LEVERAGING SUPPLY NETWORK RELATIONSHIPS TO DRIVE PERFORMANCE

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LEVERAGING SUPPLY NETWORK RELATIONSHIPS TO DRIVE PERFORMANCE

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For my grandparents, Eliseo Esquibel, Casilda Esquibel, Kenneth Bellamy, and Malissa Bellamy: Thank you for pouring out your love, encouragement, and timeless wisdom that keeps me lifted up and inspires to be my best

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TABLE OF CONTENTS

CHAPTERS

LIST OF TABLES

LIST OF FIGURES

SUMMARY

Effective supply chain management requires focal firms to develop capabilities to manage a myriad of multi-tier, interconnected relationships often spanning multiple industries. Conventional assessments of supply chain relationships as linear or dyadic structures, rather than as a network, limit academician and managerial approaches to overcome challenges to effectively manage supply chains. Further, empirical research on innovation and performance implications of supply network structure and its corresponding relationship dynamics is still fairly nascent.

My research focuses on leveraging supply network relationships to drive performance. Specifically, in my dissertation I examine how the structural, knowledge, and dependency differences in a firm’s supply network can affect knowledge and information flow, and ultimately the firm’s innovative, operational, and financial performance. My first chapter (CH. 2) contributes to current research at the interface of supply chain management and innovation. My second (CH. 3) and third chapter (CH. 4) incorporate the intensity of each supply network link, reflective of focal firms as customers (suppliers) that may rely heavier on a supplier (customer) based on their percentage of cost (revenue) that goes to (is generated from) that supplier (customer). All three chapters extend current research findings by bringing a more holistic assessment of firms that are embedded in a supply network, addressing the need for deeper structural analysis.

CHAPTER 1

INTRODUCTION

Today's supply chains can be characterized as a globally distributed set of vertical and horizontal interactions among suppliers, manufacturers, distributors, retailers, and customers, which have transformed the traditional linear supply chain into a complex supply network of member interactions. Effective supply chain management consequently requires focal firms to develop capabilities to manage a myriad of multi-tier, interconnected relationships often spanning multiple industries. Conventional assessments of supply chain relationships as linear or dyadic structures, rather than as a network, limit academician and managerial approaches to overcome challenges to effectively manage supply chains. Although researchers have made some headway in characterizing a firm's supply network as a source of innovation and performance, empirical research on innovation and performance implications of supply network structure and its corresponding relationship dynamics is still fairly nascent.

My research focuses on leveraging supply network relationships to drive performance. Specifically, my body of work examines how the structural, knowledge, and dependency differences in a firm's supply network can affect knowledge and information flow, and ultimately the firm's innovative, operational, and financial performance. All three chapters extend current research findings by bringing a more holistic assessment of firms that are embedded in a supply network, addressing the need for deeper structural analysis.

In my first chapter (CH. 2), I examine the structural characteristics of supply networks and investigate the relationship between a firm's supply network accessibility and interconnectedness and its innovation output. I also examine potential moderating effects of absorptive capacity and supply network partner innovativeness on innovation output. I hypothesize that firms will experience greater innovation output from (1) higher levels of supply network accessibility and supply network interconnectedness; (2) the interaction between the levels of these two structural characteristics; and, (3) the moderating role of absorptive capacity on supply network accessibility and the moderating role of supply network partner innovativeness on supply network interconnectedness. Supply network partner relationships were investigated in the context of the electronics industry using data from multiple sources. Social network analysis was used to create measures for each supply network structural characteristic.

Using regression techniques to test the relationship between these structural characteristics and firm innovation for a sample of 390 firms, I find that supply network accessibility has a significant association with a firm’s innovation output. The results also indicate that interconnected supply networks strengthen the association between supply network accessibility and innovation output. Moreover, the influence of the two structural characteristics on innovation output can be enhanced by a firm’s absorptive capacity and level of supply network partner innovativeness. By addressing the need for deeper structural analysis, this chapter contributes to supply chain research by accounting for the embedded nature of ties in supply networks, and showing how these structural characteristics influence the knowledge and information flows residing within a firm’s supply network.

In my second chapter (CH. 3), I incorporate relationship value and supply network structure in tandem to move towards a richer understanding of how to manage supply network relationships for improved performance. I investigate several underlying characteristics of customer and supplier relationships and their influence on firm performance. In particular, I analyze supply chain relationship data for firms in the electronics industry, using the proportion of the firm’s business that each of its partners is responsible for (in terms of customer cost and supplier revenue) as a proxy for relationship dependence. This chapter adds an additional layer to prior literature by examining relationship dependence from the perspective of the focal firm, both as a customer and a supplier. I also examine whether the structural characteristics of the supply network facilitate the effect of a firm’s relationship dependency characteristics on its performance. I draw upon research on buyer-supplier relationships and dependency theory. Initial results from my analysis suggest that firm performance is influenced by how a firm distributes its cost and revenue streams both upstream (as a customer) and downstream (as a supplier) and that this effect is facilitated by the way that a firm’s supply network is structured.

In my third chapter (CH. 4), I investigate supply networks of focal firms in multiple industries, from high velocity and low velocity industry contexts. I expect that firms operating primarily in a low velocity industry (e.g., automotive) will benefit differently from firms operating primarily in a high velocity industry (e.g., electronics) in terms of how they manage their cost and revenue concentration levels both upstream and downstream. I also expect notable differences in the facilitating effects from other supply network characteristics, such as network structure and supply network partner attributes. Finally, I conclude my research in the last chapter (CH. 5) by taking stock of my body of dissertation work and contributions made as a result.

CHAPTER 2

SUPPLY NETWORK STRUCTURE AND FIRM INNOVATION

1. Introduction

Supply chains manifest networks that are comprised of not only a focal firm's direct ties to each of its supply network partners (e.g., suppliers and customers), but also its indirect ties to partners of the firm's direct partners (Choi et al., 2001). Both anecdotal evidence and research on supply networks highlight the operational benefits of effectively managing a supply network. Firms such as Toyota and Schneider Electric have been creating and reevaluating their supply networks to maintain efficiencies in inventory, improve product quality, enhance delivery performance, mitigate supply chain disruptions and enhance profitability (Dyer and Hatch, 2004; Voxant FD Wire, 2009).

Besides these operational benefits, the supply network of a firm has also been viewed as a source of innovation. For example, Procter and Gamble (P&G) has set an imperative of sourcing innovation from outside the firm. P&G's CEO, A.G. Lafley, confirmed this imperative in 2002 by stating "we will acquire 50% of our technologies and products from outside P&G" (Huston and Sakkab, 2006). These sources included amongst others, consumers, universities and suppliers. Examples are also aplenty in knowledge-intensive industries such as electronics. For instance, the CEO of Direct Methanol Fuel Cell Corporation (DMFCC) announced that the firm "has been establishing a global network of suppliers to manufacture fuel cartridges and other fuel cell products" (PR Newswire, 2007). In particular, the announcement cites the role of its supplier, Tyco Electronics Corporation, in developing and commercializing the innovation on fuel cell technology. Similarly, in 2012, Dell, with the help of its reverse logistics provider GENCO, has initiated innovation in products and processes with several of its suppliers

(Gilmore, 2012). In line with these examples, research has also conceptualized a firm's partners as sources of innovation and empirically examined the role of partner integration into innovation and new product development activities (Von Hippel, 1988; Dyer and Nobeoka, 2000; Choi and Krause, 2006; Azadegan et al., 2008).

However, little is known about the underlying structural characteristics of a firm's supply network and whether these characteristics have any influence on firm innovation output. Several supply chain researchers have emphasized the value in incorporating network structure when considering firm innovation and performance implications (Autry and Griffis, 2008; Choi and Kim, 2008; Bernardes, 2010). A recent research note by Narasimhan and Narayanan (2013) discusses the role of structural characteristics of a firm's supply network on innovation. The note also emphasizes the role of absorptive capacity, in integrating information flows from supply network partners, to facilitate innovation output. Specifically, absorptive capacity reflects a firm's ability to recognize, assimilate, leverage, and deploy the available external knowledge (Cohen and Levinthal, 1990). Moreover, the emerging paradigm of open innovation suggests that innovations are also derived outside a firm's internal endeavors, and that greater, more novel learning is often gained from external sources (Chesbrough, 2003). Accordingly, firms are recognizing the advantages of leveraging the innovativeness of their supply network partners to influence their innovation output. Specifically, s*upply network partner innovativeness* reflects the magnitude of available knowledge residing in a firm's supply network partners (Azadegan et al., 2008).

This chapter builds on the conceptualization presented in extant research and empirically addresses two interrelated research questions: *First,* w*hat is the association between the structure of a firm's supply network and its innovation output?* Specifically, we examine two important structural characteristics of supply networks: *supply network accessibility* – the speed and effectiveness of information and knowledge access opportunities between a firm and its supply network – and *supply network interconnectedness* – the extent to which a firm's supply network partners are inter-linked. *Second, what moderating role does a firm's absorptive capacity and its supply network partner innovativeness play in the association between the structural characteristics of a firm's supply network and its innovation output?* To empirically test the hypothesized relationships, we collected firm-level data from several archival sources that included data on buyer-supplier relationships, alliances, and patenting activity and used social network analysis to develop the structural characteristics.

We contribute to the literature on examining a firm's supply network partners as a source of innovation in the following ways. First, a firm's level of innovation output is a by-product of its knowledge creation activities and often results in inventions and commercialization that reflect advancements over existing technology or practices. Previous research recognizes a firm's partners as sources of innovation, with firms tapping into the knowledge of their partners (Von Hippel, 1988; Dyer and Nobeoka, 2000). Further, other scholars have argued the need for future research using a more comprehensive structural analysis that accounts for the embedded nature of knowledge among members in the supply network (Kim et al., 2011; Villena et al., 2011). Moreover, prior research has conjectured that the way a firm's supply network is structured, formally termed as structural characteristics, will bear influence on its innovation performance, and have therefore called for future research to empirically examine and test such conjectures (e.g., Autry and Griffis, 2008). We extend these stances by specifically examining the structural characteristics of a firm's supply network and its association with innovation performance by taking a more holistic view of firms that are embedded in a supply network, rather than the traditional dyadic view. In this regard, we consider the influence of two key structural characteristics in a supply network on innovation: supply network accessibility and supply network interconnectedness.

Second, in addition to addressing the influence of structural characteristics of a supply network on innovation, we also examine the moderating role of two critical knowledge variables, the presence of which may strengthen the relationship between the two structural characteristics and innovation output. We examine the moderating role of *absorptive capacity*, represented by the firm's research and development (R&D) intensity. We also consider the role of *supply network partner innovativeness*, that is, the magnitude of available knowledge or more formally, the average level of patent stock that exists among a focal firm's supply network partners. While the structural characteristics of a supply network facilitate knowledge and information flows between partners, both knowledge availability in the network and the capability to combine the knowledge may enable firms to translate the benefits of high levels of supply network accessibility and supply network interconnectedness into higher innovation output. Our findings confirm this conjecture, suggesting that opportunity exists for firms in knowledge-intensive industries such as electronics – which outsource parts of their product development to supply network partners – to supplement growth in their innovation output through leveraging its absorptive capacity and the innovativeness of its supply network partners (Dedrick et al., 2010). Overall, taking the main effects of structural characteristics together with the moderating effects of knowledge variables provides a coherent theoretical framework to potentially extend the literature on the influence of the structural characteristics of supply networks on innovation.

The remainder of this chapter is organized as follows. In Section 2, we discuss the literature on innovation, supply chain management, and networks and develop hypotheses relating supply network structural characteristics to firm innovation output. We describe our research methodology in Section 3 and our empirical analysis and results in Section 4. In Section 5 we discuss our research findings, implications for theory and practitioners, and future research opportunities. Lastly, we conclude this chapter in Section 6.

2.1 Theoretical background and hypotheses development

Buyer-supplier relationships have been conventionally viewed as linear or dyadic structures, rather than as a network (Kim et al., 2011). However, given a supply chain's complex and increasingly interdependent nature, a network approach provides a richer view by considering the various interactions taking place among firms in the supply network (Choi et al., 2001; Buhman et al., 2005; Borgatti and Li, 2009). In contrast to the conventional approach, where firms are viewed as autonomous and self-reliant entities striving to use their resources to compete with other such entities, the network approach focuses on the structural elements of the firm and its inter-organizational network partners (Granovetter, 1985). We define a supply network as an inter-linked network of firms consisting of manufacturers, suppliers, customers, third party service providers, and alliance partners that interact to execute the supply chain activities of the firm. The various firms in the supply network are generally referred to as supply network partners of a given focal firm in the network.

The theory on social networks helps explain the benefits derived by a firm viewed as embedded within a larger network of structurally interdependent partners. This lens emphasizes that the benefits accrued from access to knowledge, resources, and information available within a network of relationships can lead to an organizational advantage (Granovetter, 1973). Nahapiet and Ghoshal (1998) elaborate on this notion across three dimensions: cognitive, relational, and structural. The cognitive dimension refers to those resources that help generate shared language and vocabulary and the sharing of collective narratives (Nahapiet and Ghoshal, 1998). Collective goals and aspirations between partners can thus enhance the cognitive dimension and help stifle opportunistic behavior and improve joint returns for both parties (Villena et al., 2011). The relational dimension refers to the degree of mutual respect, trust, and close interaction that exists between a firm and its partners (Granovetter, 1992; Kale et al., 2000). From a relational view, firms can profit from collaborative efforts with supply network partners by creating joint benefits that may have not been possible to create by either firm in isolation (Dyer and Singh, 1998). Lastly, the structural dimension refers to the overall pattern of connections between partnering firms, mapping who a particular firm reaches and how they reach them. From this dimension, the network structure derived from a firm's compendium of ties determine, in part, opportunities and constraints to access valuable resources and information that would help them sustain a competitive advantage (Burt, 1992). As mentioned earlier, in this chapter we focus on the structural dimension, and investigate the influence of two key *structural* characteristics of a firm's supply network on its innovation output – supply network accessibility and supply network interconnectedness –to examine the role of supply network structure as a source of innovation.

2.2 Supply network as a source of innovation

Innovation acts as an enabler to develop unique products and services that help a firm gain competitive advantage. It is well established in the literature that the accrual of knowledge assets that drive innovation in firms come from two primary sources: internal knowledge generation and knowledge derived from external sources. Generating internal knowledge assets can come from, for example, the progression of technical systems for effective experimentation, prototyping, simulation, and testing during product or service development (Thomke, 1998;

Gaimon and Bailey, 2012). Deriving knowledge from external sources is part of vicarious learning, whereby organizations acquire knowledge and experience from other external organizations (Dutton and Freedman, 1985; Hora and Klassen, 2013). Past literature in organizational learning has also emphasized the potential knowledge gain from external sources, such as suppliers, customers, service providers, and alliance partners in a firm's supply network (Yli-Renko et al., 2001). Thus, supply networks serve as important conduits and sources of information and knowledge access, and act as catalysts for the development and dissemination of new ideas, applications, and supply chain practices. This organizational phenomenon is espoused by social network theorists asserting that innovation performance advantage can be accrued by the knowledge and information assets derived from the structural linkages among firms in a network.

A core principle of the creation of the structural dimension in the social network is that firms are embedded in a larger network of supply partners, comprising of other firms that are able to provide access to unique resources, information, and influence (Granovetter, 1973). In that light, supply networks not only contain dyadic relationships between partners but also act as critical conduits of knowledge and information flow. Firms can leverage this dimension to facilitate the knowledge flows by influencing the conditions necessary for exchange and combination amongst its partners to occur (Nahapiet and Ghoshal, 1998). Several studies have underlined the benefits of structural characteristics such as a firm's structural position in its supply network (e.g., Burt, 2001; Yli-Renko et al., 2001; Zaheer and Bell, 2005; Kim et al., 2011).

2.3 Structural characteristics of supply networks

From the social network perspective, a network consists of entities (e.g., individuals, groups, firms) represented as nodes and ties between them represented as links (Wasserman and Faust, 1994). In the supply network context, the entities reflect suppliers, manufacturers, service providers, alliance partners, and customers that are linked together through activities related to the procurement and transformation of raw materials in order to produce and deliver goods and services (Lamming et al., 2000; Kouvelis et al., 2006). Two important structural characteristics that may act as important enablers of the flow of information and knowledge in the network are (i) how effectively a firm is able to access the different sources of information and knowledge assets in the network, formally termed *supply network accessibility*, and (ii) how these sources of information and knowledge are structurally inter-linked together in the network, formally termed *supply network interconnectedness.* We posit that these two structural characteristics of a supply network have significant influence on the innovation output of firms. These relationships are depicted in Figure 2.1, and discussed in more detail in the ensuing sections.

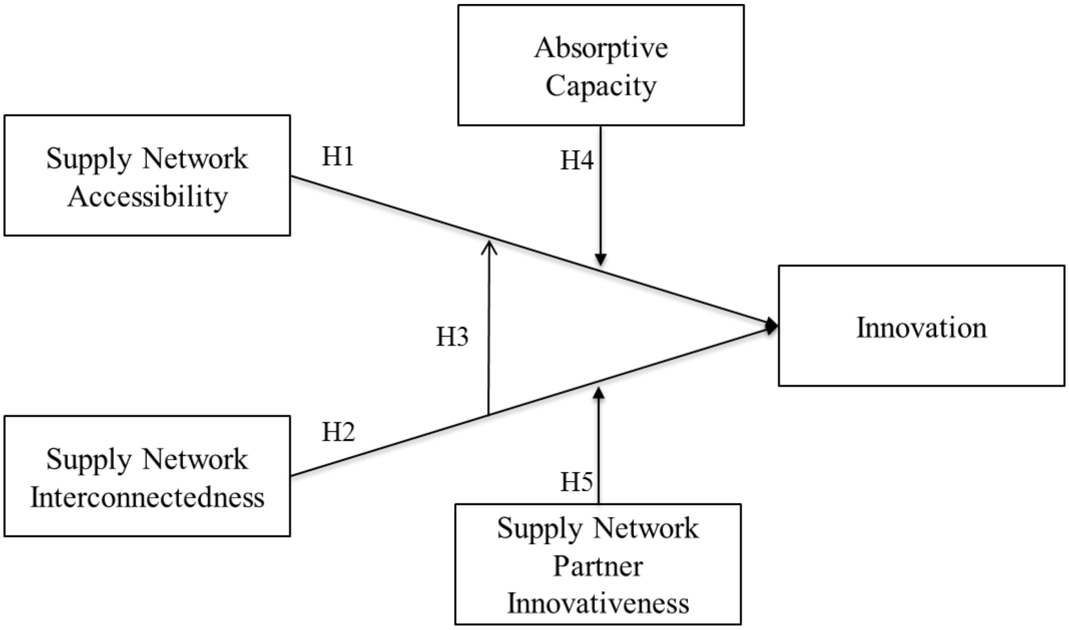


Figure 2.1. Conceptual model.

2.3.1 Supply network accessibility

Supply network accessibility refers to the effectiveness with which a firm can access information and knowledge from other members in its supply network, including indirect access to members with whom they do not share a direct relationship with. In addition, it also reflects the speed of information access. While the formal measure of this structural characteristic is given in Section 3.3.1, the ease and effectiveness of information and knowledge access by a focal firm from members in the supply network is influenced by the distance between each member and the focal firm in terms of the mean length of the path between them. In other words, high (low) levels of supply network accessibility allow a firm to traverse fewer (more) steps or connecting points to reach supply network members, for example, lower tier suppliers. Figure 2.2 illustrates the different levels of accessibility that a firm can have in its supply network.

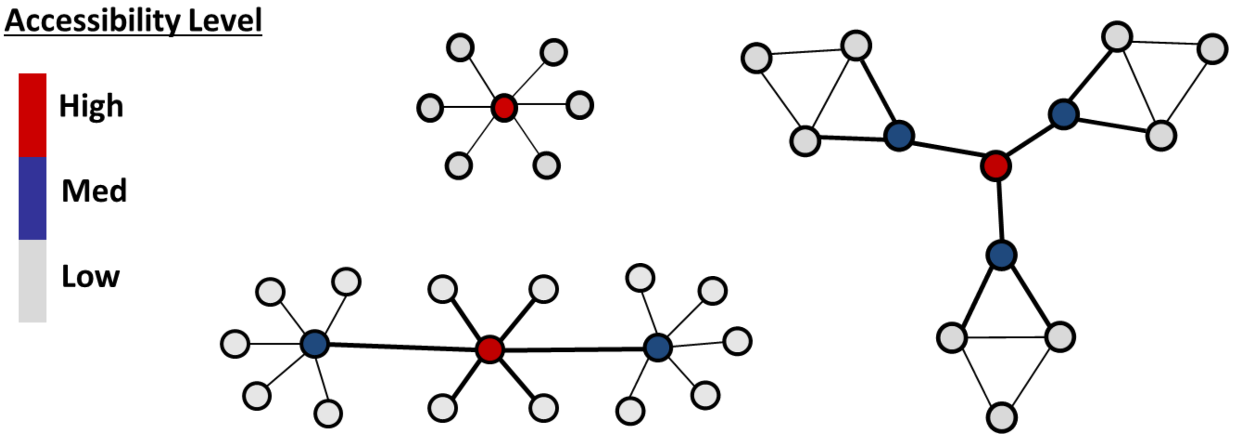


Figure 2.2. Illustration of firms with different levels of supply network accessibility.

Certain relationships in a firm's supply network – both direct and indirect – may be more suited to foster innovation. Because of their unique structural position within the network, some firms may be able to avail high levels of supply network accessibility and can thus access and transmit knowledge and information across the supply network faster. Such firms are able to reach a large number of members through a fewer number of intermediate connecting points (i.e. partners, other members) and are better positioned to obtain information quickly and with reduced risk of information distortion (Schilling and Phelps, 2007). Firms that have this favorable structural position in the supply network are referred to as central firms (Kim et al., 2011), and are reflected in Figure 2.2 as the darker nodes.

While prior studies have shown several operational benefits that derive from information access and transmission among supply chain members – such as reduced supply chain costs, shorter lead times and smaller batch sizes (Cachon and Fisher, 2000), lower inventory holding and shortage costs (Lee et al., 2000), and reduced stockouts (Kulp et al., 2004) – , there are also other benefits which lead to an increase in a firm's innovation output. Thus, firms with high levels of supply network accessibility may have access to more opportunities to obtain novel information or, in the case of R&D technology-sharing, to develop products sooner than their competitors (Borgatti and Molina, 2005). This information-based advantage becomes more critical in the context of fast-moving industries characterized by uncertain demand, low product life cycles, and highly innovative products (Kanda and Deshmukh, 2008).

Therefore, we argue that possessing higher levels of supply network accessibility allows a firm wider reach and access to knowledge and information in the network, which will enhance their potential to receive knowledge spillovers faster than others, and thus increases the likelihood of higher innovation output.

Hypothesis 1. *The level of accessibility in a firm's supply network is positively associated with its innovation output.*

2.3.2 Supply network interconnectedness

While supply network accessibility reflects the effectiveness with which a firm can access the knowledge and information sources in the supply network at large, supply network interconnectedness reflects the potential sources or ports of knowledge that reside because of the shared linkages among a firm’s direct partners. More formally, supply network interconnectedness refers to the degree to which supply network partners of a focal firm are connected to each other, and thus share direct links amongst themselves. Supply networks are considered to be densely interconnected when there are a large number of shared linkages that exist between the supply network partners of a focal firm. The notion of supply network interconnectedness can be seen through the simplified illustration shown in Figure 2.3. These illustrations depict two companies with similar supply network size, but with different levels of supply network interconnectedness. The depiction on the left of Figure 2.3 shows a focal firm with all of its direct partners only connected to it and no other source, leading to a network with low interconnectedness. Conversely, the depiction on the right shows a focal firm with the same number of direct partners, but this time where each partner shares at least three direct links with the other remaining partners, thus increasing the level of interconnectedness of the firm’s supply network.

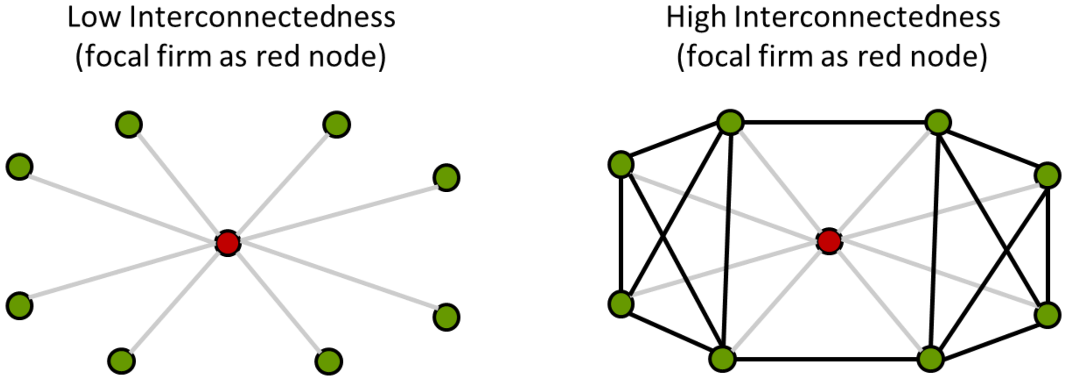


Figure 2.3. Illustration of a lowly versus highly interconnected supply network.

We posit that increased interconnectedness in a supply network is expected to positively influence innovation output for the following reasons. Inkpen and Tsang (2005, p. 152) suggest that interconnectedness through multiple knowledge connections enables “ease of knowledge exchange” for a focal firm and can thus enhance the flow of information and knowledge among its members. These benefits from increased interconnectedness in a supply network are derived due to the potential for richer collaboration, resource pooling, and problem solving within structurally embedded, dense cliques (Ahuja, 2000; Schilling and Phelps, 2007). Lavie (2006) conceptualized such benefits as inbound spillovers for the focal firm which may provide a competitive advantage. In addition, a highly interconnected network allows a focal firm to alleviate appropriation concerns and consider its partners more trustworthy (Echols and Tsai, 2005). Accordingly, collaborative environments within the supply network can facilitate the sharing of knowledge, enhance knowledge creation, and increase innovation activities in general (Inkpen, 1996; Simatupang and Sridharan, 2002). Moreover, the series of redundant ties – where a focal firm has multiple indirect ties to the same partner through more than one direct relationship – also enables the focal firm to validate the reliability of information that is exchanged in its supply network. Taken together “interconnected ties provide a firm with the kind of highly reliable and trustworthy partnerships needed to protect and advance its special knowledge” (Echols and Tsai, 2005, p. 223). Thus, in the context of supply networks, we propose that high levels of interconnectedness provide the focal firm, through the fostering of a more collaborative environment, a greater opportunity for accruing the benefits of knowledge spillovers in its innovation output.

Hypothesis 2. *The level of interconnectedness in a firm’s supply network is positively associated with its innovation output.*

2.3.3 Interaction between supply network accessibility and interconnectedness

In our first two hypotheses, we argued that knowledge and information flow benefits are expected from both supply network interconnectedness and supply network accessibility. Building on the basis that both supply network structural characteristics can lead to knowledge and information flow improvements in their own respect, we also posit a positive effect of the interaction of supply network interconnectedness and supply network accessibility on firm innovation output. In particular, firms operating in supply networks that possess both high both potential for collaboration enabled by many direct partners being inter-linked, and quicker ability to reach and access to knowledge and information in the network by accessibility, should experience greater innovation output.

Lower levels of interconnectedness between a focal firm's supply network partners may lead to lower levels of trust and a higher threat of opportunistic behavior, and hence lower resource-sharing benefits, potentially hindering innovation gains from relationships established. While firms with high supply network interconnectedness have a higher concentration of shared ties among its direct partners, a lack of connectivity in the wider network of a given industry can be exploited by boundary-spanning firms that cultivate more opportunities to increase their level of access to diverse information across the wider supply network (i.e. increase their supply network accessibility). Firms that span these clusters often occupy positions of considerable influence (Provan et al., 2007), suggesting that firm efforts to increase their level of supply network interconnectedness and supply network accessibility in tandem should further enhance their ability to positively influence innovation output. In sum, we predict an interaction effect between supply network interconnectedness and supply network accessibility in their effect on knowledge and information flow benefits to the focal firm.

Thus, we posit that firms that maintain highly interconnected supply networks while having higher levels of supply network accessibility will experience greater knowledge and information access and sharing, which is expected to have a positive effect on innovation output.

Hypothesis 3. *Higher levels of interconnectedness in a firm's supply network positively moderates the association between its supply network accessibility and innovation output.*

2.4 Moderating roles of knowledge variables on innovation output

In addition to the structural characteristics of a supply network developed above, we also examine the moderating influence of two important knowledge variables on the innovation output of firms. Specifically, we examine the moderating role of a firm's *absorptive capacity*, represented by the firm's ability to recognize, assimilate, and leverage knowledge, as well as the role of *supply network partner innovativeness*, reflecting the magnitude of knowledge available in the firms constituting the supply network. While the structural characteristics of a supply network reflects the effectiveness of how knowledge and information can be accessed as well as shared among the network partners, the knowledge variables – absorptive capacity and level of supply network partner innovativeness – are expected to beneficially influence innovation output. This provides the opportunity to investigate a more coherent theoretical framework, whereby the moderating effect of the knowledge variables can be ascertained in addition to the main and interaction effects of the structural variables on the innovation output of firms in a supply network.

2.4.1 Moderating role of absorptive capacity

While supply network accessibility can lead to greater access to information from supply network members, we further posit that focal firms that can absorb and internalize this available information and knowledge will gain additional benefits related to its innovation performance. The extent of absorbing this knowledge is termed as absorptive capacity, and is defined as a firm's ability to understand, assimilate, and deploy knowledge obtained from other firms, and leverage this knowledge to their benefit (Cohen and Levinthal, 1990; Yli-Renko et al., 2001). A focal firm's access to knowledge and information flow from its supply network members may provide a diverse set of ideas, expertise, and capabilities (Deeds and Decarolis, 1999). This heterogeneous knowledge base in the supply network has the potential of resulting in greater innovation for the focal firm (Tsai, 2001). However, the absorptive capacity of a firm influences its ability to adapt the available and accessible external information for its own needs for knowledge creation (Weigelt and Sarkar, 2009).

Ernst and Kim (2002) argue that the combination of both accessibility of information in the network and absorptive capacity are important for a focal firm to develop its innovation capabilities from external knowledge. Furthermore, Easterby-Smith et al. (2008, p. 679) suggest that "absorptive capacity and intra-organizational transfer capability are interrelated in the sense that an organization which is good at absorbing external knowledge should also be well equipped for diffusing the knowledge within its own boundary". In other words, absorptive capacity enables a focal firm to absorb available and accessible external information and knowledge from its partners in the supply network, and ensure that it can be leveraged for its own knowledge creation. In the absence of high absorptive capacity, a firm can still benefit from having access to knowledge in its supply network, but its ability to leverage this information to improve its innovation performance will be very limited. Therefore, we posit a moderating effect of a focal firm's absorptive capacity on the relationship between its supply network accessibility and its innovation output.

Hypothesis 4. *A firm's absorptive capacity positively moderates the association between its supply network accessibility and innovation output.*

2.4.2 Moderating role of supply network partner innovativeness

Supply network partner innovativeness refers to the level of technological know-how, unique knowledge, and other innovation related capabilities a network partner has accumulated over time. Insights into each potential partner's level of innovativeness can offer an indication of the magnitude of available knowledge that can spill over to other firms in the supply network, and consequently benefit a firm's future innovation-based activities. Azadegan et al. (2008) suggest that supplier innovativeness not only provides the buying firm with improved manufacturing capabilities due to the embedded nature of the supplied component, but also key learning from its suppliers in the process.

We argue that higher levels of innovativeness among the members in a supply network also enhance a firm's potential to benefit from the higher quality knowledge spillovers, and thus provide novel ways to recombine and leverage knowledge, problems, and solutions. Thus, while operating in a highly interconnected supply network can help facilitate knowledge flow and sharing opportunities among partners, the magnitude of knowledge available from a firm's partners can significantly benefit its innovation output. Consequently, this effect should trickle down to help enable the focal firm to develop new technology in its future endeavors (Stuart, 2000). Thus, we conjecture that the existence and level of external knowledge available to a focal firm via the innovativeness of its supply network partners, beneficially moderates the influence of the firm's supply network interconnectedness on its innovation output.

Hypothesis 5. *The innovativeness of a firm's supply network partners positively moderates the association between its supply network interconnectedness and innovation output.*

3. Methods

In this section, we describe our data sources, steps in constructing the dataset, operationalization of variables and model specification.

3.1 Research setting and data collection

We constructed a database from the following data sources: the Electronics Business 300 (EB 300) listings, the Connexiti database, and the Thomson Reuters SDC Platinum Joint Ventures/Alliances (SDC) database. Our data consisted of active supplier, customer, and alliance partner relationships found for firms in the electronics industry. The electronics industry has transitioned from being dominated by large vertically integrated companies – such as IBM, HP, Toshiba and Fujitsu – into an industry where companies have formed vastly global networks. Further, industries such as electronics are characterized with high market unpredictability, shorter product life cycles, and globalization (Sodhi and Lee, 2007) and that have been relying more on outside suppliers for integration of knowledge and technology (Dedrick et al., 2010). This environment puts greater pressure on firms to make use of the knowledge and technology of their partners to continually produce product and process innovations that add customer value. Thus, we find the supply networks of firms in the electronics industry to be a fitting research setting since we are interested in the knowledge flow that arises from the series of supply network relationships. To follow, we summarize our data collection and supply network building approach in four steps. Figure 2.4 portrays these steps.

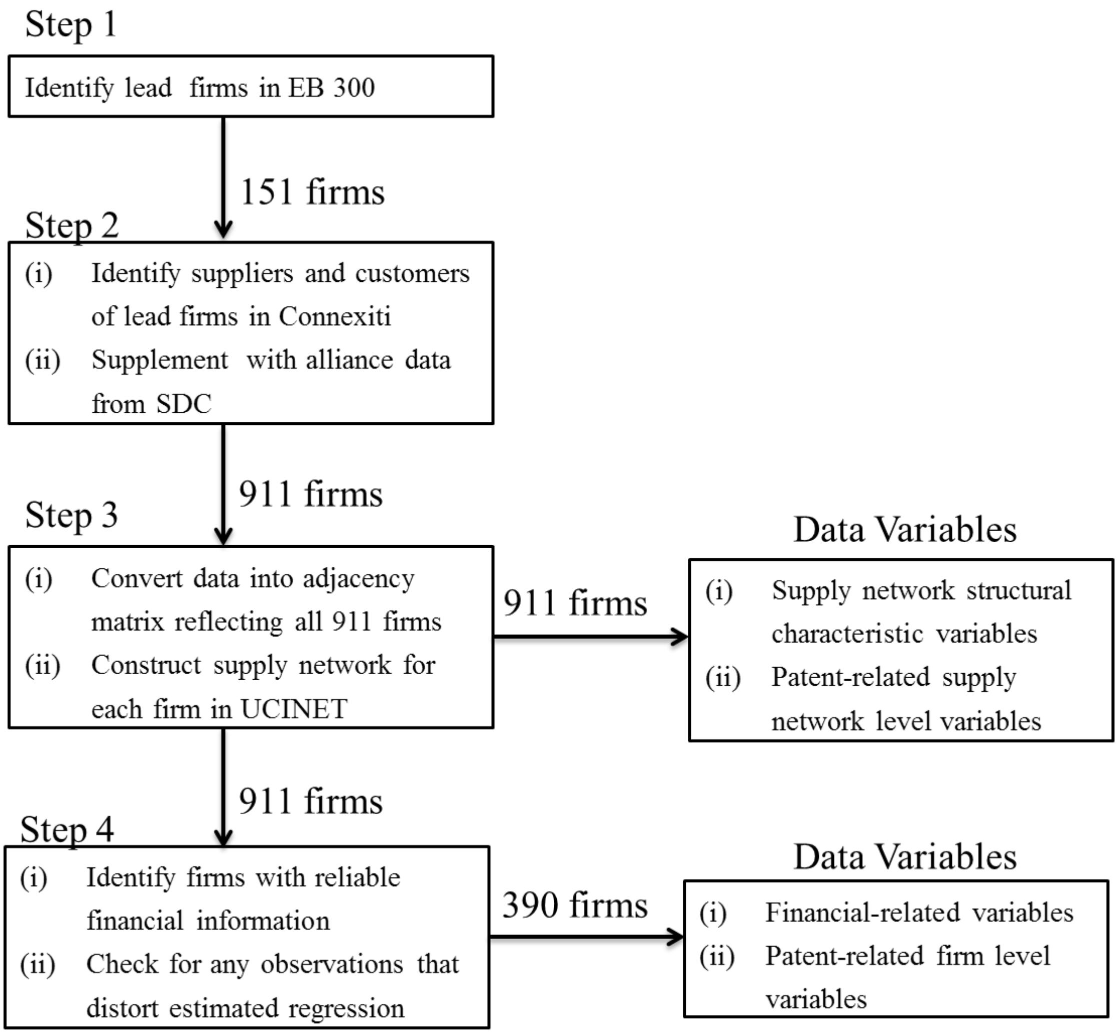


Figure 2.4. Steps involved in constructing the dataset for supply network and other data variables.

Step 1: First, we identified all firms listed in the EB 300 dataset from 2005 to 2009. The EB 300 dataset is an annual listing of the global 300 electronics firms ranked by revenue (from the sale, service, license or rental of electronics and computer equipment, software, or components), created by Electronics Design, Strategy, and News (EDN). From this list, we retrieved 151 unique firms that were identified as lead companies, contract and original design manufacturers, and component suppliers. We term these firms as "lead firms".

Step 2: Second, we identified the supply network relationships for these 151 lead firms using the Connexiti database. Connexiti is a comprehensive supply chain intelligence database consisting of supplier and customer relationships for nearly 20,000 companies. It contains information on suppliers, customers, and competitors, where information is retrieved from SEC filings, company press releases, website updates, analyst reports, and earning transcripts. Previous research has used Connexiti to study networks (e.g., Basole, 2009). Using each of the 151 lead firms as an initial source, we extracted all supply network relationships in Connexiti that were present during years 2007 and 2008. We then cross-validated and augmented our sample dataset with information from the SDC database, a commonly used source that includes data on strategic alliances as well as supply, manufacturing R&D, marketing and licensing agreements. The SDC database has been used in a number of empirical studies on strategic alliances and inter-firm networks (e.g., Schilling and Phelps, 2007; Rosenkopf and Padula, 2008).

Step 3: Third, by combining the relationship data from step 2 with the initial set of 151 leading firms, our final dataset from which to construct the entire sample of supply networks consisted of 911 firms. Thus, this larger dataset reflecting the full sample of supply networks was used to operationalize the theoretical constructs, supply network accessibility and interconnectedness, which are conjectured in our hypotheses to influence a firm's innovation output.

Step 4: While we had 911 firms from which to build our supply networks and calculate measures related to the structural characteristics, our final sample of firms for the regression analysis step was further reduced due to lack of financial data (e.g., missing data for either creating independent and control variables or for averaging the corresponding measures) or observations identified as outliers. Additionally, finding reliable financial information for private firms was not possible and thus reduced our sample size for analysis to 409 firms. To account for observations whose inclusion unduly distorted the regression model, we calculated the Cook's D values (Cook, 1977) for each observation to find any with very large residuals and with an extreme value on any one of the predictor variables. We excluded any observations that lied above the conventional cut-off of $4/n-k-1$, where n is the sample size and k is the number of predictor variables in the model. This reduced our final sample size for sake of regression analysis to 390 firms.

For our innovation-related variables, we retrieved the patent data from the United States Patent and Trademark Office (USPTO) and Classification and Search Support Information System (CASSIS) Database. We obtained data on patents issued to each company in our sample and cleaned and organized the data on an annual basis. We include a patent in a given year based on its date of application. Using a granted patent's application date allows us to have a closer indication of when the invention occurred, as an invention is estimated to have occurred about three months prior to the patent application date (Darby and Zucker, 2003). Inventions can then be used to trace back a firm's knowledge creation activity. The underlying logic is that inventions serve as a way to instantiate knowledge creation (Schmookler, 1966) and the accumulation of knowledge engrained in inventions is used to facilitate a firm's processes that generate novel actions from a given set of resources (Hargadon and Fanelli, 2002).

3.2 Dependent variable: Innovation output

We use the number of patents granted as an indicator of a firm's innovation output (e.g., Shan et al., 1994; Penner-Hahn and Shaver, 2005; Rothaermel and Hess, 2007). Patents serve as a useful measure of innovation output that reflect advancements over existing technology and are externally validated. Hauser et al. (2006) argue that protecting one’s lead in technological evolution, and hence achieving competitive advantage, is done by securing patents. Recent studies have also shown that firms that possess a large number of patents are more likely to transform their inventions into a larger number of new products and services introduced to the market (Joshi et al., 2010). Prior research shows that firms in the semiconductor, computer, and communications equipment sectors – all prevalent sectors in our sample – actively patent (Levin et al., 1987). Similar to other studies, we represent the innovation output of a firm by the average number of patent applications granted over three years (2009-2011) (e.g., Benner and Tushman, 2002; Ceccagnoli, 2009). In addition, we have included Table 2.1 which provides a description of innovation output and of other constructs, their corresponding operationalization, variable type, years for which the data corresponds to, the representative measure, and the data sources.

Table 2.1
Description of variables.

Construct	Variable	Variable Type	Year	Measure	Data Source(s)
Innovation Output	Granted Patents	Dependent	2009-2011 (Avg)	$Innov_i = Patents_i$	USPTO, CASSIS
Firm Size	Natural Log of Sales	Control	2004-2008 (Avg)	$Firm\_Size_i = Ln(SALES_i)$	Compustat
Firm Age	Firm Age	Control	N/A	Age_i	Compustat
Industry Concentration	Herfindahl–Hirschman index (HHI)	Control	2004-2008 (Avg)	$Ind\_Con_i = \sum_{j=1}^{S} \left(\frac{SALES_i}{SALES_{SIC_j}} \right)$	Compustat
Industry Growth	Percent Change in Sales	Control	2004-2008 (Avg)	$Ind\_SG_i = \%SALES\_Growth_{SIC_j}$	Compustat
Prior Innovation	Time-Varying Patent Stock	Control	2006-2008 (Avg)	$Prior\_Innov_i = Time\_Var\_Patent\_Stock_i$	USPTO, CASSIS
Prior Knowledge Breadth	No. of Classes Patented In	Control	2004-2008 (Avg)	$Know\_Bre_i = No\_Unique\_Pat\_Classes_i$	USPTO, CASSIS

Table 2.1 continued
Description of variables.

Supply Network Accessibility	Information Centrality	Independent	2007-2008	$IC_i = \left[c_{ii} + \left(\sum_{j=1}^{n} c_{jj} - 2 \sum_{j=1}^{n} c_{ij} \right) / n \right]^{-1}$ $B = D(r) - A + J, \quad C = (c_{ij}) = B^{-1}$	EB300, Connexiti, SDC, UCINET
Supply Network Interconnectedness	(1-Network Efficiency)	Independent	2007-2008	$Interc_i = 1 - \left[\sum_{j} \left[1 - \sum_{q} p_{iq} m_{jq} \right] \right] / n_i$	EB300, Connexiti, SDC, UCINET
Absorptive Capacity	R&D Intensity	Independent	2004-2008 (Avg)	$Abs\_Cap_i = \frac{R\&D_i}{SALES_i}$	Compustat
Supply Network Partner Innovativeness	Average Patent Stock of a Firm's Supply Network	Independent	2004-2008 (Avg)	$SN\_Part\_Innov_i = \left[\sum_{j=1}^{n_i} Prior\_Patent\_Stock_j \right] / n_i$	USPTO, CASSIS

We acknowledge that there are concerns associated with the use of patent count data that merit discussion. The first concern is the potential right censoring bias when using patent applications granted, as the majority of patent applications are either granted or abandoned within two to three years of application. In fact, over the past ten years, we verified that the average time from the patent application filing date to the date of disposition (granted or abandoned) has been 2.5 years (USPTO, 2001-2011). In order to mitigate any right censoring bias, our dataset consists of all patents applied for in 2009-2011 that were granted up until Jan 2014.

The second concern is the argument that citation-weighted patent counts better reflect an innovation's quality than patent counts alone. Prior empirical research, however, has established patent count data as reliable in itself by showing the high correlation between patent count and citation-weighted patent measures. In fact, correlations for the two measures were found to be 0.925 ($p < 0.001$) in the electronics and communications industry, 0.973 ($p < 0.001$) in the computers and office machinery industry, and greater than 0.80 ($p < 0.001$) in the semiconductor industry (Stuart, 2000; Hagedoorn and Cloodt, 2003), rendering this assertion more generalizable. Hence, our use of patent counts to reliably proxy the same underlying theoretical construct as citation-weighted patent counts. Further, patent counts have been shown to be positively correlated with new product introductions (Brouwer and Kleinknecht, 1999) and technical capabilities (Hoetker, 2005), and have been regarded as valid and robust indicators of knowledge creation (Trajtenberg, 1987).

3.3 Independent and moderating variables

We operationalize two structural characteristics: (1) *information centrality* used to measure supply network accessibility and (2) *network efficiency* to measure the interconnectedness a firm’s direct partner supply network. To calculate these two measures, we first construct an undirected binary adjacency matrix reflecting the series of supply network relationships among all firms in our sample. Within our binary adjacency matrix, each cell entry is marked as 1 if there exists a buyer-supplier or alliance relationship between two companies and 0 otherwise. We chose to represent multiple relationships between the same pair of firms as one link in our network for two reasons. First, our primary focus is whether a relationship between two companies exists and not with multiplex relationships. Second, collaborative relationships are typically considered to be bidirectional (Newman et al., 2000). For example, several high-tech products require the integration of sophisticated components that result in ongoing communication and interaction between supply network partners about process and design phases for assembling and testing these products.

We used UCINET 6.365, a social network analysis package (Borgatti et al., 2002), to compute the two independent variable measures. The measures are based on the use of social network analysis, grounded in principles from matrix algebra and graph theory (Wasserman and Faust, 1994). A growing number of supply chain management studies have adopted concepts and tools suggested by Borgatti and Li (2009) that are founded in social network theory (e.g., Carter et al., 2007; Autry and Griffis, 2008; Kim et al., 2011). We describe both measures to follow. For even further clarification on how these measures are calculated, readers can refer to Stephenson and Zelen (1989), and Burt (1992).

3.3.1 Supply network accessibility

Supply network accessibility incorporates potential ports of access to knowledge and information across the supply network. We operationalize *supply network accessibility* by using *information centrality* (Stephenson and Zelen, 1989). *Information centrality* is measured by using the harmonic mean length of paths ending at a node i, with this length being smaller if *i* has many short paths connecting it to other nodes in the network:

$$\boldsymbol{IC_i = \frac{n}{nc_{ii} + \sum_{j=1}^{n} c_{jj} - 2\sum_{j=1}^{n} c_{ij}}}$$

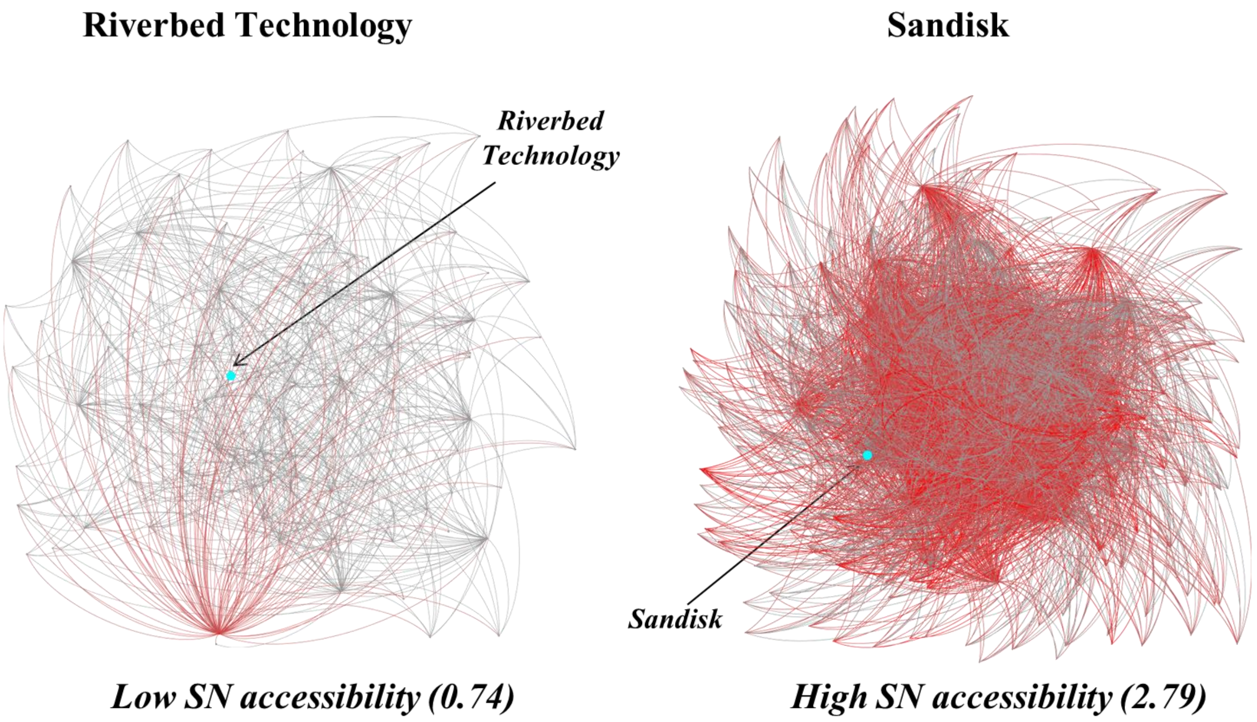
$$\boldsymbol{= \left[c_{ii} + \left(\sum_{j=1}^{n} c_{jj} - 2\sum_{j=1}^{n} c_{ij}\right)/n\right]^{-1}} \qquad (1)$$

where $$\boldsymbol{B = D(r) - A + J, \qquad C = (c_{ij}) = B^{-1}} \qquad (2)$$

First, the matrix B is constructed by taking the diagonal matrix $\mathrm{D(r)}$ of the number of direct ties firm *i* has, subtracting it from the adjacency matrix A of the supply network, and adding the matrix J with all elements at unity. Next, information centrality scores are calculated using element entries of C, the inverted matrix of B, and the number of firms in the network n. The index has a minimum value of 0, but no maximum value. In our sample, the values for information centrality ranged from a minimum of 0.69 to a maximum of 2.80.

This measure of information centrality focuses on a firm's opportunities to access information and knowledge contained in all paths that originate (and end) at a particular node in a network. This measure is rooted in the theory of statistical estimation, where a path connecting two nodes is considered as a signal and the noise in the transmission of the signal is measured by the variance of this signal. The measure of information available through each transmission would then be the reciprocal of the variance (Stephenson and Zelen, 1989). For the sake of our model, information centrality serves as a measure of *supply network accessibility* to represent the speed and extent of opportunities a firm has to access information and knowledge from other members in the supply network.

Figure 2.5 illustrates a comparison of two companies with different levels of accessibility within the overall supply network. The darker lines reflect the connections shared among that focal firm’s partners, and the focal firm is indicated by the biggest node in the graph. Here we highlight the wider supply network that a focal firm has access to via its indirect connections. The firm Riverbed Technology appears to have a relatively low level of accessibility to other members in the supply network compared with another firm, Sandisk, which appears to possess a relatively high level of supply network accessibility.


Riverbed Technology

Sandisk

Low SN accessibility (0.74)

High SN accessibility (2.79)

Figure 2.5. Comparison of firms with high and low information centrality levels.

3.3.2 Supply network interconnectedness

We capture *supply network interconnectedness* by assessing the number of shared relationships that exist between the supply network partners of a focal firm. As mentioned earlier, we are also interested in capturing the extent to which a firm's supply network partners are densely (sparsely) connected. Assessing shared relationships helps provide insights into how closely knit a focal firm's partners are with each other and into possible redundant ties that are built into the supply network. More formally, *network efficiency* accounts for the level of *supply network interconnectedness* by adapting the efficiency equation from Burt (1992):

$$\boldsymbol{Interc_i = 1 - Effic_i = 1 - \left[\sum_j \left[1 - \sum_q p_{iq} m_{jq}\right]\right] / n_i} \qquad (3)$$

where p_{iq} is the proportion of focal firm i's ties invested in the relationship with q, m_{jq} is the marginal strength of the tie between members j and q (that are both directly connected to i) and n_i is the total number of direct partners of focal firm i. Since our supply network representations are binary, the values of m_{jq} are set to 1 if a tie is present between members j and q and 0 otherwise.

The notion of network efficiency suggests that, if a focal node has at least one pair of direct sources who are also directly connected to each other, then its network is considered to be inefficiently connected. Thus, a network is considered to be inefficiently connected in a sense that there is at least one tie in the network that indirectly connects the focal node to the same source of knowledge, resource, or information. This tie would be considered as a redundant tie. Therefore, we use network efficiency to measure how interconnected a supply network is based on the number of redundant ties present in the supply network. Based on this operationalization, a larger network efficiency score would correspond to a lower level of *supply network interconnectedness* and vice versa.

The values for the measure of network efficiency range from 0 to 1, where a value of 1 indicates that all of a firm's partners share no ties to each other. Thus, since this measure works in the opposite direction as our hypothesized construct and spans from 0 to 1, we calculated *supply network interconnectedness* as (1- *network efficiency*) to help avoid ambiguity in interpreting its hypothesized effect. In our sample, the values for network efficiency ranged from a minimum of 0.33 to a maximum of 1. This reverse coding resulted in minimum and maximum *supply network interconnectedness* values of 0 and 0.67, respectively. The illustrations in Figure 2.6 provide a comparison of two companies with different supply network structures, but with a similar number of direct ties. The lighter lines indicate a focal firm’s direct connections, while the darker lines reflect the connections among that focal firm’s partners. The focal firm is indicated by the biggest node in the graph. Eastman Kodak appears to have a supply network characterized by low interconnectedness and hence a high level of efficiency. Conversely, Intel appears to have a highly interconnected supply network with the multitude of ties offering several ports of access to knowledge, resources, and information. Network efficiency has been used in other interfirm studies as a redundancy based measure of structural holes at the local level, based only on ties between a focal firm’s direct partners (Ahuja, 2000; Schilling and Phelps, 2007; Paruchuri, 2010).

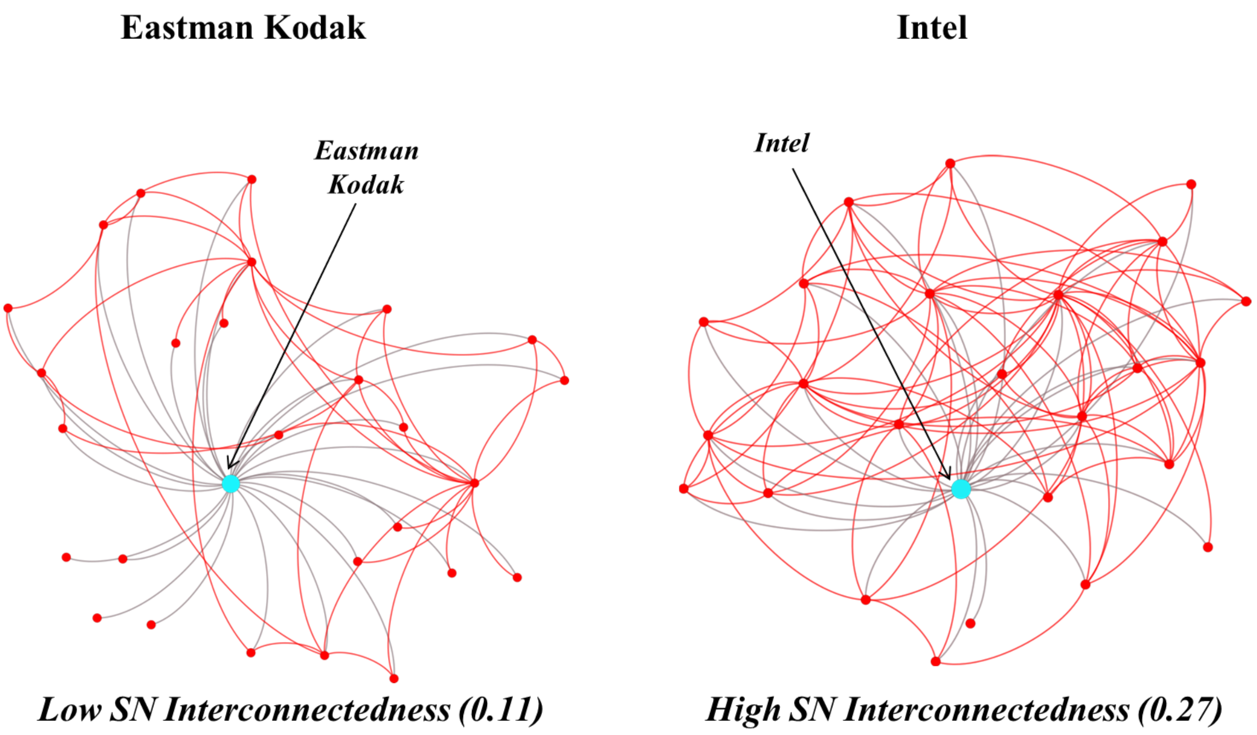


Figure 2.6. Comparison of firms with low and high interconnectedness.

3.3.3 Absorptive capacity: R&D intensity

A firm's absorptive capacity – the ability to recognize, assimilate, and deploy outside knowledge – is a crucial element affecting its innovation output levels. Research has suggested that a firm's absorptive capacity is largely a function of its investment in R&D and its level of prior related knowledge (Cohen and Levinthal, 1990). The rationale is that firms conducting their own R&D are better equipped to make use of externally available information. While the notion of absorptive capacity can also be explained in terms of a firm's direct involvement in the manufacturing process or the cognitive structures that underlie learning, we rely on the more readily available measure of investment in R&D as a proxy for a firm's ability to recognize and exploit new knowledge from external sources in their supply network (Cohen and Levinthal, 1990). Thus, we included *R&D intensity* as it can contribute to a firm's ability to absorb outside knowledge (Rothaermel and Hess, 2007). We calculated *R&D intensity* as the R&D expenditures measured as percentage of total sales.

3.3.4 Supply network partner innovativeness: Average patent stock of firm's partners

To capture *supply network partner innovativeness*, we consider the total knowledge accumulated from each supply network partner, based on the partner's respective history of patenting activities. Assessing the amount of knowledge accumulated by each of its partners over time gives the firm a better sense of the magnitude of knowledge that may spill over as the relationship develops. We operationalize *supply network partner innovativeness* as follows. First, we calculated the average patent stock of each supply network partner by summing a partner's patent stock over the previous five years (2004-2008). Next, for each firm, we then measured supply network partner innovativeness by taking the mean of the average patent stock of all of a firm's partners. Lastly, we normalized this measure of supply network partner innovativeness for use in the analysis (Narin et al., 1987). Previous scholars point out how a firm's current technological stance is often dependent on its previous level of technological know-how, due to the cumulative nature of technology. A firm's level of *patent stock*, also referred to as technical capital in prior literature, can be seen to represent the depth of a firm's technological resources (Silverman, 1999). *Patent stock* has been used in previous studies looking at high-tech industries to assess technological impact, calculated as a firm's patenting activity in the previous five years (e.g., Ahuja, 2000; Vanhaverbeke et al., 2009). Thus, we calculated the cumulative patent stock of each firm in the sample from 2004-2008.[1]

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[1] As a note, we also ran our analysis using the previous three and four years separately. Our results were robust to these changes.

3.4 Control variables

As shown in Table 2.1, we control for the following variables: Firm size, firm age, prior innovation, knowledge breadth, lead firm indicator, and industry-level control variables (industry concentration and industry growth). Financial data for the moderating and control variables was retrieved from the Compustat database and cross-examined using the Mergent Online database. *Firm size* may influence a firm's level of innovation output, as larger firms have more financial means and greater resources to invest in innovation-related activities than smaller firms. Interestingly, firm size can both positively or negatively influence its innovation output (Teece, 1992). We controlled for firm size using the natural log of sales. Next, we controlled for *firm age*, as older firms are expected to leverage more of their existing technological competencies while younger firms are expected to experiment more with new technologies (Sorensen and Stuart, 2000). *Firm age* was calculated as the number of years from the date of the firm's founding to the current year of 2013. We also include the following two industry-level control variables, with industry defined at the two-digit Standard Industry Classification (SIC) level: industry concentration (captured by the Herfindahl-Hirschman Index (HHI)) and industry growth (captured by the percentage change in annual industry sales). The use of industry controls help ensure that our findings are robust to industry effects, as industry may influence a firm's patenting behavior. Next, we incorporate two variables into our model to control for past innovation activity: prior innovation and knowledge breadth. Prior innovation is used to capture the time-varying patent stock of a firm, while knowledge breadth is used to capture the number of unique classes a firm has patented in. Lastly, we control for lead firms in our sample, to isolate the effect of such firms on innovation output. We operationalize this as a binary variable with a “1” indicating that the focal firm was one of the lead firms and a “0” otherwise.

3.5 Model Specification

We operationalize innovation output by using the number of granted patents as our dependent variable. A count variable that takes on only non-negative integer values makes a linear regression model inappropriate as it assumes the distribution of residuals to be homoscedastic, normally distributed. This could lead to coefficient estimates that are both biased and inconsistent (Greene, 2003). Poisson and negative binomial regression are more appropriate models for count data. Because of the presence of overdispersion in our patent data, the assumption of Poisson regression that the mean and variance are equal does not hold. The negative binomial model accounts for overdispersion and helps avoid spuriously high levels of significance due to coefficients whose standard errors are underestimated (Cameron and Trivedi, 1986). By inspecting the likelihood ratio test, we found strong evidence for the negative binomial model as more appropriate than the Poisson model for our data (p < 0.001).

The negative binomial model has the following form (Hilbe, 2011):

$$\boldsymbol{\mathcal{L}} = \sum_{\boldsymbol{i=1}}^{\boldsymbol{n}} \left\{ \boldsymbol{y_i} \ln \left(\frac{\boldsymbol{\alpha} \exp(\boldsymbol{x_i'\beta})}{\mathbf{1} + \boldsymbol{\alpha} \exp(\boldsymbol{x_i'\beta})} \right) - \frac{\mathbf{1}}{\boldsymbol{\alpha}} \ln(\mathbf{1} + \boldsymbol{\alpha} \exp(\boldsymbol{x_i'\beta})) \right. \\ \left. + \ln \Gamma \left(\boldsymbol{y_i} + \frac{\mathbf{1}}{\boldsymbol{\alpha}} \right) - \ln \Gamma \left(\boldsymbol{y_i} + \mathbf{1} \right) - \ln \Gamma \left(\frac{\mathbf{1}}{\boldsymbol{\alpha}} \right) \right\} \tag{4}$$

The above equations for the model are expressed as log-likelihood functions, as is typical for a count model. In the above equations, y_i refers to the outcome variable measured by patent count, the x_i's refer to each explanatory variable (*firm size, firm age, industry concentration, industry growth, prior innovation, knowledge breadth, lead firm, supply network accessibility, supply network interconnectedness, absorptive capacity, supply network partner innovativeness, supply network accessibility*supply network interconnectedness, supply network accessibility*absorptive capacity, supply network interconnectedness* supply network partner* *innovativeness*), $\propto$ reflects the value of the heterogeneity or overdispersion parameter, and β represents the model coefficients.

4. Results

We ran all analyses in STATA Version 13. We first report summary statistics by industries defined at the two-digit SIC level in Table 2.2. The descriptive statistics and simple correlations are presented in Table 2.3. We also took several measures to account for multicollinearity. First, we used the grand mean-centered values of all explanatory variables used in the interaction terms, mitigating multicollinearity. Second, we ensured that the variance inflation factor (VIF) scores for each predictor variable were below a value of 10, indicating that multicollinearity is not an issue in the given dataset (Neter et al., 1996). Each of the VIF scores for our dataset met this requirement (mean score of 1.43) after we mean-centered the necessary variables.

Table 2.2
Summary statistics by industries defined at the two-digit Standard Industry Classification (SIC) level.

SIC	Industry	# Obs	Firm Innov	Firm Size	Firm Age	Indus Conc	Indus Grow	Prior Innov	Prior Kno Bre	SN Acc	SN Int	Abs Cap	SN Part Innov
2800-2899	Chemicals & Allied Products	4	17.3	5.44	37	0.25	0.097	-0.12	36	2.15	0.097	0.037	0.075
3000-3099	Rubber & Misc. Plastics Products	3	2.67	6.44	17.3	0.19	-0.0090	0.038	12	1.41	0.019	0.023	0.025
3300-3399	Primary Metal Industries	4	10.3	7.22	19	0.31	0.056	0.29	4.50	1.90	0.25	0.012	0.025
3500-3599	Industrial Machinery & Computer Equip.	79	12.1	5.73	20.8	0.41	0.11	-0.092	15.3	2.02	0.19	0.15	0.079
3600-3699	Electronic, Electrical Equip. & Compts., Not Computer Equip.	185	27.4	5.71	22.3	0.19	0.074	0.017	18.8	2.18	0.18	0.18	0.080
3700-3799	Transportation Equip.	3	13	8.87	62	0.34	0.083	-0.25	80	1.87	0.27	0.033	0.049
3800-3899	Instruments & Related Products	28	11.9	5.38	22.7	0.27	0.066	-0.081	15.7	2.01	0.17	0.16	0.064
3900-3999	Misc. Manufacturing Industries	2	8	8.12	20.5	0.33	0.18	-0.076	15	2.57	0.028	0.029	0.080
4800-4899	Communications	10	30.8	6.58	20.7	0.16	0.044	0.011	12.5	1.41	0.083	0.073	0.018
5000-5099	Wholesale Trade - Durable Goods	9	2.22	7.80	32.4	0.34	0.075	0.15	2.67	1.71	0.068	0.00088	0.028
7300-7399	Business Services	63	37.7	5.72	19.2	0.20	0.063	0.022	12.8	1.81	0.11	0.17	0.056
Total	All Industries	390	23.7	5.82	22.1	0.25	0.078	-0.0091	16.8	2.04	0.17	0.16	0.071

Table 2.3

Descriptive statistics and correlations[a].

	Variable	Mean	Std. Dev.	1	2	3	4	5	6	7	8	9	10	11	12
1	Firm Innovation	23.65	82.84	1.00											
2	Firm Size	5.82	2.20	0.48	1.00										
3	Firm Age	22.11	12.05	0.18	0.37	1.00									
4	Industry Concentration	0.25	0.17	-0.08	0.00	0.08	1.00								
5	Industry Growth	0.08	0.05	-0.03	0.04	-0.02	0.19	1.00							
6	Prior Innovation	-0.01	0.35	-0.16	-0.18	-0.10	-0.05	-0.02	1.00						
7	Prior Knowledge Breadth	16.78	27.53	0.66	0.65	0.32	-0.04	0.00	-0.27	1.00					
8	Lead Firm	0.22	0.42	0.41	0.67	0.29	0.03	0.09	-0.18	0.60	1.00				
9	SN Accessibility	2.04	0.61	0.16	0.32	0.13	-0.07	0.13	-0.02	0.30	0.45	1.00			
10	SN Interconnectedness	0.17	0.13	0.07	0.15	0.04	-0.01	-0.01	-0.09	0.11	0.10	0.30	1.00		
11	Absorptive Capacity	0.16	0.20	-0.08	-0.38	-0.20	-0.10	0.13	-0.05	-0.11	-0.15	-0.07	-0.03	1.00	
12	SN Partner Innovativeness	0.07	0.12	0.07	0.23	0.11	-0.01	0.14	0.02	0.20	0.35	0.53	0.00	-0.01	1.00

[a] N = 390 observations. All correlations with magnitude >|0.095| are significant at $p<0.05$ level.

4.1 Main results

The results of the negative binomial regression are presented in Table 2.4. The effects are introduced sequentially in models 1 through 5 to help ensure model stability and to make sure that any significant effect is robust to the inclusion of other effects. For each model, we performed Wald tests based on the null hypothesis that that all of the estimated coefficients that were not present in the previous model are equal to zero. The chi-square statistics and significance levels are found below the log likelihood values in Table 2.4. Model 1 includes only the control variables. Some of the control variables are significant. Specifically, firm size, and prior knowledge breadth are shown to positively affect the level of innovation output. Conversely, firm age and industry concentration have a negative influence on innovation output, suggesting that older firms tend to rely on more heavily on existing technology and less on patenting new innovations and that more concentrated industries have lesser innovation output. Model 2 includes the main effects of supply network accessibility, supply network interconnectedness, absorptive capacity, and supply network partner innovativeness. The results suggest that the level of innovation output increased with an increase in supply network accessibility ($p < 0.001$), thus providing support for Hypothesis 1. The model displays an insignificant relationship between supply network interconnectedness and innovation output, showing lack of support for Hypothesis 2. Models 3 and 4 incrementally include interactions related to Hypothesis 3 and 4. Lastly, Model 5 includes the interaction related to Hypothesis 5 and represents the full model.

As seen in Table 2.4, the positive association between supply network accessibility and innovation output (Hypothesis 1) remains throughout to the full model. Also, the coefficients reflecting the effect of supply network interconnectedness are all positive as expected

(Hypothesis 2) albeit only significant in the full model. Further, Hypothesis 3 that posited supply network interconnectedness has a positive and significant interaction effect on supply network accessibility is at least partially supported ($p<0.10$). Moreover, the results suggest that the positive association between supply network accessibility and innovation output is positively moderated by a firm's absorptive capacity ($p < 0.05$), thus providing support for Hypothesis 4. Lastly, the positive and significant association between the moderation of supply network partner innovativeness on supply network interconnectedness ($p < 0.05$) indicates support for Hypothesis 5. The results shown in Model 5 are an improvement over all previous models (e.g., compared with Model 4, likelihood ratio test statistic: 4.92; $p < 0.05$).

Table 2.4

Negative binomial regression model – innovation output (2009-2011 patents)[a].

Variables:	Model 1	Model 2	Model 3	Model 4	Model 5
Controls					
Firm Size	0.62***	0.67***	0.66***	0.66***	0.68***
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Firm Age	-0.01*	-0.01	-0.01*	-0.01	-0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Industry Concentration	-1.90***	-1.69***	-1.47***	-1.41***	-1.39***
	(0.39)	(0.38)	(0.39)	(0.39)	(0.39)
Industry Growth	1.94	1.56	1.23	1.85	2.06
	(1.43)	(1.39)	(1.37)	(1.38)	(1.37)
Prior Innovation	0.24	0.21	0.16	0.18	0.18
	(0.18)	(0.18)	(0.17)	(0.17)	(0.17)
Prior Knowledge Breadth	0.02***	0.02***	0.02***	0.02***	0.02***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Lead Firm	0.09	-0.24	-0.33	-0.22	-0.32
	(0.19)	(0.21)	(0.21)	(0.21)	(0.21)
Direct effects					
SN Accessibility[b]		0.50***	0.68***	0.69***	0.63***
		(0.15)	(0.15)	(0.15)	(0.15)
SN Interconnectedness[b]		0.11	0.87	0.83	1.28*
		(0.54)	(0.57)	(0.56)	(0.59)
Absorptive Capacity[b]		0.93*	0.80	1.24*	1.30*
		(0.46)	(0.46)	(0.54)	(0.53)
SN Partner Innovativeness[b]		-0.36	-0.30	-0.52	0.12
		(0.64)	(0.61)	(0.61)	(0.69)
Moderation effects					
SN Access * SN Interc			3.14***	3.19***	2.00
			(0.93)	(0.93)	(1.07)
SN Access * Abs Cap				1.80*	1.78*
				(0.87)	(0.85)
SN Interc * SN Partner Innov					19.58*
					(8.79)
Constant	-1.97***	-2.28***	-2.30***	-2.41***	-2.46***
	(0.28)	(0.30)	(0.30)	(0.30)	(0.30)
Log Likelihood	-1035.64	-1025.42	-1019.91	-1016.45	-1013.99
LR Test		20.44***	11.02***	6.91**	4.92*
N	390	390	390	390	390

[a] Standard errors in parentheses; *** p<0.001, ** p<0.01, * p<0.05

[b] Variables were grand mean-centered.

4.2 Moderating effects

Further interpretation of each moderating effect can be enriched by using interaction plots of the variables of interest. We graph the predicted innovation output with changes in each corresponding variable, using high and low values of the variable values as one standard deviation above and below the mean, respectively. Figure 2.7 shows the plot of the interaction between a firm's supply network accessibility and its level of interconnectedness. The "Low SN interconnect." line relates to the moderating effect of supply network interconnectedness, and depicts the slope of the effect of supply network accessibility on patents when the value of supply network interconnectedness is set to one standard deviation below its (mean-centered) mean. In contrast, the "High SN interconnect." line reflects the slope of the effect of supply network accessibility on innovation output when the value of supply network interconnectedness is set to one standard deviation above its (mean-centered) mean. High levels of supply network interconnectedness are shown to positively reinforce the effect of supply network accessibility on the firm's innovation output.

Figure 2.8 shows the plot representing the moderating effect of absorptive capacity on a firm's supply network accessibility. The "Low Abs. Cap." line relates to the moderating effect of absorptive capacity, and depicts the slope of this effect on supply network accessibility on innovation output when the value of absorptive capacity is set to one standard deviation below its (mean-centered) mean. In contrast, the "High Abs. Cap." line reflects the slope of the effect of supply network accessibility on innovation output when the value of absorptive capacity is set to one standard deviation above its (mean-centered) mean. High levels of absorptive capacity are shown to positively reinforce the relationship between supply network accessibility and innovation output.

Lastly, Figure 2.9 shows the plot representing the moderating effect of supply network partner innovativeness on supply network interconnectedness. The “Low SN Partner Innov.” line relates to the moderating effect of supply network partner innovativeness, and depicts the slope of this effect on supply network interconnectedness on innovation output when the value of supply network partner innovativeness is set to one standard deviation below its (mean-centered) mean. In contrast, the “High SN Partner Innov.” line reflects the slope of the effect of supply network interconnectedness on innovation output when the value of supply network partner innovativeness is set to one standard deviation above its (mean-centered) mean. High levels of supply network partner innovativeness are shown to positively reinforce the relationship between supply network interconnectedness and innovation output.

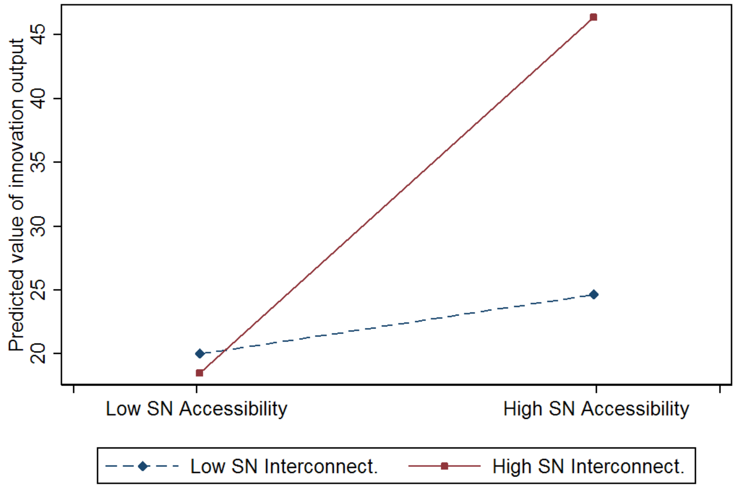

Figure 2.7. Moderating effect of supply network interconnectedness on supply network accessibility.

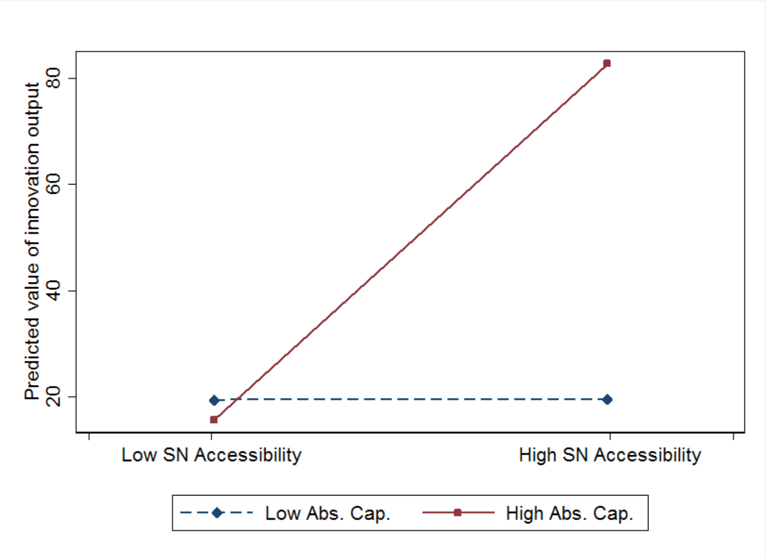

Figure 2.8. Moderating effect of absorptive capacity on supply network partner innovativeness.

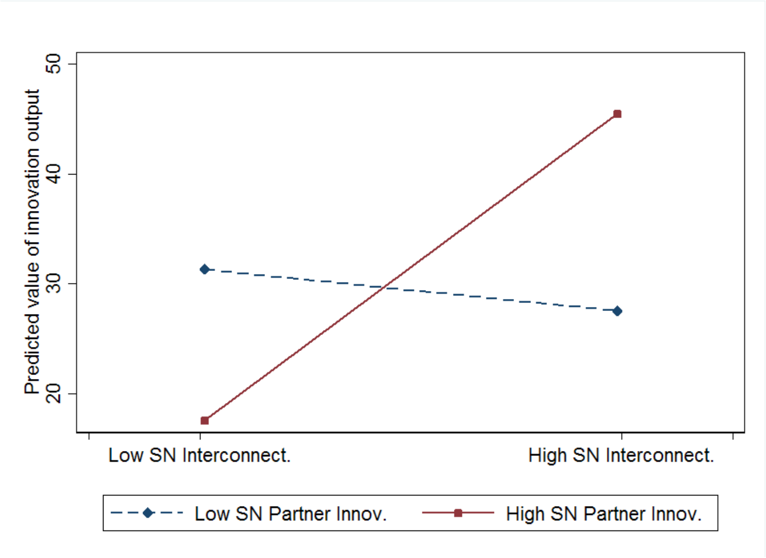

Figure 2.9. Moderating effect of supply network partner innovativeness on supply network interconnectedness.

4.3 Robustness checks

We also estimated the model using a zero-inflated negative binomial. This alternative specification helps to account for the large number of zeros that are present in our dataset (27.18% of firms). While many firms decide to protect their innovative ideas through patents, others may wish to protect theirs through other means, such as trade secrets. However, this decision is unobserved. This leads to two types of zeros: those zeros due to a firm not reporting their innovation via a patent and zeros due to the firm not actually having any innovation to patent for a given year. One way to account for this is to use the zero-inflated negative binomial approach, first introduced by Lambert (Lambert, 1992). This model first generates two separate models: a negative binomial count model and the logit model for predicting excess zeros (Hilbe, 2011). First, the logit model is generated to capture the zeros for those firms that may had decided to report their innovation by means of a patent ("certain zeros"), predicting the probability of a firm falling in this category or not. Second, the negative binomial model is generated to predict the counts for those firms that may have decided not to report their innovation by patenting it (not a part of the "certain zeros"). In the next step, the negative binomial and logit models are combined, forming the following zero-inflated negative binomial–logit model, (referred to as the zero-inflated negative binomial model for short). Results of this alternative model can be seen on Table 2.5. To test for the suitability of the zero-inflated negative binomial over the negative binomial model, we inspect the commonly-used Vuong test (Vuong, 1989). We followed the standard that the zero-inflated model is suitable if the Voung statistic is greater than 1.96 (Long, 1997). The Vuong test yielded values above the threshold for Models 1-5 (e.g. 2.96 in Model 5), signifying that the zero-inflated variant as an appropriate alternative model. We obtained results structurally similar to our negative binomial model. The hypothesized effects are in the same direction as our negative binomial model. Compared to the negative binomial regression results, we find support for Hypotheses 1, 3, 4, and 5, whose hypothesized effects are all significant at $p<0.05$.

Table 2.5
Alternative zero-inflated negative binomial model – innovation output (2009-2011 patents)[a].

Variables:	Model 1	Model 2	Model 3	Model 4	Model 5
Controls					
Firm Size	0.62***	0.66***	0.65***	0.65***	0.66***
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Firm Age	-0.01*	-0.01*	-0.01*	-0.01*	-0.01*
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Industry Concentration	-2.05***	-1.91***	-1.68***	-1.61***	-1.60***
	(0.36)	(0.36)	(0.36)	(0.36)	(0.36)
Industry Growth	1.48	1.32	0.96	1.62	1.80
	(1.35)	(1.32)	(1.30)	(1.31)	(1.30)
Prior Innovation	0.21	0.19	0.14	0.15	0.16
	(0.17)	(0.17)	(0.16)	(0.16)	(0.16)
Prior Knowledge Breadth	0.02***	0.01***	0.01***	0.01***	0.01***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Lead Firm	0.19	-0.08	-0.17	-0.05	-0.15
	(0.17)	(0.19)	(0.19)	(0.19)	(0.20)
Direct effects					
SN Accessibility[b]		0.47***	0.64***	0.65***	0.60***
		(0.14)	(0.14)	(0.15)	(0.15)
SN Interconnectedness[b]		-0.26	0.49	0.45	0.85
		(0.51)	(0.54)	(0.53)	(0.55)
Absorptive Capacity[b]		0.67	0.51	0.85	0.91
		(0.45)	(0.44)	(0.56)	(0.55)
SN Partner Innovativeness[b]		-0.58	-0.49	-0.72	-0.16
		(0.57)	(0.54)	(0.55)	(0.62)
Moderation effects					
SN Access * SN Interc			3.25***	3.34***	2.19*
			(0.88)	(0.88)	(1.01)
SN Access * Abs Cap				2.10*	2.03*
				(0.93)	(0.91)
SN Interc * SN Partner Innov					18.04*
					(8.04)
Constant	-1.70***	-1.98***	-2.00***	-2.10***	-2.15***
	(0.28)	(0.29)	(0.29)	(0.30)	(0.30)
Log Likelihood	-1005.38	-997.9	-991.39	-987.39	-984.87
LR Test		20.44***	11.02***	6.91**	4.92*
Voung	2.98**	2.98**	2.82**	2.91**	2.96**
N	390	390	390	390	390

[a] Standard errors in parentheses; *** p<0.001, ** p<0.01, * p<0.05
[b] Variables were grand mean-centered.

Lastly, we had not proposed a quadratic functional form that could possibly describe the relationship between accessibility and innovation output (Hypotheses 1). However, to verify possible non-linearity, we provide an alternative model with the squared term of accessibility as a control variable in the regression models. Similarly, though we do not hypothesize for the curvilinear effect for interconnectedness (Hypotheses 2), we tested an alternative model to control for its possible non-linearity. Thus, in a separate regression, we have tested an alternative model using both squared terms of accessibility and interconnectedness as controls. Both the squared terms are not significant and their inclusion leads to similar results that agree with the findings in our model without the terms.

4.3.1 Endogeneity

We also took further measures to account for potential issues of endogeneity arising in our model. There is a possibility that firms exhibiting high innovation output may select or come to occupy favorable structural positions and influence its partners to become more inter-linked by being able to form network ties that lead them to display such structural characteristics. Thus, if this source of endogeneity existed, the error terms of the endogenous explanatory variables would be correlated with the error terms of the dependent variable, leading to biased and inconsistent results (Greene, 2003).

To address the potential endogeneity problem between each supply network structural characteristic and innovation output, a two-stage least squares (2SLS) estimation procedure was adopted. In the first stage, each structural characteristic was regressed on all assumed exogenous variables on two separate regressions – one for supply network accessibility and another for supply network interconnectedness – in order to obtain predicted values for these potentially endogenous variables. In the second stage, the predicted values from the first stage were included as independent variables to replace the values of the assumed endogenous variables.

Before the 2SLS was executed, we had to identify instrumental variable candidates that met validity requirements. First, in a regression with only assumed exogenous variables from the original count model, we identified candidates that were not significantly correlated with innovation output at the 5% significance level. From this step, we chose industry sales growth and prior innovation as instruments for both structural characteristics (significance levels can be seen in Tables 4 and 5; we also verified this using a joint chi-square test). We also used prior innovation as an instrument as a primary concern here is whether high patenting activity significantly influences network structure. Second, we identified two other variables related to structural characteristics that were not significantly correlated with innovation output but significantly correlated with at least one of the assumed endogenous structural characteristics: degree centrality and number of pairs. Degree centrality is a more simplified measure of a firm's structural position found in network analysis literature, and is measured as the number of supply network partners (i.e. direct ties) they have. The number of pairs is a measure capturing the total number of unordered pairs of distinct nodes that are directly connected to a focal node (Wasserman and Faust, 1994). In our case, this measures the total number of potential ties between every partner pair, of all partners who share a direct tie with the focal firm. To sum, we chose industry sales growth, prior innovation, degree centrality, and number of pairs as instruments for potentially endogenous variables supply network accessibility and supply network interconnectedness. The table in Appendix A (Models (1) and (2)) shows the results of the first stage regressions for supply network accessibility and supply network interconnectedness.

Though we cannot directly test the statistical independence of an instrument from the error terms of the dependent variable, we can assess the adequacy of our instruments using a test of overidentifying restrictions (Baum, 2006). A test of the overidentifying restrictions also suggests that the chosen instruments are exogenous. Specifically, after regressing on innovation output with exogenous variables from the original count model plus all instruments, the null hypothesis that the instruments are uncorrelated with the error term of the dependent variable (innovation output) cannot be rejected at 5% significance level. We examined the explanatory power of instruments when used as independent variables in regressions on each assumed endogenous variable. Joint tests of the null hypothesis that the corresponding instruments have no effect on supply network accessibility and supply network interconnectedness show chi-square statistics of 59.34 ($p<0.001$) and 5.60 ($p<0.001$), respectively. Thus, we can reject the null that the corresponding instruments have no effect, suggesting that there is a significant correlation with the instruments and network structural characteristics. Taking stock of all validity checks, we conclude that we have valid instruments for each potentially endogenous variable.

Appendix A (Model (3)) shows the results of the second stage regression with the predicted values from the first stage included as independent variables to replace the values of the assumed endogenous variables, supply network accessibility and supply network interconnectedness. After running the 2SLS, we performed a Durbin-Wu-Hausman postestimation test of endogeneity, which adds the error terms from the first stage (using robust variance estimates) and separately tests whether they are correlated with error terms in the original count model (Cameron and Trivedi, 2009). Using the error terms from the first stage for the assumed endogenous variables in separate tests, both endogeneity test statistics had p-values greater than 0.10, indicating that we fail to reject the null that these variables are exogenous. In other words, the endogeneity tests associated with supply network accessibility and supply network interconnectedness were both insignificant. Hence, the parameter estimates for these variables in our original count model do not appear to be unduly influenced by endogeneity.

5. Discussion

Scholars in operations management have exhorted future research to examine the structural dimension of social networks, specifically, accounting for the embedded nature of buyer-supplier dyads (Autry and Griffis, 2008; Villena et al., 2011). Building on extant research, this chapter examines the association between the structural characteristics (supply network accessibility and supply network interconnectedness) of a firm’s supply network and its innovation output. We find that supply network accessibility is positively associated with innovation output. Conversely, no significant association exists between supply network interconnectedness and innovation output. However, there is at least a partially significant interaction effect between these structural characteristics and innovation output. Besides investigating the effects of structural characteristics, we also examine the moderating role of absorptive capacity and supply network partner innovativeness in strengthening the associations between the structural characteristics and innovation output. The findings suggest significant moderating roles of both absorptive capacity and supply network partner innovativeness. Table 2.6 summarizes our overall findings.

Table 2.6
Summary of findings.

Hyp.	Factor(s)	Impact on Innovation	Support?
1	SN Accessibility	Positive	Yes
2	SN Interconnectedness	Positive	No
3	SN Accessibility * SN Interconnectedness	Positive	Partially Supported
4	SN Accessibility * Absorptive Capacity	Positive	Yes
5	SN Interconnectedness * SN Partner Innovativeness	Positive	Yes

5.1 Theoretical implications

This chapter contributes to the literature by addressing the interface between supply networks and innovation by investigating how a firm can accrue knowledge and information flow benefits from its supply network to enhance its innovation output. Integration and collaboration with supply network partners has been recognized not only to improve product quality, service levels, and revenue enhancements, but also as a key source of innovation. We extend this literature by explicitly examining supply networks and their two key inherent structural characteristics as a source of innovation.

The results for Hypothesis 1 illustrate that the level of network accessibility that a firm has to the resources and knowledge assets of its supply network partners – as derived from its structural position in the supply network – influences its innovation output. This finding is in agreement with the evidence in the literature showing that firms with high network accessibility experience a greater volume and diversity of information from their partners in the supply network in which they operate (Schilling & Phelps, 2007). Findings for the main effect of supply network interconnectedness on innovation output are inconclusive, indicating lack of support for

Hypothesis 2. Our main premise was that this interconnectedness helps foster collaborative initiatives that provide access to knowledge, resources, and information from other partners.

Lack of support for a direct relationship between supply network interconnectedness and innovation output suggests that interconnectedness, in isolation, may not be a significant driver of a firm's innovation output. One explanation may be that, while certain levels of supply network interconnectedness benefit firms in terms of operating performance, there are other contingencies in the context of innovation that make its effect on knowledge creation and innovation outcomes unclear (Vanhaverbeke et al., 2009). In this regard, the partial support for Hypothesis 3 provides some evidence that while the main effect of supply network interconnectedness is not significant, it may help moderate the influence of supply network accessibility on innovation output. In other words, we find some indication that higher levels of network interconnectedness may strengthen the beneficial effect of supply network accessibility on innovation output. This evidence suggests that establishing highly interconnected supply networks may facilitate collaboration among supply network partners and act as one of the moderating mechanisms to magnify the positive effect of supply network accessibility on innovation output.

This chapter also provides evidence that while structural characteristics in a supply network can enable information and knowledge flows to enhance innovation output, this association can be capitalized by two knowledge variables, absorptive capacity and supply network partner innovativeness. The results show that investing more in R&D, as a manifestation of absorptive capacity, can be used to positively moderate the effects of supply network accessibility on innovation output. An example echoing this phenomenon is Milliken & Company, an innovative firm possessing expertise in several areas including specialty chemical, floor covering, and performance materials. Not only do they invest heavily in R&D themselves but also have access to a network of suppliers and partners (PR Newswire, 2013). As of 2013, Milliken & Company had developed one of the largest collections of patents held by a private U.S. company.

Finally, the finding that supply network partner innovativeness moderates the relationship between supply network interconnectedness and innovation highlights the advantage of firms in drawing from knowledge assets of their supply network partners to further their innovation. In other words, while operating in highly interconnected supply networks has potential for firms to facilitate knowledge flow and sharing opportunities among partners, it is the magnitude of knowledge availability among a firm’s partners that actually enhance any trickle down effects that improve the firm’s subsequent efforts to generate innovation output (Stuart, 2000).

5.2 Managerial implications

This chapter provides suggestions that can have managerial implications related to the influence of a firm’s supply network structure on its innovation output. First, managers should recognize the important role of structural capital – in the form of supply network structural characteristics – in maintaining and facilitating knowledge creation. This perspective would require firms to consider the value of their key supply network partners that exists directly and indirectly through each partner’s extended network of relationships. If firms want to accrue benefits in their innovation activity from their supply network, they should proactively cultivate the structural characteristics of their supply networks that lead to greater innovation output because of superior knowledge-sharing practices among their suppliers (Von Hippel, 1988). Accordingly, managers might need to promote more interactions within their supply network to help facilitate effective information and knowledge flow throughout the supply network.

Managing structural characteristics will also help to focus their strategy on maximizing opportunities to access external knowledge (Nyaga et al., 2010) as well as solicit supply network partner input and feedback during its innovation processes (Koellinger, 2008). In other words, adopting a supply network perspective can help firms to focus on knowledge and information flow opportunities residing in its supply network to benefit its innovation output.

Second, the perspective of supply network partner value can also apply to the manager's future selection and supply network configuration strategy. Autry and Griffis (2008) note the prospect of future research to investigate a firm's decision "to invest in competitive intelligence that can be used to optimize the structure of the supply chain by identifying the most attractive partnering opportunities" (p.168). This sort of strategic approach suggests that a firm can focus more on investments that promote structural changes (related to the supply network structure) or relational ones (related to direct investments in relationships with partners in its supply network) that facilitate more effective knowledge and information sharing. The former approach could also result in more direct intervention of a buying firm to reconfigure its suppliers' external networks or communications structures (Choi & Kim, 2008). For supply chain managers whose focus of building competitive advantage is through innovation leadership, this chapter suggests significant benefits from assessing a firm's level of supply network accessibility, and the level of interconnectedness among supply network partners, on influencing the lead time of information and knowledge flow and increasing ports of access for knowledge and information sharing.

Finally, the findings also suggest that firms should not overlook the innovativeness of their partners since working with innovative partners may have a direct bearing on their own innovation capabilities. This finding is in line with the trend of firms building core competencies in-house but outsourcing non-core competencies, making them more dependent on the knowledge and expertise of their supply network partners to avoid sub-optimal solutions to problems, to innovate, and to adapt (Zacharia et al., 2011). For example, Mercedes-Benz recently announced that to maintain its high innovative activity it will “rely on its internal expertise and its network of suppliers around the world”(Reuters, 2013).

5.3 Limitations and directions for future research

While the insights found in this chapter are important, we acknowledge that it has its limitations. Part of the motivation for this chapter was to help address the call for deeper structural analysis accounting for the embedded nature of buyer-supplier dyads (Autry and Griffis, 2008; Villena et al., 2011). Thus, we drew our analysis from a unique dataset that allowed us to use a supply network lens and incorporate the embedded nature of each supply network partner dyad. This chapter thus emphasizes the embeddedness of a firm and the interconnectedness of its partners. We did not incorporate relationship strength, reflecting the importance or value of each supply network link. Some suppliers may be providing very standard components with little value added whereas other suppliers may be providing a critical component that adds considerable market value. Also, firms may rely heavier on a certain customer based on the percentage of revenue they receive from that customer. If data on such variables is available, future studies on supply networks and innovation would also benefit from incorporating relationship strength and other complementary variables.

Further, while we include R&D intensity as a reflection of a firm’s absorptive capacity, there may be other important factors capturing the firm’s amount of experience and potential ability to absorb incoming external knowledge. Future research should delve further into other aspects that may affect a firm’s ability to absorb knowledge residing in the supply network. Also, we used patent counts as a proxy for innovation output. While prior studies have shown patent counts to be valid and robust indicators of knowledge creation (Trajtenberg, 1987) and highly correlated with citation-weighted patent measures (Stuart, 2000; Hagedoorn and Cloodt, 2003), we acknowledge that additional measures that account for originality and generality as well as type of innovation output are also of importance. An innovation can thus be distinguished based on a backward(forward)-looking measure of originality(generality)(Trajtenberg et al., 1997) or along an innovation continuum of incremental to radical based on the degree of new knowledge embedded in an innovation (Dewar and Dutton, 1986). We do not distinguish between originality, generality, or type of innovation in this chapter, but future studies accounting for this distinction could aid in help in reducing the current gap between the empirical assessment and conceptualization of firm innovation.

6. Conclusion

In this chapter, we find further evidence supporting the argument that network structures and relationships that form supply networks are critical components for identifying strategic imperatives in supply chain management (Borgatti and Li, 2009; Kim et al., 2011). Our findings suggest improved knowledge and information flows arising from supply network accessibility influences a firm’s innovation output. The results also indicate that interconnected supply networks may help moderate the improved knowledge and information flow from accessibility. Additionally, the results show that the influence of the two structural characteristics on innovation output can be enhanced by a firm’s absorptive capacity and level of supply network partner innovativeness. In sum, the chapter contributes to the body of literature on both supply chain management and innovation by highlighting the role of the structural characteristics of supply networks, along with knowledge variables, in facilitating knowledge creation and thereby improving upon a firm’s level of innovation output.

CHAPTER 3

MANAGING SUPPLIER AND CUSTOMER NETWORK DYNAMICS TO DRIVE FIRM PERFORMANCE

1. Introduction

A growing stream of research has identified supply chains as a key source of competitive advantage and superior performance for firms (Ketchen and Hult, 2007). The continual rise in globalization and pressure to keep up with technological and environmental changes is an ongoing issue that leaves firms in a constant flux to find better strategies to manage their supply chains and outperform competition (Cheung et al., 2010). The ongoing pressure to sustain such changes in the competitive environment have led firms to rely on their supply chain partners for more external capabilities that were once handled internally. Researchers have since contributed to conceptual studies advocating a firm strategy that leverages its portfolio of customer and supplier relationships as an important strategic asset to improve performance (Johnson, 1999; Tang and Rai, 2012), elevating competition based on a battle of firm strategies to a battle of supply chain strategies (Ketchen Jr and Giunipero, 2004; Boyer et al., 2005).

Contemporary supply chain management involves leveraging the capabilities of a multitude of partners both upstream and downstream in the supply chain. One challenge, however, is that effective management of a network of interdependent customer and supplier relationships is extremely complex (Bozarth et al., 2009), warranting an examination of supply relationship dynamics that account for such interdependencies as strategic assets that impact performance (Choi et al., 2001). Research studies have accordingly evolved in their examination of this issue, from earlier work on transactional make-buy considerations (e.g., Walker and Weber, 1987) to more recent work on collaboration mechanisms (e.g., Cachon and Fisher, 2000;

Cachon and Lariviere, 2005; Paulraj et al., 2008; Cheung et al., 2010; Nyaga et al., 2010; Cao and Zhang, 2011) and multi-tier sourcing decisions (Majumder and Srinivasan, 2008; Agrawal et al., 2013) to improve performance. While much insight has been gleaned as a result of these studies, it is still not clear how the vast number of interdependences prevalent in the supply chain may in fact be swaying a firm's performance benefits. Prior literature has made traction in identifying two key supply relationship dynamics impacting a firm's performance: customer-supplier relationship dependency and supply network structure (Dyer, 1996; Dyer and Singh, 1998; Choi and Kim, 2008).

The first supply relationship dynamic, customer-supplier relationship dependency has been examined primarily from the perspective of resource dependence theory (Pfeffer and Salancik, 1978) and social capital theory (Tsai and Ghoshal, 1998), and has been linked to level of trust, power, and influence (Handfield and Bechtel, 2002; Benton and Maloni, 2005; Ireland and Webb, 2007; Krause et al., 2007; Terpend et al., 2008; Terpend et al., 2011). Many firms in a supply chain operate in a dual role as customer and a supplier. As customers, these firms concentrate their total annual cost among each relationship to a different degree and for a different purpose. For example, though Hewlett Packard (HP) and Apple Inc. shared several of the same suppliers, their proportion of total cost tied in each supplier relationship varied substantially, as illustrated in Figure 3.1[2]. Apple and HP had over 50 percent and 15 percent of their total cost, respectively, concentrated in Foxconn Technology Group, the world's biggest contract manufacturer of electronics and maker of Apple's iPhones and iPads as well as a major assembler of PCs for HP. Conversely, both firms had less than four percent of their total costs

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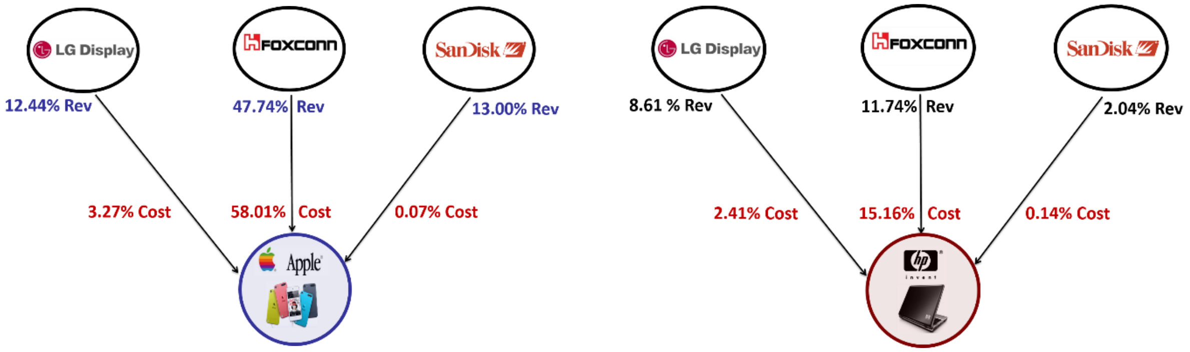
[2] Data reflects reports from the fiscal year 2012

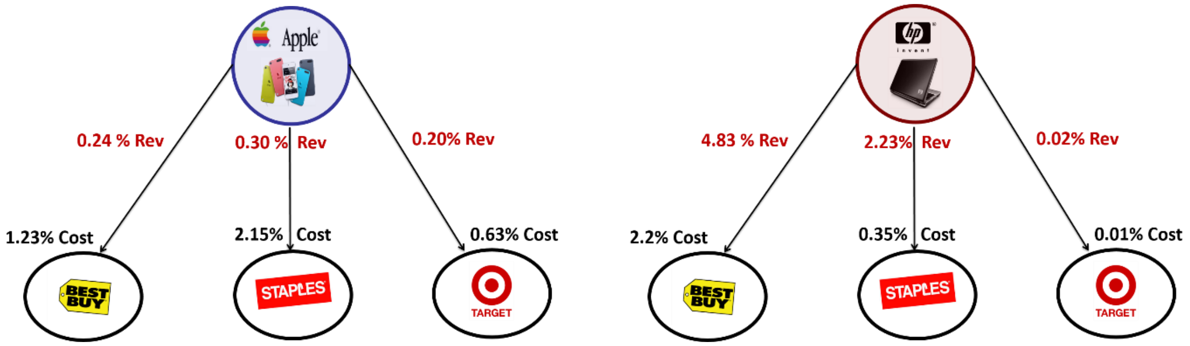
concentrated in LG Display Co., a core producer of LCD panels, and less than one percent in Sandisk, a supplier of flash memory chips to both firms (Bloomberg, 2012). This same observation can be made viewing both HP and Apple in their role as suppliers, as depicted in Figure 3.2.



Apple’s cost concentration among LG, Foxconn, and Sandisk

HP’s cost concentration among LG, Foxconn, and Sandisk

Figure 3.1. Sample of a cost and revenue concentrations for Apple and HP in role as customers (Source: Bloomberg Database).



Apple’s cost concentration among LG, Foxconn, and Sandisk

HP’s cost concentration among LG, Foxconn, and Sandisk

Figure 3.2. Sample of a cost and revenue concentrations for Apple and HP in role as suppliers (Source: Bloomberg Database).

The proportion of the firm’s business that the partner is responsible for serves as a proxy for relationship dependency and has been linked to the trust and commitment fostered between a firm and its partners (Flight et al., 2008; Autry and Golicic, 2010; Handley and Benton Jr, 2013). At the same time, literature has also identified potential negative effects from a firm being over-reliant or vulnerable to its partner, leading to a lag in ensuing performance (Forker, 1997; Handfield and Bechtel, 2002; Villena et al., 2011). Thus, insight into how a firm’s cost and revenue are concentrated across its supply network both upstream and downstream offers a potentially clearer portrayal of performance implications. One limitation of previous studies is that they have considered performance implications of relationship dependency predominantly only at the dyad level (e.g., customer-supplier), thus not factoring in the wider performance effect arising from the variance in the way a firm’s relationship dependency is concentrated across its supply chain. This chapter differs from prior related empirical work in the following ways. First, it factors for the dual role that several firms occupy, that operate as a customer to certain partners and as a supplier to others. Second, it goes beyond effects at the dyad level by examining the degree to which a focal firm concentrates its cost upstream (as a customer) and revenue downstream (as a supplier).

The second supply relationship dynamic, supply network structure, factors in structural characteristics of the supply network as drivers and facilitators of firm performance. A network analytic approach to investigate supply relationship dynamics helps account for the embedded nature of supply networks and of the various interactions taking place between customers and suppliers within the supply network (Kim et al., 2011). A firm’s customers and suppliers share several business processes with each other as well as other members along each supply chain tier, causing them to be embedded in a larger supply network (Rowley et al., 2000; Choi et al., 2001; Choi and Kim, 2008). Thus, the supply network structure derived from the embeddedness of a firm’s supply network partners can influence that firm’s ability to lower costs, integrate and coordinate its supply chain activities, and increase knowledge spillovers from its partners (Camuffo et al., 2001; Choi and Krause, 2006). Prior literature points to the way that a supply network is structured as an important factor driving firm performance (Kim et al., 2011), and we show empirical support for its facilitating role to moderate the effect of relationship dependency on performance. To account for supply network structure, we examine four related characteristics: the level of efficiency of shared relationships between a firm’s suppliers upstream and customers downstream—defined in this chapter as supplier and customer network efficiency—and the speed at which a firm can reach suppliers upstream and customers downstream in the supply network—defined in this chapter as upstream and downstream closeness.

In sum, we build on prior research by investigating the effect of supply network partner cost concentration, revenue concentration, and the way that a supply network is structured on firm performance. Alongside any direct effect from the way that the supply network is structured, we emphasize the moderating role of network structure on a firm’s concentration levels. Specifically, we aim to address the following research questions: How does the way that a firm concentrates its cost and revenue across its supply network impact its performance? How is firm performance influenced and facilitated by the way that its supply network is structured?

We develop our theoretical framework by drawing on prior research on buyer-supplier relationships, supply chain management, and dependency theory. We then empirically validate our model by analyzing supply chain relationship and financial data from the Bloomberg database for firms in the electronics industry. This chapter makes use of a unique set secondary data that reveals the cost and revenue concentration between a focal firm and its corresponding customers and suppliers. Also, instead of potentially averaging out the effects of the way that a firm's cost and revenue are concentrated among customers and suppliers in our analysis, we make use of this richer model to factor in the wider effects of the variance in its concentration.

We offer contributions to both theory and practice in operations management in this chapter. First, by shedding light on the intricacies and performance implications from dependency and structural aspects of supply relationship dynamics, we offer a richer understanding of the joint effects of supply chain management decisions and contextual factors on a firm's ability to operate profitably and efficiently. Second, our joint focus on relationship dependency and supply network structure helps address the call for future research that advances existing theories on supply networks and firm performance (e.g., Chen and Paulraj, 2004; Kim et al., 2011). Consideration of supply relationship dynamics at multiple levels of analysis in a common framework allow for richer insight into the underlying mechanisms of supply networks.

The remainder of this chapter proceeds as follows. In Section 2, we discuss the related literature on buyer-supplier relationships, supply chain management, and dependency theory. In Section 3, we describe our data collection and research methodology. We present our empirical model, analysis, and results in Section 4. We conclude in Section 5 with a discussion of our findings, their implications, and suggested directions for future research.

2. Theoretical framework and hypotheses

2.1. Relationship dependency

Assessment of relationship dependency has been documented by scholars studying buyer-supplier relationships, some with emphasis on performance implications (e.g. Cousins and Menguc, 2006; Golicic and Mentzer, 2006; Krause et al., 2007; Autry and Golicic, 2010).

Research in this area highlights the importance of content and relative intensity of each relationship in affecting supply chain outcomes. Relationship dependency is rooted in the notion of relational embeddedness, where strength relates to the extent to which the relationship between two network entities is strong, weak, or absent (Granovetter, 1985). Relationship dependency has since been identified as a key dimension of social capital that refers to the degree of mutual respect, trust, and close interaction that exists between a firm and its partners (Granovetter, 1992; Kale et al., 2000). Two facets identified to help embody relationship dependency are the proportion of a firm's cost going to each of its suppliers and revenue coming from each of the firm's customers.

2.1.1. Cost concentration and revenue concentration as indicators of relationship dependency

Supply network cost and revenue concentration can be viewed as one form of relationship dependency, represented by the proportion of a firm's business activities that a particular partner is responsible for (Barry et al., 2008; Autry and Golicic, 2010). Taking this perspective, relationship dependency can manifest itself in two ways: as supplier dependence and customer leverage. Supplier dependence in this context is based on the proportion of the supplier's sales revenue that comes directly from a focal customer. From the other perspective, a firm as a customer who contributes more to proportion of the supplier's sales can be in a better position to achieve more leverage over its supplier. Prior research has shown that contributing to a larger proportion of a partner's revenue is likely to lead to a greater commitment and long-term orientation with the partner, but with the customer in a more powerful and influential position (e.g. Sheu et al., 2006). Customer leverage is based on the proportion of the customer's cost that is tied directly to its relationship with a particular supplier. Supply chain concentration, involving a heavier concentration of spend among suppliers and its customers, implies more extensive utilization of modern supply chain management practices, which should decrease transaction costs and increase the diffusion of knowledge throughout the supply network (Lanier Jr et al., 2010). A more highly integrated relationship is expected between a customer and supplier if that customer purchases a high percentage of its resources from the supplier and as a result, may lead to greater returns on the performance benefits accrued by the focal firm (Uzzi, 1996; Flight et al., 2008).

Summarizing, prior research suggests that relatively higher relationship dependency, through customer leverage, can lead to more efficient supply network benefits and better operating performance for firms, as they often have more power and influence to dictate terms and ensure that suppliers adopt practices more to their internal protocols. However, greater supplier dependence may make the firm more vulnerable and start to experience minimal improvements in its performance. Along similar lines to prior literature, we conjecture that a firm as a suuplier being over-reliant or dependent, through heavily concentrated supplier dependence of revenue from fewer customers, may actually lead to a lag in ensuing performance (Forker, 1997; Handfield and Bechtel, 2002; Villena et al., 2011). Overall, we expect the following:

Hypothesis 1. *Supply network partner cost concentration has a positive relationship with firm operating performance.*

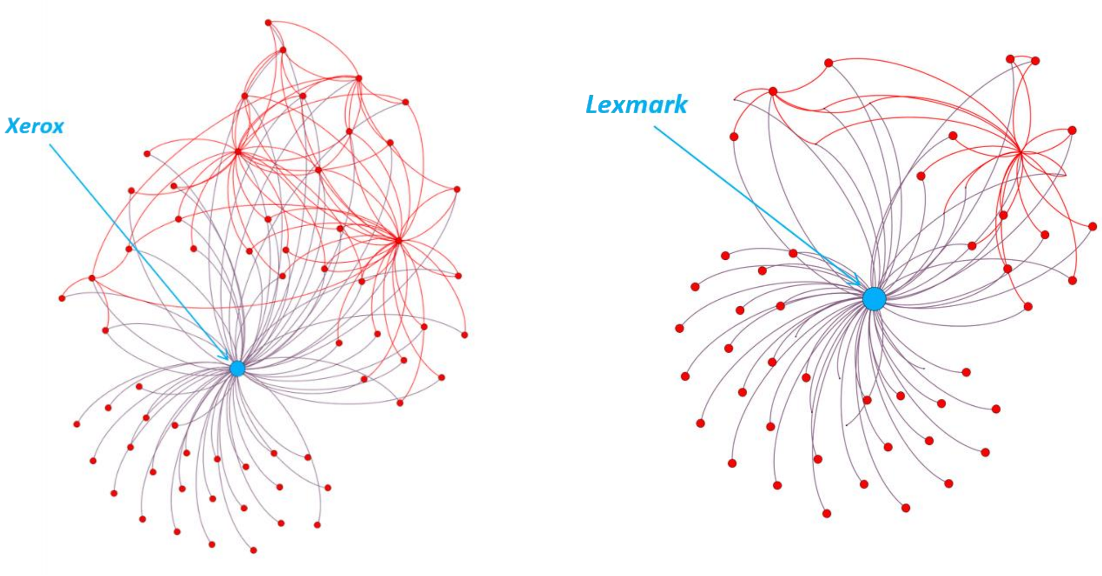
Hypothesis 2. *Supply network partner revenue concentration has a negative relationship with firm operating performance.*

2.2. Supply network structure

Several streams of literature on supply chain management are benefitting from a focus on supply chains as a single system or network as opposed to sole analysis of fragmented subsystems and dyads. Some such examples are research on supply relationship governance (Detoni and Nassimbeni, 1995), supply chain integration (Vickery et al., 2003), supply chain risk (Nair and Vidal, 2011; Basole and Bellamy, 2014), and knowledge sharing (Dyer and Nobeoka, 2000; Dyer and Hatch, 2004).

2.2.1. Supplier and customer network efficiency

Also emerging from supply network research are the collaborative benefits a firm can accrue by having a more interconnected networks (e.g. Dyer, 1996; Skjoett-Larsen et al., 2003). However, studies have also found that the extent to which a firm’s partners are nonredundant can enhance its knowledge creation (Baum et al. 2000). Further, the less redundant the ties between partners, especially customers of a supplier, the less opportunities a firm’s partners have to collude or to use knowledge of the firm’s pricing policies to demand lower pricing from the firm’s product or service (Schilling 2007). Greater supplier and customer network efficiency translates to less ties connecting any two firms, where the increase in one tie also increases the redundancy of exchange among the same set of supply network partners, and potentially opens up opportunity space for partners to collude. In Figure 3.3, we provide supply networks of two representative firms from our sample, Lexmark and Xerox, to help illustrate the differences in supply network portfolios according to both their level of supplier and customer network efficiency. Viewing Figure 3.3, supplier and customer network efficiency is depicted by the level of redundancy in all links between that go from partner to partner.



Xerox: Low Network Efficiency Lexmark: High Network Efficiency

Figure 3.3. Representative firm (ego) supply networks.

2.2.2. Supply network partner efficiency and cost (revenue) concentration

Aside from the already addressed benefits of both supply network interconnectedness and relationship dependency on their own, we also suspect that an interaction of the two factors to have an influence on firm performance. The coordination, communication, and information flow from having a densely connected supply network should be reinforced by the presence of several strong ties (i.e. high concentration of supply network revenue, on average) between each supply network dyad. Researchers in organizational research have used a linear combination of relational and structural components, in particular, tie strength and network density (Sosa, 2013) to reflect the quantity of time and energy that dyads invest in their relationship with each other as well as with common partners, and how scoring high in this composite measure can lead to improved outcomes benefiting both parties. Similarly, for our context, we postulate that higher supply network revenue concentration, on average, in a firm's supply network will strengthen the positive influence of supply network interconnectedness on firm performance, both in terms of efficiency gains and financial gains.

> **Hypothesis 3.** *Highly efficient supplier networks accentuate the positive effect of supply network partner cost concentration on operating performance.*

> **Hypothesis 4.** *Highly efficient customer networks mitigate the negative effect of supply network partner revenue concentration on operating performance.*

2.2.3. Upstream and downstream closeness

Upstream and downstream closeness relates to how quickly a firm can reach partners of the supply network. In this sense, a focal firm can reach each partner either (i) directly if it has a direct relationship with that partner (i.e. it is a direct customer or supplier to the firm), or (ii) indirectly through the use of its intermediate partner relationships. Previous studies have found a strong linkage between closeness and firm performance, suggesting that firms in central positions in a network have far more pathways than their counterparts to access knowledge, information, and resources from other members in the supply network (Burt, 1992; Dyer and Singh, 1998; Koka and Prescott, 2008). Higher centrality gives the firm the ability to navigate the network with greater autonomy (Kim et al., 2011), offering multiple ports to retrieve reliable information about demand shifts, lean approaches used by other customers or suppliers that have yet to have been established as best practices, and to richer insight into potentially new, complementary resources from other members in the supply network. Greater closeness and thus ability to collect information from multiple sources will help reduce the risk that key information used by the firm has somehow been distorted in the transmission process (Schilling and Phelps, 2007). We expect that greater closeness both upstream and downstream to impact a firm’s ability to efficiently manage its inventory well, maintain improved margins from the flexibility in being able to access resources quicker than its less central counterparts, and thus better utilizing its resources.

Hypothesis 5. *A firm's upstream closeness within the supply network accentuates the positive effect of supply network partner cost concentration on operating performance.*

Hypothesis 6. *A firm's downstream closeness within the supply network mitigates the negative effect of supply network partner revenue concentration on operating performance.*

3. Data and model development

3.1. Sampling and data collection

The primary source of data used for testing our empirical model is the Bloomberg database. Bloomberg maintains a vast historical database of company financials covering both international and domestic markets. This database has been used in numerous studies for financial data (e.g. Jaillet et al., 2004; Longstaff et al., 2005; Longstaff, 2010). All of the financial data for the firms in our sample were obtained from the Bloomberg database.

As an additional check on the reliability of the Bloomberg data, we cross-validated our financial measures with Standard & Poor's COMPUSTAT database. To check for similarity in finances from the two databases, we first developed some custom coding that matched firms according to their 9-digit Committee on Uniform Security Identification Procedures (CUSIP) number, which consists of a 6-digit issuer number, a 2-digit security number, and a check digit as the 9th character. We then ran a series of paired t-tests on net income, total assets, inventory, cost of goods sold (COGS) and sales. In total, we used 498 firm paired observations. The dependent-sample or paired t-test is used when the observations are not independent of one another. It tests to see whether the difference in means from two variables of interest, on the same set of subjects, is equal to zero. Our results indicated that the mean difference between each pair was not significantly different from zero, indicating similarity in financials from the two data sources.

In addition to the rich historical financial data, Bloomberg also began capturing supply chain relationship data on more than 35,000 companies globally in more than a dozen languages, making use of an algorithmic design for deriving proprietary data. We used the Bloomberg database to build our network of customers and suppliers. First, we had to identify and map each lead firm to its customers and suppliers. Next, we took each of the supply chain members who were not a part of the initial lead firm list, and retrieved data on all of each new member's customer and supplier relationships listed in the Bloomberg database.

In order to get a broader understanding of the industries represented in our supply network dataset, we used Global Industry Classification Standard (GICS) codes, a classification standard developed by Morgan Stanley Capital International (MSCI) and Standard & Poor's (S&P). It is intended to be a more universal score that allows for classification firms across the globe. It comprises 10 two-digit sectors, 24 four-digit industry groups, 68 six-digit industries, and 154 eight-digit sub-industries.

3.2. Dependent variables: firm performance

We use the measure of return on assets (ROA) as a proxy for performance at the firm level. ROA has been linked to higher firm financial performance (e.g. Hendricks and Singhal, 2009) and has been deemed as appropriate measures for operations management contexts (Chen et al., 2005). Measures for firm performance were obtained from the Bloomberg database.

3.3. Independent variables

3.3.1. Supply network partner cost and revenue concentration

We operationalize relationship dependency in two ways. First, we capture the proportion of supplier sales revenue and customer cost that comes through each customer-supplier dyad relationship in the sample. For each pair of supply network dyads, *supply network partner revenue concentration* is calculated using the concentration of a supplier's sales revenue that comes directly from its direct customers and *supply network partner cost concentration* is calculated using the concentration of a customer's costs that are incurred from its direct suppliers. A simple illustration is shown in Appendix B depicting the aggregation process of cost and revenue information for each of a focal firm's dyads. Other studies have adopted a similar measure to proxy for relationship dependency and to reflect high-quality interactions (Sheu et al., 2006; Flight et al., 2008; Autry and Golicic, 2010; Handley and Benton Jr, 2013).

3.3.2. Supplier and customer network efficiency and closeness

For supplier and customer network efficiency, we use the measure of network density to reflect the extent to which partners of a focal firm are also partners of each other into a single measure as follows (Wasserman and Faust, 1994):

$$Effic_i = 1 - \frac{L_i}{g_i(g_i - 1)/2}$$

where L_i represents the number of existing ties among all g_i direct partners of focal firm *i*. We operationalize a firm's closeness in the network by closeness centrality, calculated using the following equation (Wasserman and Faust, 1994):

$$CC_i = (g_i - 1)/\left[\sum_{i=1}^{g_i} d(n_i, n_j)\right]$$

where $d(n_i, n_j)$ represents the number of edges in the shortest path(s) linking n_i and n_j (also referred to as the geodesic distance(s) from n_i to n_j), g_i corresponds to the number of direct partners of focal firm i, and $(g_i - 1)$ reflects the minimum possible total distance. This measure has been cited as a guide to capture the extent to which a firm has freedom from the controlling actions of others in terms of accessing information in the supply network (Kim et al., 2011). We calculate our measures through the use of the social network analysis software package, UCINET 6.365 (Borgatti et al., 2002).

3.4. Control variables

We controlled for various measures related to firm performance that may affect our analysis. We included firm size, operationalized as average annual sales, to control both for the effect of size on supplier and customer network efficiency and firm performance. Larger firms naturally have greater availability of resources, which may also explain why they are performing well (Tsai, 2001). Further, we included a firm's sales growth to account for any contribution from their past to current financial performance (McNamara et al., 2003). A description of all variables and their data source is summarized in Table 3.1.

We include dummy variables accounting for both industry and geographical differences in our sample. Descriptive statistics by industry can be found in Table 3.2. As depicted in Table 3.2, our final sample of firms represents a wide range of industries with seven distinct two-digit GICS sectors. In terms of the highest industry sector representation, more than 86% of firms in the sample do business related to information technology (IT), 5.78% related to financials, and 5.2% related to consumer discretionary. Conversely, the lowest concentration is in telecom services (1.16% of firms), healthcare (1.16% of firms), and consumer staples (0.58% of firms).

Table 3.1
Variable descriptions and sources.

Variable Type	Variable Name	Description	Calculation	Sources
Dependent	Financial Performance	Return On Assets (ROA) as measure of efficiency of resource utilization	$ROA_i = \frac{(Net\ Inc)_i}{Avg\ Total\ Assets_i}$	Bloomberg, Compustat
Independent	Cost Concentration	Cost concentration of focal firm as a customer	$CostConc_i = \sum_{j=1}^{S_i} \left(\frac{COGS_{ij}}{COGS_i}\right)^2$	Bloomberg
	Revenue Concentration	Revenue concentration of focal firm as a supplier	$RevConc_i = \sum_{j=1}^{S_i} \left(\frac{SALES_{ij}}{SALES_i}\right)^2$	Bloomberg
	Supplier (Customer) Efficiency	Proportion of shared relationships between a focal firm's suppliers (customers)	$Effic_i = 1 - \frac{L_i}{g_i(g_i - 1)/2}$	Bloomberg, UCINET
	Upstream (Downstream) Closeness Centrality	A focal firm's closeness to suppliers (customers) based on level of centrality	$Close_i = (g_i - 1) / \left[\sum_{i=1}^{g_i} d(n_i, n_j)\right]$	Bloomberg, UCINET
Control	Firm Size	Proxy for size based on sales volume	$Size_i = Ln(Sales_i)$	Bloomberg, Compustat
	Capital Intensity	Capital expenditures relative to sales	$Cap\_Int_i = \frac{Captial_i}{Sales_i}$	Bloomberg, Compustat
	Regional Effects	accounting for geographic differences	$Reg_i \epsilon \{0,1\}$	Bloomberg
	Industry Effects	accounting for industry differences	$Industry_i \epsilon \{0,1\}$	Bloomberg

Table 3.2
Descriptive statistics (mean) by industry – defined at the 2-digit global industry classification standard (GICS) level.[a]

GICS Sector	Sector Name	Percent	ROA	Firm Size	Cap Int	Sales Growth	Sup Effic	Cus Effic	Up Close	Down Close	Cost Conc	Rev Conc
25	Consumer Discretion.	5.2	-0.05	5.19	0.06	0.05	0.89	0.91	0.03	0.04	0.01	0.03
30	Consumer Staples	0.58	0.05	8.39	0.03	-0.02	1.00	0.98	0.00	0.01	0.00	0.05
35	Health Care	1.16	0.02	4.86	0.03	0.10	0.79	0.90	0.00	0.07	0.00	0.04
40	Financials	5.78	0.01	8.13	0.04	0.01	1.00	0.91	0.05	0.05	0.00	0.01
45	Info. Technology	86.13	-0.03	6.28	0.05	0.04	0.88	0.85	0.05	0.18	0.02	0.06
50	Telecom. Services	1.16	0.02	5.05	0.20	0.10	1.00	0.77	0.00	0.06	0.00	0.04
	Total (Avg.)	100	-0.03	6.31	0.05	0.04	0.89	0.86	0.05	0.16	0.02	0.06

[a] N = 173 observations.

Table 3.3

Descriptive statistics and correlations.[a]

	Variable	Mean	Std. Dev.	1	2	3	4	5	6	7	8	9	10
1	ROA	-0.027	0.21	1.00									
2	Firm Size	6.31	2.06	0.47	1.00								
3	Capital Intensity	0.048	0.050	-0.04	-0.02	1.00							
4	Sales Growth	0.038	0.19	0.30	-0.02	-0.04	1.00						
5	Supplier Net Effic	0.89	0.16	0.19	0.05	0.21	0.06	1.00					
6	Customer Net Effic	0.86	0.14	0.17	0.25	-0.10	0.11	0.08	1.00				
7	Upstream Closeness	0.050	0.097	0.15	0.51	-0.05	-0.04	-0.09	0.18	1.00			
8	Downstream Closeness	0.16	0.19	0.21	0.42	0.11	-0.04	0.00	0.01	0.18	1.00		
9	Cost Concentration	0.019	0.038	0.12	0.10	-0.11	-0.02	-0.12	0.04	0.36	0.13	1.00	
10	Revenue Concentration	0.055	0.092	-0.27	-0.23	-0.02	0.01	-0.12	-0.15	-0.08	0.02	0.19	1.00

[a] N = 173 observations. All correlation coefficients above |0.13| are significant at $p < 0.05$ level.

4. Analysis and results

4.1. Model specification

The descriptive statistics for the overall sample can be found in Table 3.3. To mitigate issues with multicollinearity, we grand-mean centered all continuous variables used in interactions (Kreft et al. 1995). Further, we calculated the variance inflation factors (VIFs) and found all of our variables to be below the common threshold of 10 (Neter et al., 1996), with the mean VIF scores of 1.98. This finding, along with the grand-mean centered approach, helped ensure that any traces of multicollinearity in our data were well-mitigated.

We employed an ordinary least squares (OLS) model for analysis. As a robustness check, we also used a two-stage least squares (2SLS) approach to account for the potentially endogenous nature of the supply network closeness measures. Specifically, we first predict upstream and downstream closeness as a function of exogenous instruments and other variables not posing endogeneity concerns. Next, these predicted scores are used to estimate the regression parameters for operating performance as the dependent variable. The 2SLS procedure helps to mitigate any bias in estimates from a conventional OLS procedure with endogenous variables not properly accounted for. We used several alternative models to determine which model best reflected the data appropriately. In general, each model had structurally similar results in terms of the key variables of interest.

4.2. Results

Results for the OLS regression models are presented in Tables 3.4 and 3.5. We postulated in that increases supply network partner cost and revenue concentration lead to a positive and negative curvilinear effect in firm performance, respectively. The expected and significant signs of the regression coefficients seen in Tables 5 and 6 indicate support for our second assertion of the benefits associated with cost concentration (Hypothesis 1) and the negative effect from supply network partner revenue concentration (Hypothesis 2). As far as the accentuating or mitigating effects of efficiency (Hypotheses 3-4), both coefficients are in the expected directions, though there only the mitigating effect of customer network efficiency was significant (Hypotheses 4). Lastly, the positive and significant interaction between downstream closeness and supply network partner revenue concentration indicates support for Hypothesis 6. This supports the assertion that a firm's downstream closeness within the supply network positively facilitates the effect of supply network partner revenue concentration on its operating performance. The interaction plots in Figures 3.4 and 3.5 further validate our support for Hypotheses 4 and 6. The results remained consistent with both OLS and 2SLS models.

Table 3.4
Regression results on firm performance – US only focal firms.

ROA	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9
Firm Size	0.05***	0.05***	0.05***	0.04***	0.04***	0.05***	0.05***	0.05***	0.05***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Capital Intensity	-0.23	-0.18	-0.17	-0.13	-0.18	-0.18	-0.18	-0.26	-0.25
	(0.23)	(0.26)	(0.26)	(0.26)	(0.26)	(0.26)	(0.26)	(0.26)	(0.26)
Sales Growth	0.30***	0.32***	0.32***	0.33***	0.33***	0.32***	0.33***	0.31***	0.31***
	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)
Supplier Network Efficiency		0.20*	0.21*			0.18*	0.19*	0.21*	0.22*
		(0.09)	(0.09)			(0.08)	(0.09)	(0.08)	(0.08)
Customer Network Efficiency				0.00	-0.02	-0.01	-0.01	-0.03	-0.04
				(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)
Upstream Closeness		-0.31+	-0.27			-0.33+	-0.26	-0.30+	-0.26
		(0.17)	(0.21)			(0.17)	(0.20)	(0.16)	(0.20)
Downstream Closeness				0.06	0.08	0.04	0.04	0.06	0.07
				(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)
Cost Concentration		0.74*	0.79*			0.96*	1.02**	0.92*	0.96*
		(0.37)	(0.38)			(0.38)	(0.39)	(0.37)	(0.38)
Cost Conc*Up Closeness			-1.08				-1.27		-1.18
			(1.69)				(1.67)		(1.63)
Cost Conc*Supplier Net Effic			2.79				2.01		3.15
			(3.11)				(3.07)		(3.03)
Revenue Concentration				-0.41**	-0.34*	-0.45**	-0.45**	-0.36*	-0.35*
				(0.15)	(0.15)	(0.15)	(0.15)	(0.15)	(0.15)
Rev Conc*Down Closeness					3.33*			3.63*	3.81**
					(1.47)			(1.43)	(1.44)
Reve Conc*Customer Net Effic					2.03*			1.95*	1.97*
					(1.00)			(0.97)	(0.97)
Constant	-0.34***	-0.37***	-0.37***	-0.29***	-0.29***	-0.33***	-0.33***	-0.32***	-0.32***
	(0.04)	(0.05)	(0.05)	(0.05)	(0.05)	(0.06)	(0.06)	(0.05)	(0.05)
Observations	183	173	173	173	173	173	173	173	173
R-squared	0.304	0.356	0.360	0.343	0.375	0.390	0.394	0.424	0.429

Standard errors in parentheses *** $p<0.001$, ** $p<0.01$, * $p<0.05$, + $p<0.10$

Table 3.5

Regression results on firm performance – including global focal firms.

ROA	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9
Firm Size	0.03***	0.03***	0.03***	0.02***	0.02***	0.03***	0.03***	0.03***	0.03***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Capital Intensity	-0.05	0.01	0.01	-0.01	-0.01	-0.00	-0.00	-0.00	-0.00
	(0.08)	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)
Sales Growth	0.14***	0.16***	0.16***	0.16***	0.15***	0.16***	0.16***	0.15***	0.15***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Supplier Network Efficiency		0.06	0.07+			0.06	0.06	0.06	0.07+
		(0.04)	(0.04)			(0.04)	(0.04)	(0.04)	(0.04)
Customer Network Efficiency				0.03	0.04	0.03	0.03	0.04	0.04
				(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Upstream Closeness		-0.13**	-0.13*			-0.13**	-0.13*	-0.13**	-0.14**
		(0.05)	(0.05)			(0.05)	(0.05)	(0.05)	(0.05)
Downstream Closeness				0.06+	0.06+	0.05	0.05	0.05	0.05
				(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Cost Concentration		0.28+	0.35+			0.35*	0.45*	0.33*	0.43*
		(0.15)	(0.18)			(0.15)	(0.18)	(0.15)	(0.18)
Cost Conc*Up Closeness			-0.44				-0.72		-0.73
			(0.74)				(0.74)		(0.72)
Cost Conc*Supplier Net Effic			1.68				1.80		2.51
			(1.63)				(1.61)		(1.59)
Revenue Concentration				-0.22**	-0.30***	-0.24***	-0.24***	-0.32***	-0.33***
				(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)
Rev Conc*Down Closeness					1.75**			1.87**	2.01**
					(0.65)			(0.64)	(0.64)
Reve Conc*Customer Net Effic					1.53**			1.46**	1.47**
					(0.47)			(0.47)	(0.47)
Constant	-0.19***	-0.21***	-0.21***	-0.17***	-0.16***	-0.19***	-0.19***	-0.19***	-0.19***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Observations	419	390	390	390	390	390	390	390	390
R-squared	0.271	0.309	0.311	0.311	0.339	0.333	0.336	0.361	0.365

Standard errors in parentheses *** p<0.001, ** p<0.01, * p<0.05, + p<0.10

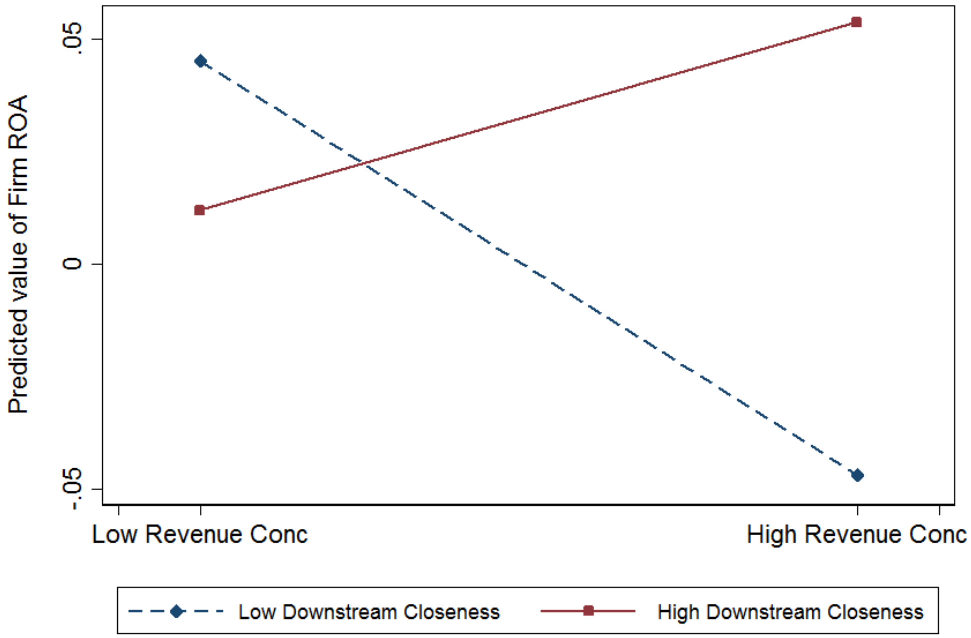


Figure 3.4. Moderating effect of downstream closeness on supply chain revenue concentration.

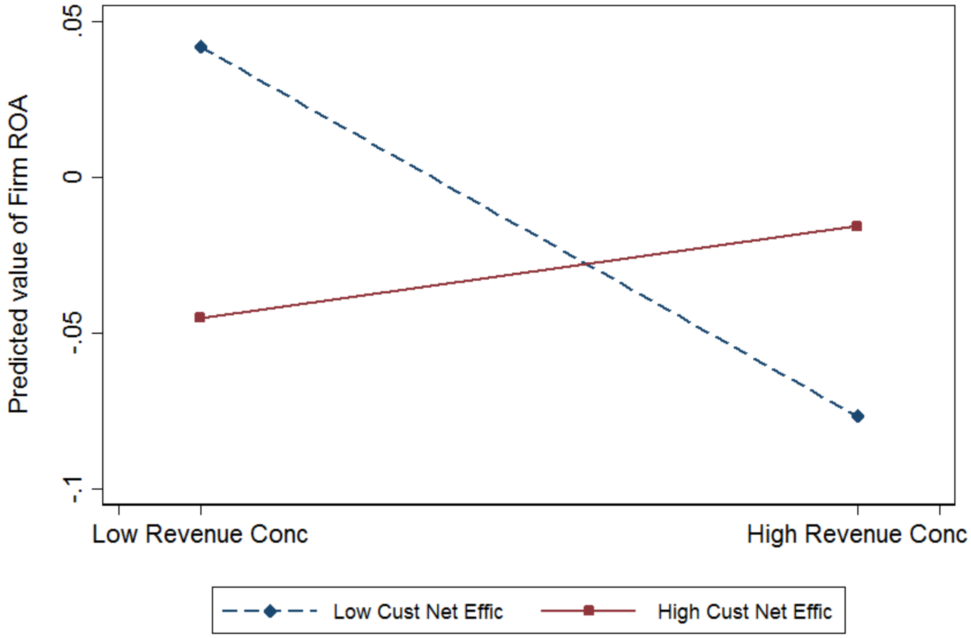


Figure 3.5. Moderating effect of customer network efficiency on supply chain revenue concentration.

5. Discussion and conclusion

This chapter was motivated in part by the recognition in the operations management community that more research is needed that explains the linkage between network structure and supply chain performance (Chen and Paulraj, 2004) and the call for more research incorporating relationship dependency and supply network structure into a single framework (e.g. Kim et al., 2011). This chapter complements earlier research efforts characterizing supply relationship dynamics (e.g. Dyer, 1996; Dyer and Nobeoka, 2000; Choi et al., 2001; Harland and Knight, 2001; Chen and Paulraj, 2004; Choi and Krause, 2006; Choi and Wu, 2009a) by using a unique customer and supplier dataset to account for supply network characteristics at the firm, dyad, and network level, and ultimately to enrich our understanding of the joint effect of these characteristics on a firm's performance.

Our results indicate that supply network cost and revenue concentration bear significant influence on firm performance, and that the effect of revenue concentration can be moderated by customer network efficiency and closeness centrality. These findings are line with prior studies suggesting the benefits from the right balance of relationship dependence and supply network structure. These studies have conceptually argued or empirically demonstrated certain knowledge gains that are contingent in part on the relationship dependencies between dyads in a network (Yli-Renko et al., 2001). Our contribution comes by jointly considering the interaction of supply network cost and revenue concentration – a form of relational capital and a proxy for relationship dependency– and supply network structure –a form of structural capital –, as a clear benefit aside from each of these factors in isolation. Taking these findings collectively, we corroborate the past scholarly premonition calling for future studies to factor in advantages and constraints derived from the structural positions held by customers and suppliers embedded in a larger supply network, which ultimately impact the dependency of social capital derived from these customer and supplier relationships (Villena et al., 2011).

5.1. Limitations and future research

We extend existing research on supply networks and performance by exploring several underlying factors that have not been jointly accounted for in prior supply chain empirical studies. Though we believe this chapter provides important implications for supply chain and operations management research, we acknowledge certain limitations which we hope that future research can help resolve.

First, our current dataset is cross-sectional. The static nature of our supply network data make it difficult to study how supply networks evolve and impact performance over time. As other researchers are well aware of, it is difficult to retrieve extensive historical data on proprietary elements such as customer and supplier relationships. Some researchers have made good strides to try and resolve this issue, looking to annual 10K filings and segment data on the Compustat database to build partial supply networks, which comprise almost exclusively of only major customers and suppliers. Nonetheless, future research would benefit tremendously from a longitudinal analysis, but with more of a comprehensive supply network. This would help capture the dynamic nature of supply networks to test the sensitivity of performance implications in the long run.

Second, other measures of operating performance could be considered to ensure that our results are robust to different considerations. Also, we analyzed supply chain relationship and financial data for focal firms classified as operating primarily in the electronics industry. Further insight can be drawn from investigating how the magnitude of the supply relationship dynamics differs across other industries as well.

Lastly, it is possible that the supply network partner cost and revenue concentration measures suffer from endogeneity. It is possible that firms that performed well may very well are more inclined to adopt a strategy to concentrate a relatively large proportion of their cost among a select subset of suppliers. Or similarly, to concentrate a relatively large proportion of their revenue among a select subset of customers. Any such endogeneity leading to biased and inconsistent results (Greene, 2003). One possibility to correct for the endogeneity biases is to use instrumental variables for each suspicious independent variable that influences the first-stage outcome – in this case, regressing on the supply network partner cost and revenue concentration variables separately – but not the second-stage dependent variable, firm operating performance. The challenge is to identify appropriate instruments that meet a test of overidentifying restrictions. Based on our sample, two potential instruments that appear to be correlated with the cost and revenue concentration variables but not correlated with firm operating performance are: the number of direct partners a firm has (measured by degree centrality) and the total number of ties or linkages one level upstream and downstream in a firm's supply network. Future research can incorporate such instruments to help mitigate endogeneity concerns.

5.2. Conclusion

We used cost and revenue supply chain relationship data for manufacturing firms in the electronics industry to estimate the effects of customer-supplier relationship dependence on a firm's operating performance. We also examined the extent to which structural characteristics of the firm's supply network facilitate the effect of relationship dependence on performance. The findings in this chapter complement the growing stream of supply chain management research by investigating relationship dependence and supply network structure in tandem for insight into how to manage supply network relationships for improved performance. Further, it adds an additional layer to prior literature by examining relationship dependence from the perspective of the focal firm, both as a customer and a supplier. Our results suggest that while firm performance is influenced by how it concentrates its cost and revenue upstream and downstream, this effect can be attenuated or enhanced by the way that its supply network is structured.

CHAPTER 4

THE EMERGENCE OF THE NETWORK ANALYTIC LENS TO UNDERSTAND AND MANAGE SUPPLY NETWORKS: A CROSS INDUSTRY INVESTIGATION

1. Introduction

Contemporary supply chains can be characterized as a globally distributed set of vertical and horizontal interactions among suppliers, manufacturers, distributors, retailers, and customers, which have transformed the traditional linear supply chain into a complex supply network of member interactions (Basole and Rouse, 2008). The hypercompetitive complex nature of today's business environment requires firms to continuously seek ways to innovate, decrease operational costs, provide satisfactory customer service, and minimize disruption risks by designing and managing efficient supply chains (Liao et al., 2010). Effective supply chain management consequently requires focal firms to develop capabilities to manage a myriad of multi-tier, interconnected relationships often spanning multiple industries. Conventional assessments of supply chain relationships as linear or dyadic structures, rather than as a network, limit academician and managerial approaches to overcome challenges to effectively manage supply chains.

An emerging interdisciplinary lens that can be leveraged in overcoming such challenges is the network analytic lens (Basole et al., 2011). Network analysis draws on theories from the social, organizational, and complexity sciences and leverages graph theoretic methods to model, analyze, and visualize the structure, dynamics, and strategies that shape supply networks. There has been a surge in scholarly studies modeling a supply network as a complex network of interactions between system entities since the seminal work by Choi and colleagues (Choi et al., 2001; Choi and Hong, 2002) and more recently Borgatti and Li (2009). However, there is no directing and orgoranizing framework to facilitate an understanding of the supply chain management (SCM) issues examined using a network analysis lens. Consequently, there is a window of opportunity to review and illustrate the value in adopting the network lens to better understand, design, and manage supply chains as complex systems.

In this chapter, we first identify and provide a systematic review of network analysis studies in the supply chain literature and organize these into an integrative framework. This systematic review in full has been published and is now available online (Bellamy and Basole, 2013). To pursue these objectives, we conducted a comprehensive study of research adopting perspectives from social network theory, complexity theory, systems theory, evolutionary economic theory, institutional theory, resource-based view, resource dependence theory, social capital theory, and social exchange theory. Our multidisciplinary analysis and framework draws on a variety of research fields, including systems engineering, operations management, economics, physics, strategic management, sociology, marketing, and biology. Next, we demonstrate the usage of the network lens through two multi-industry studies and discuss key findings from the studies. The first study (Study A) in full has been published and is now available online (Basole and Bellamy, 2014). Finally, we suggest future research directions for network analysis in the context of supply chains.

The remainder of the chapter is structured as follows. We discuss our findings and the details of our integrative framework in Section 2. In Sections 3 and 4, we adopt elements of the network lens to two multi-industry studies. We conclude in Section 5 with a discussion of research opportunities for using the network analytic-driven framework in supply chain research.

2. Research background and framework

We systematically review and analyze the relevant literature and, drawing on a multi-disciplinary theoretical foundation, develop an integrative framework. Motivated by previous work (Burt, 1980; Provan et al., 2007; Ahuja et al., 2011) and our own review of relevant literature, we argue that three themes are fundamental to research on network analysis in supply chain management: network structure, network dynamics, and network strategy. In our own review, we considered interfirm and intrafirm studies that examined some aspect of network analysis in the SCM context from 1995-2011.We chose 1995 to be the starting date as this was the first occurrence (Detoni and Nassimbeni, 1995) of a related article in SCM to the best of our knowledge. We included several commonly used scholarly databases, including Academic Search Complete (EBSCO), ProQuest, ISI Web of Knowledge, and Google Scholar. We seeded our search by focusing on studies in the top 30 journals (based on impact factor and quality rating) in OM and operations research (Olson, 2005; Meredith et al., 2010). Figure 4.1 presents the integrated framework.

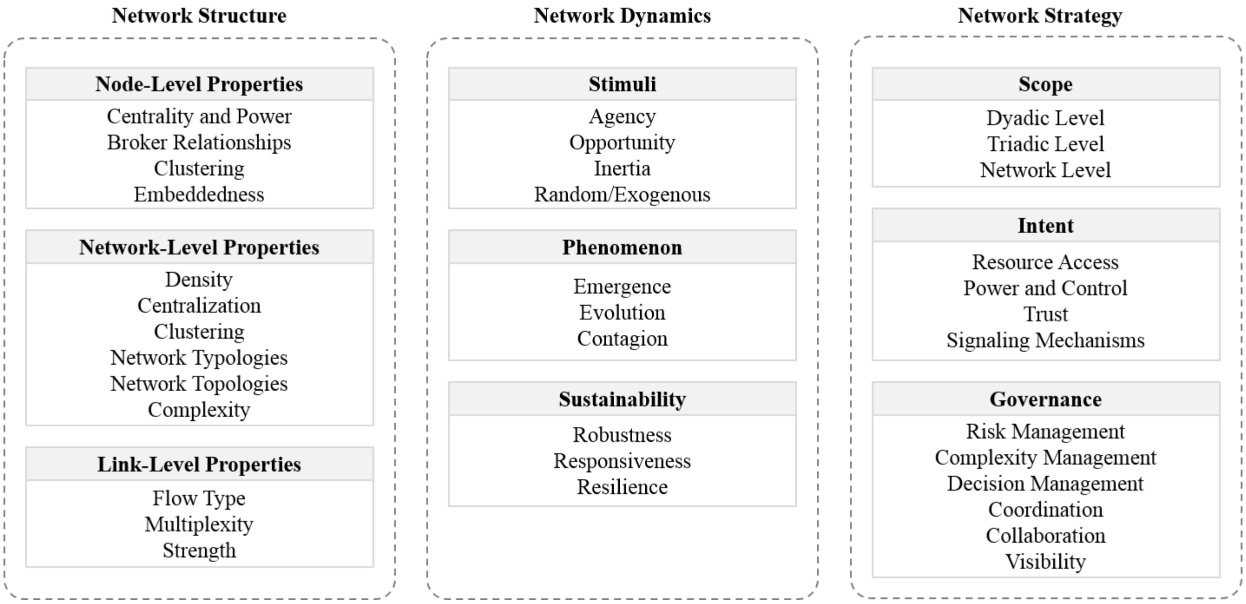


Figure 4.1. Integrated framework

- Theme 1: Network Structure: This theme focuses on the structural/architectural properties of supply networks such as supply chain components, connectivity, firm-level (node-level) structural properties, the degree and pattern of interfirm cohesion, flow type, nature of multiplexity, and strength of ties.
- Theme 2: Network Dynamics: This theme focuses on the formation, change, and evolution of supply networks and its relationship to robustness, responsiveness, and resilience, incorporating research developments in complexity theory, evolutionary economic theory, and systems theory.
- Theme 3: Network Strategy: This theme focuses on strategies that firms employ and leverage to improve supply network performance. Strategies are differentiated by levels of scope (dyadic-, triadic- or network-level), intent, and nature of governance.

Each of these research themes draws on different theoretical foundations and provides significant value to supply network research as summarized in Table 4.1.

Table 4.1
Focus areas, key references, and research methods for each theme.

	Theoretical Motivation	Related Disciplines	C	E	M/S	R
Network Structure	Social Network Theory; Complexity Theory; Systems Theory	Organizational Theory and Behavior; Strategic Management; Sociology	18	31	5	5
Network Dynamics	Complexity Theory; Evolutionary Economic Theory; Systems Theory	Evolutionary Biology; Ecology; Computational Physics; Systems Engineering	10	8	4	3
Network Strategy	Institutional Theory; Resource-Based View; Resource Dependence Theory; Social Capital Theory; Social Exchange Theory	Economics; Organizational Theory and Behavior; Strategic Management; Sociology; Marketing	61	66	9	13

Conceptual (C), Empirical (E), Modeling/Simulation (M/S), Review (R)

2.1. Network structure representing system architecture

System architecture is defined as "the fundamental organization of a system embodied in its components, their relationships to each other and to the environment, and the principles guiding its design and evolution" (p. 147; 15) (Maier, 2006; Cloutier et al., 2010). The supply network architecture can be modeled as a complex network (Basole et al., 2011), where nodes represent the system components, such as firms, suppliers, facilities, and customers among many others. Social network analysis (SNA) provides researchers a descriptive and statistical method to understand how supply network components are positioned, connected, and embedded within the supply network. SNA provides both node- and network-level measures (Wasserman and Faust, 1994). SNA has proven to be a valuable lens and mechanism to compute and analyze salient structural and relational properties in numerous disciplines, including organizational theory and behavior, strategic management, business studies, sociology, computer science, physics, and psychology, with a large body of research examining joint ventures and inter-firm alliances, knowledge transfer, and innovation (Provan et al., 2007). Surprisingly, there is comparatively little work that uses SNA in SCM. Borgatti and Li (2009) provide an initial overview of SNA and its potential network mechanisms and properties that can be implemented by SCM researchers. Ahuja, Soda, and Zaheer (2011) describe in great detail network architecture primitives in the organizational context. However, to our knowledge, there lacks a study integrating the insight gained from conceptual, empirical, and modeling/simulation work on supply network architecture. In this section we catalog and synthesize this work and highlight the node-, network-, and link-level properties that drive and shape the supply network architecture.

2.1.1. Node-Level properties

One of the most commonly used SNA metrics is node centrality. Centrality refers to the relative importance or prominence of a firm in the supply network, where firms with higher levels of centrality are found to have more power and control over peripheral firms. There are many variants of the centrality measure, such as those based on direct ties (*degree*), shortest path (*closeness*), and others based on geodesic distance (*betweenness* or *brokerage*). Each captures a different aspect of firm power and influence in a supply network (Kim et al., 2011). Studies have utilized several centrality measures to explain the various capabilities that central firms possess due to their network position (Yu et al., 2008; Li and Choi, 2009; Kim et al., 2011; Nair and Vidal, 2011). In the context of complex product development, for instance, studies have used several centrality measures to evaluate task interactions and bring to light previously undetected trends and properties in the product development process (Collins et al., 2009; Gokpinar et al., 2010; Bartolomei et al., 2012). A well-known measure not yet exploited in operations and SCM literature is *Bonacich power centrality,* which will give a higher score to a firm directly connected to several other well-connected entities, making this focal firm both central and powerful (Bonacich, 1987).

Another common node-level property used in the supply network literature is the *clustering coefficient,* defined as the proportion of its direct links that are also directly linked to each other. In the context of alliance-based networks, firms with dense clustering have been shown to experience greater collaboration, resource pooling, and problem solving because of factors such as increased trust within structurally embedded, dense cliques (Schilling and Phelps, 2007). With the exception of Nair and Vidal (2011), there is a void of operations and SCM studies examining the linkage between clustering and firm or supply network performance. Another important supply network measure is *embeddedness*, which combines centrality and clustering. Supply network entities (e.g. buyers) benefit more by evaluating and managing other supply network entities (e.g. suppliers) based on both their internal capabilities as well as their structural and relational embeddedness within the supply network (Autry and Griffis, 2008; Choi and Kim, 2008; Bernardes, 2010).

2.1.2 Network-Level properties

At the network level, there are several key measures for describing supply network architecture. The first is network *density,* defined as the proportion of actual ties in the network over the maximum possible number of ties in the network. A highly dense supply network is not always desirable or beneficial, especially given the added coordination burden placed on network entities as well as a great deal of unnecessary and costly redundancy that may arise (Kim et al., 2011). Another measure, *centralization,* measures the extent that one or more actors in the network are considerably more centrally connected than others, and can be used to identify the distribution of power and prestige across the supply network (Choi and Hong, 2002; Kim et al., 2011). A third dimension is *clustering*, is sometimes calculated as the average clustering for each firm, and speaks to whole network modularity. In a less cohesive network (low overall clustering), power is centralized, information is concentrated, there is a segmented structure, and a good amount of inequality.

Network typologies can be used to classify supply network architecture and often highlight distinguishing factors of the different types of supply networks that can aid researchers and managers in understanding how supply networks function. Vereecke and Meyer (2006) use network analysis to formulate a typology of four distinct roles that manufacturing plants occupy: the isolated plants, the receivers, the hosting network players, and the active network players. Harland (2001; 2001) discusses how different types of supply networks can be created and operated in great detail. Skilton and Robinson (2009) develop a typology portraying the effect of different types of complex supply network architecture on traceability of adverse supply network-related events.

Network topologies portray the overall structure or configuration of a network. Developing supply network topologies will help advance existing theories on supply network architecture (Borgatti and Li, 2009; Kim et al., 2011). Random, small-world, and scale-free network topologies are commonly used to portray complex systems such as supply chains (Nair and Vidal, 2011; Xuan et al., 2011). A random network exhibits low clustering and small average distance between nodes, and is the most widely used topology in modeling and empirical studies on complex networks and serves as a benchmark for sake of comparison for many modeling and empirical studies (Callaway et al., 2000). Small-world networks have characteristics of high clustering and small average distance between nodes. Lastly, scale-free networks contain hubs and skewed, heavy tailed degree distributions, following a power law distribution of links (Strogatz, 2001). This leads to supply networks characteristic of a small number of entities with the most power and control in the system, with the majority of entities lying on the system's periphery with little influence on the behavior of other entities and the entire supply network.

Another important network-level measure is supply *network complexity*. Complexity has been conceptualized and operationalized from numerous perspectives, such as vertical, horizontal, and spatial complexity (Choi and Hong, 2002; Danese, 2010), information-theoretic entropy of the system (Battini et al., 2007; Basole and Rouse, 2008), and the number of connections among supply network entities weighted according to their position in the network (Caridi et al., 2010). For large-scale socio-technical systems, such as supply networks, the structural embeddedness and interactions among components (e.g. suppliers, firms, suppliers, facilities, and customers) can significantly impact system complexity (Osorio et al., 2011). Despite the ability of SNA tools to help quantify and depict supply network complexity—taking into account properties such as distribution of power and overall embeddedness—it is surprising that very few studies have actually adopted SNA metrics to enrich our understanding of supply network complexity. One notable exception is the work by Skilton and Robinson (2009), where they theorize and demonstrate that the level of *network complexity* and *clustering* influence the traceability of adverse events, using examples from food supply networks.

2.1.3. Link-Level properties

Links in supply networks refer to the connections between system components. Connections can depict buyer-supplier relationships, material flow, and information exchange, among many others. Three key link-level properties include *flow type*, *multiplexity* (multiple ties), and *tie strength*. Several researchers have used the network lens to examine information, knowledge, physical, quality, research, and financial *flow* (Cox et al., 2001; Kinder, 2003; Giannakis and Croom, 2004; Vereecke et al., 2006; Pedroso and Nakano, 2009; Kim et al., 2011). Only a few studies have introduced *tie strength* into their models, finding a positive association between strength of ties and new product development project outcomes (Oke et al., 2008; Oke and Idiagbon-Oke, 2010). Other related studies incorporate *tie strength* factors such as relationship magnitude, quality, permanence, frequency, and duration to provide greater and often complementary insight into the intricacies within the supply network architecture and its relation to performance (Kotabe et al., 2003; Golicic and Mentzer, 2006; Samaddar et al., 2006; Carter et al., 2007; Autry and Griffis, 2008; Holweg and Pil, 2008).

2.1.4. Implications

An increasing number of studies across disciplines are adopting a network lens to understand the symbiotic relationship of a firm's role and importance in the supply network and the implications of supply network architecture on firm behavior and performance (Borgatti and Li, 2009; Galaskiewicz, 2011; Kim et al., 2011). Still, studies that explicitly use network theoretic tools and SNA metrics to model, analyze, and visualize supply network structure are fairly nascent. As illustrated in this section, there are a wide variety of SNA measures that are great fits for advancing existing theories on supply network complexity as well as on the topological and typological archetypes of supply networks.

2.2. Network dynamics representing system behavior

System behavior refers to the formation, change, and evolution of supply networks over time and is rooted in evolutionary biology, ecology, computational physics, and systems engineering. We identified three common foci in the literature under this theme: *stimuli*, *phenomena,* and *sustainability*.

2.2.1. Stimuli

Stimuli relates to the primary drivers of the formation, change, and evolution of a supply network. Broadly, these stimuli are driven by agency, opportunity, inertia, and random or exogenous factors (Zaheer and Soda, 2009; Ahuja et al., 2011). *Agency* relates to a firm’s ability to self-organize and adapt to changes within the supply network and the environment, changing their behaviors accordingly, and causing changes in overall supply network behavior and performance over time. While firms, modeled as agents, are interdependent, they often have conflicting goals and behavior based on their independent needs (Martinez et al., 2001; Sage and Rouse, 2009). Hence, central firms in a supply network may attempt to dampen the control and information power of other brokers by filling disadvantageous structural holes and creating ties with other supply network entities, or alternatively, they may dissolve or weaken ties to enhance their own brokerage power. Hence, conscious and deliberate *agency* transpires where supply network structures emerge as a consequence of self-interested, utility-maximizing behavior by focal entities in the system (Choi et al., 2001; Ahuja et al., 2011). *Opportunity* relates to networking behavior driven by trust and convenience, as a by-product of referrals, proximity, or prior alliance history. *Inertia* relates to the ties that persist or develop from a set of schema among supply network entities, where their behavior is moderated and influenced by norms and interfirm routines. When driven by *inertia*, ties are created or destroyed due to norms and routines that develop within the complex network of interactions between system entities. Lastly, random or *exogenous factors* may also cause changes to system behavior and performance

(Ahuja et al., 2011). This can include political instability, economic conditions, or adverse environmental events. This factor relates to the random processes outside of a firm's control.

2.2.2. Phenomena

Phenomena relates to the nature of supply network change that occurs over time. Adopting a complex adaptive system (CAS) perspective to supply networks helps firms to understand, manage, and prepare for network change and *evolution*. The CAS perspective has proved useful in studying ecology, biology, health care, and military applications (Rouse, 2000). Analogous to characteristics and functions of a CAS, many supply networks are nonlinear and dynamic, comprising multiple interdependent entities that operate within a larger evolving system, where the same characteristic pattern of behavior often emerges despite small changes (Surana et al., 2005; Holweg and Pil, 2008). As pointed out in the literature, a useful distinction should be made between control—resulting from an orderly architecting process— and *emergence*—resulting from natural or social evolution over long periods of time— of the system architecture (Osorio et al., 2011). Attempting to impose too much control on the supply network can lead to lower levels of innovation and flexibility, while simply responding to the emerging supply network architecture can undercut managerial abilities to plan, predict, and prepare for unexpected changes (Choi et al., 2001).

A few studies examine risk *contagion* and the change and evolution of supply network structure, cohesion, and embeddedness over time. Pathak et al. (2007b; 2009) portray five primary topological structures that supply networks may form—linear, flat, hierarchical, federated, and starburst— and empirically as well as experimentally show that certain environmental and firm-level factors could impact how such topologies grow, evolve, and adapt over time. Xuan et al. (2011) experimentally show the real-world supply network benefits derived from random, scale-free, and product similarity network topologies. An increasing number of studies have shown the rich potential in agent-based (AB) and computational modeling as a more rigorous approach to examine the complex patterns of buyer, supplier, and customer behavior in supply networks over time (Li et al., 2009; Nair et al., 2009; Li et al., 2010a). This approach provides the capability to extend the linear supply chain context to a complex supply network characterized by distinct network architectures and driven by autonomous but interconnected agent behavior over an extended time horizon (Nair and Vidal, 2011). Researchers should continue to leverage AB and computational modeling approaches, which if modeled and used appropriately, will serve as a wonderful aid in decision-making on system policies and controls (Choi et al., 2001; Sheard and Mostashari, 2009).

2.2.3. Sustainability

Sustainability refers to the ability of a firm and its supply network to remain *robust*, *responsive*, and *resilient* to disruption and failure. A firm will reduce their vulnerability to risk and increase their ability to bounce back from a disruption by developing more holistic assessments of supply network robustness, responsiveness, and resilience and by investing more time into understanding key random environmental factors that drive these disruptions, both feats that are well-conceptualized by a few authors (Peck, 2006; Klibi et al., 2010; Pettit et al., 2010). Pettit et al. (2010) develop a conceptual framework that describes resilience in terms of supply chain-based capability constructs, and offer several ways to operationalize each construct. They define supply chain capabilities as: “attributes that enable an enterprise to anticipate and overcome disruptions” (p. 6). These capabilities include flexibility, agility, adaptability, and visibility among others, and are also linked to supply network robustness and responsiveness in other studies (Klibi et al., 2010; Pettit et al., 2010). Nair and Vidal (2011) extend the linear supply chain context to a complex supply network by examining robustness against disruptions under random, small-world, and scale-free network topologies. Many of the experimental studies listed in the “Phenomena” sub-section also shed light on firm or supply network sustainability over time. Network analysis of supply networks can provide verification of intuition or may highlight novel insights that are counterintuitive, but that are based on quantitative measures grounded in network and graph theory. For example, Bartolomei (2012) used network analysis to discover that a stakeholder initially viewed as less important turned out to be far more central and had greater influence in the overall engineering system of study. They also showed how the loss of a couple of core stakeholders caused system-wide changes, such as disrupting the cohesion of the group.

2.2.4. Implications

This discussion on system behavior highlights the interdependence of the three identified themes. Studying the supply network dynamics without insight about the system’s architecture may severely limit the level of analysis and findings into how a supply network forms, changes, and evolves over time. With that said, experimentally investigating supply network change and evolution under different architectural and behavioral conditions has proven to be insightful in its own right (Pathak et al., 2007b; Xuan et al., 2011). However, many researchers and practitioners are more concerned with how these findings map to decisions to be made for improved and sustained performance, thus demanding greater emphasis on managerial and supply networks engineering implications (Pathak et al., 2009; Li et al., 2010a). Thus, incorporating small changes in policies or controls followed by components in the system, and examining how these changes alter behavior and performance, adds yet another level of rich insight into understanding, designing, and managing complex systems (Sheard and Mostashari, 2009).

2.3. Network strategy representing system policy and control

System policy and control relates to the art of devising, adapting, and executing a plan of action to meet desired firm objectives; it embodies the many elements of firm strategy (Smartt and Ferreira, 2011). This section puts emphasis on strategies used to prepare for and manage the supply network-related issues that arise with system change and evolution. We have divided this section into three parts: *scope*, *intent*, and nature of *governance*.

2.3.1. Scope

SCM research has experienced a shift in focus from the individual firm to interfirm collaboration at the *dyadic level* (Pathak et al., 2007a). An increasing number of studies are realizing the importance of information sharing, the focus on the total supply network, and mutually beneficial performance goals between suppliers (Dyer, 1996; Chen et al., 2004). For instance, a buyer will be much more accurate when assessing the value of a supplier by enhancing their understanding of a current/potential supplier’s structural embeddedness in supply network. The reasoning is that a buyer will better understand to what degree a particular supplier’s performance is contingent upon other firms in its supply network that it shares a (indirect or direct) connection with (Detoni and Nassimbeni, 1995; Cox et al., 2001; Choi and Kim, 2008; Choi and Wu, 2009a; Choi and Wu, 2009b). The buyer can assess the supplier’s overall value by looking at its number of connections to high/low performing firms, technologically advanced firms, and operationally advanced firms.

This need for a holistic understanding is even more apparent for firms operating within large scale, global supply networks (Buhman et al., 2005). Choi and Wu (2009a; 2009b) challenge researchers to go beyond dyadic analysis to study *triads* (e.g. buyer-supplier-supplier). These authors build upon their own challenge, along with a few other colleagues and researchers, (Wu and Choi, 2005; Li and Choi, 2009; Skilton and Robinson, 2009; Wu et al., 2010) and have contributed to our knowledge of supply network architecture and dynamics. The disadvantage in adopting only a dyadic or triadic perspective is the lack of metrics or structural properties that capture the holistic nature and value accounted for by the entire supply network (Wareham et al., 2005; Frankel et al., 2008; Wilhelm, 2011). The broadest level of scope includes the whole network which considers the interplay between the dyadic relationships among firms and the complex structure and dynamics of the entire supply network. At the *network level*, systems engineers can evaluate how individual firms affect the overall supply network and/or evaluate how the supply network architecture and dynamics affect each individual firm. Several studies have demonstrated the rich insight in better understanding and managing the structure and dynamics of interfirm relationships at the network level (Dyer and Nobeoka, 2000; Basole and Rouse, 2008; Frankel et al., 2008).

2.3.2. Intent

Resource-based view (RBV), social capital, and social network theories are all related to firm intent and are commonly used in sociology, organizational science, and strategic management. In a RBV, firm focus is on ability to manage its resources and capabilities as the markets evolve, with emphasis on maintaining a competitive advantage over other firms within the network (Fagerström and Olsson, 2002; Paulraj et al., 2008; Cheung et al., 2010; Cao and Zhang, 2011). The social capital perspective considers the shared goals, values, and experiences among the respective firms within a supply network, incorporating interfirm cooperation and the influence of network resources on firm capabilities into their strategy. This view provides opportunity for firms to go beyond productivity or operational measures to consider the opportunity to access another firm's core competencies and knowledge via collaboration (Harland et al., 1999; Dyer and Hatch, 2004; Harland et al., 2004). Several studies have empirically shown cognitive, relational, and structural capital to have a positive impact on firm operational and strategic performance (Cousins and Menguc, 2006; Krause et al., 2007; Lawson et al., 2008; Bernardes, 2010; Carey et al., 2011; Villena et al., 2011). The three theories have been adopted in numerous supply chain-related studies to describe how a firm can leverage system architecture and relationships to gain a competitive advantage and improve performance through *resource access, power and control, trust, and signaling mechanisms* (Giannakis and Croom, 2004; Ireland and Webb, 2007; Li et al., 2008; Li and Choi, 2009; Li et al., 2010b; Corsten et al., 2011; Galaskiewicz, 2011; Wagner et al., 2011).

2.3.3. Governance

Many studies highlight strategies for central firms in the position to manage *coordination*, *collaboration*, and competition in network relations (Bitran, 2007; Paulraj et al., 2008; Nyaga et al., 2010; Vijayasarathy, 2010; Terjesen et al., 2011; Wilhelm, 2011). For example, a focal firm can manage the supply network such as to keep certain plants or suppliers as isolates or periphery players to maintain more structural flexibility (Rudberg and Olhager, 2003; Vereecke et al., 2006). Several conceptual studies have made headway towards theory development on *managing risk and complexity* (Choi et al., 2001; Hameri and Paatela, 2005; Choi and Krause, 2006; Bonabeau, 2007). Wei, Dong, and Sun (2010) use an inoperability input-output model (IIM) to describe the propagation effects and the impacts of disruptions on supply networks. They provide insight into risk mitigation strategies for planning and evaluating potential policy actions for managing the adverse effects of disruptive events. They also validate the accuracy of the IIM via a simulation model accounting for the complex interdependencies among firms in the supply network. Firms can better manage supply network risk and complexity by building redundancy to hedge against disruption or increasing flexibility for sustaining a competitive advantage in day-to-day operations (Sheffi and Rice Jr, 2005; Wei et al., 2010). Also important is a firm's level of supply network *visibility*, where increased visibility can lead to responsive risk identification, allowing firms more time to incorporate protective measures to be better insulated from risk (Caridi et al., 2010).

2.3.4. Implications

Forming an effective portfolio of policies and controls for a complex system requires an integrated approach drawing insight from the state and evolution of the architecture, accounting for the complex network of interactions in the system entities over time (Beckerman, 2000; Osorio et al., 2011). Firms who continue to adopt strategies in dyadic fashion (e.g. buyer-supplier relationships) will suffer from limited scope and awareness of risks currently "hidden" in the supply network. Updating one's supply network strategy to account for systemic risk and structural complexity becomes even more relevant with greater integration and collaboration in today's globalized environment.

2.4. Summarizing framework and study motivation

There are many structural and behavioral issues inherent in supply networks that must be considered to gain a holistic understanding of systemic risks and performance implications for firms and their respective supply chain (Buhman et al., 2005; Pathak et al., 2007a; Jaehne et al., 2009; Wagner, 2011). We proposed an integrative framework around three central themes: network structure, network dynamics, and network strategy. This integrative framework has great potential to be used as a lens and mechanism to model, analyze, and visualize interdependencies across the multiple tiers of a supply network, to help determine how network structure impacts the performance, and to identify governance mechanisms that significantly reduce systemic risks. To follow, we demonstrate the usage of the network lens and several elements of its three underlying themes through two multi-industry studies.

3. Study A: structure and visibility as drivers of risk diffusion and supply network health

In this first study, we examine the impact of network structure on risk diffusion and ultimately supply network health (e.g., system performance). We also explore how structural visibility into lower tiers of supply networks can reduce and potentially mitigate cascading risks. To achieve this, we develop an agent-based (AB) approach that borrows from the classic SIR model, in which individuals are divided into three infection states, namely susceptible (S), infectious (I), and recovered (R) (Anderson and May, 1992). A susceptible entity, or firm i, that comes into contact with an infectious entity becomes infected themselves at a specified probabilistic rate (inf_i). We preserve the two standard assumptions of three stages and a fixed population. However, we relax the assumption of permanent immunity, where supply network entities stay in the system and do not simply disappear from the supply network once they have recovered. We acknowledge that this is a somewhat simplified representation of real-world business environments as corporate transformations (e.g., bankruptcy, mergers, and acquisitions) can potentially remove suppliers from the system. However, we believe that our approach is more reflective of established supply chain contexts, where a buyer or supplier may suffer from poor performance during a major disruption, but is not completely wiped out and can eventually recover, at a specified probabilistic rate (rec_i), and once again be susceptible to future risks. Moreover, our methodology could be adapted to relax this assumption, as AB models have the capability to accommodate much more complicated classifications and evolutions between states.

As risks spread through a supply network and infect firms, the health of a supply network deteriorates. Similar to the biological theory of an ecosystem, the health of a supply network is highly dependent on the health of each entity within the network and vice versa. A detailed discussion of supply network health is beyond the scope of this study. Interested readers are referred to Basole and Bellamy (2012). The health of a supply network can be defined as the system's ability to be productive, agile, and resilient. This ability is influenced by a range of factors including operational, financial, collaboration, and strategic aspects (Basole and Bellamy, 2012). Each of these represents a source of risks. Supply chain-related risks are exacerbated through the increasing interdependency among firms. Efficiency-driven SCM and extensive outsourcing of research and development (R&D) and manufacturing activities are very prevalent in today's supply networks, leading to greater dependence on supplier capabilities (Wagner et al., 2009). Previous research has shown that poor financial and operational health of individual suppliers in a focal firm's supplier portfolio can lead to increased supply chain risk and diminished firm performance (Wagner and Neshat, 2010; Blome and Schoenherr, 2011; Thun and Hoenig, 2011). The supply network health level is thus a function of the rate at which risks spread through the network and is influenced by the rate at which individual firms can recover.

Drawing on these theoretical foundations, we argue that network structure influences the rate at which risk propagates through the supply network and in turn determines the level of supply network health. This association is influenced by the initial health level of the supply network and the level of visibility into the supply network.

3.1. Supply network structure, visibility, and initial health level

The extent of supply network risk diffusion is not only dependent on infection and recovery rates, but also on the nature of interconnectivity between supply network entities. An examination of supply network structure is therefore essential. Our study examines risk diffusion in three complex network topologies: random, small-world, and scale-free (Strogatz, 2001; Airoldi et al., 2011). Previous research has shown that these three network topologies commonly characterize real-world networks (Strogatz, 2001), including supply networks (Nair and Vidal, 2011).

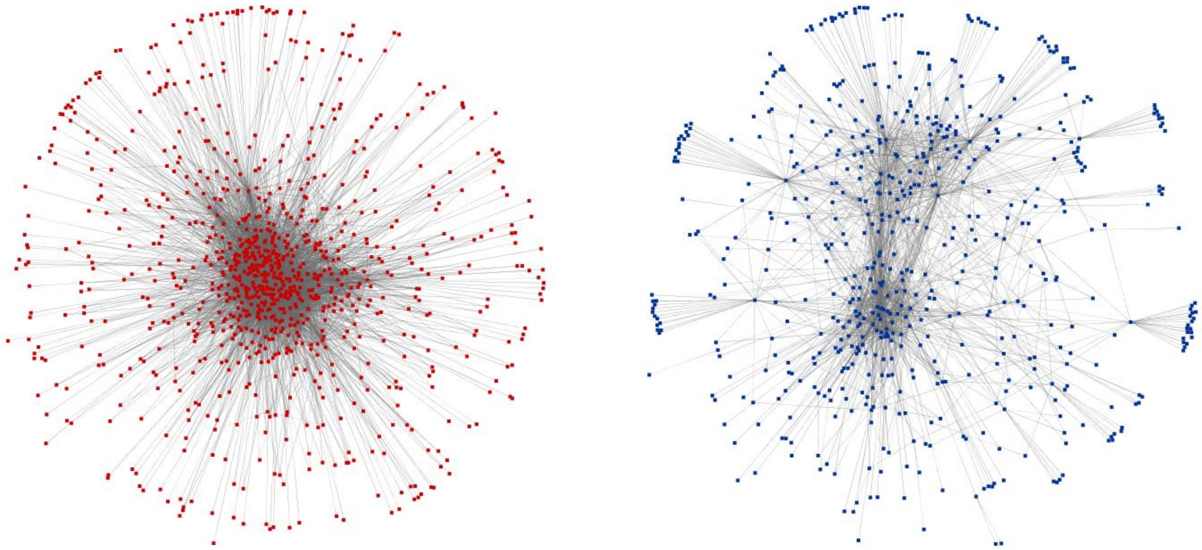
Random networks are characterized by low clustering among entities. It has been the most widely used topology in modeling and empirical studies on complex networks, and we include it for purposes of a comparison benchmark (Callaway et al., 2000). Small-world networks have characteristics of high clustering and small average path length between nodes. The model starts with a ring lattice of n nodes, with each node connected only to its nearest neighbors. Then, with probability p_n, links are detached from one end and rewired to another random node in the population, with duplicate links not allowed (Watts and Strogatz, 1998). Scale-free networks are characteristic of hub nodes that are highly connected and follow a power law degree distribution, $P(k) \sim k^{-\alpha}$. This results in networks with a heavy tailed degree distribution among nodes. They are formed based on a preferential attachment algorithm. In our model, scale-free networks start with m individuals connected to each other in a ring, where the rest of the $n - m$ individuals are added to the structure by attaching new nodes at random to previously existing nodes. The probability of attachment is proportional to the degree of the target node, with well-connected nodes picked more often than sparsely-connected nodes. Outside of the well-connected hubs, the majority of nodes tend to have very few connections (Albert and Barabási, 2002). Figure 4.2 gives a visual depiction of each of the three network topologies. The applicability of these network topologies for modeling real-world industry supply networks is exemplified by characterization of the large-scale supply networks of the electronics and automotive industry, as seen in Figure 4.3.

(a) Random. Each node is connected to a random set of the remaining nodes (Gilbert, 1959)

(b) Small-World. Each node is connected to several of its neighbors and a few distant nodes (Watts & Strogatz, 1998)

(c) Scale-Free. Most of the nodes are connected to a few other nodes, while a small number of nodes are connected to many other nodes (Albert & Barabasi, 2002)

Figure 4.2. Common supply network topologies (adapted from Airoldi et al., 2011).



(a) Electronics

Network size: 911
Clustering coefficient: 0.175
Avg. path length: 2.734
Avg. neighbors: 16.020
Density: 0.018
Heterogeneity: 1.614

(b) Automotive

Network size: 600
Clustering coefficient: 0.075
Avg. path length: 3.249
Avg. neighbors: 6.666
Density: 0.011
Heterogeneity: 1.868

Figure 4.3. Representative industry supply network topologies.

For the purpose of our study, we operationalize structural visibility as a spectrum-based measure assuming the integration of the aforementioned four visibility areas. Our visibility measure ranges from low to medium to high, reflecting a firm's investment into creating supply network capabilities (e.g. information sharing, policies, controls) that generate greater insights into their supply network. In terms of its effect, we characterize structural visibility as an immunity measure, where more visibility leads to greater insight into the interactions taking place within the supply network. This in turn leads to greater potential for the focal firm to identify and strategize for the risk earlier in its stages of diffusion through the supply network. However, the value of investing in more visibility can diminish after a certain point, where the costs of obtaining, monitoring, collecting, and integrating information begin to outweigh the marginal benefits with additional insight into more aspects of the supply network. For instance, previous work has shown that technological and infrastructure-based costs required to create integrated information technology (IT) systems can potentially surpass the cost savings or benefits from disruption discovery and recovery (Blackhurst et al., 2005). Thus, we have modeled visibility to have an exponential effect on the rates of risk infection and recovery, to reflect the diminishing value of increased investments in visibility to help mitigate risk spread and improve recovery. This leads to the following visibility-adjusted infection and recovery rates:

$$adj\_inf_i = inf_i \times e^{-\gamma \times vis_i} \tag{5}$$

$$adj\_rec_i = rec_i \cdot (1 - e^{-\gamma \times vis_i}) \tag{6}$$

where inf_i is the probabilistic rate of infection, rec_i is the probabilistic rate of recovery, γ is the parameter that impacts the rate of growth or decay in infection (recovery) levels, and vis_i is the visibility level. Past researchers have defined visibility as the ability to access information across the supply chain, visibility of customer and supplier operational activities (e.g. point-of sale data, customer levels of inventory), and the extent and quality of exchanged information (Swaminathan and Tayur, 2003; Barratt and Oke, 2007). Though no universal definition of visibility exists in SCM literature, greater supply chain visibility has been suggested by numerous authors to help improve operational performance, responsiveness, planning and replenishment capabilities, and improved decision making (Caridi et al., 2010; Barratt and Barratt, 2011).

Initial health levels of a firm’s supply network were also considered as such conditions can play an important role in the risk outcomes of supply networks. Drawing an analogy from the medical sciences, research in this area has shown that future health outcomes (of individuals) often depend in part on the initial health status (Korotkov and Hannah, 2004). Individuals in poor physical health are—in absence of an intervention—more likely to progress to a weaker health state in comparison to their healthier counterparts due to lower immunity levels and higher potential for comorbidities, which together can accelerate the well-documented downward spiral of disease where the sick get sicker, or the weak get weaker. Along similar lines, companies that are connected to firms in poorer health are more likely to become affected negatively than those that are in good health ceteris paribus. An illustrative recent example is the rapid deterioration of the automotive industry, where over 200 key suppliers of major manufacturers faced insolvency (Blome and Schoenherr, 2011). Similarly, good health levels can also spillover to connected firms as it may promote support, collaboration, and recovery and encourage joint-risk identification and mitigation. Based on these considerations, we found it important to consider the initial health distribution levels of the supply network, and have thus incorporated them into our model.

3.2. Agent-Based model

We develop an AB model to gain a better understanding of the risk diffusion process in complex supply networks. We create various simulated supply network structures to mimic actual industry supply networks and track their performance over time. Our AB model incorporates both network structure and a risk-diffusion approach in order to better assess how risk spreads through a supply network, how performance changes under different network topologies, and how different levels of visibility impact the level of insight into risk. The agents in our model represent the many firm-level entities in the supply network, such as customers and suppliers. At *t*=0, agents are randomly assigned to one of three health states: good (G), moderate (M), or toxic (T). The percentage of agents initially in each health state is determined by the initial health distribution ($health_{G-M-T}$). Each agent has its own visibility-adjusted infection rate (adj_inf_i) and recovery rate (adj_rec_i) (see Equations (2) and (3)). Incorporation of the supply network gives each agent a set of neighboring agents. An agent's subsequent state of health is dependent on the health levels of each of the agents whom they interact with (i.e. each of their neighbors). The interaction rules in place between neighboring agents—representing supply network partners—help govern the emerging health level of the supply network. Thus, each agent has a unique probability p_{ij} of transitioning from their current state i into state j at each time step not only based on their visibility-adjusted infection and recovery rates but also dependent on the health of their neighbors (see Equations (4)–(6)). We executed our AB model under different experimental conditions using AnyLogic®, a multi-method simulation software platform.

3.3. Risk diffusion

For the risk diffusion and health, we create parameters for probability of infection, rate of infection, initial health states, and visibility level. In our model, we assign a level of health to all supply network entities randomly using an initial health distribution. Following suit with the SIR model (Anderson and May, 1992), we incorporate three health states for each supply network entity as follows: good (G), moderate (M), and toxic (T). Thus, we have a MTG model (analogous to the SIR model), where firms are not completely immune once recovered, but have the potential to be re-infected. The SIR model can be viewed as a unique Markov chain for each entity in the system (Aleman, 2012). An entity in the supply chain system has a unique probability of transitioning from their current state *i* into state *j* at each time step. A particular entity currently in a good state of health can remain in the same state, transition to a moderate state, or transition to a dire toxic state, each with a certain probability. In similar fashion, an entity in either a moderate or toxic state will be in one of the three states each with a certain probability. The resulting transition diagram is shown in Figure 4.4. It is important to note that our model takes a much more holistic approach to the traditional SIR model by computing the level of health of each supply network entity as a function of the health of its corresponding neighbors. This is an important differentiation from previous approaches as it helps to account for the negative (positive) effects of being connected to others who are currently under (over) performing. In doing so, we capture inherent interdependency in supply networks and address the call for and value in more modeling approaches that consider the systemic impact of supply network disruptions (Blackhurst et al., 2005). The resulting transition probabilities are as follows:

$$p_{i,j} = w \propto_i \left[1 + \left(\frac{\sum_{j \neq i} Ego_j}{\sum_j Ego_j}\right)\right] \forall i, j, i \notin [Moderate] \qquad (7)$$

$$p_{i,j} = w \propto_i \left[1 + \left(\frac{Ego_j}{\sum_j Ego_j}\right)\right] \forall i, j, i \notin [Good, Toxic] \qquad (8)$$

where $$\propto_i \in [adj\_inf_i, adj\_rec_i],\ w = \begin{cases} 1\ if\ j\ 1\ state\ away\ from\ i \\ 0.5\ if\ j\ 2\ states\ away\ from\ i \end{cases} \qquad (9)$$

Ego_j equals the number of the focal entity's neighbors in state of health j. This reflects the fact that when a focal supplier is in a good or moderate state of health, but shares many direct ties to other entities in a toxic state, the focal supplier may get infected with a certain probability.

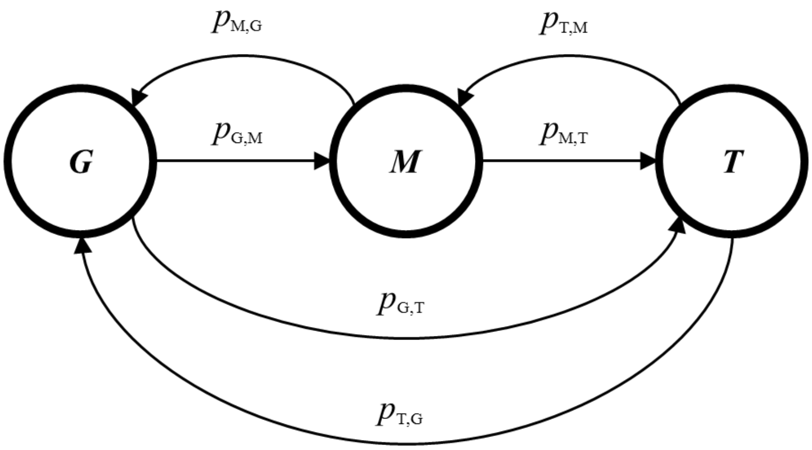


Figure 4.4: Health state transition.

3.4 Experimental design

Tables 4.3 and 4.4 provide a description of our complete research design. The experimental design of our network model parameters is motivated by the previous body of work examining evolution and risk diffusion in complex networks as well as characteristics of real-world supply networks (Barthélemy et al., 2005; Christley et al., 2005; Buzna et al., 2006; Rahmandad and Sterman, 2008; Zhao et al., 2011). In an effort to reflect prior parameter considerations for diffusion in complex networks, we decided to range network size from 100 to 1,000, average degree from 2 to 20, neighbor link fraction from 0.25 to 0.75, and initial hub ranges from 5 to 50 (Table 4.2). Also, our choice of the three topologies (random, small-world, and scale-free) are all very common in the body of literature studying network evolution and diffusion. As reflected in Table 4.3, we modeled the risk diffusion to vary in infection and recovery rates, percentage of entities initially in each health state, and visibility levels. We fixed degree of visibility's impact on the rate of growth or decay in infection and recovery levels (γ) to equal 2 based on the premise that increased visibility mitigates risk spread and improves recovery, but at a diminishing rate. This was done to represent the high costs associated with building the technology and infrastructure to integrate all information eventually outweighing the savings in improved knowledge of current and impending risks.

Table 4.2
Design of experiments for supply network.

Network topology	**Parameters**	**Parameter description**	**Samples**
Random	$n =$ nodes, $k =$ neighbors	$n = (100,500,1000), k = (5,10,15,20)$	12
Small-World	$n =$ nodes, $k =$ neighbors, $p_n =$ neighbor link fraction	$n = (100,500,1000), k = (5,10,15,20), p_n = (0.25,0.5,0.75)$	36
Scale-Free	$n =$ nodes, $m =$ initial no. of hubs	$n = (100,500,1000), m = (10,20,30,40,50)$	15

Table 4.3
Design of experiments for risk diffusion and health.

Category	Parameters	Parameter configuration	Samples
Risk Diffusion	inf_i = infection rate $rec_i =$ recovery rate	$inf_i = (0.05,0.15, 0.25)$, $rec_i = (0.05,0.15,0.25)$	9
Health	$health_{G-M-T} =$ initial dist. of health states, visibility level = vis_i	$health_{G-M-T} =$ $(80/10/10, 50/25/25, 10/10/80)$, $vis_i = (0.25, 0.5, 0.75)$	9

3.5. Analysis

We simulated the model for a total period of ten years (or 40 quarters) of supply chain risk diffusion. Previous studies have been not explicit arguing their choice of simulation length. In the epidemiology literature, it has been argued that the simulation length should be equal to the time it takes for the outbreak to end (i.e. the time until no latent or infectious individual remains). In general, studies have chosen time horizons that allow the contagion/diffusion/risk spread to peak and stabilize or die out. The length of our simulation allows for a peak and stabilizing outcome of typical supply chain risks. The length also represents two five-year Chapter 11 bankruptcy recovery cycles. For example, we calculated the standard deviation and variance for the last five to six periods, and both stayed below 1. This would signify that we considered a stable network when the variance (or percent change in health states) remained below 1% for at least five consecutive periods.

Every simulation was repeated 100 times for the entire parameter space to average out stochastic effects. We systematically explored the variation in supply network health levels over the parameter space by using ordinary least squares (OLS) regression analysis. For our base regression model, we estimated the effects of network structure, visibility, and initial supply network health distribution on risk diffusion and supply network health. We then re-ran the analysis incorporating any interaction effects corresponding to our hypotheses. The use of regression analysis for the evaluation of simulation results is particularly applicable as it enables analyzing high-dimensional empirical data whose underlying model is uncertain (Hanaki et al., 2007). In fact, previous research has utilized OLS to test the impact of network structure on diffusion level, speed, and breadth over a variety of network topologies in AB and computational models (Gibbons, 2004; 2007). As a robustness check, we tested for several of the key model assumptions that coincide with using an OLS regression (e.g. homoscedasticity, nonlinearity). We ran all analyses in STATA Version 11.

3.6. Key findings

The simulation results are presented and discussed in this section. A summary of findings from the OLS regression analyses are shown in Tables 4.5 and 4.6. Figures 4.5-4.7 depict the evolution of the health state distributions for the random, small-world, and scale free supply network topologies. We included the grand mean centered network type and initial health distribution measures in the models. For visibility, we used the reverse helmet coding scheme in STATA to compare levels of visibility with the mean of its previous levels, as this comparison is more meaningful for ordinal variables (Ender and Mitchell, 2003; Edillo et al., 2004). Our results have important supply network system performance implications related to (i) the supply network structure, (ii) supply network visibility, and (iii) the initial distribution of supply network health levels.

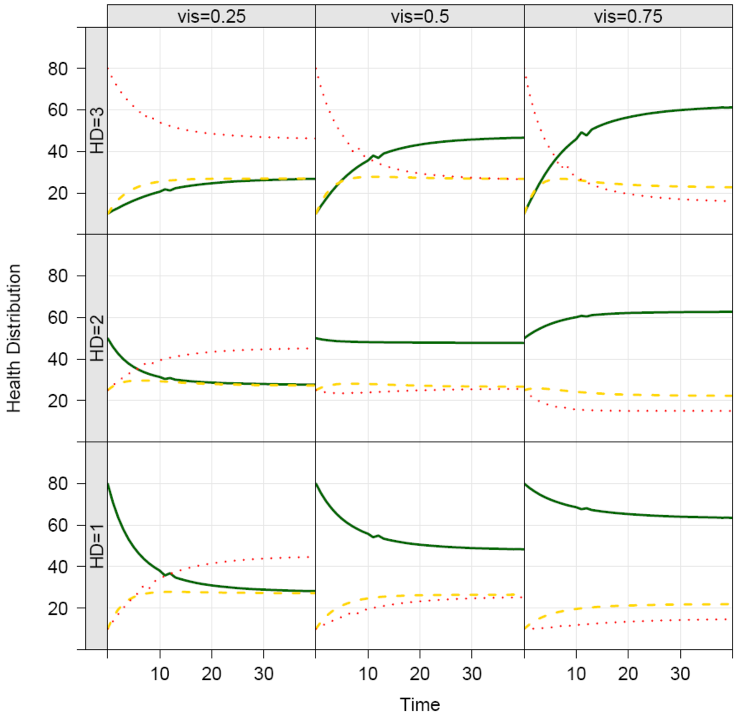


Figure 4.5. Evolution of health state distribution (random supply network topology).

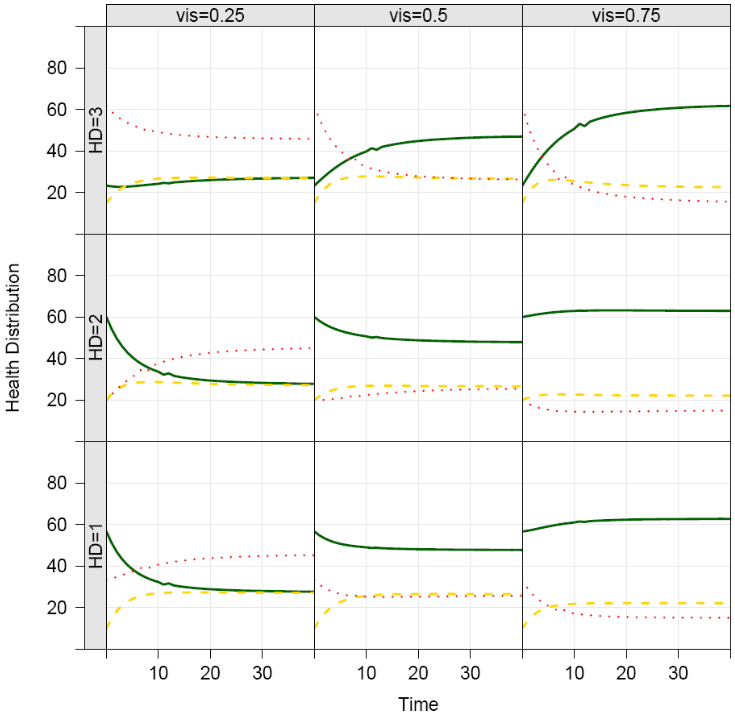


Figure 4.6. Evolution of health state distribution (small-world supply network topology).

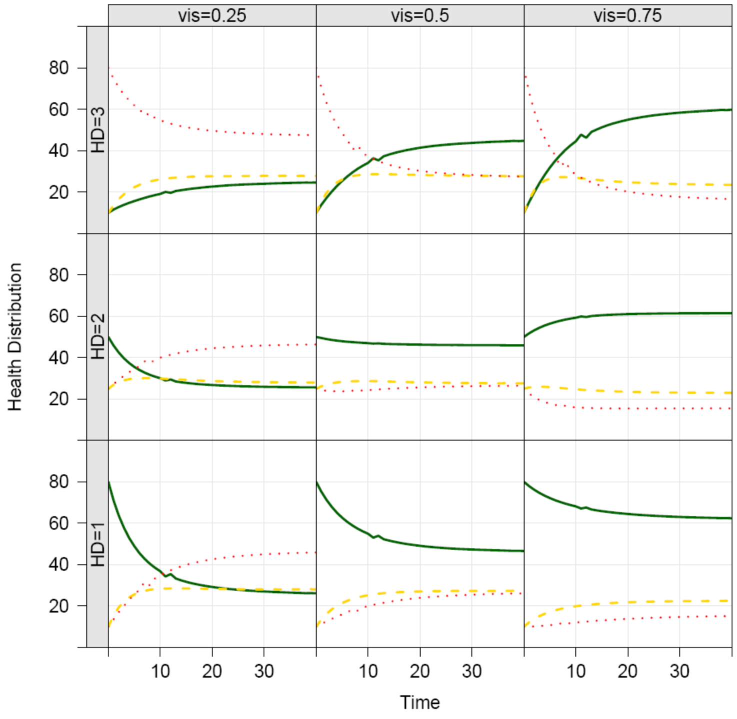


Figure 4.7. Evolution of health state distribution (scale-free supply network topology).

Table 4.4
Summary of findings.

Hypothesis	Factor(s)	Impact on risk propagation	Impact on desired health level outcome	Support?
H1a	Small-World	(-)	(+)	Yes
H1b	Scale-Free	(+)	(-)	Yes
H2a	Small-World, high visibility	(-)	(+)	Yes
H2b	Scale-Free, high visibility	(-)	(+)	Yes

Table 4.5 continued
Summary of findings.

Hypothesis	Factors	Promotes slower recovery than small-world and high initial distribution?	Relative unit of (+) impact on desired health level outcome	Support?

H3a	Random, high initial health distribution	Yes	< 1/3	Yes
H3b	Scale-Free, high initial health distribution	Yes	< 1/3	Yes

3.7. Implications

3.7.1. Implications of supply network structure

Our results show that the structure of the supply network has a significant impact on risk diffusion and health level outcomes. Irrespective of supply network design, insight into a supply network's structural properties can consequently enhance risk assessment and mitigation strategies. At a high-level, our results confirm that supply chain managers can use a network analytic lens to guide network governance policies for more favorable health level outcomes to guard against extensive risk exposure. It may be difficult in certain circumstances to change structural properties for existing supply networks without significant redesign and cooperation from major partners. However, this research demonstrates that supply networks can be fashioned or engineered if possible to follow desirable structural characteristics that lead to better performance and sustainability. Firms can leverage evolutionary principles associated with random, small-world, and scale-free networks to build supply networks that perform well in the wake of exposure to the multiplicity of risks. As supply networks grow and transform over time, the structural aspect must therefore be taken into account.

3.7.2. Implications of visibility

Our results provide strong evidence that structural visibility into the lower tiers of the supply network has a significant mitigating impact on cascading risks, irrespective of the type of supply network structure. Consequently, it can be concluded that enhanced visibility is an important and perhaps essential capability for effective supply chain risk identification and mitigation. Supply chain managers must therefore move beyond a simplified dyadic or triadic view to a more holistic approach when developing risk identification and mitigation strategies. This implication takes into consideration that understanding the structure of the entire supply network—as described in the previous section—is very difficult or even impossible to achieve. Instead, decision makers must focus on obtaining at least a partial view into their supply network. This can be achieved through different visibility mechanisms, including collaboration, alliances, and improved information systems. Partial visibility into first tier and highly limited visibility into sub-tiers can lead to delayed risk identifications; our results further show that the magnitude of risk mitigation is highly dependent on level of visibility. Thus, structural visibility serves as a means to communicate risk and is a key component in moving towards a system-wide approach to managing risk and complexity in supply networks. We acknowledge, however, that this may be a function of the operationalization of visibility as an immunity measure.

3.7.3. Implications of initial health level

The criticality of the network structure becomes more even prevalent with lower initial health levels of entities in the supply network. Our results show that it is quite difficult for the supply network to recover when it is characterized by predominantly poor performing entities as risk diffuses much faster. For supply chain decision makers, this implies that greater emphasis should be placed on promoting the health of their supply network partners through improved support and collaboration in order to avoid cascading risks. Furthermore, it undermines the importance of continuously monitoring and improving the health of the supply network.

3.8. Summarizing study A

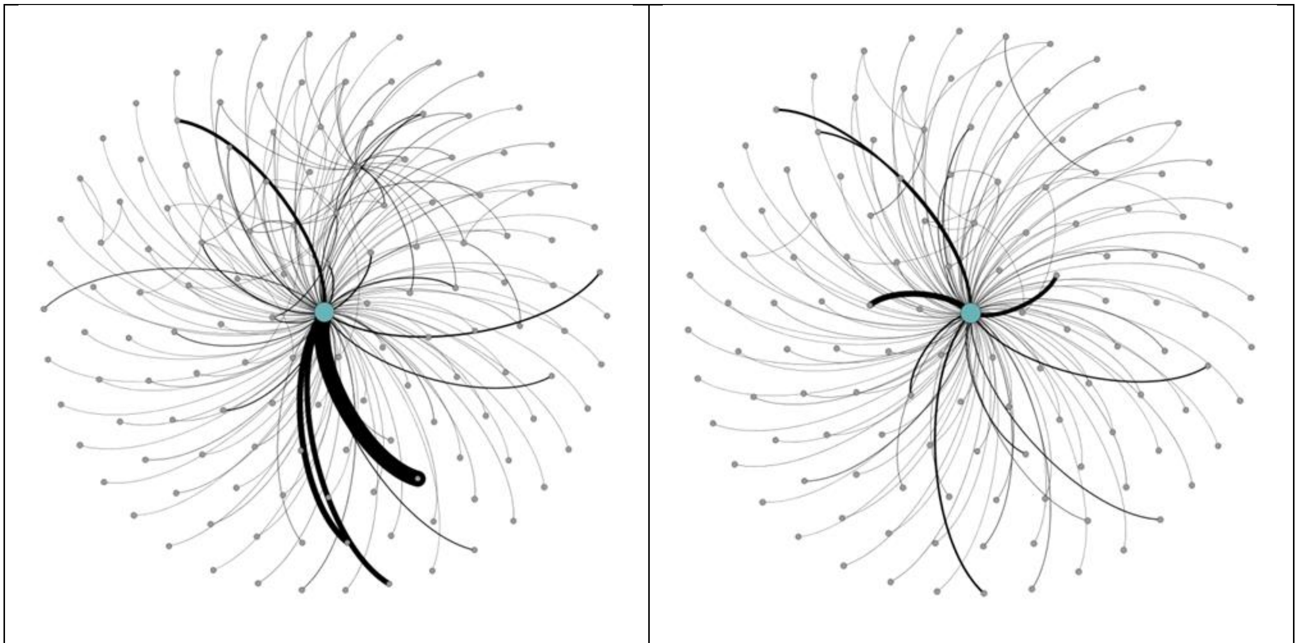
Our study illustrates, through a computational approach, the value and importance of adopting a network analytic lens to understanding risk and risk diffusion in global supply chains. Risks originating in seemingly unrelated and distant parts of the entire network can quickly propagate, disrupting and potentially crippling the entire network. We demonstrate that a network analytic lens provides a more holistic assessment of these risks and helps to explain the propagation of poor (strong) supplier performance through the supply network over time. Our results indicate that there is a significant association between supply network structure and both risk diffusion and supply network health. In particular, we find that supply networks with a small-world structure consistently outperform scale-free supply networks, and they recover at a faster rate than both random and scale free topologies given low initial levels of healthy entities. Our study also shows that greater visibility greatly enhances risk mitigation regardless of the structural properties of the supply network.

4. Study B: supply networks in automotive, pharmaceutical, and electronics industries

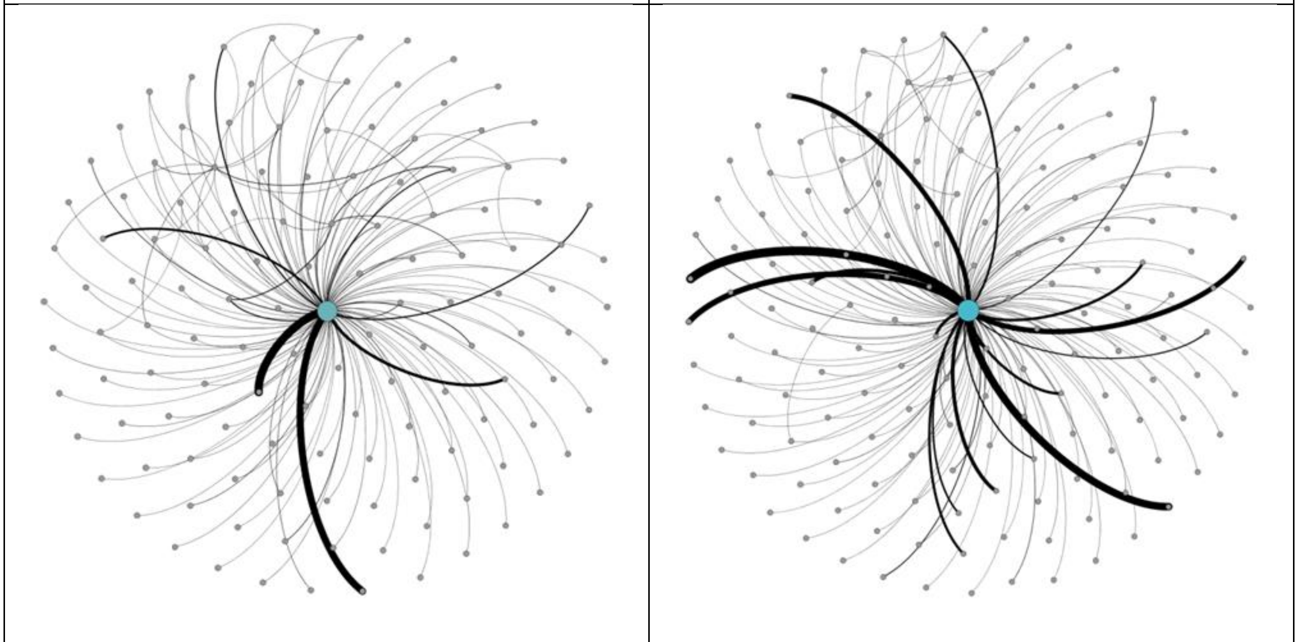
In this second study, we demonstrate differences in supply networks of focal firms in multiple industries, from high velocity and low velocity industry contexts. High velocity industries, such as the electronics industry, are characterized by short product lifecycles as well as a high rate of change in technology and market conditions (Fine, 2000; Sodhi and Lee, 2007). Low velocity industries, such as the automotive industry, have been noted as such contexts where high levels of interfirm specialization and tightly integrated production networks are likely to benefit firm performance due to more reciprocal interdependence between suppliers and automakers (Dyer, 1996).

4.1. Cross-Industry comparison

The differences in the supply network characteristics within and between industries is exemplified by the representative examples in Figure 4.8 and 4.9. We expect that firms operating primarily in a low velocity industry will take a supply chain management strategy that differs from firms operating primarily in a high velocity industry in terms of how they manage their cost and revenue concentration levels both upstream and downstream. Moreover, we expect notable differences in the facilitating effects from other supply network characteristics, such as network structure and supply network partner attributes.

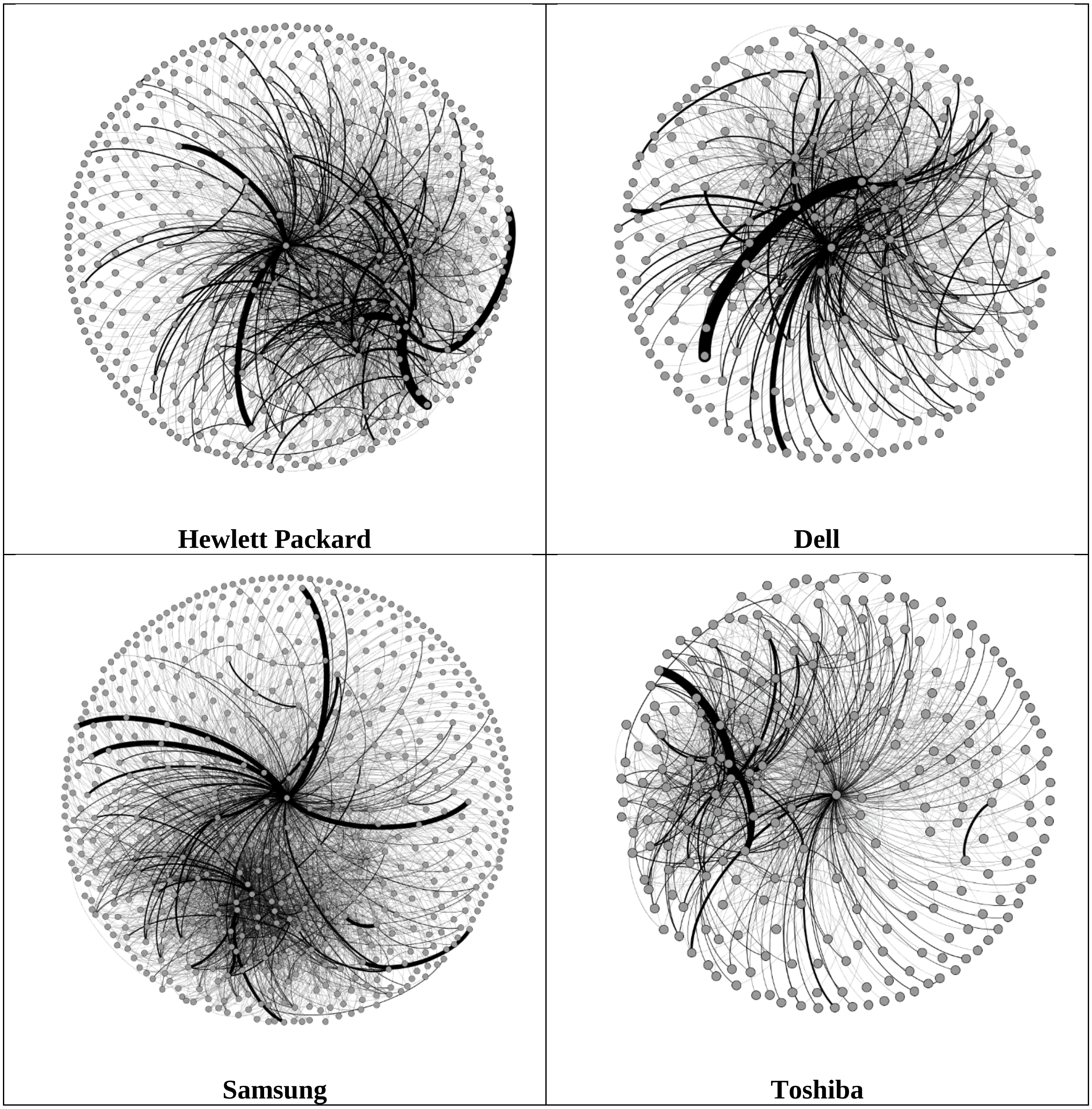


Ford **Honda**



General Motors **Toyota**

Figure 4.8. Comparison of cost and revenue concentration of select firms in auto industry.



Hewlett Packard

Dell

Samsung

Toshiba

Figure 4.9. Comparison of cost and revenue concentration of select firms in electronics industry.

4.2. Data and model development

The primary source of data used for this study is the Bloomberg database. As described in Chapter 3, Bloomberg maintains a vast historical database of company financials covering both international and domestic markets as well as supply chain relationship data on more than 35,000 companies globally. We used the Bloomberg database to build our network of customers and suppliers.

In line with other operations studies (e.g. Chen et al., 2005; Hendricks and Singhal, 2009), we use the measure of return on assets (ROA) as a proxy for performance at the firm level. Similarly to previous studies operationalizing relationship dependency (Sheu et al., 2006; Flight et al., 2008; Autry and Golicic, 2010; Handley and Benton Jr, 2013), we proxy for supply network partner revenue concentration by the concentration of a supplier's sales revenue that comes directly from its direct customers and supply network partner cost concentration as the concentration of a customer's costs that are incurred from its direct suppliers. We use the measure of network density to capture supplier and customer network efficiency (Wasserman and Faust, 1994) and closeness centrality to capture a firm's closeness in the network upstream and downstream (Wasserman and Faust, 1994). All network related measures were calculated using the social network analysis software package, UCINET 6.579 (Borgatti et al., 2002). We controlled for several measures related to firm performance, such as firm size (operationalized as the log of a firm's annual sales), firm sales growth, and firm capital intensity. The sample of focal firms for each industry includes both firms with US and global headquarters. The descriptive statistics for the overall sample can be found in Table 4.6. Preliminary results for each industry were calculated using an ordinary least squares regression, with firm performance as the dependent variable and all other described variables as independent and control variables.

Table 4.6
Descriptive statistics.

(a) Focal manufacturing firms whose primary industry is electronics and their direct partners

	Variable	Obs	Mean	Std.Dev.	Min	Max
1	ROA	390	0.017	0.12	-0.50	0.24
2	Firm Size	390	7.36	2.20	2.42	11.6
3	Capital Intensity	390	0.052	0.059	0.00065	0.38
4	Sales Growth	390	0.045	0.18	-0.48	1.67
5	Supplier Net Effic	390	0.91	0.14	0.46	1
6	Customer Net Effic	390	0.88	0.17	0	1
7	Upstream Closeness	390	0.071	0.12	0	0.57
8	Downstream Closeness	390	0.11	0.14	0	0.61
9	Cost Concentration	390	0.014	0.036	1.6e-07	0.33
10	Revenue Concentration	390	0.036	0.076	4.0e-08	0.47

N = 173 observations.

(b) Focal manufacturing firms whose primary industry is auto and their direct partners

	Variable	Obs	Mean	Std.Dev.	Min	Max
1	ROA	157	0.046	0.068	-0.22	0.18
2	Firm Size	157	8.32	1.94	3.03	12.3
3	Capital Intensity	157	0.058	0.068	0.0025	0.48
4	Sales Growth	157	0.043	0.16	-0.36	0.88
5	Supplier Net Effic	157	0.96	0.074	0.50	1
6	Customer Net Effic	157	0.91	0.17	0	1
7	Upstream Closeness	157	0.10	0.19	0	0.83
8	Downstream Closeness	157	0.17	0.19	0	0.78
9	Cost Concentration	157	0.0059	0.015	1.0e-08	0.083
10	Revenue Concentration	157	0.037	0.082	9.0e-08	0.48

N = 157 observations.

(c) Focal manufacturing firms whose primary industry is pharmaceutical and their direct partners

	Variable	Obs	Mean	Std.Dev.	Min	Max
1	ROA	87	0.019	0.19	-1.11	0.22
2	Firm Size	87	8.01	2.29	1.55	11.6
3	Capital Intensity	87	0.040	0.029	0.0021	0.17
4	Sales Growth	87	0.080	0.24	-0.71	1.17
5	Supplier Net Effic	87	0.97	0.052	0.78	1
6	Customer Net Effic	87	0.91	0.18	0	1
7	Upstream Closeness	87	0.086	0.13	0	0.61
8	Downstream Closeness	87	0.11	0.17	0	0.73
9	Cost Concentration	87	0.0095	0.031	1.3e-07	0.19
10	Revenue Concentration	87	0.080	0.15	1.2e-06	0.78

N = 87 observations.

4.3. Preliminary results

Preliminary results for the cross-industry comparison are found in Tables 4.7-4.9. Before drawing any strong assertions from the reported results, analysis of the data needs to be further vetted through a series of data normalizations (e.g., incorporation of industry-adjusted measures for cross comparison) and proper robustness checks (e.g., alternate measures, time lag of independent measures, endogeneity concerns). Nonetheless, by comparing the initial results, we observe that a firm's performance appears to respond differently to its supply network partner cost concentration, depending on which primary industry that it operates in. For example, while it was observed that there were positive benefits associated cost concentration and performance among firms in the electronics industry, it appears that the positive association may flip or become less of a significant driver of performance in other industries. Further, the facilitating effect of a firm's supply network structure on its supply network partner cost concentration, whether positive or negative, may also be sensitive to which industry they operate in. Moreover, though the sign of the influence from a firm's supply network partner revenue concentration remains nearly the same across all models, we observe that the facilitating effect from its supply network structure may also be sensitive to which industry the firm operates in.

Table 4.7

Preliminary results.
(a) Firms from the Electronics Industry

ROA	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Firm Size	0.03***	0.03***	0.03***	0.02***	0.02***	0.03***	0.03***	0.03***	0.03***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Capital Intensity	-0.05	0.01	0.01	-0.01	-0.01	-0.00	-0.00	-0.00	-0.00
	(0.08)	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)
Sales Growth	0.14***	0.16***	0.16***	0.16***	0.15***	0.16***	0.16***	0.15***	0.15***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Supplier Network Efficiency		0.06	0.07+			0.06	0.06	0.06	0.07+
		(0.04)	(0.04)			(0.04)	(0.04)	(0.04)	(0.04)
Customer Network Efficiency				0.03	0.04	0.03	0.03	0.04	0.04
				(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Upstream Closeness		-0.13**	-0.13*			-0.13**	-0.13*	-0.13**	-0.14**
		(0.05)	(0.05)			(0.05)	(0.05)	(0.05)	(0.05)
Downstream Closeness				0.06+	0.06+	0.05	0.05	0.05	0.05
				(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Cost Concentration		0.28+	0.35+			0.35*	0.45*	0.33*	0.43*
		(0.15)	(0.18)			(0.15)	(0.18)	(0.15)	(0.18)
Cost Conc*Up Closeness			-0.44				-0.72		-0.73
			(0.74)				(0.74)		(0.72)
Cost Conc*Supplier Net Effic			1.68				1.80		2.51
			(1.63)				(1.61)		(1.59)
Revenue Concentration				-0.22**	-0.30***	-0.24***	-0.24***	-0.32***	-0.33***
				(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)
Rev Conc*Down Closeness					1.75**			1.87**	2.01**
					(0.65)			(0.64)	(0.64)
Reve Conc*Customer Net Effic					1.53**			1.46**	1.47**
					(0.47)			(0.47)	(0.47)
Constant	-0.19***	-0.21***	-0.21***	-0.17***	-0.16***	-0.19***	-0.19***	-0.19***	-0.19***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Observations	419	390	390	390	390	390	390	390	390
R-squared	0.271	0.309	0.311	0.311	0.339	0.333	0.336	0.361	0.365

Standard errors in parentheses *** $p<0.001$, ** $p<0.01$, * $p<0.05$, + $p<0.10$

Table 4.7 continued
Preliminary results.

(b) Firms from the Auto Industry

ROA	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Firm Size	0.01***	0.02***	0.02***	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Capital Intensity	0.01	-0.02	-0.01	-0.01	0.02	-0.03	-0.02	0.00	0.01
	(0.08)	(0.07)	(0.08)	(0.08)	(0.09)	(0.08)	(0.08)	(0.08)	(0.09)
Sales Growth	0.02	0.03	0.03	0.04	0.02	0.04	0.03	0.02	0.02
	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)	(0.03)	(0.04)	(0.03)	(0.04)
Supplier Network Efficiency		0.14*	0.14*			0.13+	0.13+	0.13+	0.13+
		(0.07)	(0.07)			(0.07)	(0.07)	(0.07)	(0.07)
Customer Network Efficiency				-0.02	-0.01	-0.01	-0.01	-0.01	-0.01
				(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Upstream Closeness		-0.06+	-0.05			-0.05	-0.05	-0.05	-0.05
		(0.03)	(0.04)			(0.04)	(0.04)	(0.03)	(0.04)
Downstream Closeness				0.04	0.06*	0.03	0.03	0.05+	0.05
				(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Cost Concentration		-0.06	0.12			-0.10	0.02	-0.19	-0.08
		(0.36)	(0.46)			(0.36)	(0.48)	(0.36)	(0.47)
Cost Conc*Up Closeness			-0.34				-0.13		0.03
			(1.15)				(1.17)		(1.15)
Cost Conc*Supplier Net Effic			-3.71				-2.99		-3.65
			(6.29)				(6.34)		(6.24)
Revenue Concentration				-0.08	-0.04	-0.06	-0.06	-0.02	-0.01
				(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)
Rev Conc*Down Closeness					1.75*			1.86**	1.87**
					(0.70)			(0.69)	(0.70)
Reve Conc*Customer Net Effic					0.05			-0.01	-0.01
					(0.48)			(0.47)	(0.48)
Constant	-0.06*	-0.09**	-0.09***	-0.06*	-0.06*	-0.08**	-0.08**	-0.08**	-0.08**
	(0.02)	(0.03)	(0.03)	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)
Observations	167	157	157	157	157	157	157	157	157
R-squared	0.122	0.187	0.189	0.161	0.195	0.198	0.199	0.236	0.238

Standard errors in parentheses *** p<0.001, ** p<0.01, * p<0.05, + p<0.10

Table 4.7 continued
Preliminary results.

(c) Firms from the Pharma Industry

ROA	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Firm Size	0.05***	0.05***	0.05***	0.05***	0.04***	0.06***	0.06***	0.05***	0.05***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Capital Intensity	-0.27	-1.17+	-1.16+	-0.62	-0.42	-1.03	-1.02	-0.87	-0.85
	(0.24)	(0.60)	(0.61)	(0.64)	(0.66)	(0.63)	(0.64)	(0.65)	(0.66)
Sales Growth	0.20**	0.17*	0.16*	0.21**	0.24**	0.17*	0.16*	0.20*	0.19*
	(0.06)	(0.07)	(0.07)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)
Supplier Network Efficiency		0.21	0.20			0.18	0.17	0.17	0.16
		(0.35)	(0.35)			(0.36)	(0.36)	(0.36)	(0.37)
Customer Network Efficiency				0.05	0.06	0.07	0.07	0.08	0.08
				(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)
Upstream Closeness		-0.33+	-0.40*			-0.35*	-0.43*	-0.34+	-0.42*
		(0.17)	(0.19)			(0.18)	(0.20)	(0.18)	(0.20)
Downstream Closeness				0.05	-0.14	-0.02	-0.02	-0.17	-0.17
				(0.11)	(0.20)	(0.11)	(0.11)	(0.19)	(0.19)
Cost Concentration		-1.14+	-1.21			-1.13+	-1.21	-1.13+	-1.17
		(0.60)	(1.12)			(0.61)	(1.15)	(0.61)	(1.15)
Cost Conc*Up Closeness			3.05				3.16		3.16
			(3.76)				(3.81)		(3.83)
Cost Conc*Supplier Net Effic			0.90				1.25		0.45
			(20.20)				(20.58)		(20.80)
Revenue Concentration				0.10	-0.20	0.11	0.12	-0.12	-0.12
				(0.14)	(0.29)	(0.13)	(0.13)	(0.28)	(0.29)
Rev Conc*Down Closeness					-4.14			-3.16	-3.24
					(3.67)			(3.53)	(3.57)
Reve Conc*Customer Net Effic					-0.34			-0.38	-0.37
					(0.61)			(0.59)	(0.60)
Constant	-0.39***	-0.37***	-0.37***	-0.35***	-0.36***	-0.40***	-0.40***	-0.41***	-0.41***
	(0.06)	(0.08)	(0.08)	(0.08)	(0.09)	(0.10)	(0.10)	(0.10)	(0.10)
Observations	96	87	87	87	87	87	87	87	87
R-squared	0.398	0.410	0.416	0.329	0.342	0.420	0.426	0.429	0.435

Standard errors in parentheses *** $p<0.001$, ** $p<0.01$, * $p<0.05$, + $p<0.10$

4.4. Implications

Collectively, our preliminary findings suggest two important implications related to industry context that merit further investigation, both from a research and a managerial standpoint. First, the industry context appears to play a role in terms of the network structural characteristics, where the characteristics of an average representative firm in each industry vary considerably. Second, when considering what supply relationship dynamics to focus on cultivating, there is an indication that the industry context itself should be explicitly controlled for as it may result in varying performance outcomes directly and indirectly. Thus, a firm may be better off explicitly varying its strategy contingent upon which primary industry in which it operates. For example, downstream closeness may not play a significant role in facilitating firm performance in the automotive industry because the majority of customers are auto dealers, providing less of an advantage to being closely linked downstream as a focal firm. Whereas firms operating primarily in the electronics industry may have several customers downstream who are competing partners such as retailers purchasing a manufacturer's products or services, providing more of an incentive to be better connected with these entities, as more closeness downstream may provide valuable insight into pricing and availability schemes allowing a focal firm to better manage its products and services as they flow downstream to such customers.

4.5 Summarizing study B

We investigated supply networks of focal firms in multiple industries, from high velocity and low velocity industry contexts. We expected differences in how firms manage their cost and revenue concentration levels both upstream and downstream as well as in how supply network characteristics facilitated their effect on performance. As in study A, the preliminary results of study B suggest that performance outcomes may indeed be contingent upon the supply network dynamics of the particular industry in which a firm operates. These findings offer further motivation for future research that investigates the impact of industry clock speed on design and performance of supply networks.

5. Conclusion and future research opportunities

Our framework identifies three distinct, but interdependent themes that characterize the study of supply networks: network structure, network dynamics, and network strategy. There are many promising research opportunities for understanding supply networks through a network analytic lens, some of which were explored through studies A and B. Developing capabilities to explore, discover, and analytically make sense of complex supply networks is an increasingly important domain with the continuously increasing amount of data. The fusion of empirical with visual analytics, visualization with computational modeling, and empirical with modeling present an exciting opportunity for researchers looking to further our understanding of supply networks as strategic assets to the firm. Table 4.8 presents some of the key, but non-exhaustive list of current research limitations and knowledge gaps found, and suggests promising directions for future research.

Table 4.8
Research gaps and future directions.

Theme	Research Gaps	Suggested Research Directions
Network Structure	Translation of existing graph theoretic and social network properties into the SCM context	Operationalization of structural and relational embeddedness, complexity; Alliance types
	Impact of traditional tier structure on network metrics (e.g. tie strength, importance)	Operationalization of criticality for each entity based on tier level
	Impact of firm position, connections, and embeddedness on firm and supply network performance	Empirical assessment of association between system architecture and performance
	Impact of industry clock speed on design and performance of supply networks	Cross-industry comparison of structurally equivalent entities and its impact on performance
	Determinants and characteristics of supply tie strength	Empirical assessment of contracts, business models (e.g. performance based-logistics), and relationship types
	Evaluation of the global nature of supply networks	Cross-national and -cultural studies
Network Dynamics	Temporal nature of supply network emergence, evolution, and risk contagion	Visualization of dynamic networks and risk diffusion
	Lack of theoretical insight into the association between system architecture, visibility, and risk spread in supply networks	Longitudinal studies and AB models on supply network behavior and performance; Operationalization of emergence, autonomy, and visibility
	Impact of responsiveness and resilience on supply network design	Integration of agent-based theory, network theory, and epidemiology
Network Strategy	Design and development of dashboard for operational and strategic support	Identification and integration of key performance metrics
	Management of global supply networks with partial/incomplete data	Identification of better proxies and means of obtaining data to populate and analyze supply networks; Integration of SNA, AB modeling, and visualization software
	Nature and effectiveness of strategies used to moderate adverse impacts and unexpected events	Design and analysis of risk identification, management, mitigation strategies

CHAPTER 5

CONCLUSION

The main premise of my dissertation research was to highlight supply networks as rich sources that can enhance a firm's innovation, ability to identify and mitigate risk, and its operating performance. To achieve this, I drew on theories such as network science, social capital, network learning, risk diffusion, and supply chain management to properly ground my research models and corresponding frameworks.

In my first research chapter (CH. 2), the research focus was on a firm's supply network as a source of innovation, and the research context was that of firms relying on the knowledge flow to improve upon their own innovation output. In my second research chapter (CH. 3), the research centers on the notion of relationship dependence and network structure as a direct and indirect drivers of a firm’s operating performance, and the research context was that of firms who operate both as customers concentrating their costs upstream and as suppliers concentrating their revenues downstream. In my third research chapter (CH. 4), the research focus was on building as well as applying a framework for applying the network analytic lens to supply chain context, and the research context was that of firms in different industries who can use knowledge of supply relationship dynamics to mitigate risk and improve performance.

With each of the three chapters, I varied the objective and research context with the intent to contribute to the current body of work on supply chain and operations management in a different and meaningful light. Collectively, this dissertation provides rich empirical insight into innovation and performance implications of supply network structure and its corresponding relationship dynamics. My dissertation contributes broadly to supply chain research by shedding light on the many dynamics of supply networks that have considerable influence on firm performance. It provides headway for prior calls to improve upon research that accounts for the embedded nature of buyer-supplier dyads. I show that supply networks can be leveraged as important catalysts driving greater innovation, operating performance, and mitigated risk. I emphasize this by highlighting structural and relational characteristics that facilitate knowledge and information flow in a firm’s supply network, make their supply networks more resilient to risk, and improve their own ability to innovate and perform.

APPENDIX A

2SLS MODEL TESTING FOR ENDOGENEITY [a]

Variables:	(1) SN Accessibility (OLS)	(2) SN Interconnectedness (OLS)	(3) Innovation Output (2SLS)
Controls			
Firm Size	0.00	0.01	0.67***
	(0.02)	(0.01)	(0.06)
Firm Age	-0.00*	-0.00	-0.01*
	(0.00)	(0.00)	(0.00)
Industry Concentration	-0.15	0.00	-1.67***
	(0.11)	(0.04)	(0.32)
Industry Growth[i]	0.75	-0.09	
	(0.39)	(0.18)	
Prior Innovation[i]	0.02	-0.02	
	(0.05)	(0.02)	
Prior Knowledge Breadth	0.00	0.00	0.02***
	(0.00)	(0.00)	(0.00)
Lead Firm	0.03	-0.02	0.23
	(0.06)	(0.02)	(0.20)
Degree Centrality[i]	0.04***	0.00	
	(0.00)	(0.00)	
Number of Pairs[i]	-0.00***	-0.00***	
	(0.00)	(0.00)	
Direct effects			
SN Accessibility			0.49**
			(0.18)
SN Interconnectedness			0.67
			(1.12)
Absorptive Capacity	-0.10	0.02	0.95
	(0.14)	(0.04)	(0.52)
SN Partner Innovativeness	0.04	0.16**	-0.36
	(0.41)	(0.06)	(0.63)
Constant	0.30**	-0.02	-2.31***
	(0.10)	(0.03)	(0.41)
N	390	390	390

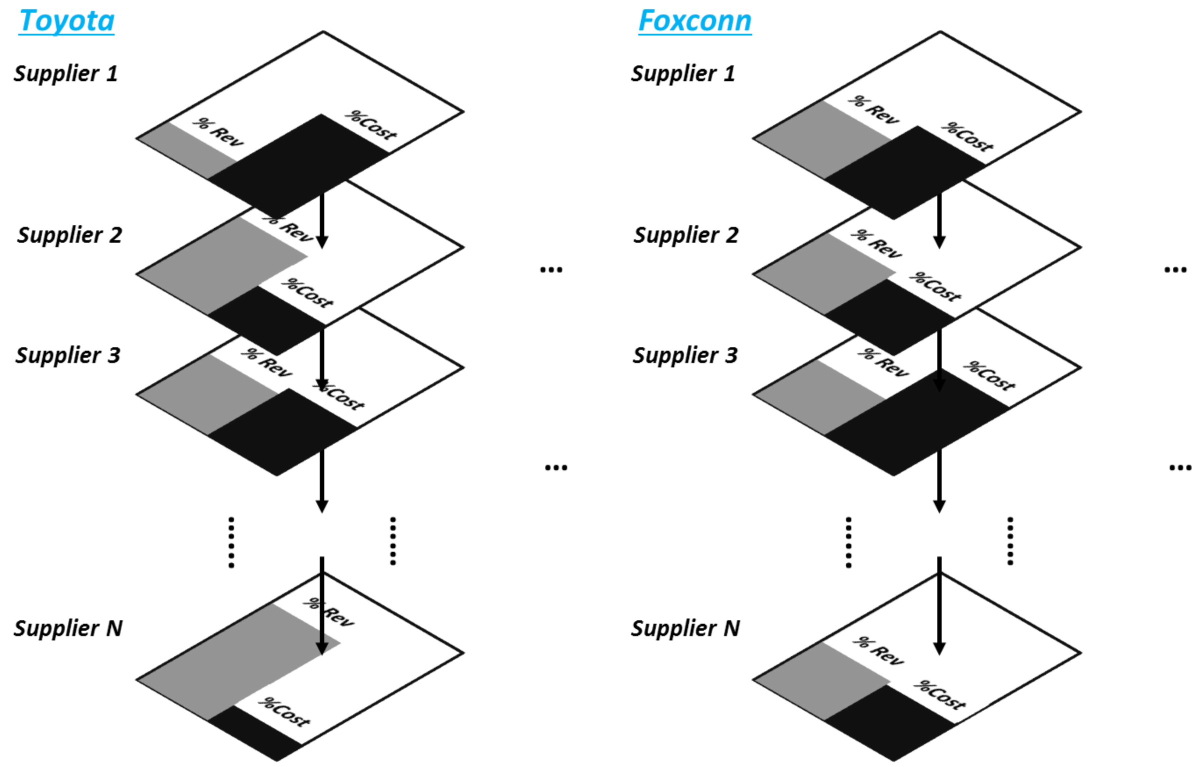
[a] Standard errors in parentheses; *** p<0.001, ** p<0.01, * p<0.05

[i] variables used as instruments for assumed endogenous variables

Notes: Models (1) and (2) depict the results for the first-stage regression considering potentially endogenous variables supply network accessibility and supply network interconnectedness, respectively. Model (3) is the resulting 2SLS incorporating the predicted values from the first stage as independent variables to replace the values of the assumed endogenous variables.

APPENDIX B

ILLUSTRATION: DYADIC DATA AGGREGATION FOR EACH FOCAL FIRM



Toyota

Avg %Rev	Avg %Cost
0.435	0.276

Foxconn

Avg %Rev	Avg %Cost
9.29	10.26

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