, increasing competition in the global pharmaceutical market is driving focal companies to spend a tremendous amount of their budgets on R&D to develop "blockbuster" drugs, a product with annual sales of over $1 billion (Li 2014). To this end, the long time-to-market and the low success rate in new-product development result in high uncertainties in pharmaceutical supply chains (Lainez et al. 2012). In addition, given the potential negative impact on public health, the pharmaceutical industry is subject to strict market conditions and governmental regulations (Shah 2004). For these reasons, we examined the pharmaceutical industry to understand a business context where mixed product and market characteristics exist. We expect focal companies with dense and centralized supply network structures to exhibit better performance in this context.

To further demonstrate the different structural nature of supply networks in the selected industries, we visualize three industry-level supply networks respectively by Gephi 0.9.2. The networks are visualized via Fruchterman-Reingold layout (Fruchterman and Reingold 1991). We illustrate the two significant structural differences across the industries in Figure 1.1. First, the automotive supply network had a denser structure, while the other two had relatively sparse layouts in terms of the overall interconnectedness. The blank space in each graph demonstrates the difference between the three industry networks. Also, the average number of connections to each entity within the network was the highest for the automotive industry (7.4), followed by the pharmaceutical (4.2) and food & beverage industries (3.7). Second, the overall layout of each network also distinguished the three industries. The graph's colors are classified by modularity, which classifies the firms and supply relationships into distinct groups. The automotive industry network's large overlapping area demonstrates that the industry has a large, shared supply base. In contrast, the other two industries showed several out-facing circular sector forms, representing exclusive supply chain relationships controlled by a specific focal firm.

Figure 1.1 Visualization of Socio-centric Supply Networks of Three Different Industries



2.4. Operationalization of Variables and Data

2.4.1. Network-Level Metrics

We follow the definitions of the measures established in the literature (Marsden 1990; Marsden 2005; Scott 1991; Wasserman and Faust 1994). First, network density is a measure of the overall connectedness of a network: for each focal firm *i*, we calculated network density D_i as the ratio of the number of actual edges in the network to the number of potential edges between all available pairs of nodes in the network, where *e* is the total number of edges and *n* is the total number of nodes. The value ranges from zero to one, and the network is denser and more cohesive when the value is higher. As network density shows a skewed distribution, we used a logit-transformed density score in the statistical analyses to ensure the normality assumption.

$$D_i = \frac{2e}{n \times (n-1)}$$

Network centralization captures how central a network's most central node is with respect to all other nodes. The term *centrality* is restricted to node-level centrality, while the term *centralization* is used to refer to the property of an entire graph (Scott 1991). Network centralization shows the variation of node-level centrality scores within a network. It is an index that measures the degree of dispersion of all node centrality scores in a network from the maximum centrality score of a node in the network (Sinclair 2009). If a few central nodes dominate the connections in a highly centralized network, the network centralization will be closer to one. In contrast, if the node-centrality scores are almost evenly distributed, the network centralization will be close to zero. This represents a decentralized or distributed network structure.

We calculated the sum of differences in centrality between the most central node in a network and all other nodes and divided the result by the theoretically largest sum of differences in any network of the same size (Freeman 1978). The formula below shows Freeman's (1978) network centralization C_i, where $c(\max)$ is the maximum node centrality score and c_{ij} is the node centrality for node j in the supply network of focal firm i. For node-level centrality, we used eigenvector centrality, representing a weighted sum of both the direct and indirect connections of each node (Bonacich 1972; 2007):

$$C_i = \frac{\sum_{j=1}^{n}[c(\max) - c_{ij}]}{(n-1)(n-2)}$$

2.4.2. Buyer Performance and Controls

In this study, we used return on assets (ROA) – a measure of profitability – to determine the focal companies' performance. ROA measures how a company utilizes its resources to generate financial returns. Therefore, it is used as an indicator of the operational performance of a company (Basole et al. 2018; Hendricks and Singhal 2008). We calculated ROA as the focal firm's earnings before interest, taxes, depreciation, and amortization (EBITDA) divided by total assets (AT).

We controlled for several other factors that might influence the dependent variables and/or the relationship between the independent and dependent variables. Consistent with existing literature that deals with firm-level performance (Miller 2006; Zhou 2011), we controlled for firm size, R&D intensity, and capital intensity. For instance, firms with high R&D can produce more successful products, and higher performing firms tend to spend more on R&D. R&D intensity was measured as R&D expenses divided by sales (XRD/SALE). The capital intensity was measured as total assets divided by sales (AT/SALE). We then controlled for firm size because larger firms may benefit from economies of scale and may influence the relationships of interest. We used the log-transformed total employees (EMP) as a proxy for firm size. Lastly, we included time dummies to account for any year-specific effects that may have influenced the empirical results.

2.4.3. Data

This study constructed network-level data from buyer-supplier relationship records using the *Factset Revere* S*upply Chain Relationship* database. The database provides researchers with information on historical supply chain relationships for various sectors. The supply chain relationship information is collected from various sources, including SEC filings, press releases, and analyst reports. Therefore, the supply chain relationship information in the *Factset Revere* database is richer and more comprehensive than the information obtained solely from the SEC.

We collected the buyer-supplier relationship data from the three selected industries for four years, from 2015 to 2018, to investigate our research questions. The unavailability of financial information after 2018 and the limited reliability of supply chain relationship data before 2015 increased the difficulty of creating a more extensive dataset. First, we selected the major focal companies for each industry with sufficient suppliers necessary for network creation. Then, we constructed the network dataset for each industry, utilizing the supply chain relationships among the focal companies, their direct first-tier suppliers, and subsequent second-tier suppliers. Lastly, we generated ego-networks specific to every focal firm to compute network-level metrics associated with their supply network structures. Relevant financial information was collected from COMPUSTAT for the dependent variable and control variables. The final sample sizes were 76 for the automotive industry, 66 for the pharmaceutical industry, and 105 for the food & beverage industry. Table 1.1 presents the summary statistics and the correlation matrices for the relevant variables in each industry.

Table 1.1 Descriptive Statistics and Correlations

Automotive (N = 76)		**Mean**	**SD**	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Network Density	(1)	0.010	0.005	1.000					
Network Centralization	(2)	0.939	0.023	-0.865***	1.000				
ROA	(3)	0.091	0.033	0.436***	-0.386***	1.000			
Capital Intensity	(4)	1.338	0.415	-0.623***	0.499***	-0.501***	1.000		
R&D Intensity	(5)	0.038	0.013	-0.326***	0.300***	0.071	0.215*	1.000	
Firm Size	(6)	4.844	0.806	-0.811***	0.646***	-0.305***	0.535***	0.343***	1.000
Pharmaceutical (N = 66)									
Network Density	(1)	0.017	0.018	1.000					
Network Centralization	(2)	0.920	0.037	-0.833***	1.000				
ROA	(3)	0.129	0.046	-0.157	0.143	1.000			
Capital Intensity	(4)	2.267	0.918	-0.349***	0.250**	-0.500***	1.000		
R&D Intensity	(5)	0.147	0.102	-0.313**	0.073	0.200	0.098	1.000	
Firm Size	(6)	3.471	1.108	-0.762***	0.691***	0.152	0.240*	0.146	1.000
Food & Beverage (N = 105)									
Network Density	(1)	0.041	0.048	1.000					
Network Centralization	(2)	0.872	0.066	-0.835***	1.000				
ROA	(3)	0.130	0.039	-0.088	0.097	1.000			
Capital Intensity	(4)	1.207	0.441	-0.362***	0.287***	-0.507***	1.000		
R&D Intensity	(5)	0.008	0.008	-0.132	0.057	-0.085	0.332***	1.000	
Firm Size	(6)	3.002	1.635	-0.616***	0.404***	-0.119	0.166*	0.314***	1.000

*p < 0.10, **p < 0.05, ***p < 0.01.

2.5. Results

Our empirical model relied on a random-effects panel regression with robust standard errors to examine the focal relationships. We ran Hausman (1978) specification tests to decide between a fixed-effects model and a random-effects model in the panel data analysis (Greene 2003). The test results are insignificant for all three industries. Therefore, we failed to reject the null hypotheses and presented the random-effects model for the main results. Considering the relatively short panel ($T = 4$) and small sample size, we selected the random-effects model to be the main model (Clark and Linzer 2015).

We present the results of the panel regression models in Table 1.2. We estimated three models for each industry (automotive, pharmaceutical, and food & beverage). We first presented the results of the baseline model with the control variables. Then, we added the main independent variables in the second model. Lastly, we tested the interaction effect of network density and network centralization on firm performance by including the product term between the two measures in the third model.

2.5.1. Automotive Industry

We first investigated the relationships between two network measures and the focal firm's profitability in the automotive industry. First, the coefficients of network density and network centralization were not statistically significant in Model 1.2. However, the coefficients for both variables were significant and positive in Model 1.3 ($B = 0.115$, $p < .05$; $B = 2.058$, $p < .10$). The results indicated that the association between supply network structures and the focal firm's performance should be jointly considered. In Model 1.3, we found a negative interaction effect between the two network measures. The coefficient of the product term between network density and network centralization was significant ($B = -1.085$, $p < .05$) in Model 1.3. The interaction effect between two continuous variables was derived by taking the high and low values for the main variables (i.e., network density and network centralization) as one standard deviation above and below the mean, as recommended by Aiken and West (1991). Figure 1.2 depicts the margins plots for predicted ROA in Model 1.3 to provide a visual interpretation of the result. The interaction effect through the estimated means of ROA indicated that the impact of network density on focal firm profitability was less positive for firms with high centralization, as represented by the difference in the two slopes. The plot demonstrated that companies with denser supply network structures had greater profitability. Furthermore, companies that had supply networks with lower centralization experienced faster growth in profitability as network density increased. Our results suggest that network density and network centralization are both important measures, which should be carefully interpreted in explaining the association between a focal firm's profitability and its supply network structure in the automotive industry.

2.5.2. Pharmaceutical Industry

Now we examine the impact of supply network structures on focal companies' performance in the pharmaceutical industry. The direct effects of network density and network centralization on firm profitability were not significant in Models 2.2 or 2.3. However, we found a positive interaction effect from the product term's coefficient between network density and network centralization in Model 2.3 ($B = 0.198$, $p < .05$). To describe the interaction effect, we provide the margins plots for predicted ROA in Model 2.3 in Figure 1.3. Consistently, we represent high and low values of both density and centralization by one standard deviation above and below the mean, which is the common approach in examining the moderation effect (Dawson 2014). The plot shows that, at high centralization levels, increasing the density of the network increased profits. The plot also shows that the direction of the slope inversely changed at the interaction point. The focal firms would show high profitability when they were high in both structural dimensions. However, if they were low in density but high in centralization (i.e., below the intersection point), they would show low performance. Our findings demonstrated that the focal firms with dense and centralized supply network structures would show the greatest profitability in the pharmaceutical industry. Based on the results, we found that the impact of supply network structures on the focal firm's performance was appropriately explained when both density and centralization were considered jointly.

2.5.3. Food & Beverage Industry

Lastly, we analyzed the effect of network density and network centralization on the profitability of the focal companies in the food & beverage industry. The negative coefficient of network density in Model 3.2 indicated that firms with sparse networks (low in density) would show greater profitability (B = -0.012, $p < .05$). In Model 3.3, the impact of density on profitability was negative and significant (B = -0.016, $p < .01$), that of centralization on profitability was positive and significant (B = 0.102, $p < .10$), and the interaction term had a negative and significant influence on profitability (B = -0.050, $p < .01$). We plotted these interaction effects at high and low levels of density and centralization by taking +1 and -1 standard deviations from the mean for both dimensions in Figure 1.4. The interaction effect through the estimated means of ROA implied that the negative impact of network density on a focal firm's profitability was stronger for firms high in centralization, as represented by the difference in the two slopes in Figure 1.4. The negative relationship between density and profitability became more significant as centralization increased. We claim that the focal firms with a sparse and centralized supply network structure show greater performance in the food & beverage industry.

Table 1.2 Regression Model Results for Profitability as measured by ROA

	Automotive (N =76)			**Pharmaceutical (N =66)**			**Food & Beverage (N =105)**		
Dependent variable: ROA	Model 1.1	Model 1.2	Model 1.3	Model 2.1	Model 2.2	Model 2.3	Model 3.1	Model 3.2	Model 3.3
Constant	0.160*** (0.048)	0.004 (0.106)	0.061 (0.077)	0.160*** (0.032)	0.150*** (0.039)	0.136*** (0.045)	0.203*** (0.019)	0.217*** (0.020)	0.227*** (0.020)
Firm Size	-0.003 (0.010)	0.022 (0.018)	0.011 (0.011)	0.017*** (0.006)	0.017** (0.007)	0.022*** (0.007)	-0.005 (0.004)	-0.008** (0.004)	-0.010*** (0.004)
Capital Intensity	-0.043*** (0.013)	-0.032* (0.017)	-0.032* (0.017)	-0.044*** (0.013)	-0.041*** (0.013)	-0.041*** (0.013)	-0.064*** (0.013)	-0.062*** (0.012)	-0.066*** (0.012)
R&D Intensity	0.133* (0.464)	0.177 (0.366)	0.319 (0.323)	0.098 (0.108)	0.109 (0.117)	0.097 (0.116)	1.696** (0.864)	1.502* (0.840)	1.513* (0.807)
Network Density		0.046 (0.050)	0.115** (0.051)		0.006 (0.012)	0.021 (0.017)		-0.012** (0.006)	-0.016*** (0.006)
Network Centralization		-0.431 (0.564)	2.058* (1.136)		0.074 (0.170)	0.021 (0.184)		0.027 (0.054)	0.102* (0.054)
Density × Centralization			-1.085** (0.421)			0.198** (0.100)			-0.050*** (0.017)
Year Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
sigma_u	0.025	0.026	0.027	0.035	0.030	0.032	0.033	0.028	0.028
sigma_e	0.015	0.014	0.013	0.017	0.017	0.017	0.014	0.014	0.014
rho	0.731	0.770	0.811	0.810	0.756	0.773	0.846	0.795	0.800
Within R^2	0.127	0.293	0.425	0.429	0.437	0.452	0.499	0.501	0.521
Between R^2	0.311	0.359	0.361	0.460	0.454	0.474	0.215	0.347	0.391
Overall R^2	0.276	0.342	0.371	0.373	0.369	0.388	0.259	0.385	0.425

Clustered standard errors in parentheses; *p < 0.10, **p < 0.05, ***p < 0.01.

Figure 1.2 Margins Plots of Estimated ROA for Model 1.3 for the Automotive Industry

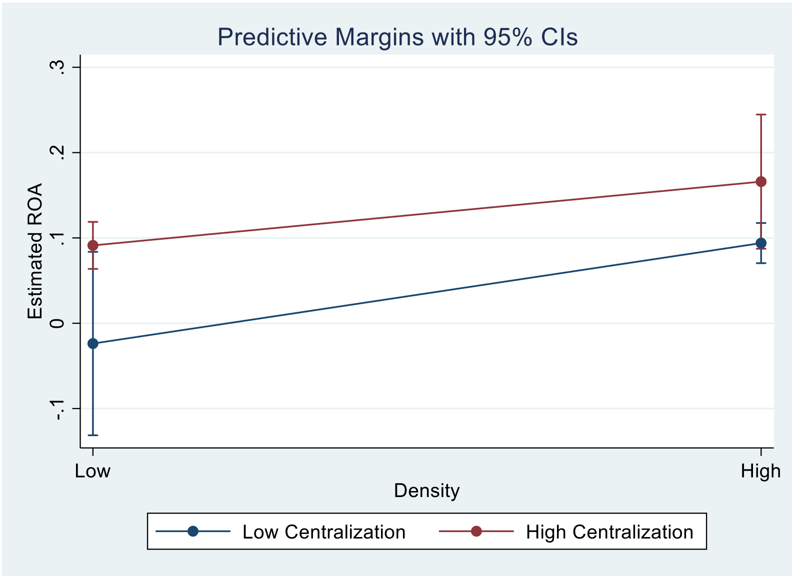


Figure 1.3 Margins Plots of Estimated ROA for Model 2.3 for the Pharmaceutical Industry

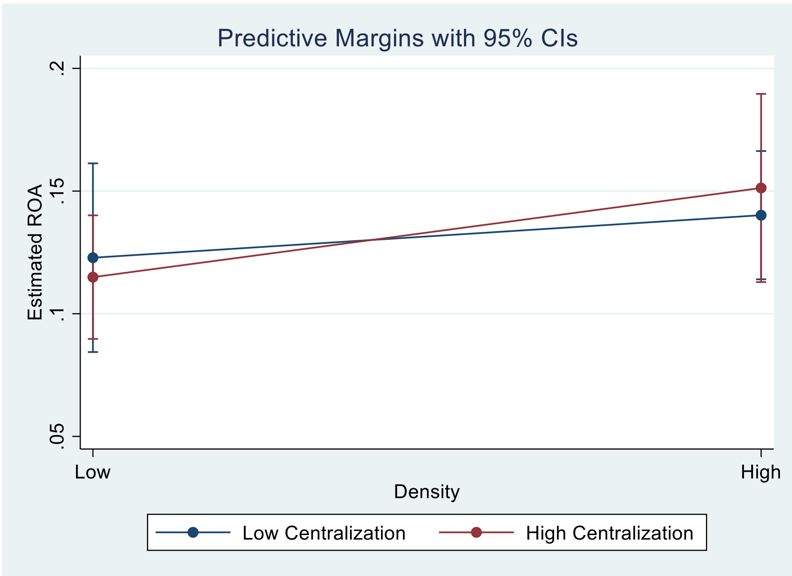
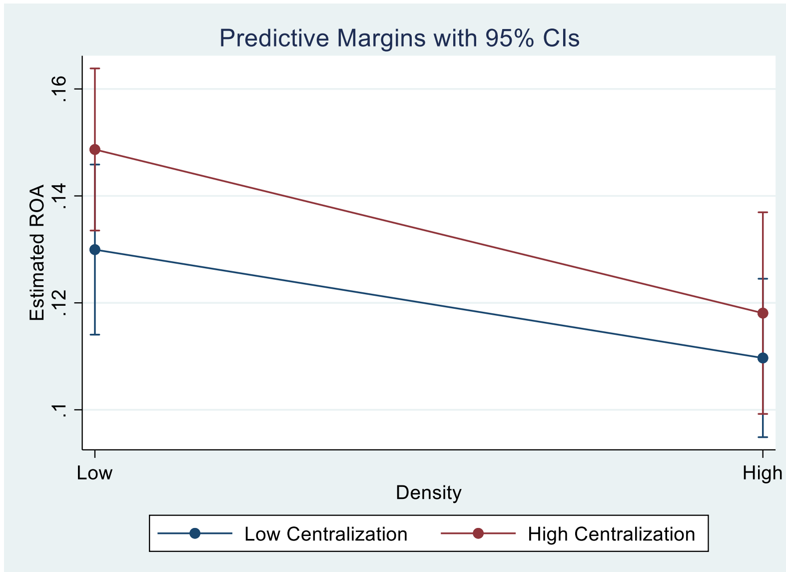


Figure 1.4 Margins Plots of Estimated ROA for Model 3.3 for the Food & Beverage Industry



2.6. Discussion and Conclusion

2.6.1. Academic Contributions

This study investigated the link between a focal firm's supply network structure and its performance, utilizing two established measures to describe different network structures. We contribute to the empirical literature about supply networks by examining the importance of those supply networks' structures in explaining the performance of a focal company.

Specifically, our results provided two important theoretical implications. First, we suggest that the impact of supply network structures on a buying firm's performance is dependent on the industry context. To the best of our knowledge, no network-oriented supply chain research has considered cross-industry comparison in investigating this question. From our cross-industry examination, we argued that a specific industry's findings are not straightforwardly generalizable to other industries. We demonstrated that varying industry-specific patterns arise due to relationships between network density, network centralization, and the focal company's performance. For example, we found that dense and centralized networks led to superior profitability in the pharmaceutical industry, while sparse and centralized networks were profitable for the focal firms in the food & beverage industry. Our findings supported the claim that the relationship between a focal company's performance and its supply network structure should be interpreted within the industry context. This suggested that supply networks are shaped by the industry and product characteristics, and accordingly, the performance experienced by the firms may also be driven by those factors.

Second, contrary to the conventional argument in the supply chain literature that emphasizes the impact of network density on performance (Basole et al. 2018; Lu and Shang 2017), we argued that network density should be jointly considered with network centralization for a comprehensive understanding of the relationship between network structure and firm performance. Theoretically, network density and network centralization are complementary concepts that represent different structural aspects of supply networks. Network density explains the cooperation and collaboration between the supply chain entities, and network centralization shows the power asymmetry and control mechanisms in buyer-supplier relationships.

From the results, we found support for the interaction effect between these two measures for all three industries. For example, if a focal firm has a highly central and dense supply network, it will exhibit greater profitability in the automotive or pharmaceutical industry but not in the food & beverage industry. This provides important contributions to the literature, as existing studies have not focused on the impact of centralization and decentralization on firm performance, despite their significance.

2.6.2. Managerial Implications

From a practical standpoint, this essay provides specific recommendations for focal companies in managing their supply base from a network structure perspective. Our results offer guidance for focal companies that seek to enhance their performance by engineering a high-performing supply network structure. We emphasize the importance of long-term investment in designing the supply network, which has further implications for managerial decisions in supplier selection, supplier rationalization, and supply base optimization.

We also demonstrated that different industry contexts have a significant influence on how the focal companies should manage and design their supply networks. We provided two-way contour plots for a detailed investigation of our findings. The contour plot is often used to describe a three-dimensional surface on a two-dimensional plane, which is also useful in illustrating the interaction between two continuous variables. In our study, network density was reflected by the x-axis, network centralization by the y-axis, and the estimated profitability (ROA) by the contours filled in different colors. By comparing the green area (lowest ROA) and red area (highest ROA), we can visually interpret the joint effect of network density and network centralization on the focal firm's profitability across different industries. The contour plot also describes how the effect of density on the predicted ROA differs across levels of centralization and vice versa.

Figure 1.5 shows the contour plot of the estimated ROA in the automotive industry. We anticipated that focal companies with dense and decentralized supply networks would be the highest performers where interfirm collaboration and information sharing were crucial to the success of the focal company. However, the red-colored region in the contour plot reveals that the highest performers in the automotive industry had either dense and centralized or dense and decentralized supply network structures. In contrast, the green-colored zone tells us that focal firms with sparse and decentralized supply bases will exhibit the lowest profitability. These findings confirmed our prediction about the positive impact of network density on the focal firm's performance. The results in Model 1.3 did not support our prediction about the negative association between centralization and firm performance. Instead, they revealed a negative interaction effect between two structural dimensions, such that the focal relationship between density and performance weakened as centralization increased. We suggest that the focal firms in the automotive industry should focus primarily on designing a dense supply network structure to support collaboration and cohesion within the supply base, which in turn will lead to an improvement in the firms' performance.

The contour plot in Figure 1.6 describes the estimated ROA in the pharmaceutical industry. We discussed how the pharmaceutical industry was chosen to represent an environment where centralized decision-making and cooperative innovation were both important. For this reason, we expected that focal firms that had dense and centralized network structures would show better performance in this context. The data shown in the contour plot confirmed our prediction: the red area corresponds to high values in both dimensions, such that the focal firms were expected to show the highest profitability when they had very dense and centralized supply networks. In addition, the positive coefficient of the product term in Model 2.3 also validated the projection.

Lastly, a contour plot of the estimated ROA in the food & beverage industry is presented in Figure 1.7. We predicted that focal companies with sparse and centralized network structures would perform better in terms of profitability in this environment, considering the relatively stable market environment. The data presented in the contour plot supported our prediction, shown by the red area that is characterized by low density (i.e., high sparsity) and high centralization. In contrast, the green-colored region illustrates that focal firms that were high in density and/or low in centralization were expected to show the lowest profitability. The empirical results discussed in Table 1.2 and Figure 1.4 substantiated the anticipated relationships between network structures and firm profitability. Based on our findings, we recommend that focal firms in the food & beverage industry should engineer their supply base to be more efficient via sparse and centralized network structures.

As shown by the varying patterns illustrated in these three contour plots, we have demonstrated the importance of cross-industry examination of our research question. In the discussion, we provided managerial insights for focal firms informed by their business environment. We suggest that the focal companies should have a profound understanding of their products and environments before making long-term decisions about engineering their supply network. The mirroring hypothesis, which highlights the relationship between the organizational design of a firm and the technical structure of its products (Colfer and Baldwin 2016), also supports our argument. Existing studies based on the mirroring hypothesis (MacCormack et al. 2012; Cabigiosu and Camuffo 2012) have focused on the relationship between product architecture and internal organizational structure. We extended the argument to a supply network context, relating network structure to product characteristics.

Figure 1.5 Contour Plot of Estimated ROA for Model 1.3 for the Automotive Industry

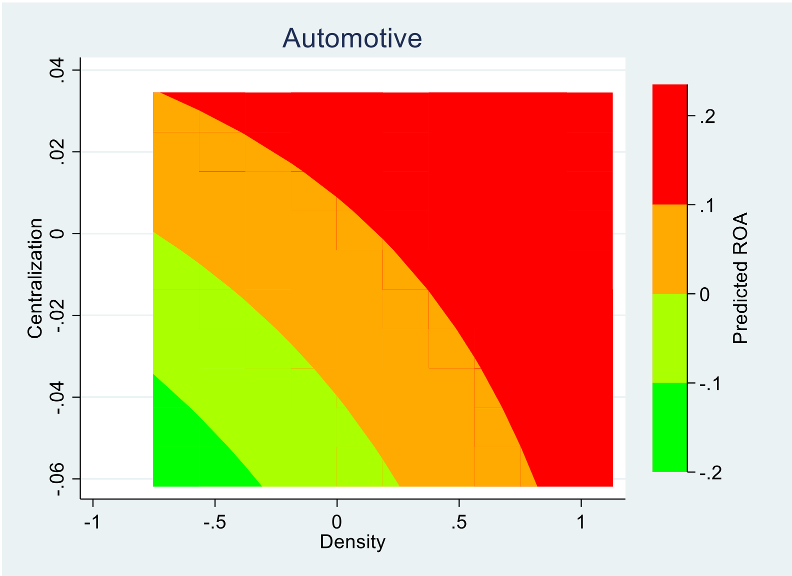


Figure 1.6 Contour Plot of Estimated ROA for Model 2.3 for the Pharmaceutical Industry

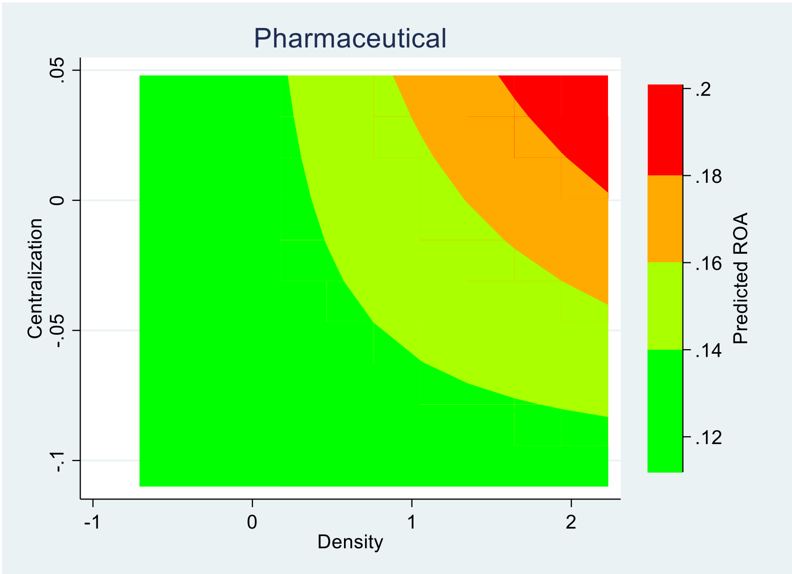
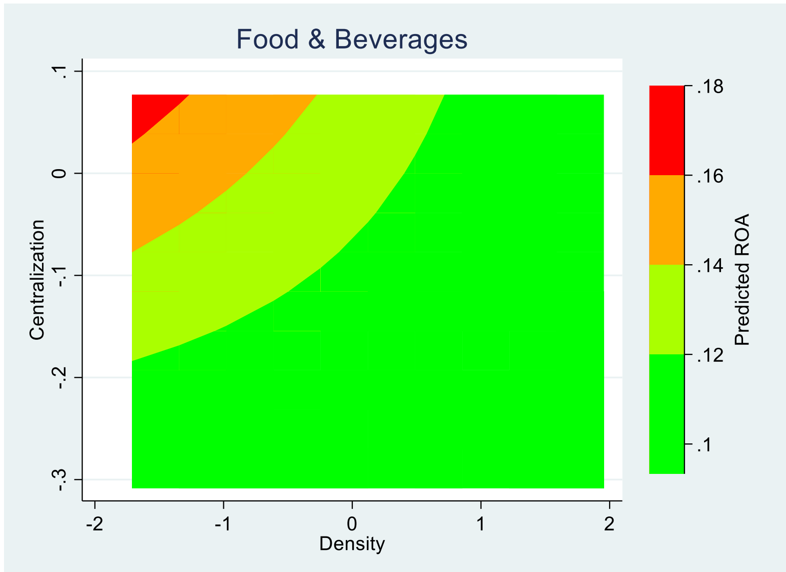


Figure 1.7 Contour Plot of Estimated ROA for Model 3.3. for the Food & Beverage Industry



2.6.3. Limitations and Future Research Directions

In this study, we investigated the impact of supply network structures on a focal firm's performance under different contextual settings. Despite the contributions and implications of the findings, this study is not without limitations. First, our sample was limited, as we restricted the samples specific to each industry. If we had increased the number of focal companies, we would have run the risk of losing industry-specific implications. We also found it difficult to increase the length of the panel because of the limited coverage of the supply chain relationship data before the year 2015. Therefore, collecting data for additional time periods would be a way for future researchers to better validate the findings in this study.

Second, we have investigated the relationships for only a limited number of industries. Only the three industries selected in this study had a sufficient number of focal companies available in the database we consulted. It would be challenging to expand the range of industries because only a few major focal firms have a sufficient number of suppliers in their supply networks in each market. We also hope that future improvements to the data sources will allow for more extensive investigations of the focal relationship in other industries.

Third, we limited our focus to the upstream supply base when we constructed the network data. It was reasonable to include only upstream suppliers in the research scope of this study, as we focused on supply networks in the manufacturing industries. However, the downstream supply chain may also play a significant role in a particular context, such as the retail and the healthcare sectors. Future work that comprises both downstream and upstream supply chain relationships will enhance our understanding of various real-world supply chain structures. Such information is still difficult to obtain. However, we expect that such data will be accessible in the future with the increasing attention to data-driven research.

Many of the above concerns are due to data limitations. We cannot easily expand the sample unless we have a complete record of the actual supply network. Still, the *Factset Revere* database is the best available source in creating supply network panel data at this point, even though it is not a perfect reflection of the real-world supply chain relationships. In addition, we utilize profitability (ROA) as the sole measure of the focal company's performance in this study. To broaden our understanding, future researchers may include other firm performance metrics, such as inventory turnover, sales growth, and market share, with appropriate data sources available.

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CHAPTER 3 - The Impact of Structural and Operational Efficiencies on Supplier Performance: A Multi-Dimensional Investigation

3.1. Introduction

As the global business environment becomes more complex, it becomes increasingly important to build relationships with strategic suppliers. To this end, focal firms should develop long-term collaborative relationships with key strategic suppliers (Bensaou 1999; Dyer and Singh 1998; Gadde and Snehota 2000) to ensure the efficient management of their supply chains. These strategic suppliers are also known to substantially influence the buying firm's performance (Kraljic 1983). Thus, a better understanding of the performance drivers of these suppliers is critical in managing an efficient supply network (Wu and Blackhurst 2009).

Choi et al. (2015) highlight the importance of effectively identifying critical suppliers in managing the overall supply chain. They note that these key suppliers are often "hidden" because of the increasing size and complexity of global supply chains. The complexity of the global supply networks makes it harder for companies to recognize these critical suppliers (Shao et al. 2018). Furthermore, limited visibility into higher tiers makes it even more difficult for focal firms to have a comprehensive understanding of their supply chains (Geodis 2017; SDC Executive 2019).

The traditional view of buyer-supplier relationships in research has long focused on dyadic relationships between buyers and suppliers (Borgatti and Li, 2009). However, the dyadic view is limited. Specifically, it is difficult to capture the multi-tiered nature of real-world supply chains in a dyadic setting. Thus, researchers suggest adopting a network perspective to comprehend the dynamic relationships and interdependent structures of supply networks (Borgatti and Li 2009; Choi et al. 2001; Galaskiewicz 2011; Hearnshaw and Wilson 2013; Pathak et al. 2007). From a network perspective, we propose a structural efficiency measure that reflects a supplier's structural position and investigate how it influences supplier performance in a complex supply network.

Given the importance of the comprehensive identification and assessment of the right suppliers in a complex environment, we focus on two efficiency measures (i.e., operational efficiency and structural efficiency) in investigating the impact of these measures on the performance of first-tier suppliers in the global automotive industry. We focus on first-tier suppliers because of the focal firm's dependence on these key suppliers that closely manage the sub-tiers and their strategic importance in driving the focal firm's performance.

In this study, we examine the direct effects of structural and operational efficiencies on the first-tier suppliers' performance. We also test the moderating role of structural efficiency in the relationship between operational efficiency and supplier performance. We utilize multiple firm performance measures for a comprehensive assessment of supplier performance.

Our findings present a new perspective on the current body of supply chain network literature. Specifically, we suggest important implications regarding the impact of structural efficiency on supplier performance. Although much of the existing literature suggests a direct and positive effect on network characteristics (Bellamy et al. 2014; Basole et al. 2018), our results reveal that the impact of a supplier's structural efficiency on its performance varies depending on the context. We show that structural efficiency plays a moderating role in explaining supplier performance rather than impacting it directly.

The remainder of the study is organized as follows. In the next section, we develop our research hypotheses. The following section presents the operationalization of variables and a detailed description of our dataset. Subsequently, we use panel regression models to present our empirical findings. We also present a set of robustness checks to support the results. Finally, we conclude the study by providing theoretical and managerial insights and offering future research directions.

3.2. Hypothesis Development

3.2.1. Operational Efficiency and Performance

We first investigate the impact of the operational efficiency of a supplier on its performance. Operational efficiency reflects how efficient a firm is in converting its internal inputs to outputs (Priem and Butler 2001; Coelli et al. 2005). Like operational efficiency, operations capability is defined as the efficient use of resources in performing organizational activities (Krasnikov and Jayachandran 2008). Dutta et al. (1999) similarly defined operational capability as the ability to increase output while minimizing labor and capital input and demonstrated a positive relationship between operations capability and financial performance. Jacobs et al. (2016) proposed a construct called operational productivity and confirmed its positive impact on firm performance based on a sample of 476 manufacturing firms in the US.

Conceptually, the positive influence of operational efficiency on performance aligns with the theory of production competence, which proposes that companies achieve greater performance when their operational capabilities are aligned with their business objectives (Cleveland et al. 1989). Since then, numerous researchers in operations and supply chain management have investigated the theory of production competence. Kim and Arnold (1993) presented a framework for manufacturing competence based on the concept of production competence and proposed that manufacturing competence positively affects business performance. Vickery et al. (1993) also suggested that production competence positively affects business performance and showed how various business strategies moderate the relationship between production competence and performance. Choe et al. (1997) tested this relationship using a sample of 170 firms operating in

US manufacturing industries. They found a significant and positive association between production competence and business performance. Schmenner and Vastag (2006) validated the theory using two datasets (International Plant Productivity Data and Global Manufacturing Research Group Survey). They confirmed that overall, production competence is positively related to business performance. Avella and Vázquez-Bustelo (2010) also offered empirical evidence of the positive impact of production competence on business performance using a sample of 274 manufacturing companies. Schoenherr and Narasimhan (2012) further extended the theory by assessing the model with a plant-level multi-country survey. They specifically focused on the impact of production competence on plant productivity improvements in terms of plant cycle time and manufacturing throughput time.

In sum, existing research has established a positive impact of operational efficiency on firm performance. We extend the discussion to a supply chain context to understand supplier performance in a supply network. Given the importance of leveraging internal resources to enhance performance, we expect that a supplier's operational efficiency will be positively associated with its performance. Therefore, we posit the following:

H1: The operational efficiency of a supplier is positively associated with its performance.

3.2.2. Structural Efficiency and Performance

We suggest that suppliers with prominent structural positions will show better performance and achieve greater intangible market value than their competitors by efficiently utilizing available resources and relational linkages. To this end, we define structural efficiency as a measure of how efficient a supplier is in achieving a prominent position compared to other suppliers in the network.

To support our argument, we use social capital theory (SCT), which has been widely used in the extant literature to explain complex inter-organizational relationships. The theory asserts that organizations can gain advantages through the resources derived from social relationships (Adler and Kwon 2002; Nahapiet and Ghoshal 1998; Tsai and Ghoshal 1998). Nahapiet and Ghoshal (1998) proposed that social capital facilitates the creation and sharing of intellectual capital in inter-organizational settings. They further claimed that organizations that invest in social capital would have an advantage in the market. Tsai and Ghoshal (1998) suggested that the structural and relational dimensions of social capital are positively associated with product innovation. Using data collected from a multinational electronics company, they showed that social capital facilitates interunit resource exchange and value creation. Adler and Kwon (2002) devised a theoretical framework that identifies the sources, benefits, risks, and contingencies of social capital in the context of organizational theory. Their work synthesizes the concept and theory of social capital to support its utility in inter-organizational research.

The supply chain management literature has utilized SCT in investigating the benefits of the social capital derived from supply chain relationships on firm performance (Carey et al. 2011; Krause et al. 2007; Lawson et al. 2008; Min et al. 2008). Krause et al. (2007) suggested that buyer commitment and social capital accumulation with key suppliers can improve buyers' performance. From this perspective, the study highlights the value of social capital developed with key suppliers through supplier development. Lawson et al. (2008) utilized SCT to develop a theoretical model that links social capital to buyer performance, focusing on relational and structural aspects of social capital. Min et al. (2008) presented a conceptual model on the role of social identity and social capital in the supply chain context. They propose that social capital positively influences information sharing, collaboration, and resource exchange among supply chain partners and improves performance. Carey et al. (2011) examined social capital in supply chains based on large manufacturing firms' buyer-supplier relationships. They found a positive impact on social capital on cost performance and innovation.

The literature has addressed the impact of a firm's structural positional attributes on its performance. Zaheer and Bell (2005) utilized SCT to find support for a positive relationship between a firm's network characteristics and its performance. In particular, they considered the role of firms that bridge the structural holes in an inter-organizational network. However, they focused on mutual fund companies, making their results less related to supply chain research. Kim et al. (2011) applied social network analysis in investigating the firms' structural characteristics in a supply network. They utilized three product-level automotive supply networks reported in Choi and Hong (2002), which may raise potential concerns regarding the limited sample. Basole et al. (2018) suggested that structural prominence positively influences firm performance using a sample from the electronics industry. They found that the network position positively influences asset utilization, cost performance, and inventory efficiency. However, they did not focus on supplier performance, examining the relationship at a general firm level.

While existing research has primarily focused on buyer performance, we investigate the impact of the structural dimension of social capital on supplier performance. Examining the structural dimension of social capital on performance may be important because suppliers can jockey for key positions in the network and control the information flow to the buyer. This provides the benefits that can be leveraged in positive ways. In sum, we posit the following:

H2*: The structural efficiency of a supplier is positively associated with its performance.*

3.2.3. The Moderating Role of Structural Efficiency

In terms of operational and structural efficiencies, we expect a potential moderating role of structural efficiency in the relationship between operational efficiency and firm performance. The literature also confirms the joint effect between firms' internal capabilities and the value of social capital from external inter-firm relationships. Burt (1997) claims that a firm's internal capabilities are contingent on its social capital. In other words, firms should utilize external relationships to seek more business opportunities and thus benefit from internal resources. Lee et al. (2001) show that external relationships with collaborative partners (e.g., venture capital and universities) and internal capabilities positively affect firm performance.

The above discussion suggests that internal capabilities and external social capital should be simultaneously considered in understanding firm performance. This study expands the implication to the supply chain context to examine structural efficiency's moderating effect on the focal relationship between operational efficiency and performance. In other words, we posit that suppliers that have both high structural efficiency and operational efficiency will have greater performance. Specifically, suppliers with prominent positions in the supply network will take advantage of their efficient use of internal resources to attain greater performance. Suppliers that occupy structurally important positions in the network can better leverage network resources. A prominent network position allows a firm to have better access to external information and knowledge, which are sources of innovative practices (Bell, 2005). Bellamy et al. (2014) also suggest that network accessibility and connectedness positively influence firm innovation. To this end, these suppliers can exhibit greater performance because of learning and innovation accomplished via their network position. Furthermore, they will also have higher visibility and coordinate external information better than other suppliers while improving their internal efficiencies.

In contrast, suppliers that are not centrally positioned may find it difficult to generate value from their internal resources because of limited resources and information exchange opportunities with other entities. This is likely to hinder internal planning and control, reducing their ability to leverage internal systems and processes more efficiently. Based on the above discussion, we devise our hypothesis on the potential moderating role of structural efficiency on the focal relationship. Thus, suppliers high in structural efficiency will benefit more from making operational efficiency gains to improve performance.

H3: The structural efficiency of a supplier positively moderates the relationship between its operational efficiency and performance.

3.3. Operationalization of Variables and Data

3.3.1. Operationalization of Efficiencies

We operationalize the efficiency measures (i.e., operational efficiency and structural efficiency) via data envelopment analysis (DEA), which evaluates the relative efficiencies of a set of decision-making units (DMUs) by utilizing multiple input and output measures (Charnes et al. 1978). We first define operational efficiency as the effectiveness of a supplier's utilization of its resource inputs in generating outputs (Priem and Butler, 2001; Coelli et al. 2005).

There is no universally accepted definition of operational efficiency. The literature has captured operational efficiency through various dimensions, such as cost, quality, delivery, and flexibility. For example, Cleveland et al. (1989) use cost, quality, dependability, and flexibility to measure manufacturing performance. In contrast, the extant literature has also relied on survey-based perceptual measures of operational performance (Ketokivi and Schroeder 2004). In this study, we adopt a resource utilization standpoint and use the DEA to overcome the uni-dimensional aspect of existing measures of operational efficiency. Flynn and Flynn (2004) assert that a single dimension of operational and manufacturing capabilities may not adequately represent the underlying multi-dimensional construct. Prior research has also utilized multi-dimensional approaches in capturing a firm's operational efficiency. Talluri et al. (2013) measure a firm's manufacturing efficiency using cost, quality, time, flexibility, and innovativeness as inputs and ROA, ROI as outputs of the DEA model. Jacobs et al. (2016) propose a measure for operational productivity by utilizing labor, inventory, and fixed assets as inputs and firm sales as the output of the DEA model.

In evaluating operational efficiency, we utilize labor (based on the number of employees), property, plants, and equipment as inputs to reflect on various resources a firm utilizes and use sales as the output in the DEA model. The DEA model enables the assessment of relative efficiency among suppliers across the network, without making specific assumptions avoiding the production process. It also avoids potential misspecification problems. This study uses a constant return-to-scale model to construct these independent variables as we control for firm size in the main analysis (Charnes et al. 1978). To this end, operationally efficient suppliers maximize their sales while utilizing minimal labor and assets.

We define structural efficiency from a social capital perspective based on the structural position of a node within a network (Borgatti and Everett 1992; Knoke and Burt 1983). Thus, if a firm is structurally efficient, it has an important network position. However, existing studies rely on a single dimension of network centrality (e.g., degree, eigenvector) to measure structural prominence. They do not fully capture the various structural position dimensions reflected through various node-level centrality metrics in SNA despite the significance of each measure. To overcome such approaches' limitations, we suggest a holistic measure of structural efficiency, operationalized as a weighted ratio of various centrality measures.

We use four node-level centrality metrics as inputs and outputs in the DEA model to operationalize structural efficiency. These node-level centrality metrics capture various aspects of the structural position of a node. We follow established definitions of the types of node centrality (Marsden 1990; Marsden 2005; Scott and Carrington 2011; Wasserman and Faust 1994) in the operationalization of the measures.

First, degree centrality is defined as the sum of adjacent edges. Degree centrality is the simplest measure based on the number of connections each node holds. In our context, degree centrality represents the number of supply chain relationships held by a first-tier supplier or its degree of influence. Second, betweenness centrality measures the number of times each node exists on the shortest path between other nodes. It identifies the nodes that act as bridges in a network. A high betweenness centrality score indicates that the firm has a brokerage role in the supply network and can exert control and influence over the relationships between disparate entities within the network. Third, eigenvector centrality measures a supplier's ability to connect with influential partners within a network (Polidoro Jr et al. 2011; Kim and Zhu 2018). It extends the degree centrality metric by considering the number of direct links and links of connected nodes, assuming that a node is more important and influential if connected to other influential nodes. Lastly, closeness centrality explains the average distance of a certain node to all other nodes. It indicates how a node influences the entire network in terms of speed due to its relative distance to others. In this study, if a supplier has high farness, it means the supplier occupies a distant and remote supply network position.

Shao et al. (2018) provide a unified metric called the Nexus Supplier Index (NSI) that combines multiple centrality measures via DEA, as discussed below. The model maximizes the ratio of the weighted sum of outputs (degree, betweenness, eigenvector) to the weighted sum of input (farness) for a supplier *p*, subject to the constraints that the weighted ratios of all suppliers in the set are less than or equal to 1. In other words, a structurally efficient supplier reveals its influence, power, and control over the network in terms of degree, betweenness, and eigenvector centralities while occupying a position close to other entities. The characterization of inputs and outputs in evaluating structural efficiency is based on the logic that factors for which lower levels are better are treated as inputs and factors for which higher levels are better are treated as outputs. Thus, farness, defined as the reciprocal of closeness centrality, is considered as the input. Degree, betweenness, and eigenvector centralities are treated as outputs.

$$\text{Maximize } NSI_p = \frac{\alpha D_p + \beta B_p + \gamma V_p}{\sigma F_p}$$

$$\text{subject to} \quad \frac{\alpha D_i + \beta B_i + \gamma V_i}{\sigma F_i} \leq 1 \; (i = 1, \ldots, N)$$

$$\alpha, \beta, \gamma, \sigma \geq 1$$

D = degree centrality, *B* = betweenness centrality, *V* = eigenvector centrality, *F* = farness
α, β, γ, σ = weights to degree centrality, betweenness centrality, eigenvector centrality, and farness

We revise the index suggested by Shao et al. (2018) to overcome the measure's limitation. Because their model treats farness as the input in the DEA model, the measure receives a fixed weight (i.e., $\sigma = 1/F$). The restricted weight of the farness measure undermines one of the strengths of DEA, that is, the unrestricted weight flexibility on the network measures. To overcome this issue, we propose a revised formulation by placing a dummy unit value of 1 for input and the four centrality measures as outputs of the DEA model. By doing so, we restore the unrestricted weight flexibility strength to the DEA model by allowing a DMU to emphasize each of the four centrality measures appropriately. We can also retain the original closeness centrality metric instead of creating a reciprocal-based farness measure. To this end, our model maximizes the ratio of the weighted sum of outputs (degree, betweenness, closeness, and eigenvector) for a supplier, subject to the constraints, with a dummy input of 1. These metrics are operationalized for all first-tier suppliers, using UCINET 6 to represent suppliers' structural prominence. The non-linear version of our revised DEA model is presented below:

$$\text{Maximize } SE_p = \frac{\alpha D_p + \beta B_p + \gamma V_p + \delta C_p}{\sigma}$$

$$\text{subject to} \quad \frac{\alpha D_i + \beta B_i + \gamma V_i + \delta C_i}{\sigma} \leq 1 \ (i = 1, \dots, N)$$

$$\alpha, \beta, \gamma, \delta \ \geq 1$$

D = degree centrality, *B* = betweenness centrality, V = eigenvector centrality, *C* = closeness centrality
α, β, γ, δ = weights to degree centrality, betweenness centrality, eigenvector centrality, and closeness centrality

The linearized version of the DEA model is as follows.

$$\text{Maximize } SE_p = \alpha D_p + \beta B_p + \gamma V_p + \delta C_p$$

$$\text{subject to} \quad \alpha D_i + \beta B_i + \gamma V_i + \delta C_i - \sigma \leq 0 \ (i = 1, \dots, N)$$

$$\sigma = 1$$

$$\alpha, \beta, \gamma, \delta \ \geq 1$$

D = degree centrality, *B* = betweenness centrality, V = eigenvector centrality, *C* = closeness centrality
α, β, γ, δ = weights to degree centrality, betweenness centrality, eigenvector centrality, and closeness centrality

3.3.2. Supplier Performance

In capturing supplier performance, we utilize multiple dependent variables for a comprehensive investigation. Specifically, we consider a supplier's profitability, cost performance, inventory efficiency, and intangible market value. This allows for a multi-dimensional investigation of supplier performance because each metric is aligned with the buying focal firm's strategic priorities based on the surrounding environment. For example, focal firms in the auto industry would emphasize profit maximization and cost minimization in assessing their supplier base because margins are generally restricted. In addition, auto suppliers also vie to be important by focusing on internal processes and creating product and process competencies within the supply network. This allows them to emphasize maximizing intangible value from network resources. The measures are operationalized based on the data obtained from the COMPUSTAT North America – Fundamentals – Annual database.

Firm profitability (ROA): First, return on assets (ROA) measures overall asset utilization and profitability, depicts how a firm utilizes its resources for financial earnings (Basole et al. 2018; Hendricks and Singhal 2008). It is calculated as the firm's earnings before interest, taxes, depreciation, and amortization (EBITDA) divided by total assets (AT).

Cost performance (COGS/SALE): The cost of goods sold divided by sales (COGS/SALE) measures the proportion of firm sales that covers the cost of the product or inventory sold (Greer and Theuri 2012). The ratio indicates a cost-based efficiency such that firms with lower COGS/SALE values have a cost advantage over other suppliers in the network (Corbett et al. 2005).

Inventory performance (INVT/SALE): Inventory value over sales (INVT/SALE) represents a firm's operational capability in inventory management (Capkun et al. 2009; Shah and Shin 2007; Swamidass 2007). For the same sales level, a supplier that efficiently manages its inventory should have a lower INVT/SALE value than other suppliers. We use the average inventory value via $(INVT_t + INVT_{t-1})/2$ to calculate the inventory level in the numerator.

Intangible value (Tobin's q): Tobin's q is a ratio of the firm's market value to its replacement cost (Lindenberg and Ross 1981). We measure Tobin's q following Chung and Pruitt (1994), calculating it as (MKVALT + PSLTK + DEBT) / AT, where MKVALT is the share price multiplied by the common shares outstanding, PSLTK is the liquidation value of the outstanding preferred stock, and DEBT is the sum of the book value of inventories (INVT), long-term debt (DLTT), and current liabilities (LCT) minus current assets (ACT).

3.3.3. Control Variables

We control for several other factors that might influence the dependent variables and/or the relationship between the independent and dependent variables. Consistent with existing literature that deals with firm-level performance (Miller 2006; Zhou 2011), we control for firm size, R&D intensity, and capital intensity. Both R&D intensity and capital intensity are common controls for firm performance. For instance, firms high in R&D can produce more successful products, and higher performing firms tend to spend more on R&D. R&D intensity is measured as R&D expenses divided by sales (XRD/SALE). Capital intensity is measured as total assets divided by sales (AT/SALE). We then control for firm size because larger firms may benefit from economies of scale and influence the relationships we are interested in. We use log-transformed total employees (EMP) as a proxy for firm size. Lastly, we also control for year-specific effects.

3.3.4. Data and Summary Statistics

Bloomberg and Factset are the most widely accepted data sources for academic research among the various supply chain database providers. The relationships in the databases are identified through various sources, including SEC filings, press releases, and analyst reports, and therefore, the supply chain relationship information in such databases is richer and more comprehensive than those obtained only from SEC filings. Researchers have been utilizing Bloomberg (Agarwal et al.

2017; Elking et al. 2017; Osadchiy et al. 2016; Schwieterman et al. 2018) and Factset (Osadchiy et al. 2018; Wang et al. 2020; Gofman et al. 2020; Andrade and Chhaochharia 2018) data to address research questions from a network perspective. In this study, we formulate a network-level dataset from the buyer-supplier relationship records using the *Factset Revere* S*upply Chain Relationship* database. Factset is more comprehensive in collecting historical data than Bloomberg SPLC or COMPUSTAT (Osadchiy et al. 2018). It allows researchers to access information on supply chain relationships across multiple years, which is more difficult through the Bloomberg database.

We use the buyer-supplier relationship data from the global automotive industry for four years, from 2015 to 2018 to investigate our research questions. To construct a comprehensive automotive network, we set the largest 20 global automotive manufacturers as the focal companies. These companies represent more than 80% of the total automotive production worldwide, based on the OICA (International Organization of Motor Vehicle Manufacturers) report (OICA 2017). We first collect the relationships between the focal companies and their direct first-tier suppliers by labeling the focal companies as buyers. After collecting the buyer-supplier relationships for the first-tier level, we repeat the process to collect tier-2 data by setting first-tier suppliers as buyers. We then convert the collected information into a consolidated network dataset compatible with a specific network analysis software program such as UCINET, Pajek, and Gephi. In a traditional approach that focuses on the companies' ego-centric networks, we cannot observe all relevant parties' complex interconnectedness in the network. Rather than focusing on a specific ego- (a focal company) centered network, we conceptualize the structural position of the suppliers by utilizing all available first-tier and second-tier suppliers in the network to create a socio-centric network that uses the information on entire relationships across all nodes within a social network

(Freeman 1979; Marsden 2002), which reflects the comprehensive supply network of the automotive industry.

Subsequently, we formulate the network-level dataset, calculate various centrality metrics that describe the structural position of suppliers in the network, and use them to compute structural efficiency via DEA. We then collect financial information for each of the first-tier suppliers in our dataset using the Compustat database to calculate operational efficiency. We also gather other financial information from COMPUSTAT to construct control variables. The final sample size is n = 278 (observations) and N = 75 (suppliers), with an average of 3.7 observations per firm. Table 2.1 presents the summary statistics and the correlation matrix for the variables of interest.

Table 2.1 Descriptive Statistics and Correlations (N = 278)

		Mean	**SD**	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
Operational Efficiency	(1)	0.268	0.155	1.000								
Structural Efficiency	(2)	0.809	0.067	-0.186***	1.000							
ROA	(3)	0.114	0.081	-0.018	0.210***	1.000						
COGS/SALE	(4)	0.671	0.139	-0.111*	-0.090	-0.161***	1.000					
INVT/SALE	(5)	0.148	0.071	-0.117*	-0.122**	-0.508***	-0.028	1.000				
Tobin's q	(6)	1.339	0.718	0.022	0.004	0.446***	-0.515***	-0.117*	1.000			
Capital Intensity	(7)	1.201	0.566	-0.078	-0.081	-0.299***	-0.506***	0.379***	0.129*	1.000		
R&D Intensity	(8)	0.061	0.062	0.117*	-0.053	-0.353***	-0.562***	0.228***	0.232***	0.503***	1.000	
Firm Size	(9)	2.068	1.910	-0.204***	0.385***	0.440***	0.200***	-0.311***	0.033	-0.081	-0.319***	1.000

$^*p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

3.4. Results

We present the regression results for each dependent variable in Table 2.2. We estimated panel regression models for various performance metrics to examine the relationships of interest. We ran Hausman (1978) specification tests to determine the use of the fixed versus random-effects model (Greene 2003). The test results are insignificant for all dependent variables, implying that the random-effects model should be preferred to the fixed-effects model. Also, considering the short length of the panel (T=4), we present random-effects models as the main results. However, researchers point out that selecting the appropriate model should not be solely technical but guided by the research objective and context (Clark and Linzer 2015; Bell and Jones 2015). Therefore, we provide fixed-effect model results in the robustness section. The results are largely consistent for both random-effects and fixed-effects models.

For each dependent variable, we estimate three models. We first enter the control variables in the first model, then add the main independent variables in the second model, and then include the product term between efficiency scores in the third model to test the interaction effect. We also include year dummies in all models to account for any exogenous year-specific events that may influence firm results. To illustrate the interaction effects between structural and operational efficiencies, we additionally provide the margins plots by taking the high and low levels of structural efficiency as one standard deviation above and below the mean value, following the recommendations of Aiken and West (1991).

Table 2.2 Regression Model Results (N = 278)

Dependent variable	*ROA*			*COGS/SALE*			*INVT/SALE*			*Tobin's q*		
	Model 1.1	Model 1.2	Model 1.3	Model 2.1	Model 2.2	Model 2.3	Model 3.1	Model 3.2	Model 3.3	Model 4.1	Model 4.2	Model 4.3
Constant	0.175*** (0.022)	0.157*** (0.022)	0.158*** (0.022)	0.685*** (0.023)	0.703*** (0.030)	0.704*** (0.030)	0.111*** (0.017)	0.131*** (0.018)	0.131*** (0.018)	1.483*** (0.185)	1.405*** (0.191)	1.424*** (0.195)
Firm Size	0.011* (0.005)	0.016** (0.005)	0.017** (0.005)	0.010† (0.006)	0.006 (0.007)	0.006 (0.007)	-0.008† (0.004)	-0.013** (0.005)	-0.013** (0.005)	0.032 (0.047)	0.057 (0.044)	0.058 (0.044)
Capital Intensity	-0.046*** (0.010)	-0.038*** (0.010)	-0.038*** (0.010)	-0.004 (0.009)	-0.009 (0.011)	-0.009 (0.011)	0.036** (0.012)	0.029* (0.011)	0.028* (0.011)	-0.271† (0.140)	-0.250 (0.153)	-0.256† (0.155)
R&D Intensity	-0.528** (0.238)	-0.512** (0.239)	-0.510** (0.237)	-0.404** (0.150)	-0.482** (0.164)	-0.488** (0.165)	0.207 (0.133)	0.163 (0.117)	0.174 (0.113)	0.663 (1.806)	0.470 (1.775)	0.466 (1.757)
Operational Efficiency (OE)		0.173*** (0.052)	0.172*** (0.051)		-0.097† (0.056)	-0.096† (0.056)		-0.143*** (0.040)	-0.150*** (0.039)		0.498 (0.530)	0.504 (0.517)
Structural Efficiency (SE)		0.014 (0.056)	0.028 (0.052)		-0.033 (0.042)	-0.036 (0.041)		-0.004 (0.036)	0.009 (0.036)		-0.914 (0.825)	-0.712 (0.788)
OE × SE			0.661** (0.255)			-0.115 (0.172)			0.542* (0.243)			5.140* (2.262)
Year Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Clustered standard errors in parentheses; †p < 0.10, *p < 0.05, **p < 0.01, ***p < 0.001.

3.4.1. Main results

3.4.1.1. Profitability (ROA)

Models 1.1 through 1.3 in Table 2.2 present the results for the models with ROA as the dependent variable. We find support for Hypothesis 1, but we do not find support for Hypothesis 2. The coefficient of structural efficiency in Model 1.2 is not significant, while operational efficiency is positive and significant ($b = 0.173, p < .001$). The results indicate that operationally efficient first-tier suppliers exhibit better performance through higher profitability. We also find support for Hypothesis 3, which posits a positive interaction effect between structural and operational efficiencies. The coefficient of the product term between operational efficiency and structural efficiency in Model 1.3 is positive and significant, as expected for ROA ($b = 0.661, p < .01$). Figure 2.1 depicts the predicted margins plots for Model 1.3 and provides a visual interpretation of the result. Although there is no significant evidence of the direct impact of structural efficiency on supplier profitability, we observe a positive interaction between two efficiency measures on the profitability of first-tier suppliers.

3.4.1.2. Cost Performance (COGS/SALE)

Models 2.1 through 2.3 in Table 2.2 present the results for cost performance (COGS-to-sales ratio) as the dependent variable. A lower COGS-to-sales ratio will represent a higher cost advantage for a firm; therefore, a negative coefficient suggests better performance through higher manufacturing productivity. To this end, we find support for Hypothesis 1 through the negative coefficient of operational efficiency in Model 2.2 ($b = -0.097, p < .10$). The result indicates that operationally efficient first-tier suppliers exhibit better cost performance through lower COGS-to-sales ratios. However, we do not find support for Hypotheses 2 and 3. In other words, we find no evidence for either a direct or moderating impact on structural efficiency on the cost performance of first-tier suppliers.

3.4.1.3. Inventory Performance (INVT/SALE)

Models 3.1 through 3.3 in Table 2.2 present the results for the average inventory-to-sales ratio as the dependent variable. A lower inventory-to-sales ratio represents the efficient management of inventory levels. Therefore, the negative coefficient of the ratio suggests superior inventory performance. We find support for Hypothesis 1 but no support for Hypothesis 2. The coefficient of operational efficiency in Model 3.2 is negative and significant ($b = -0.143, p < .001$), indicating that operationally efficient first-tier suppliers manage their inventory more efficiently than others. We fail to find support for Hypothesis 3. The coefficient of the product term between operational and structural efficiencies in Model 3.3 is positive and significant ($b = 0.542, p < .05$), which is the opposite of what Hypothesis 3 predicted. This indicates a negative moderation effect on structural efficiency on the impact of operational efficiency on suppliers' inventory management efficiency. Figure 2.2 depicts the predicted margins plots for Model 3.3 on inventory performance.

3.4.1.4. Intangible Value (Tobin's q)

Model 4 in Table 2.2 presents the regression results for the models with Tobin's *q* as the dependent variable. Tobin's *q* is a measure of a firm's intangible value (Megna and Klock 1993). We do not find support for Hypothesis 1 nor Hypothesis 2. In other words, we do not find any direct effects on operational and structural efficiencies on the intangible value of the supplier. However, we find support for Hypothesis 3 in the coefficient of the product term between two efficiency scores in Model 4.3, which is positive and significant ($b = 5.140, p < .05$). The interaction effect depicted in Figure 2.3, estimated based on Tobin's *q*, shows the moderating role of structural efficiency on the relationship between operational efficiency and intangible value of the first-tier suppliers in the automotive industry.

Figure 2.1 Margins Plots of Estimated ROA for Model 1.3.

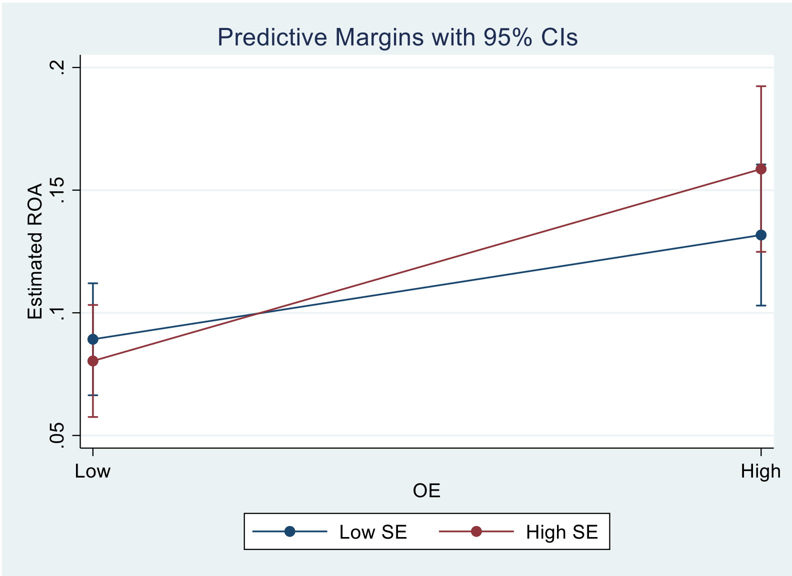


Figure 2.2 Margins Plots of Estimated INVT/SALE for Model 3.3.

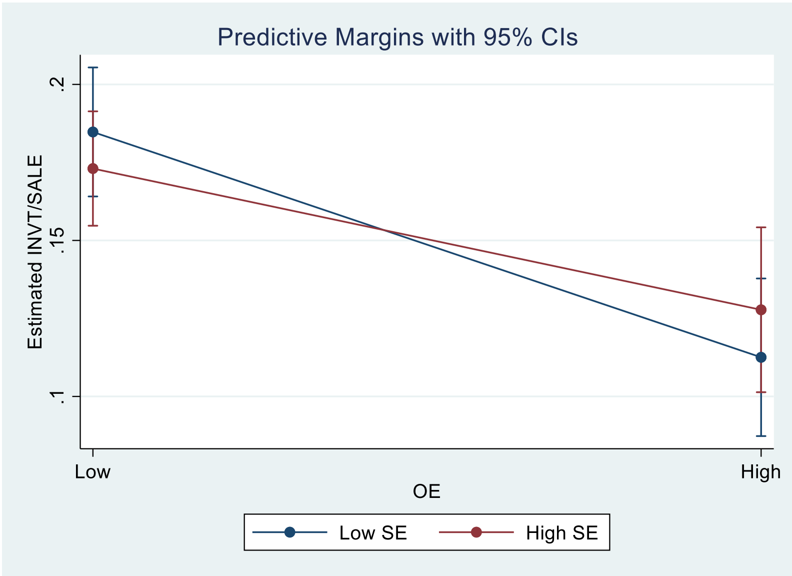
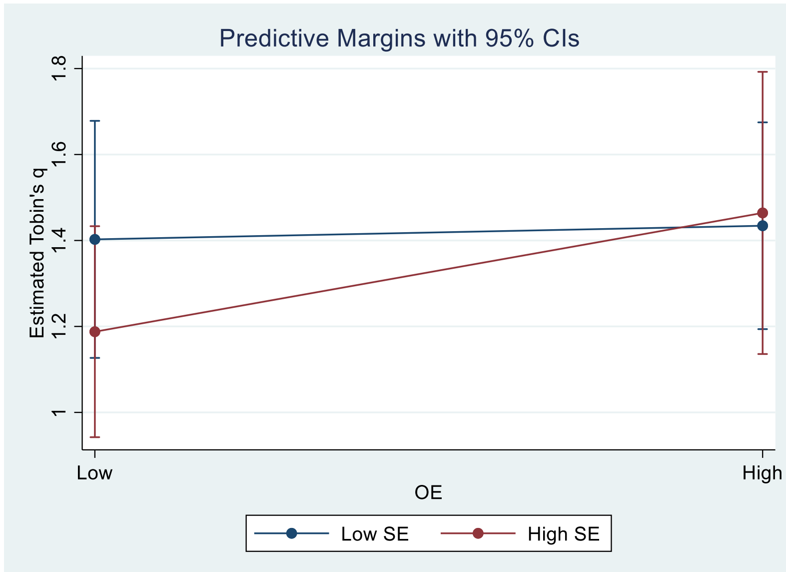


Figure 2.3 Margins Plots of Estimated Tobin's q for Model 4.3.



3.4.2. Robustness Tests

To ensure the robustness of our two DEA-based efficiency measures, we first ran the models with additional sets of scores using super-efficiency and cross-efficiency models. These models provide a way to rank efficient DMUs, all of which have a score of 1 in traditional DEA models. The super-efficiency model assumes that the DMU being evaluated is excluded from the reference set (Andersen and Petersen 1993) and enables efficiency scores greater than 1 for efficient DMUs. Cross-efficiency evaluation has also been suggested as an alternative method of ranking DMUs (Doyle and Green 1994), and the cross-efficiency scores are obtained via peer evaluation. The regression model results obtained using super-efficiency and cross-efficiency scores for both operational and structural efficiency operationalization are presented in Table 2.3 and 2.4, respectively. Additionally, we provide the results of fixed-effects models in Table 2.5 to check for the robustness of our random-effects estimation.

Lastly, we ran a two-stage least-squares (2SLS) estimation to account for potential endogeneity concerns. Unlike a more established operational efficiency measure, structural efficiency may be influenced by omitted predictors in our analysis. To address potential endogeneity concerns, Basole et al. (2018) utilized degree and eigenvector centralities as potential instrumental variables for their main independent variable (Bonacich Centrality). Because the DEA-based operationalization of structural efficiency in this study already includes degree and eigenvector centralities, we treat log-transformed beta centrality as the instrumental variable for structural efficiency in this research.

We use STATA's *xtivreg* command for this 2SLS estimation on our panel dataset. Because our primary findings include the product term between two efficiency measures, we manually generate the product term between lagged operational efficiency and log-transformed beta centrality and use it as the instrumental variable. We also establish the appropriateness of the instruments via underidentification, overidenficiation, and weak instrument tests using the *xtoverid* command (Schaffer and Stillman 2006). Table 2.6 reports the results of the panel 2SLS regression models, which are largely consistent with the main results.

Table 2.3 Regression Model Results with Super-Efficiency Operationalization (N = 278)

Dependent variable	*ROA*			*COGS/SALE*			*INVT/SALE*			*Tobin's q*		
	Model 1.1	Model 1.2	Model 1.3	Model 2.1	Model 2.2	Model 2.3	Model 3.1	Model 3.2	Model 3.3	Model 4.1	Model 4.2	Model 4.3
Constant	0.175*** (0.022)	0.162*** (0.021)	0.159*** (0.022)	0.685*** (0.023)	0.697*** (0.026)	0.700*** (0.026)	0.111*** (0.017)	0.128*** (0.017)	0.126*** (0.017)	1.483*** (0.185)	1.415*** (0.189)	1.417*** (0.197)
Firm Size	0.011* (0.005)	0.014** (0.005)	0.016** (0.005)	0.010† (0.006)	0.008 (0.006)	0.007 (0.007)	-0.008† (0.004)	-0.012* (0.004)	-0.011** (0.004)	0.032 (0.047)	0.051 (0.044)	0.061 (0.045)
Capital Intensity	-0.046*** (0.010)	-0.040*** (0.010)	-0.038*** (0.010)	-0.004 (0.009)	-0.008 (0.010)	-0.009 (0.011)	0.036** (0.012)	0.029* (0.011)	0.029* (0.011)	-0.271† (0.140)	-0.255† (0.149)	-0.251 (0.154)
R&D Intensity	-0.528** (0.238)	-0.527** (0.237)	-0.517** (0.234)	-0.404** (0.150)	-0.457** (0.156)	-0.476** (0.161)	0.207 (0.133)	0.183 (0.119)	0.196† (0.119)	0.663 (1.806)	0.471 (1.788)	0.454 (1.741)
Operational Efficiency (OE)		0.114* (0.051)	0.161*** (0.043)		-0.065* (0.031)	-0.081* (0.036)		-0.130*** (0.025)	-0.114** (0.038)		0.337 (0.371)	0.600 (0.385)
Structural Efficiency (SE)		0.010 (0.051)	0.037 (0.049)		-0.038 (0.040)	-0.046 (0.039)		-0.007 (0.031)	0.002 (0.031)		-0.880 (0.738)	-0.636 (0.734)
OE × SE			0.794*** (0.300)			-0.221 (0.168)			0.255 (0.173)			4.727* (2.116)
Year Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Clustered standard errors in parentheses; †p < 0.10, *p < 0.05, **p < 0.01, ***p < 0.001.

Table 2.4 Regression Model Results with Cross-Efficiency Operationalization (N = 278)

Dependent variable	*ROA*			*COGS/SALE*			*INVT/SALE*			*Tobin's q*		
	Model 1.1	Model 1.2	Model 1.3	Model 2.1	Model 2.2	Model 2.3	Model 3.1	Model 3.2	Model 3.3	Model 4.1	Model 4.2	Model 4.3
Constant	0.175*** (0.022)	0.157*** (0.021)	0.158*** (0.021)	0.685*** (0.023)	0.703*** (0.030)	0.703*** (0.030)	0.111*** (0.017)	0.132*** (0.018)	0.132*** (0.018)	1.483*** (0.185)	1.400*** (0.190)	1.416*** (0.193)
Firm Size	0.011* (0.005)	0.016** (0.005)	0.017** (0.005)	0.010† (0.006)	0.006 (0.007)	0.006 (0.007)	-0.008† (0.004)	-0.013** (0.005)	-0.013** (0.004)	0.032 (0.047)	0.058 (0.044)	0.061 (0.043)
Capital Intensity	-0.046*** (0.010)	-0.038*** (0.010)	-0.038*** (0.010)	-0.004 (0.009)	-0.009 (0.012)	-0.009 (0.012)	0.036** (0.012)	0.028* (0.011)	0.027* (0.011)	-0.271† (0.140)	-0.246 (0.154)	-0.253 (0.156)
R&D Intensity	-0.528** (0.238)	-0.512* (0.237)	-0.506* (0.234)	-0.404** (0.150)	-0.484** (0.165)	-0.487** (0.166)	0.207 (0.133)	0.163 (0.115)	0.178 (0.110)	0.663 (1.806)	0.452 (1.780)	0.463 (1.759)
Operational Efficiency (OE)		0.190** (0.063)	0.188** (0.062)		-0.110 (0.069)	-0.108 (0.069)		-0.172*** (0.048)	-0.180*** (0.046)		0.608 (0.619)	0.618 (0.607)
Structural Efficiency (SE)		0.024 (0.059)	0.035 (0.056)		-0.036 (0.045)	-0.038 (0.045)		-0.005 (0.038)	0.005 (0.036)		-0.944 (0.863)	-0.800 (0.828)
OE × SE			0.795* (0.348)			-0.133 (0.219)			0.713** (0.246)			6.117* (2.691)
Year Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Clustered standard errors in parentheses; †p < 0.10, *p < 0.05, **p < 0.01, ***p < 0.001.

Table 2.5 Regression Model Results with Fixed-effects Estimation (N = 278)

Dependent variable	*ROA*			*COGS/SALE*			*INVT/SALE*			*Tobin's q*		
	Model 1.1	Model 1.2	Model 1.3	Model 2.1	Model 2.2	Model 2.3	Model 3.1	Model 3.2	Model 3.3	Model 4.1	Model 4.2	Model 4.3
Constant	0.237*** (0.044)	0.146** (0.047)	0.145** (0.046)	0.652*** (0.027)	0.659*** (0.042)	0.659*** (0.042)	0.088** (0.031)	0.153*** (0.038)	0.152*** (0.036)	2.085*** (0.277)	2.050*** (0.380)	2.043*** (0.375)
Firm Size	0.004 (0.016)	0.035* (0.016)	0.036* (0.016)	0.010 (0.010)	0.008 (0.013)	0.008 (0.013)	-0.003 (0.014)	-0.025† (0.015)	-0.024† (0.014)	0.155 (0.129)	0.156 (0.140)	0.174 (0.141)
Capital Intensity	-0.057*** (0.012)	-0.043*** (0.012)	-0.044*** (0.012)	0.008 (0.010)	0.006 (0.013)	0.007 (0.013)	0.035** (0.013)	0.026* (0.013)	0.025* (0.012)	-0.540* (0.207)	-0.534* (0.227)	-0.548* (0.225)
R&D Intensity	-1.097* (0.419)	-0.822† (0.448)	-0.816† (0.437)	-0.059 (0.182)	-.0.081 (0.213)	-0.082 (0.213)	0.417* (0.162)	0.217 (0.147)	0.223 (0.136)	-7.468** (2.724)	-7.703** (2.636)	-7.683** (2.566)
Operational Efficiency (OE)		0.302*** (0.071)	0.288*** (0.069)		-0.024 (0.082)	-0.022 (0.082)		-0.217** (0.069)	-0.234* (0.069)		-0.089 (1.150)	-0.250 (1.159)
Structural Efficiency (SE)		-0.031 (0.057)	-0.019 (0.057)		-0.001 (0.038)	-0.002 (0.038)		0.009 (0.038)	0.024 (0.036)		-1.054 (0.827)	-0.888 (0.808)
OE × SE			0.521† (0.294)			-0.070 (0.184)			0.627* (0.263)			4.436 (3.112)
Year Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Clustered standard errors in parentheses; †p < 0.10, *p < 0.05, **p < 0.01, ***p < 0.001.

Table 2.6 Regression Model Results with 2SLS IV Estimation for the Interaction (N = 243)

Dependent variable	*ROA*			*COGS/SALE*			*INVT/SALE*			*Tobin's q*		
Instrumental variable: Ln(Beta)	Model 1.1	Model 1.2	Model 1.3	Model 2.1	Model 2.2	Model 2.3	Model 3.1	Model 3.2	Model 3.3	Model 4.1	Model 4.2	Model 4.3
Constant	0.171*** (0.023)	0.160*** (0.021)	0.160*** (0.020)	0.688*** (0.024)	0.712*** (0.030)	0.713*** (0.030)	0.112*** (0.018)	0.132*** (0.018)	0.132*** (0.018)	1.483*** (0.185)	1.400*** (0.220)	1.414*** (0.224)
Firm Size	0.015* (0.006)	0.020** (0.007)	0.021*** (0.006)	0.011 (0.008)	0.005 (0.009)	0.004 (0.009)	-0.010† (0.005)	-0.016* (0.006)	-0.015** (0.006)	0.032 (0.047)	0.057 (0.047)	0.062 (0.046)
Capital Intensity	-0.046*** (0.010)	-0.038*** (0.010)	-0.039*** (0.010)	-0.003 (0.010)	-0.009 (0.013)	-0.009 (0.013)	0.037** (0.012)	0.029* (0.012)	0.029* (0.012)	-0.271† (0.140)	-0.248 (0.153)	-0.256 (0.157)
R&D Intensity	-0.530* (0.247)	-0.499* (0.244)	-0.499* (0.241)	-0.438** (0.169)	-0.510** (0.182)	-0.521** (0.180)	0.202 (0.144)	0.158 (0.125)	0.163 (0.124)	0.663 (1.806)	0.503 (1.767)	0.500 (1.734)
Operational Efficiency (OE)		0.187*** (0.054)	0.186*** (0.053)		-0.109† (0.061)	-0.099 (0.063)		-0.158*** (0.041)	-0.162*** (0.041)		0.493 (0.529)	0.501 (0.509)
Structural Efficiency (SE)		0.160 (0.206)	0.160 (0.187)		0.067 (0.100)	0.069 (0.095)		-0.003 (0.079)	-0.002 (0.079)		-0.935 (1.865)	-0.895 (1.744)
OE × SE			0.891* (0.405)			-0.650+ (0.388)			0.114 (0.382)			8.607* (4.002)
Year Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Clustered standard errors in parentheses; †p < 0.10, *p < 0.05, **p < 0.01, ***p < 0.001.

3.5. Discussion and Conclusion

3.5.1. Academic Contributions

The existing literature has shown that the structural characteristics of a firm's network have a positive impact on its performance. Choi and Kim (2008) note that network structural characteristics enable a buying company to function better when selecting and managing suppliers for long-term relationships. Kim (2014) used survey data collected from the US to show that suppliers' structural embeddedness helps enhance a buying firm's operational performance. Furthermore, suppliers' relational embeddedness mediates the influence of the relationship between network structure and operational performance. Bellamy et al. (2014) also suggested a positive impact on network-oriented traits on innovation outcomes.

However, our research adds a new perspective on the network-oriented supply chain literature. First, we propose structural efficiency, a multi-dimensional measure that accounts for a firm's various positional attributes. Unlike previous studies that rely on a single centrality measure, our approach considers degree, betweenness, closeness, and eigenvector centralities simultaneously via DEA. Second, we suggest a moderating role of structural efficiency in the relationship between operational efficiency and supplier performance. We do not find support for the direct effect of structural efficiency on firm performance, which contradicts the existing literature that emphasizes the positive direct impact of structural position on firm performance (Bellamy et al. 2014; Basole et al. 2018).

We provide potential explanations for the insignificant direct impact of structural efficiency on supplier performance. First, we suggest that the structural characteristics of a supplier within a network should be interpreted depending on the performance indicator of interest. Our results show different results for each supplier performance variable: profitability, cost performance, inventory performance, and intangible value. Also, we claim that industry context matters in investigating the relationship between structural efficiency and performance. Previous studies have often investigated the positive impact of network characteristics on a firm's innovation performance in the high-tech electronics industry (Bellamy et al. 2014; Basole et al. 2018). In such a business environment, collaboration, knowledge exchange, and information sharing may play a more crucial role in explaining firm performance. However, we focus on the automotive industry, where operational performance is more important than in the high-tech industry. In a supply network where the buyer-supplier relationships are more transactional than collaborative, we may not expect a direct impact on structural prominence on performance. To examine this potential external influence, future researchers may focus on a comparative analysis of how the impact of structural efficiency on supplier performance varies across industry settings.

Although we did not find support for the direct effects of structural efficiency on performance, we found the moderating effects of structural efficiency on the focal relationship between operational efficiency and supplier performance for three performance measures (ROA, INVT/SALE, and Tobin's *q*). Figure 2.1 presents the interaction effect through the estimated means of ROA, indicating that suppliers who possess a prominent structural position in the supply network perform better by utilizing both internal resources and external social capital together in attaining higher levels of profitability. Figure 2.2 shows the interaction effect of INVT/SALE. The interaction effect implies that suppliers that are high in structural efficiency may find it challenging to efficiently manage their inventory. For example, if a firm supplies multiple focal companies, it may be difficult for the supplier to manage an inventory with a variety of products and specifications. Lastly, Figure 2.3, concerning the interaction effect of Tobin's *q*, indicates that suppliers that are both centrally positioned in the network and efficient in terms of internal resource utilization will exhibit greater intangible value than others. The margins plot shows that the association between operational efficiency and intangible market value, as measured by Tobin's *q*, is stronger for structurally efficient suppliers.

In this study, we show that structural efficiency plays a moderating role in the relationship between operational efficiency and supplier performance by three key measures. Our findings also allow for the possibility that social capital from supply chain relationships may have a negative effect in a particular context. The literature has been primarily focused on the positive perspective of social capital in inter-firm relationships. However, another stream of the literature suggests a potential "dark side" of social capital (Gargiulo and Benassi 1999; Putzel 1997; Van Deth and Zmerli 2010). In the supply chain context, Villena et al. (2011) also suggested the dark side of supply chain relationships in explaining buyers' performance. From a supplier's standpoint, if the firm is centrally positioned, with many connections in the network, this may lead to increased complexity (Wilding 1998; Milgate 2001; Vachon and Klassen 2002) and poor decision-making (Grover et al., 2006; McFadyen and Cannella, 2004). In the following sections, we discuss the practical contributions of our findings from a supplier selection and evaluation standpoint. Potential directions for future research will also be discussed.

3.5.2. Managerial Implications

In a worldwide supply chain survey (Geodis 2017), most respondents answered that their supply chains were extremely complex. This increased complexity is associated with supply chain visibility concerns. With limited supply chain visibility, firms find it difficult to manage and their supply chains efficiently. Choi et al. (2015) suggest the importance of "hidden" suppliers, which are critical in the supply chain but hard for the focal company to identify. Despite the vast amount of research in the supplier selection and evaluation domain, the industry calls for a more practical and applicable framework to help reveal the critical suppliers within the complex supply base. To this end, the focal firms will be able to identify, select, and manage their key suppliers to manage their supply chains effectively.

First, our results confirm the usefulness of operational efficiency as a potential predictor of various aspects of supplier performance. We find that supplier productivity is positively associated with performance because of operational efficiency on profitability, cost efficiency, and inventory efficiency. This finding confirms the assumption that operational productivity is critical in understanding firm performance at the supplier level. Furthermore, we find no significant association between operational efficiency and intangible value, as measured by Tobin's *q*. This suggests that operational efficiency is less effective in explaining the firm performance metrics derived from stock price information (e.g., Tobin's *q*). One explanation for this is that supplier productivity is less reflected by stock market information because the profitability of automotive suppliers is often driven by the focal firm. We claim that the intangible value measured by Tobin's *q* is only realized for suppliers that exhibit high levels of both structural and operational efficiency. Suppliers high in structural efficiency are typically central to the focal firms, so they probably command more value among automotive OEMs.

Second, we extend the network perspective in supply chain research to the supplier evaluation and selection domain. From a focal company's perspective, our study intends to explain the reasoning that focal companies should be proactive in selecting and managing suppliers that are not only operationally efficient but also structurally efficient to achieve the highest levels of performance. Our study highlights the importance of building and leveraging complex relationships in supply networks from the supplier's standpoint. For example, if a supplier occupies a structurally efficient position in the network, the firm can better utilize operational productivity, together with the power, influence, and visibility derived from connections with other entities in the network. Thus, suppliers should focus on strengthening both their internal capabilities as well as external relationships to succeed. Therefore, the focal firm's supplier assessment should be based on a joint consideration of each supplier's operational and structural efficiencies.

3.5.3. Limitations and Future Research Directions

Our work is not without its limitations. These limitations also suggest potential directions for future research opportunities. First, we do not capture the differences across industries, making it difficult to generalize our findings. Given the nature of our operational efficiency measure, we only focus on manufacturing suppliers (SIC codes 20-39) in the global automotive supply network. The investigation of different industries may require a different operationalization of the efficiency measures. Also, the results may vary depending on the context. If we examine the relationships in a technology-intensive industry, we may observe a direct main effect on structural efficiency on supplier performance because the buyer-supplier relationships are more collaborative than transactional in such settings. In contrast, we may observe a lack of direct and moderating effects on structural efficiency if we consider more stable and functional supply chains.

Second, in investigating the role of operational and structural efficiency in supplier performance, we do not consider the degree of supplier risk. It may require a different research design to assess the risk of suppliers in the complex supply network, but future research could build upon the literature that utilizes social networks to understand supply chain risks (Adenso-Diaz et al. 2012, Bode and Wagner 2015; Käki et al. 2015).

Third, we have a relatively short panel (T=4), from 2015 to 2018. This is because not all firms have reported their financial information online for FY2019 as of yet. Also, the limited credibility of supply chain relationship data before 2015 makes it harder to construct a more comprehensive panel. We hope to supplement our data with additional financial information or newly available data sources in the future.

In summary, we conducted a multi-dimensional investigation of the performance of first-tier suppliers in the global automotive network to provide a comprehensive framework that assists in the focal firm's supplier selection and evaluation decisions. We confirm the criticality of operational efficiency, while we find that structural efficiency alone does not have a direct influence but does play a potential moderating role in supplier performance. We hope to provide useful insights for both researchers and practitioners, as well as interesting avenues for future research.

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CHAPTER 4 - Evaluating the Robustness of Supply Network under Disruptions

4.1. Introduction

The negative effects of supply chain disruptions have brought significant attention to the role and importance of risk management in supply chains (Manuj and Mentzer 2008; Narasimhan and Talluri 2009; Tang 2006; Sodhi et al. 2012). Supply chain disruptions are known to significantly impair the operational and financial performance of companies (Hendricks and Singhal 2003, 2005; Wagner and Bode 2008). They also hamper the productivity and capacity utilization of the buying firm (Ellis et al. 2010).

Global supply chain disruption events require companies to focus on supply chain risk management (Chopra and Sodhi 2014; Matsuo 2015). For example, a fire at a Phillips semiconductor plant in New Mexico cost Ericsson about $400 million (Chopra and Sodhi 2004), and the Japanese tsunami led to an estimated $5.6 billion loss for the automakers in Japan (Automotive News 2012). Global supply chains continue to face the challenges of natural disasters, international conflicts, and pandemics. However, few companies are fully prepared to effectively deal with supply chain disruptions (Aon Risk Solutions 2019).

Despite the numerous supply chain upheavals in the last decade, the recent COVID-19 pandemic has seriously affected global supply chains. For example, global automotive manufacturers, such as Renault, BMW, and Peugeot, have been substantially affected by the COVID-19 crisis, which has resulted in production losses of about 1.5 million vehicles and a negative impact on over a million jobs (IHS Markit 2020; ACEA 2020). The global economy was also greatly affected by the COVID-19 crisis, leading to the deepest global recession in decades (The World Bank 2020). Hence, many researchers have begun to highlight the importance of supply chain resilience and robustness both during and after the pandemic. El Baz and Ruel (2020) studied the role of supply chain risk management (SCRM) in mitigating the effects of disruption and its impact on supply chain resilience and robustness in the context of the COVID-19 outbreak, using structural equation modeling to analyze survey data. Van Hoek (2020) focused on the gap between supply chain research and industry practices to develop a more resilient supply chain. Xu et al. (2020) reviewed the effects of COVID-19 on global supply chains and suggested that enhancing supply chain resilience would be the key to reducing vulnerability during disruptive events.

Designing a robust and resilient supply chain has become even more critical for companies to ensure their survival in the global economy (Simchi-Levi and Simchi-Levi 2020). However, building a supply network structure requires a considerable amount of time and capital investment, which highlights the importance of this research. In this study, we aim to understand the types of supply network structures that are more resilient and robust to disruptions. Effective supply network structures enable focal firms to mitigate the effects of future global crises by allowing them to act pre-emptively to counter disruption events.

Specifically, we apply a network-oriented perspective to assess the robustness of supply networks under the effects of supply disruptions that vary in different network structures. We use two established metrics (i.e., network density and network centralization) to represent different supply network structures. In this study, we used real-world supply chain data collected from the global automotive industry to investigate our models. After we collected the supply network data on the focal companies, we employed a simulation-based approach to assess the effects of supply chain disruptions. We modeled supply chain disruptions by randomly removing suppliers in the network. We then measured the robustness of the supply network by the percentage change in the focal company's structural efficiency (SE) based on the notion of a positive association between positional prominence and the focal company's performance. Hence, we conclude that the stability of the focal company's SE in the presence of disruption provides an effective measure of network robustness. Based on this assertion, we suggest that a robust network is affected less by a supply chain disruption if the SE does not deviate significantly after the disruption from the baseline score before the disruption.

Our approach is of practical relevance to the current business environment. First, we focus on the role of network structures in mitigating the effects of supply chain disruptions. The reduced visibility in recent global supply chains has made it harder for companies to identify vulnerable entities in the supply base. In this study, our network-oriented approach helped the focal firms to understand the complex structure of the supply base to prepare for unexpected disruptions. It also highlighted the importance of a holistic strategy for companies to manage their supply network structure to adequately respond to disruptions. Supply chain disruptions often originate in a focal firm's supply network, not in the focal firm's facility (Kim et al. 2015). Therefore, without careful consideration of the structure of the network, focal firms are unable to attain resilience in their supply chain. Moreover, without a network perspective, companies might be misled by focusing only on a specific supplier or a fraction of their supply base.

Second, the traditional focus on a cost-efficient supply chain pushed the focal companies to have little slack in the system and to increase their dependency on specific suppliers. For example, numerous global manufacturers suffered greatly from the COVID-19 crisis because their supply bases were heavily dependent on quarantined areas in East Asia. A recent report showed that more than 90% of Fortune 1000 companies had part of their supply base in China in regions that were the most affected by the pandemic (Fortune 2020). Based on this experience, the focal companies have learned that they should not rely heavily on a specific area of their supply base to ensure uninterrupted supplies. For example, if a company had a well-distributed (i.e., decentralized) supply base, the firm might have hedged the risk more effectively by alternative sourcing options. Despite the higher costs of multi-sourcing, many companies have shifted to a resilient procurement strategy with a multi-tier sourcing base (Haren and Simchi-Levi 2020). Similarly, companies that have wider global supply chain networks and various distribution channels are known to have responded better to supply chain disruptions caused by COVID-19 (Ernst & Young 2020).

In summary, our findings suggest that dense network structures are more robust under supply chain disruption than sparse network structures. Our findings also showed that decentralized supply networks were more effective in terms of network robustness than centralized supply networks. Additionally, we found that these effects were dependent on the magnitude of the disruption events, such that they were more evident in a severe disruption scenario than in a weak disruption scenario.

We expect that the findings of this research will have implications for both academia and practice. The literature on supply chain risk management has matured substantially in recent decades (Ho et al. 2015; Pournader et al. 2020). However, few studies have focused on supply network structures in terms of risk management (Adenso-Diaz et al. 2012; Kim et al. 2015; Käki et al. 2015), and they have been based primarily on simulation models that do not completely reflect the complex nature of supply chain networks. Our study aimed to fill the knowledge gap regarding the robustness of supply network structures. We provide recommendations for a focal company to improve the robustness of its supply network under disruptions. We highlight the need for firms to understand their network structure to mitigate the consequences of supply chain risks. We also offer managerial guidance for resource allocation in designing supply networks to counter disruptions and emphasize important implications for fortification strategies in operating complex networks.

The rest of the paper is organized as follows. In the next section, we review the relevant literature on SCRM and supply network structures. The third section provides a detailed description of the methodology. We then present our empirical results in the fourth section. Finally, we conclude by offering academic and practical insights and recommend potential directions for future research.

4.2. Literature Review

4.2.1. Supply Chain Risk and Resilience

To mitigate the negative effects of supply chain disruption risks, researchers have undertaken a significant amount of work in the area of SCRM. Previous studies in SCRM mainly examined risk identification, risk assessment, risk mitigation, and risk monitoring (Ho et al. 2015). In terms of risk mitigation, the extant literature suggests various potential strategies and solutions that help deal with the negative consequences of supply chain disruptions. They include risk-sharing contracts (Chen and Yano 2010; Xiao and Yang 2009), early supplier involvement (Zsidisin and Smith 2005), supply base complexity management (Choi and Krause 2006), supplier diversification by dual- or multi-sourcing strategies (Babich et al. 2007; Costantino and Pellegrino 2010; Yu et al. 2009), and risk mitigation strategies based on flexibility and redundancy (Talluri et al. 2013).

In a recent literature review, Pournader et al. (2020) emphasized the importance of examining supply chain resilience and disruption management in SCRM research. Resilience is considered as the ability to recover and return to the original state after a disruptive event. At the firm level, it is considered as the organizational capability to survive in a turbulent environment

(Ates and Bititci 2011). Christopher and Peck (2004) defined supply chain resilience as "*the ability of a supply chain to return to normal operating performance after being disrupted.*" Another common definition of supply chain resilience is "*the adaptive capability of the supply chain to prepare for unexpected events, respond to disruptions, and recover from them by maintaining continuity of operations at the desired level of connectedness and control over structure and function*" (Ponomarov and Holcomb 2009). Hence, in a resilient supply chain, the supply chain entities exhibit stability in their performance under disruptions (Blackhurst et al., 2011).

A vast amount of academic research has been conducted in the domain of supply chain resilience. For example, Jüttner and Maklan (2011) suggested that knowledge management enhanced supply chain resilience by improving the flexibility, visibility, velocity, and collaboration capabilities of the supply chain. Pettit et al. (2013) proposed a correlation between increased resilience and improved supply chain performance based on a qualitative study of 1,369 empirical items collected from focus groups that reviewed 14 disruption events. Ambulkar et al. (2015) focused on scale development and empirical examination regarding a firm's resilience to supply chain disruptions. They also explored how firms developed resilience and discussed how various mediators affected a firm's resilience under disruption. In this study, we consider two network-related measures that influence resiliency: density and centralization. In the following section, we discuss how these well-established measures in social network analysis (SNA) relate to supply chain disruptions and robustness.

4.2.2. Network Density and Robustness Under Disruptions

In the context of a supply network, network density is closely related to network complexity, which refers to the number of entities (i.e., buyers and suppliers) and their connectedness in the network. The literature provides mixed support for the relationship between network complexity and supply chain disruptions (Adenso-Diaz et al. 2012; Bode and Wagner 2015; Craighead et al. 2007; Käki et al. 2015). First, the focal firm may benefit from reduced risks in a dense and complex supply network. Dense networks suffer less from disruptions than sparse networks do, as the companies in a dense network have enough resources to mitigate the risk. As the number of alternative sourcing options increases in dense and complex networks, we expect companies to alleviate the negative effects of disruptions in line with the benefit of a supplier diversification strategy. Taleb et al. (2009) also posited that redundancy is an important risk management strategy for companies in dealing with external changes, which is in line with diversifying the supply base. Using a simulation-based approach, Namdar et al. (2018) studied single sourcing and multiple sourcing strategies to achieve supply chain resilience under disruption risks. They suggested that a multiple sourcing strategy provides a higher service level and lower risk than a single sourcing strategy, particularly when decision-makers are risk-averse, which is the case under supply chain disruptions. In summary, diversifying supply sources is a logical approach to effectively managing the risk of a supply chain disruption (Schmitt and Tomlin 2012).

In contrast, Craighead et al. (2007) suggested that higher network complexity and density increase the severity of network disruption based on a case study and expert interviews conducted at nine companies. They claimed that the probability that a disruptive event would affect many entities within such a supply chain (i.e., more severe) would likely be lower in a sparse network. They argued that disruption would be more likely to propagate in the network when there were more interdependencies and connectedness within the network. Adenso-Diaz et al. (2012) also studied the relationship between network complexity and supply network reliability using a Monte Carlo simulation. They suggested that node complexity, network density, number of suppliers, and node criticality are positively linked to network risk. Their findings supported the positive association between network density and disruption, except the claim that the number of arcs decreases the probability of disruption. Bode and Wagner (2015) also argued that supply chain complexity could increase the frequency of supply chain disruptions. Based on primary survey data collected from 3,945 firms in Europe, they found that supply chain complexity increased the frequency of disruptions. This finding was also in line with the negative implications of a complex supply network structure for risk management.

Käki et al. (2015) studied the relationship between network structure and disruption and found mixed results. They suggested that network complexity could either increase or decrease the severity of a disruption. They concluded that complex networks tend to be riskier and have a greater number of possible disruption sources through which the disruption could be propagated. However, they also argued that a supply network might recover better in a dense and complex supply chain, which is less dependent on individual suppliers. Because of the mixed results associated with network density and resilience, we posit competing hypotheses to examine the relationship between network density and robustness of the network under disruptions.

H1a: The density of a focal firm's supply network is positively associated with its robustness.

H1b: The density of a focal firm's supply network is negatively associated with its robustness.

With respect to the impact of density on network risk, it is important to note that our work differentiates itself from existing studies by investigating this relationship in a real, large-scale supply network. In addition, our measure of robustness, which is discussed later in the paper, is multi-dimensional in nature that effectively considers a variety of network-related metrics in understanding the impact of disruptions in a holistic sense.

4.2.3. Network Centralization and Robustness Under Disruptions

In organizational research, centralization refers to the locus of decision authority and control within an organizational entity (Caruna et al. 1998; Rapert and Wren 1998). For example, in a centralized organization, all important decisions are made at the top level, whereas a decentralized structure allows for decision-making down to the lowest possible level. Because it reflects the degree of distribution of the decision-making process, a centralized structure prevents innovative solutions within the organization (Thompson, 1965). On the contrary, a decentralized environment facilitates innovation by encouraging employee awareness, commitment, and involvement (Damanpour 1991). In general, low levels of centralization are aligned with open and frequent interactions, and therefore a decentralized organizational structure facilitates an environment where employees participate in the knowledge-building process (Lee and Choi 2003). In addition, decentralization is known to increase the motivation and willingness to share organizational knowledge across units within an organization (Gupta and Govindarajan, 2000). This lends credence to the fact that a decentralized system is more agile and less dependent on other entities, which could potentially improve decision-making when certain parts of the overall system are adversely affected due to disruptions.

In an inter-organizational context, centralization reflects the power and control structure within the network, demonstrating how the number of connections and relationships are clustered around particular entities (Provan and Milward 1995). The supply chain literature suggests that a centralized supply chain is more effective for the focal company in terms of its greater power and control over the supply chain (Kouvelis and Gutierrez 1997; Lee and Whang 1999). Therefore, decentralized decision-making may not be effective in terms of supply chain planning and coordination because it may negatively affect supply chain performance in terms of inventory levels, capacity investments, and quality efforts (Perakis and Roels 2007). While these results hold from a cost optimization perspective in terms of lower inventory costs, coordination costs, and so on, they may not necessarily reduce risks in the supply chain. The reason is that higher inventories at certain strategic locations within a network can function as a mitigation strategy in the event of a disruption (Talluri et al. 2013; Chopra and Sodhi 2004). Thus, a centralized system may focus on cost efficiency and reduce slack in the system in terms of inventory, capacity, and other factors that are critical in managing risk.

A decentralized supply chain structure is known to reduce risk through supplier diversification, which helps increase the buyer's resilience to supply risks, such as shortages, defective parts, and the loss of supplier capacity (Aydin et al. 2011). In this context, a decentralized structure provides independence for individual entities in the network, allowing them to focus on their respective sourcing and supplier diversification strategies, which could positively influence their ability to respond to disruptions without depending on centralized decision-making. Schmitt et al. (2015) also suggested that decentralization could reduce supply network risk. Based on a mathematical multi-location supply chain model in which supply was subject to disruptions, they compared the expected costs and cost variances in centralized and decentralized inventory systems. They found that decentralization reduced cost variance through the risk diversification effect. They claimed that this finding was in contrast to the traditional discussion on the risk-pooling effect via centralization, suggesting that firms should choose a decentralized inventory system under the risk of supply disruption. In terms of supply chain integration and risk, Flynn et al. (2016) proposed that the effects of macro-level uncertainty on supply chain integration would be moderated by centralization such that the relationship would be strengthened in a centralized structure. In other words, decentralization would lessen the effects of external uncertainty (i.e., disruption events) on supply chain integration.

To this end, the benefits of decentralization in reducing supply risk are apparent in the literature. In this study, we extend the discussion on the effects of decentralization to a network perspective. We suggest that decentralized supply networks are more robust and are affected less by supply chain disruptions than centralized networks because the effects of disruption can be balanced in a more effective manner in a dispersed supply base. Therefore, we posit the following:

H2: The decentralization (centralization) of a focal firm's supply network is positively (negatively) associated with its robustness.

4.3. Methodology

4.3.1. Data and Measures

Figure 3.1 provides a flowchart that summarizes the methodological procedure used in this study. First, we collected supply chain relationship data to create a network-level dataset. Instead of generating hypothetical graphs of supply networks, we collected real-world data from the FactSet Revere Supply Chain Relationship database to test our model. FactSet provides comprehensive supply chain data that allow researchers to access supply chain relationships over multiple years. FactSet collects supply chain relationship data from various sources, including SEC filings, press releases, and analyst reports.

In this study, we focused on the global automotive industry because of the complex nature of this business environment, where supplier-oriented disruptions have significant effects across the supply chain. To create a comprehensive automotive supply network, we utilized all the supply chain relationships between the focal companies, their first-tier suppliers, and their second-tier suppliers. After we created the network dataset, we used UCINET with the igraph R package to compute the network density and network centralization of each focal company's ego-centric supply network.

We then computed the SE scores of the focal companies before disruption to obtain the baseline score (SE_{pre}). We defined SE as the holistic measure of a firm's positional prominence, which is operationalized as a weighted ratio of different node-level SNA measures. Unlike a unidimensional centrality metric, our SE measure captured various positional attributes reflected through different centrality metrics. Therefore, if a firm was high in SE, it had a crucial and prominent position compared with other entities in the network.

We operationalized SE using data envelopment analysis (DEA) in which a dummy of 1 was utilized as the input and node-level metrics (i.e., degree, betweenness, and eigenvector centralities) were considered as outputs. The characterization of inputs and outputs in evaluating SE is based on the logic that factors where lower levels are better are treated as inputs, and factors where higher levels are better are treated as outputs. By placing a dummy unit value of 1 for the input of the DEA model, we provide weight flexibility strength in DEA by allowing a decision-making unit to emphasize each of the centrality measures appropriately. Hence, our model maximizes the ratio of the weighted sum of outputs (i.e., degree, betweenness, and eigenvector) for a firm, subject to the constraints of the dummy input, and the ratio of a weighted sum of outputs to input of all the firms in the set from exceeding a value of 1. We excluded closeness centrality in calculating SE because the closeness measure was not defined for a disconnected graph, which was the case in a supply network after simulated disruptions.

We followed the established definitions of the node-level centrality metrics (Marsden 1990; Marsden 2005; Scott and Carrington 2011; Wasserman and Faust 1994). First, degree centrality is defined as the sum of adjacent edges, which is the simplest measure based on the number of connections of each entity. Second, betweenness centrality measures the number of times each node exists on the shortest path between other nodes, which identifies the nodes that act as bridges in a network. A high betweenness centrality score indicates that the firm has a brokerage role in the supply network and can exert control and influence over the relationships among disparate entities within the network. Third, eigenvector centrality considers the number of direct links and links of connected nodes, assuming that a node is more important and influential if it is connected to other influential nodes. The non-linear version of our DEA model for evaluating SE is as follows:

$$\text{Maximize } SE_p = \frac{\alpha D_p + \beta B_p + \gamma E_p}{\sigma}$$

$$\text{subject to} \quad \frac{\alpha D_i + \beta B_i + \gamma E_i}{\sigma} \leq 1 \; (i = 1, \ldots, N)$$

$$\alpha, \beta, \gamma \; \geq 1$$

D = degree centrality, *B* = betweenness centrality, *E* = eigenvector centrality
α, β, γ = weights to degree centrality, betweenness centrality, and eigenvector centrality

The linearized version of the DEA model is as follows.

$$\text{Maximize } SE_p = \alpha D_p + \beta B_p + \gamma E_p$$

$$\text{subject to} \quad \alpha D_i + \beta B_i + \gamma E_i - \sigma \leq 0 \; (i = 1, \ldots, N)$$

$$\sigma = 1$$

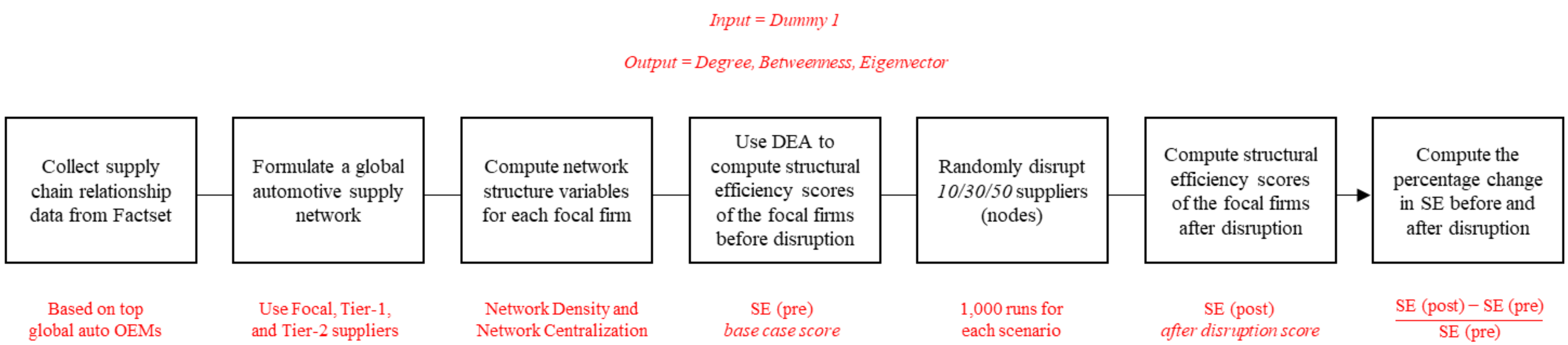
$$\alpha, \beta, \gamma \; \geq 1$$

D = degree centrality, *B* = betweenness centrality, *E* = eigenvector centrality
α, β, γ, δ = weights to degree centrality, betweenness centrality, and eigenvector centrality

As discussed, SE measures the comprehensive positional prominence of a firm. Although no previous research has used this measure, it has been suggested that structural or positional prominence has a positive effect on a firm's performance (Tsai et al. 2001; Basole et al. 2018). A structurally efficient firm occupies a highly visible and important position compared with other entities, and it exercises stronger power and influence in the supply network. Tsai et al. (2001) studied the effects of network position in terms of knowledge transfer and suggested a positive effect on unit-level innovation performance. Therefore, structurally prominent firms could facilitate the environment necessary for knowledge creation, which would lead to innovative practices and improved performance. Basole et al. (2018) claimed that a firm's structural prominence positively affects its operational performance in a complex supply network by controlling the supply chain to lower costs or improve margins. Based on the discussion, we used SE as an effective basis for the network robustness measure under disruptions.

We used SE to assess the robustness of the supply network as the percentage change in the measure after the simulated supply chain disruptions. We followed Brandon-Jones et al.'s (2014) definition of supply chain robustness as *"the ability of the supply chain to maintain its function despite internal or external disruptions."* This definition implies that the focal firm's performance would not deviate significantly even after a disruption. Hence, we defined network robustness as the change in the SE of the focal companies from the baseline DEA scores before a disruption. In other words, it is defined as the post-pre difference in SE (SE_{post} - SE_{pre}) divided by SE_{pre} (see Figure 3.1, steps 4 to 7). The disruption scenarios will be discussed in detail in Section 3.2.

Figure 3.1 Flowchart of the Methodology



4.3.2. Disruption Scenarios

In this study, we modeled supply chain disruptions using simulations to evaluate and track the robustness of different supply network structures. After we formulated the supply network, we randomly removed entities in the supply network to represent disruptions. Then we measured the negative effects of disruptions through the changes in the SE of the focal company as detailed above.

Supply chain disruptions have detrimental consequences for the performance of the affected firm (Blackhurst et al. 2011). Their negative effects on the buying firm's performance are dependent on the severity of the disruption (Sheffi and Rice Jr 2005). In this study, we utilized a simulation-based approach to examine the effects of supply chain disruptions. A simulation approach has been frequently used to study supply chain risk and disruption. Wilson (2007) utilized a system dynamics simulation to investigate the effects of a transportation disruption on supply chain performance, comparing a traditional supply chain and a vendor-managed inventory system. Nair and Vidal (2011) used a multi-agent simulation model to examine the robustness of a supply chain against disruption. Wu et al. (2012) used an agent-based simulation to study the effects of stockouts in a retail supply chain, in which the change of market share was a measure of resilience. Käki et al. (2015) assessed the risks in a supply network caused by supplier disruptions using probabilistic risk assessment. Jabbarzadeh et al. (2016) tested their optimization model of a resilient supply chain under disruptions using a Monte Carlo simulation.

To account for different types of disruptions with varying levels of effects, we developed three different supply chain disruption scenarios. This approach helped us analyze the effects of the magnitude of disruption events. Unlike previous simulation-based studies that assigned probability functions, we were interested in the number of entities (i.e., nodes) that were disrupted in each run. Therefore, the numbers of disrupted nodes in each case (i.e., 10/30/50) were determined based on the number of first-tier suppliers in each focal company's ego-centric supply network. Consequently, we randomly disrupted 10 suppliers to simulate a weak disruption, 30 suppliers to simulate a moderate disruption, and 50 suppliers to simulate a severe disruption. For the random selection of the disrupted suppliers for each run, we used a random number generator in R.

In each scenario, we repeated 1,000 runs to ensure the reliability of our simulation results. The result was a base-case supply network without disrupting any suppliers (e.g., pre-disruption) and 3,000 (1,000 runs x 3 scenarios) simulated supply networks post-disruption for each focal company. We then clustered the 30 focal companies into three groups according to two network structure variables (i.e., network density and network centralization, respectively). For example, the 10 focal firms highest in density were clustered as a high-density group, the 10 focal firms lowest in density were clustered as a low-density group, and the 10 focal firms in between were clustered as a medium-density group. A similar process was utilized for the centralization groupings. In grouping the focal companies, the threshold cut points were selected based on the tertile values of each dimension.

4.3.3. Statistical Models

We analyzed the link between the supply network structures of the focal companies and their network robustness under disruption via both parametric and nonparametric statistical tests. After we had three groups (i.e., high, medium, and low) based on the two network structure variables, we first applied analysis of variance (ANOVA) and corresponding post-hoc tests to investigate the association between network structure and robustness. ANOVA is used to examine the differences among group means by analyzing the between-group and within-group variance, which provides a statistical test of whether the mean values of interest in two or more groups are equal or not in an experimental setting (Fisher 1992).

In our context, ANOVA tests were conducted to ascertain if there were differences in the robustness with respect to density and centralization. When a significant F-test statistic derived from ANOVA confirmed group differences, we conducted post-hoc multiple comparison tests to determine which groups differed from each other (Miller 2012; Hochberg and Tamhane 1987). We compared the robustness of the focal companies in all three pairs (high-medium, high-low, and medium-low) according to each network variable (network density and network centralization). We used Tukey's HSD test (Tukey 1949) to conduct pairwise comparisons of the group means.

To demonstrate the differences between the three groups and test the hypotheses, we conducted an independent two-sample t-test to compare the means between high versus low groups in both dimensions. The independent t-test is used to determine whether the mean values of a dependent variable are equal in two independent groups (Senn 2008). Specifically, the test examines whether the mean difference between the two groups is statistically significantly different from zero (Dixon and Massey 1983). In our context, we compared the mean network robustness (as the percentage change in SE) between high-density and low-density groups and between high-centralization and low-centralization groups across the three different disruption scenarios.

Additionally, since relative efficiency scores from DEA may not lend themselves to normality, we conducted the Kruskal–Wallis rank-sum test (Kruskal and Wallis 1952), which is a nonparametric equivalent test, to ensure the robustness of the results of our analysis. The Kruskal–Wallis test is a nonparametric statistical test that employs calculations based on ranks, which is also a multi-group version of the Wilcoxon (or Mann–Whitney) rank-sum test (Wilcoxon 1992;

Mann and Whitney 1947). For the corresponding post-hoc analysis, we utilized Dunn's test (Dunn 1964), in which appropriate nonparametric pairwise multiple group comparisons are based on rank sums (Dinno 2015).

4.5. Results

In this section, we provide the empirical results of the simulation models in each disruption scenario. Table 3.1 presents the results of the one-way ANOVA and corresponding post-hoc test of network density and network centralization, respectively. The significant F-values of both network variables indicated that group differences existed in both structural dimensions. Regarding network density, the F-values were 21.67 (weak), 35.45 (moderate), and 47.06 (severe). Regarding network centralization, the F-values were 21.87 (weak), 34.50 (moderate), and 47.05 (severe) in each scenario. The F-values differed with the magnitude of the disruption. Specifically, the largest F-values of both variables were in the severe disruption case. These results suggested that group differences were more evident when the disruption was severe.

We then performed corresponding post-hoc tests to identify significant contrast groups. The results of Tukey's HSD test confirmed significant group differences in pairwise group mean contrasts.[1] Regarding network density, we found consistent results for all three disruption scenarios. We found significant contrast effects between the high-density and medium-density groups (C_{DW} = 0.00087, p < 0.001; C_{DM} = 0.00179, p < 0.001; C_{DS} = 0.00291, p < 0.001) and between the high-density and low-density groups (C_{DW} = 0.00089, p < 0.001; C_{DM} = 0.00218, p < 0.001; C_{DS} = 0.00321, p < 0.001). However, we did not find a significant pairwise difference between the medium-density and low-density groups (C_{DW} = 0.00002, p = 0.990; C_{DM} = 0.00039, p = 0.327; C_{DS} = 0.00030, p = 0.693). Overall, the group mean values were higher in the focal

[1] C_{jk} – Pair-wise Group Mean Contrasts for j = Density (D) and Centralization (C), k = Weak (W), Moderate (M), and Severe (S)

companies in the high-density group than those in the other two groups. Based on these results, H1a is supported. That is, network density was positively associated with the robustness of the supply networks in the automotive industry.

We also obtained consistent results in all three disruption scenarios regarding network centralization. Specifically, we found significant group differences in the high vs. low pairwise comparison (C_{CW} = -0.00083, $p < 0.001$; C_{CM} = -0.00194, $p < 0.001$; C_{CS} = -0.00292, $p < 0.001$) and the medium vs. low pairwise comparison (C_{CW} = -0.00092, $p < 0.001$; C_{CM} = -0.00203, $p < 0.001$; C_{CS} = -0.00321, $p < 0.001$). However, no significant group difference was found in the high vs. medium pairwise comparison (C_{CW} = 0.00010, $p = 0.801$; C_{CM} = 0.00009, $p = 0.941$; C_{CS} = 0.00029, $p = 0.705$). Across all three scenarios, the group mean values were higher for the focal companies low in centralization than those high in centralization. The results support H2. That is, network decentralization (centralization) was positively (negatively) associated with the robustness of the focal company's supply network. Therefore, based on these results, we suggest that the decentralized network structure (low in network centralization) was more resilient under supply chain disruption in the focal companies in the global automotive supply chain network.

Although we found an overall group difference in the F-test statistics derived from the ANOVA, the post-hoc test revealed no significant group differences in M vs. L for density and H vs. M for centralization. Therefore, to investigate the hypotheses, we conducted independent two-sample t-tests, the results of which are shown in Table 3.2. Regarding network density, the t-test statistics were 5.57 ($p < 0.001$), 7.61 ($p < 0.001$), and 8.40 ($p < 0.001$) in each disruption scenario. Across all cases, we rejected the null hypothesis that group differences were zero and confirmed a significant difference between the high-density and low-density groups. Regarding network centralization, the t-test statistics were 5.21 ($p < 0.001$), 6.78 ($p < 0.001$), and 7.64 ($p < 0.001$), respectively. We rejected the null hypothesis and confirmed a significant group difference between the high-centralization and the low-centralization groups. The mean values of the dependent variable supported both H1a and H2. That is, the network robustness was higher in high network density and lower in high network centralization.

We provide a series of box plots to illustrate the significant group differences derived from the t-test results. Figures 3.2 and 3.3 show network density and network centralization, respectively. Each figure includes six box plots, two of which are grouped by three disruption scenarios (i.e., weak, moderate, and severe). The x-axis represents the level of network structures in two groups (high vs. low) by density and centralization, and the y-axis represents the percentage change in SE of the focal companies. We identified the group differences in the box plots and corresponding t-test statistics. We also observed that the group differences became more noticeable as the magnitude of the simulated disruption increased, so the largest group differences were observed in the severe disruption cases.

Finally, the results of the Kruskal–Wallis rank test and Dunn's pairwise comparison test, which ensured the robustness of the main test results, are shown in Table 3.3. We provided these additional nonparametric tests based on rank sums and group medians to verify the group differences in the main analyses. Significant chi-squared values derived from the Kruskal-Wallis rank test confirmed the existence of group differences in terms of both density and centralization. The post-hoc Dunn test results also confirmed the main results based on significant rank mean contrasts in all pairwise comparisons for both dimensions. In summary, the results supported H1a and H2. That is, dense and decentralized supply network structures are more robust than sparse and centralized supply network structures.

Table 3.1 One-way ANOVA and Tukey's HSD Test Results (n =10,000 per group)

Group Variable	Scenario	Group Label	Mean	SD	Between Groups (MS)	Within Groups (MS)	F-value	Post-hoc analysis	
								Contrast groups	Contrasts
Density	Weak	High	0.00072	0.01499	0.00255	0.00012	21.67*	H vs M**	0.00087
		Medium	-0.00015	0.01002				H vs L**	0.00089
		Low	-0.00017	0.00535				M vs L	0.00002
	Moderate	High	0.00179	0.02705	0.01355	0.00038	35.46*	H vs M**	0.00179
		Medium	0.00000	0.01794				H vs L**	0.00218
		Low	-0.00039	0.00963				M vs L	0.00039
	Severe	High	0.00255	0.03633	0.03151	0.000669	47.06*	H vs M**	0.00291
		Medium	-0.00036	0.02332				H vs L**	0.00321
		Low	-0.00066	0.01203				M vs L	0.00030
Centralization	Weak	High	-0.00011	0.00517	0.00258	0.00012	21.87*	H vs M	0.00010
		Medium	-0.00020	0.01011				H vs L**	-0.00083
		Low	0.00072	0.01499				M vs L**	-0.00092
	Moderate	High	-0.00015	0.00934	0.01318	0.00038	34.50*	H vs M	0.00009
		Medium	-0.00024	0.01810				H vs L**	-0.00194
		Low	0.00179	0.02705				M vs L**	-0.00203
	Severe	High	-0.00036	0.01176	0.03150	0.000669	47.05*	H vs M	0.00029
		Medium	-0.00066	0.02346				H vs L**	-0.00292
		Low	0.00255	0.03633				M vs L**	-0.00321

* Significant at $p < .001$; ** Significant contrast groups at $p < .001$

Table 3.2 Independent Two-sample T-test Results (n =10,000 per group)

Group Variable	Scenario	Group Label	Mean	SD	95% Confidence Interval		t-statistic
					Lower Bound	Upper Bound	
Density	Weak	High	0.00072	0.01499	0.00043	0.00101	5.57*
		Low	-0.00017	0.00535	-0.00027	-0.00006	
	Moderate	High	0.00179	0.02705	0.00126	0.00232	7.61*
		Low	-0.00039	0.00963	-0.00058	-0.00020	
	Severe	High	0.00255	0.03633	0.00184	0.00327	8.40*
		Low	-0.00066	0.01203	-0.00089	-0.00042	
Centralization	Weak	High	-0.00011	0.00517	-0.00021	0.00000	5.21*
		Low	0.00072	0.01499	0.00043	0.00101	
	Moderate	High	-0.00015	0.00934	-0.00033	0.00004	6.78*
		Low	0.00179	0.02705	0.00126	0.00232	
	Severe	High	-0.00036	0.01176	-0.00059	-0.00013	7.64*
		Low	0.00255	0.03633	0.00184	0.00327	

* Significant at $p < .001$

Table 3.3 Kruskal-Wallis Rank Test and Dunn Test Results (n =10,000 per group)

Group Variable	Scenario	Group Label	Rank Sum	χ^2 (df)	Post-hoc analysis	
					Contrast groups	Rank Mean Contrasts
Density	Weak	High	1.73×10^8	1215.98 (2) *	H vs M**	22.83
		Medium	1.45×10^8		H vs L**	34.25
		Low	1.31×10^8		M vs L**	11.43
	Moderate	High	1.66×10^8	569.51 (2) *	H vs M**	16.92
		Medium	1.46×10^8		H vs L**	23.04
		Low	1.38×10^8		M vs L**	6.12
	Severe	High	1.63×10^8	355.54 (2) *	H vs M**	14.15
		Medium	1.46×10^8		H vs L**	17.87
		Low	1.41×10^8		M vs L**	3.71
Centralization	Weak	High	1.32×10^8	1196.54 (2) *	H vs M**	-10.54
		Medium	1.45×10^8		H vs L**	-33.81
		Low	1.73×10^8		M vs L**	-23.27
	Moderate	High	1.40×10^8	543.77 (2) *	H vs M**	-3.43
		Medium	1.44×10^8		H vs L**	-21.69
		Low	1.66×10^8		M vs L**	-18.26
	Severe	High	1.43×10^8	343.07 (2) *	H vs M**	-1.15
		Medium	1.44×10^8		H vs L**	-16.59
		Low	1.63×10^8		M vs L**	-15.44

* Significant at $p < .001$; ** Significant contrast groups at $p < .001$

Figure 3.2 Box-Plots for Network Density

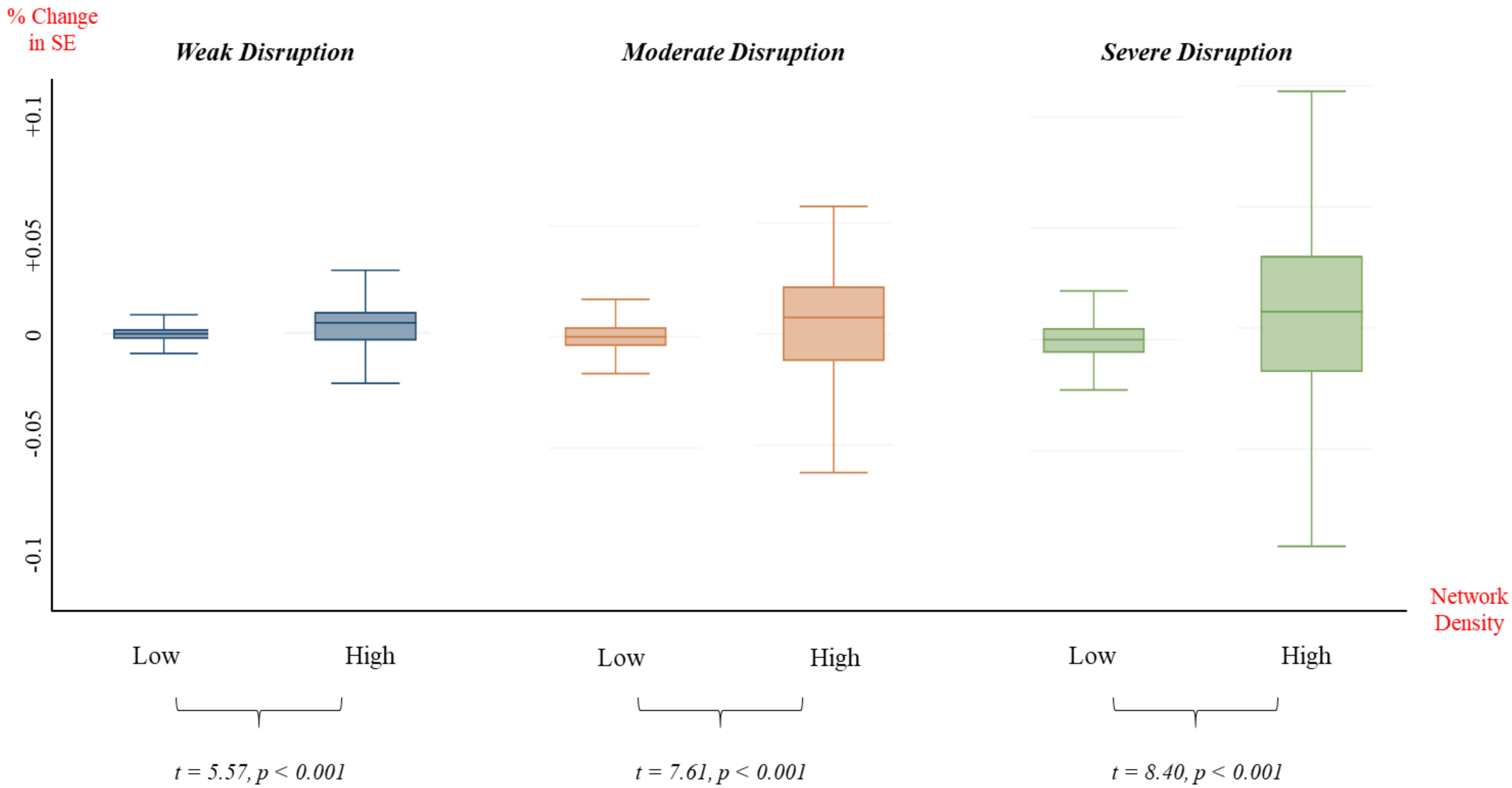
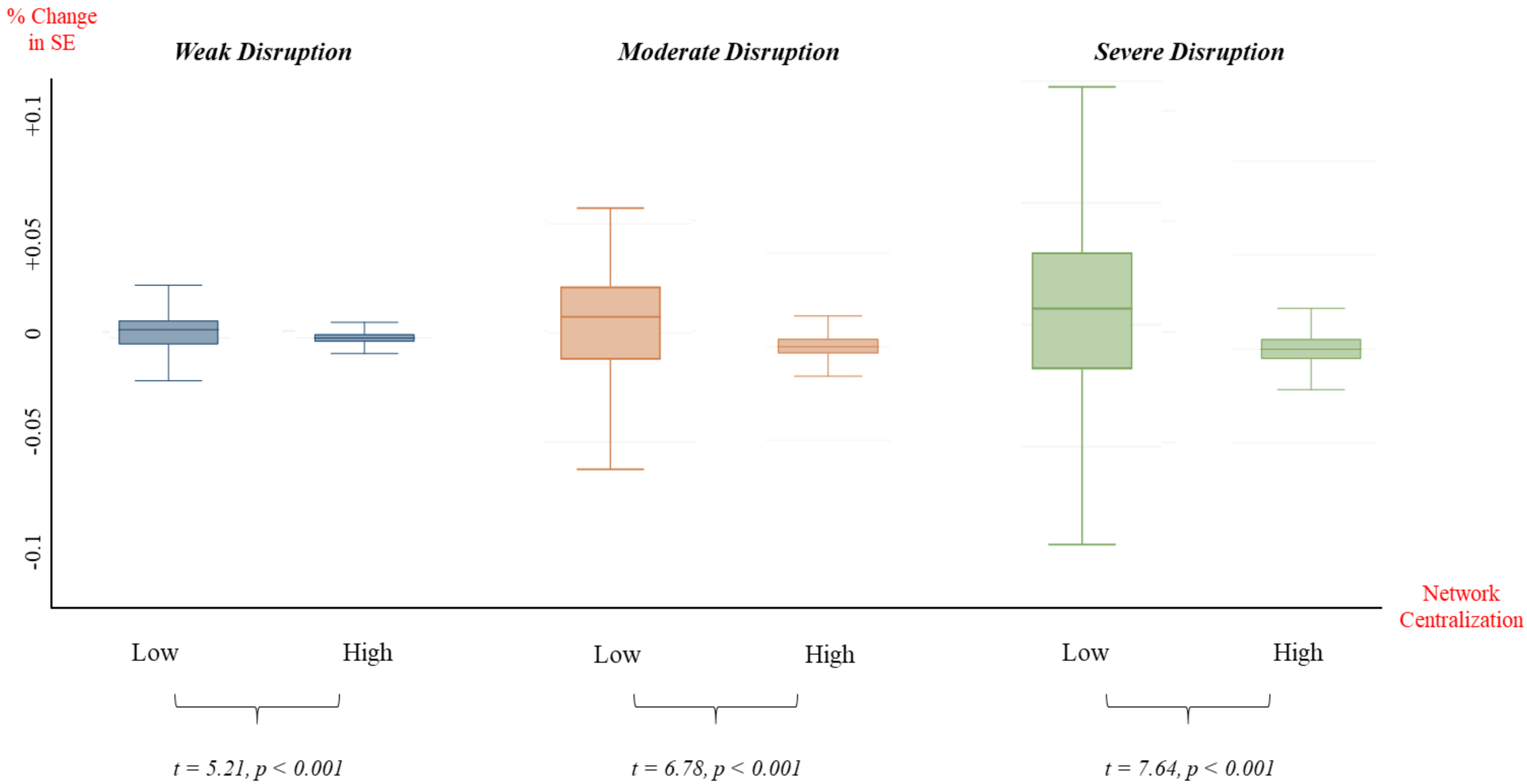


Figure 3.3 Box-Plots for Network Centralization



4.6. Discussion and Conclusion

4.6.1. Academic Contributions

In this study, we investigated the link between a focal firm's supply network structure and its robustness. Our work contributes to the scholarly literature in the area of SCRM. First, we contribute to the knowledge base regarding the robustness and resilience of the supply chain. Pournader et al. (2020) suggested that studies in supply chain resilience and disruption management are relatively scarce in the current SCRM literature compared with the number of publications in other areas, such as risk assessment and risk mitigation. They also argued that SCRM literature should convey a more realistic picture of resilience, which would encourage future operations and supply management scholars to explore the resilience and crisis management areas more in-depth. In this study, we assessed the robustness of the supply network under disruption by combining SNA and simulation. In particular, we investigated how simulated disruption affected the focal company's SE. We utilized the concepts and tools in SNA to investigate a real-world supply network that consists of numerous nodes (i.e., suppliers) and arcs (i.e., relationships). This method was in line with previous scholarly attempts to implement various aspects of SNA to broaden the theoretical scope of understanding supply chain relationships (Borgatti and Li 2009).

Second, Ho et al. (2015) suggested that a wide variety of SCRM management methods and frameworks have yet to be empirically validated because many are theoretical and conceptual in nature. To fill this gap, we offered empirical validation of the association between network structures (via density and centralization) and supply chain disruptions. The literature on SCRM is rich in many areas. Researchers have often utilized mathematical programming methods to study supply chain networks under conditions of uncertainty (Fattahi et al. 2017; Goh et al. 2007;

Sadghiani et al. 2015; Yildiz et al. 2016). In this context, researchers investigated the supply chain network design problem from an analytical standpoint that is robust and resilient in the presence of disruptions (Govindan et al. 2017; Snyder et al. 2016). However, several studies in this stream of research have tested their models using stylized networks and simulated data, making it difficult to validate and generalize the findings to the current global supply chain networks. However, compared with the analytical modeling literature, empirical research with a specific emphasis on secondary data is relatively sparse in this area. In particular, only a few previous studies have examined network data in studying supply chain risk and disruption.

4.6.2. Managerial Implications

Supply networks have become increasingly complex than ever. As supply chains become more complex, building a resilient supply chain is now a primary objective in supply chain management (Christopher and Peck 2004). The goal of supply network management has shifted from short-term cost savings to long-term strategic benefits and improved supply chain resilience (Simchi-Levi 2010). Hence, many organizations have turned their attention to supply chain risk due to the significant negative impact associated with supply chain disruptions (Chopra and Sodhi 2014). Moreover, the COVID-19 pandemic has led to calls for resilient supply chain strategies against disruptions. We offer managerial insights to supply chain professionals to ensure supply chain resilience and provide implementable suggestions in assessing the robustness of supply networks under supply chain disruptions. Our findings emphasize the importance of building a robust supply network through interconnections and the concepts of density and centralization.

In this study, we assessed the implications of robustness for different network structures. We focused on the robustness of a focal company’s supply network by examining the changes in its SE. Specifically, we examined the implications of supply disruptions for different network structures according to varying levels of network density and network centralization. Based on the findings from the global automotive industry examined in this study, we found that a dense and decentralized supply network was more effective in mitigating the negative effects of disruptive events. We also found that the effects were more apparent in severe supply chain disruptions. Despite the potential implications of our results, we note that it could be challenging to apply them in practice because we did not test the model in various industry settings. Nonetheless, our study underscores the need for firms to better understand their network structures to mitigate the consequences of supply chain risks.

The network-oriented approach used in this study would help focal companies to overcome limited visibility due to the complexities associated with supply chains. Our work contributes to the trend in the complexity of the global supply network, which was emphasized by Pournader et al. (2020). Supply chain disruptions and their effects are difficult to analyze for many reasons. Strong interdependencies within a network imply that disruptions must be tracked to a supplier, a supplier's supplier, or even further upstream in the network (Sheffi and Rice Jr 2005). Moreover, most real-world supply networks consist of numerous nodes (i.e., supply chain entities) and arcs (i.e., buyer-supplier relationships), which makes it very difficult for the focal firms to grasp the complete picture of their supply chains. Our approach was intended to effectively account for these considerations regarding supply chain complexity.

We also highlight the importance of a holistic strategy for companies to manage their supply network structure to adequately respond to large-scale disruptions. By redesigning the supply chain, firms could mitigate the effects of future global crises by taking supply chain preparedness to a higher level before a disruption occurs. At the strategic level, our research also provides criteria for how the focal company should invest in designing and managing a robust supply network structure to better cope with supply chain disruptions.

4.6.3. Limitations and Future Research Directions

In this section, we present the limitations of the study and offer possible extensions for future research. First, the results of this study were based on simulated supply chain disruptions. Although we utilized actual supply chain relationship data to construct supply networks, further validation is required to better generalize the findings. For example, event study methodology could be applied by future researchers to validate our findings based on real-world supply chain disruption events. Databases such as Factiva and Ravenpack provide a broad selection of business and news publications as sources of event announcements.

Second, the findings of this study could be extended by including regional simulation settings. We could provide additional implications for different regional disruption scenarios if we classified the suppliers based on their country of origin. Instead of randomly selecting suppliers from the entire supply network, for instance, we could select suppliers in Asia, Europe, and North America. By doing so, we could examine whether the empirical outcomes varied among different regional supply bases. The results could provide practical implications for the focal company's sourcing decisions to mitigate geographical supply chain risk.

We could also examine different industries to extend the findings. In this study, our research was based on the global automotive industry. Thus, it is challenging to generalize the implications to other business contexts. By comparing the simulation results of different industry settings, future studies could derive insightful findings that would allow them to examine potential effects on the external environment. Either the direction or the magnitude of the effects could differ even if the same model were tested.

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