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The Dynamics and Effects of Supply Network Structure

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Abstract

The rising interest in network theory among supply chain scholars reflects an emerging shift in perspective. To deliver global speed, efficiency, and responsiveness, modern firms' supply chains are becoming increasingly complex. The patterns of interactions and interdependencies among hundreds of firms interconnected by these complex supply chains cannot be adequately explored from the dyadic perspective, which has dominated supply chain research for decades. Many supply chain scholars agree that the language of networks can provide a syntax and structure to describe and explore this complex reality. The actual application of network theory in supply chain research, however, has been limited. This dissertation provides three examples of how rigorous network analysis can furnish both a theory and a method to study modern firms' supply chains and obtain new knowledge advancing both scholarly thought and business practice. In this light, this dissertation may serve as a guide for supply chain scholars seeking to leverage the potential of empirical network analysis in their research.

Essay 1 explores some of the ways in which structural properties of a firm's supply network affect the accuracy of forecasts made by stock analysts. Essay 2 examines how a firm's supply network changes its structure when the firm experiences stretches of financial difficulty. Essay 3 investigates how the structure of a firm's supply network changes as the firm unfolds a significant exploratory innovation project. Collectively, these three essays demonstrate the value of the network perspective as a great connector of ideas extending the interface between supply chain management and other business disciplines.

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INTRODUCTION

The network view is fast becoming a core perspective in supply chain management research. Network theory provides a way to explore why and how firms interact, where and when interfirm links form, and how the resulting networks affect firms' performance. Network analysis provides the math behind some of the most interesting but least explored phenomena in firms' activity and evolution. This dissertation provides several illustrations of how network theory and network analysis can be employed to yield additional insights about firms' innovation, stock returns, and reactions to changes in the conditions of their partners. Overall, the three essays show that network theory can be fruitfully applied to advance supply chain management research. Most extant studies using network theory to study supply chain phenomena rely on limited datasets. In this dissertation, I use a novel extensive longitudinal dataset to probe deeply into firms' supply networks and their evolution over time. This dissertation shows that different configurations of networks produce different advantages. Thus, developing a nuanced understanding of their networks will help firms to obtain an advantage over competitors.

Equity analysts, for instance, increasingly include supply network information into their forecasts of firms' performance. Essay 1 draws on the network and behavioral forecasting literature to identify structural properties which make supply networks more cognitively accessible for equity analysts and lead to more accurate forecasts. With a dataset used by practicing equity analysts, I map and quantify the structure of multi-tier supply networks of 25 U.S. manufacturing firms over 10 years, each network consisting of the average of 3,032 supplier firms. Analyzing these networks, I find a significant association between supply network structure and the accuracy of equity analysts' forecasts. In particular, my results show that analysts are able to produce more accurate forecasts if the firm's supply network has prominent hubs or clusters. In contrast, analysts

produce less accurate forecasts for firms with supply networks having small-world structures. This essay identifies a previously unknown determinant of equity analysts' forecast accuracy and emphasizes the importance of supply networks for outside stakeholders including equity analysts and investors.

The other two essays focus on the evolution of supply networks over time. While we know a good deal about factors influencing stability in interfirm networks, we know little about forces driving network change. In Essay 2, I examine the effects of a crucial variable – uncertainty specific to a key exchange partner – on patterns of novel tie formation and old tie deletion which together shape trajectories of network evolution. Using longitudinal data on buyer-supplier relations, I map and analyze supply networks of 30 large U.S. manufacturing firms. These dynamic webs of organizations consist of an average of 3,020 suppliers. My findings show that when environmental munificence is greater, the stretches of unique uncertainty experienced by firms are followed by an increase in both the number of novel ties formed and the number of old ties deleted by their immediate suppliers. Surprisingly, these immediate suppliers curtail their rates of novel tie formation and old tie deletion in response to changes in the focal firms' unique uncertainty when environmental munificence is lower. In this light, Essay 2 provides evidence that the influence of structural constraints on organizational action varies between stable and unstable periods.

Essay 3, in turn, examines a previously unexplored link between a firm's innovative agency and the structure of its supply network. Extant studies have shown that supply network structure powerfully enables and constrains the focal firm's innovative actions. In Essay 3, I theorize and empirically test the idea that deliberative, purposeful efforts of an individual firm – its agency – and the structure of its supply network reciprocally constitute each other. In this essay, I analyze

the dynamics of supply networks of 45 global firms, each consisting of thousands of suppliers, and find that the firms' innovative agency changes several structural properties of these networks. Specifically, I find that as these firms unfold exploratory innovation, they and their direct and indirect suppliers start forming new network ties, thus influencing the size, average path length, density, and the small-world architecture of their vast supply networks.

ESSAY 1. THE EFFECT OF SUPPLY NETWORK STRUCTURE ON EQUITY ANALYSTS' FORECASTS

Introduction

To create customer value and sustain competitive advantage, firms depend on their increasingly global supply networks connecting hundreds of other firms acting in multiple tiers. These networks have evolved to deliver global speed, efficiency, and responsiveness. At the same time, they are complex systems which generate intricate patterns of interdependencies among the member firms (Choi et al., 2001; Choi and Krause, 2006; Kim et al., 2011). In such systems, any particular exchange occurs in the context of many other exchanges and events. The outcomes of any individual firm, therefore, depend not only on its own performance or the performance of its direct partners but also on the outcomes of many other indirectly linked firms. For example, quality problems originating at a third-tier supplier can quickly reach the firm and propagate further affecting its downstream partners. The interdependencies among firms in supply networks also mean that their earnings and profits are interrelated (Hertzel et al., 2008; Pandit et al., 2011; Patatoukas, 2012). Like quality problems or other types of supply and demand risks propagating throughout a supply network, financial distress of one firm may cascade and eventually affect many other firms interlinked through direct and indirect customer-supplier relationships. Supply network, therefore, is becoming an important source of information for professionals involved in the analysis and forecasting of firms' financial performance.

The accuracy of such analyses and forecasts is critical for these professionals as well as for the firms they study. Equity analysts, for example, are financial professionals who collect information and conduct analyses to understand and predict stock price changes (Leins, 2018). Investors frequently rely on their analyses and forecasts in making decisions to buy, sell, or hold

a particular stock (Nagy and Obenberger, 1994; Womack, 1996). Analysts' forecasts, therefore, can often increase or cut short flows of capital, thus making firms prosper or perish (Leins, 2018). As such, equity analysts are important intermediaries in capital markets. At the same time, equity analysis is a field of intense rivalry as analysts compete fiercely with each other for investor attention (Baum et al., 2015). Because more accurate forecasts attract more investors, equity analysts strive to increase the accuracy of their forecasts. To achieve this, they collect and use information from many different sources, including firms' supply networks. Studies in the finance and accounting literatures indicate that equity analysts who look deep into the firms' supply base to examine the performance of and the interdependencies among actors in the supply networks achieve higher forecast accuracy (Guan et al., 2015; Luo and Nagarajan, 2015).

This is surprising because as analysts begin following along firms' supply networks in search for information, they are confronted with significant complexity. Extant studies of analysts' forecasting behavior find that factoring complex information into the process of forecasting increases the difficulty of the task, thereby reducing forecasting accuracy (Brown et al., 1987; Haw et al., 1994; Lang and Lundholm, 1996; Clement, 1999). But many analysts appear to be able to successfully incorporate information from supply networks into their forecasts and improve the accuracy of their forecasts. This suggests that analysts may follow certain heuristic rules enabling them to pierce through the complexity inherent in supply networks. Studies of cognitive aspects of information processing (e.g., Brashears, 2013; Brashears and Quintane, 2015) show that when presented with a complex body of data, individuals are able to find patterns allowing relatively simple generalizations. Finding patterns in complexity helps them to explain much with little. Observing customer-supplier ties between firms in a supply network, for example, analysts can discern patterns among these ties. Based on the observed patterns of ties, they can further grasp

the underlying structural logic holding the network together and finally infer its general structure (Janicik and Larrick, 2005; Brashears and Quintane, 2015). A general understanding of the structure of a supply network and how the network's parts are interconnected may help reduce the complexity of the forecasting task because analysts would be able to factor the complex system into simpler subsystems, analyze them individually, and then synthesize to infer the ways in which the effects of positive and negative events occurring in different parts of the network may affect a particular firm. We know little, however, about what properties might make the structure of a complex network more cognitively accessible for an outside observer. This gap leads to our central research question: how does supply network structure affect the accuracy of analysts' forecasts?

Research on cognitive aspects related to how network information is stored and retrieved from memory shows that human cognition detects some structural features better than others (Brashears and Quintane, 2015). Structural elements that are easier for analysts to detect and store in memory, therefore, may improve their perception of the network structure and facilitate more accurate forecasts. Brashears and Quintane (2015) show that individuals tend to encode network information primarily in terms of groups or clusters of ties rather than as individual dyads. Remembering clusters of ties simplifies encoding and recall and reduces cognitive load while still permitting an individual to grasp the structural logic of the network. Groups or clusters of ties, therefore, are common structural configurations which individuals become aware of, process, and store with less cognitive effort. In this research, I propose and empirically test the idea that supply networks with relatively large numbers of ties grouped either in clusters or around prominent hub nodes facilitate the accuracy of analysts' forecasts. I also examine the influence of an interesting contrasting setting – supply networks with small-world structures – on the analysts' predictive accuracy. In such networks, there is a substantial number of ties among clusters, and this is likely

to increase the difficulty of forecasting task by introducing a higher degree of interdependence among clusters in the network.

Addressing our research question, I expect to make several important contributions. First, I contribute to the growing body of literature on supply networks. Specifically, I show that supply networks and their structural properties affect firms' outcomes by influencing important stakeholders such as equity analysts. Our findings suggest that the structural properties of supply networks affect the accuracy of equity analysts in predictable ways. Second, I contribute to the finance and accounting literature. Except for Guan et al. (2015), Luo and Nagarajan (2015), and Hu et al. (2018), few studies address how supply chain information affects the accuracy of equity analyst forecasts. However, identification of additional, important determinants of forecast accuracy can be valuable to accounting and finance researchers, analysts, and investors who are interested in obtaining more accurate firm performance forecasts.

The remainder of this study is organized as follows. I proceed by providing the theoretical rationale for linking supply network structure with the accuracy of analysts' forecasts and develop specific hypotheses about the ways in which several structural properties common to many complex networks might affect the analysts' predictive accuracy. Next, I describe our research design regarding the data set and the adopted analysis approach. I then present and discuss the results of our analyses and consider the implications for theory and practice. Finally, I consider the limitations of our study and outline relevant avenues for further research.

Theoretical background and hypothesis development

Security analysts view supply networks as arenas where favorable or unfavorable events affecting some firms can influence financial performance and shareholder value of their direct and indirect partners. Financial situation at one firm may have implications for firms that are connected along

the supply chain (Hertzel et al., 2008; Pandit et al., 2011; Patatoukas, 2012). Stock returns of economically linked firms such as supply chain partners are correlated because of related fundamentals and profits (Menzly and Ozbas 2010). Financial distress originating at one firm may affect all of its partners. Financial distress may occur for various reasons. For example, studies show that more firms experience financial distress due to poor management rather than the viability of their business models or the strength of the demand for their products (e.g. Gilson, 1989; Whitaker, 1999).

For instance, in 2018, Tesla's balance sheet showed a considerable amount of debt (Higgins, 2018; Higgins *et al*., 2018). At the same time, Tesla's CEO, Elon Musk, was criticized for a number of business and personal decisions. Tesla's stock returns showed a very high volatility. As a result, the car maker's cost of capital increased. It became increasingly more difficult for Tesla to obtain liquidity from capital markets on its own. Tesla demanded its suppliers to extend additional credit. The car maker needed to hold on to cash longer and thus delayed its short-term payments. This, in turn, increased the suppliers' own uncertainty. A supplier's ability to operate efficiently depends on whether it can receive stable cash flows from its buyers (e.g., Hendricks and Singhal, 2005). Unstable cash flows could prevent Tesla's suppliers from financing their own capital or labor, thereby impacting their profitability and adding uncertainty about future. Liquidity-constrained firms often use their dependent suppliers as sources of liquidity. Dependent suppliers often have to borrow to finance additional trade credit (Cunat, 2006; Garcia-Appendini and Montiorol-Garriga, 2013), pinch funds used for hiring or investments, or raise prices to squeeze other firms along the supply chain. Other ways in which dependent suppliers frequently support their distressed buyers include allowing retrospective or late payments, offering extra discounts (Cunat, 2006) or an opportunity to return unsold products (Gerchak and Wang, 2004).

In extreme cases, suppliers dependent on a distressed firm may lose a large percent of their revenue at once. Even if this does not occur, the suppliers' stock returns are likely to experience a higher volatility because stock returns of economically linked firms such as supply chain partners are correlated due to related fundamentals (Cohen and Frazzini, 2008) and profits (Menzly and Ozbas, 2010). Stock markets can negatively react to such distress when, for example, suppliers commit into significant relationship-specific investments serving the needs of a particular buyer and having limited resale options outside of the troubled exchange relationship (Banerjee et al., 2008; Kale and Shahrur, 2007; Titman and Wessels, 1988).

The structure of a supply network determines the degree to which the distress of one firm can cascade and affect other firms in the network. In a simple chain, if firm A is a supplier to firm B, firm B is a supplier to C, and C is a supplier to D, then a distress in D can negatively affect the entire chain. But modern supply networks are large, increasingly intertwined systems in which small perturbations at a single firm can spread to many firms beyond the original firm's chain. If analysts are able to discern the underlying structural logic of supply networks, which is a key factor influencing the transmission of financial risk (Basole and Bellamy, 2014), they can better predict how favorable and unfavorable events taking place in the network will affect the firms they cover. However, analysts must often produce forecasts within a time frame which is too short for a deep analysis of complex patterns of interdependence among hundreds of firms comprising modern supply networks (Leins, 2018).

Thus, when making forecasts, analysts do not examine the myriad of interdependencies among individual firms in a supply network. They observe data on the suppliers of the firms they cover as well as their suppliers' suppliers and customers, and ask questions such as "Who is connected to whom?" and "Who influences whom?" (Leins, 2018). As networks increase in size

and complexity, these questions become difficult to answer. At this point, analysts must rely on intuition to discern structural patterns among the observed interfirm ties. Research in cognitive aspects of network perception (e.g., Janicik and Larrick, 2005; Brashears and Quintane, 2015) shows that human cognition detects some structural patterns over others. When network ties adhere to structural patterns which human cognition can easily detect, analysts can store, recall, and incorporate in their forecasts a larger amount of information about interfirm interactions. If analysts' perception of the network structure is close to its actual structure, they will be able to make better inferences about how events taking place in the network will affect the outcomes of the firms they cover. Forecasts for firms with supply networks having easily identifiable structural patterns, therefore, will be more accurate.

The ways in which humans encode and store network information in their minds determine which structural patterns they become aware of (Simpson et al., 2011; Simpson and Borsch, 2005; Kilduff et al., 2008). Cognitive and behavioral decision-making research shows that to encode and represent interactions among multiple objects and make sense of patterns of these interactions, humans rely on several basic mental frameworks, known as schemas or heuristics (DeSoto, 1960; Freeman, 1992; Janicik and Larrick, 2005; Brashears and Quintane, 2015). For example, humans frequently employ the so-called grouping schema to mentally encode and represent networks. The grouping schema (Janicik and Larrick, 2005) is a heuristic leading individuals to attend primarily to structures in which many ties are grouped together. Humans do not tend to encode relations as individual dyads. Instead, they tend to notice groups of ties. Chunking is a similar heuristic (Brashears and Quintane, 2015). Individuals tend to recall relations not as individual dyads but as larger "chunked" substructures. They tend to abstract from individual ties between firms in a network and search for grouping patterns in these ties. Therefore, structural elements within

networks which group many ties together, for instance, hubs or clusters, are likely to be more discernible to analysts.

a.) Hubs

In general, hubs are defined as nodes with relatively high degrees. The degree of a node is the number of direct ties the node has with other nodes in the network. In the context of supply networks, hubs are firms with large numbers of direct partners. As such, hubs are relatively more connected with the rest of the supply network. Supply chain scholars assign hubs important roles in supply networks (Yan et al., 2015). Hub nodes usually carry high supply, demand, and informational loads. They are often among the most critical suppliers (Yan et al., 2015) or channel leaders (Jarillo, 1988; Human and Provan, 2000; Hearnshaw and Wilson, 2013) providing system-wide coordination of the supply network.

Prominent hubs – the nodes with degrees that are very high relative to those of an average node in the network – are easily identifiable structural elements in supply networks. Because hubs participate in many interactions, they are very likely to appear frequently in the data which equity analysts collect and use in their analyses. Hubs' strong influence on the rest of the network means that a change in the state of a hub node is likely to spread quickly across its numerous partners (Barabasi and Bonabeau, 2003; Dezso and Barabasi, 2002). At the same time, hubs are exposed to incoming risks from many other nodes. If a network has several hubs, a risk originating in any node in the network will quickly reach at least one of these hubs. The hub then will pass the risk to its numerous neighbors and eventually compromise other hubs, which will spread the risk throughout the entire network. Stable hubs, on the other hand, contribute to the overall stability of the network.

For analysts, prominent hubs may not only provide reference points around which most other ties in the network are grouped, but also serve as barometers of the state of the entire network.

Changes in the states of prominent hubs indicate that similar changes in the entire network are imminent. The higher the prominence of a hub relative to the rest of the network, the more visible it is for analysts and the better reference it can provide to discern the future state of the network without the need to analyze the intricate web of interdependencies among many other firms in the network. Accordingly, I expect that the presence of prominent hubs in a firm's network facilitates more accurate forecasts of the firm's outcomes. More formally,

Hypothesis 1. Greater prominence of hub nodes in a firm network is associated with more accurate forecasts of the firm performance.

b.) Clusters

In complex networks, ties may be grouped not only around hubs but also in clusters. Clusters are communities in which nodes are densely interconnected with each other (Borgatti, 1994; Borgatti et al, 2018). These dense pockets of connectivity constitute "networks-within-networks" (Figure 1b) and can help simplify the analysis of the complex connection patterns common to supply networks of large firms. First, these communities are rather visible and can be easily identified by equity analysts. Second, they allow analysts to decompose the complex network into smaller building blocks and analyze each block separately. Firms that form a densely connected cluster are often coupled a lot stronger with each other than with the outside firms (Meade and Sarkis, 1998; DeWitt and Guinipero, 2006; Sturgeon et al., 2008; Hearnshaw and Wilson, 2013). Dense clusters often constitute functional subsystems or modules organized around a specific product or manufacturing process. When large networks are organized into clusters of dense connectivity which are rather sparsely connected with each other (Figure 1b), firms in different clusters usually perform different functions.

Analysts can exploit the visibility and specialization of clusters to produce more accurate forecasts. Simon and Ando (1961) define a nearly decomposable system as a system where the

links within subsystems are strong and the links between subsystems are weak and can be ignored in the short run. In further works, Simon argues that near decomposability also plays a major role in understandability of complex systems (e.g., Simon, 1991, 2002). Because of the difference in the number of interactions within and between subsystems, one can usually obtain good approximations of the short-run behavior of a given subsystem without considering the details of the interactions in other subsystems. Making forecasts for a firm located in a clustered supply network, analysts may employ a similar divide-and-conquer strategy and focus on the events taking place in the firm's neighborhood rather than attempt to grasp the effects of the entire system. Because in clustered networks, the number of interactions among firms within the same cluster greatly exceeds that of interactions among firms in different clusters, the short-run conditions in each of the clusters are nearly independent of the conditions in the other clusters.

At the core of clusters are triads of nodes (Borgatti et al., 2018). The extent to which a network is clustered is usually expressed by its clustering coefficient which is defined as the ratio between the number of closed triads and the number of open triads in the network (Borgatti et al., 2018). The clustering coefficient of a network measures the likelihood that two nodes connected to the same third node are also connected to each other. High levels of clustering slow down the dynamics of risk diffusion throughout the larger system (Newman, 2003, 2018; Buldyrev et al., 2010). A relatively large number of closed triads implies that the possible routes of risk diffusion are highly overlapping. Risk which originates in a node located in a dense cluster is more likely to follow a closed loop to one of the already affected nodes in the same cluster, rather than travel to a different cluster. Clusters, therefore, have quarantine-like effects on risk diffusion. This reduces the forecasting difficulty as analysts need to consider mainly the effects of risks originating in the firm's own cluster.

In clustered networks, most ties are between partners located in the same cluster. Organizational scholars show that firms tend to economize on partner search and therefore prefer to create ties with partners who are accessible being structurally close (Gulati and Garguilo, 1999; Shipilov and Li, 2012; Zaheer et al., 2010). There is usually a richer array of background information about capacities, needs, and reliability of more proximate potential partners. The exchange of such information among organizations occupying structurally close positions also tends to be richer leading to the development of mutual understanding, trust, and commitment (Larson, 1992; Gulati, 1995; Gulati and Garguilo, 1999). Closer partners are more predictable. Clusters also provide such benefits as the reduction of opportunism through collective sanctions for noncooperative behavior (Greif, 1993) and thus become attractive for firms even when there are considerable opportunity costs in the form of forgone exchange opportunities with more distant partners.

Networks with more clustered structures, therefore, provide analysts with several benefits which reduce forecasting difficulty and facilitate the accuracy of forecasts. First, clusters are usually easily identifiable structural elements. Second, analysts can focus only on the events within the firm's cluster and still produce a good forecast. Since clusters slow down the network-wide diffusion of risks, analysts making short-term forecasts need only consider the risks emanating from the firm's own cluster. Third, by reducing opportunism and facilitating the development of common behavioral norms, trust, and commitment, clusters promote homogeneity in performance. Analysts can use other firms in the cluster as reference points in their forecasts. Hence, I hypothesize that

> **Hypothesis 2.** Greater clustering in a firm's supply network is associated with more accurate forecasts of the firm's performance.

c.) Small worlds

In many networks, large clustering coefficients are associated with large characteristic path lengths. The characteristic path length of a network is the average shortest distance between any two nodes in the network (Wasserman and Faust, 1994). A large path length indicates that the number of node-to-node steps required to travel from any one node in the network to any other is large. This partially explains the effects of clusters on risk diffusion: in a more clustered network, it takes longer for risk originating in a node in one cluster to reach a node in another cluster. Conversely, smaller clustering coefficients are associated with smaller characteristic path lengths and more rapid risk diffusion. In their seminal study, Watts and Strogatz (1998) found, however, that under certain conditions networks may have very short path lengths and high clustering coefficients. This means that despite high clustering, the number of steps required to traverse from any one node in such networks to any other was quite small. These networks were obtained by introducing a handful of additional cross-cluster ties into networks with large clustering coefficients and large characteristic path lengths.

Watts and Strogatz (1998) showed that relatively few additional ties connecting nodes in different clusters may significantly change the structure of the network turning it into a so-called small world. Network theorists have since adopted the name “small worlds” to refer to networks with relatively high clustering and small path lengths. Relatively more numerous inter-cluster ties in small world networks dramatically reduce their path lengths but have very little influence on the extent of clustering. Because the path length is low, diffusion is more rapid in small world networks. Watts and Strogatz (1998) observe a strong sensitivity of diffusion dynamics to increased number of inter-cluster ties. They show that a small increase in the number of inter-cluster ties can enable risks, innovations, ideas, technologies, or fads to spread much quicker throughout the network. Analysts, however, may not notice the relatively small structural

difference between a highly clustered network and a small world network (Figure 1c). Because such small difference in connectivity leads to a large difference in the dynamics of network-wide risk diffusion, small world networks may negatively impact the accuracy of analysts' forecasts.

The degree of small world connectivity in a network depends on the number of inter-cluster ties: the higher the number of these ties, the greater the degree of small world connectivity (Watts and Strogatz, 1998; Watts 2004). When analyzing and predicting the future performance of a firm embedded in the network with a greater degree of small world connectivity, the analyst faces a relatively more difficult task. He or she has to consider numerous additional variables because the firm is exposed to risks emanating from multiple direct and indirect partners located in diverse parts of the network. In the case of small world networks, analysts must also take into account more complex and more rapid risk diffusion patterns. They no longer have the advantage of decomposability because more numerous inter-cluster ties provide a tighter coupling among clusters thus generating additional interdependencies. This increases the complexity of the forecasting task if the firm is located in a small world network. The small world connectivity may also distort analysts' perception of the network structure. Observing a large number of ties grouped in clusters, they may be drawn to rely on the grouping and chunking schemas and focus their attention on the firm's close surroundings. These heuristics are less effective in networks with small world structures because they largely ignore the few but critical ties between clusters.

If small world networks have prominent hubs, however, most ties in these networks will be between one of the prominent hubs and a node with a smaller degree. Many of the inter-cluster ties will also belong to one of the hubs. In small world networks, therefore, hubs will aggregate most of the risks traveling via both the within-cluster and between-cluster ties. For analysts, this will provide an advantage. They can focus on prominent hubs as reference points to discern the

risks which may affect the firms they follow in the near future. Changes in the states of prominent hubs will suggest what analysts should look for in their analyses. In light of this reasoning, I hypothesize that

Hypothesis 3a. Greater small world connectivity is associated with less accurate forecasts.

Hypothesis 3b. The presence of prominent hubs in networks with small world connectivity will moderate the effect of these networks on the accuracy of analysts' forecasts.

Empirical Context and Dataset Construction

In this research, I examine how the structure of a firm's supply network affects the forecasting accuracy of equity analysts. For this purpose, I constructed a dataset based on data from several different sources. The dataset was constructed in several phases. In Phase 1, I obtained data on buyer-supplier relationships from the FactSet Revere database. The FactSet Revere database provides an extensive coverage of buyer-supplier links for a period from April 2003 to present. The unit of observation in the FactSet Revere database is a buyer-supplier link between two firms. FactSet Revere collects information on firms' supplier and customer relationships from multiple sources. First, it captures buyer-supplier relationships reported by firms in accordance with Regulation SFAS 131 which requires firms to identify customers accounting for 10 or more percent of their sales. Further, FactSet Revere complements this information with additional data from SEC 10-K filings, corporate websites, press releases, investor presentations, analyst reports, executive interviews, and other sources.

The period from July 2003 through December 2010 (30 quarters) provides a particularly valuable opportunity to examine empirically how structural characteristics of supply networks affect the accuracy of equity analysts' forecasts both during the bull market (2003-2007) and the bear market (2007-2010). It also covers both the boom cycle of the US economy and the global

recession. Therefore, I chose this period as our period of interest. Next, using MATLAB, I constructed a directed binary adjacency matrix A_t which reflects all buyer-suppler relationships recorded in the FactSet Revere database in the 30 quarters of our period of interest. In this directed binary adjacency matrix A_t, the entry in each cell a_{ijt} is one if firm i is a supplier of firm j in quarter t, and zero otherwise. Using the adjacency matrix A_t I proceeded to Phase 2.

In Phase 2, I identified 25 firms operating in industries where the relationships between buyers and suppliers have been shown to be marked by high importance and substantial degree of joint dependence. These 25 firms are large manufacturers in aerospace and defense, electronics, heavy machinery, machine tools, and consumer goods industries. These 25 firms are covered by a substantial number of analysts. Using our adjacency matrix, I identified the set of direct (Tier-One) suppliers for each of the 25 firms. I further identified the set of Tier-Two suppliers, which are direct suppliers of the focal firms' Tier-One suppliers. I repeated the process to obtain the full set of suppliers in the vicinities of the 25 firms. The vicinities were bounded at Tier Five. In addition to vertical (cross-tier) buyer-supplier ties, I identified all horizontal (within-tier) ties among these suppliers.

The FactSet Revere database contains most data on buyer-supplier relations which equity analysts could find in 2003-2010. Based on the FactSet Revere database, our dataset provides a good representation of networks which equity analysts could potentially map and analyze in that period. While I do not expect that analysts actually performed such analysis, our dataset provides an approximation of what network structures analysts could potentially become aware of in 2003-2010. The supply networks which I mapped using the adjacency matrix had structures consisting of dyadic, triadic and more complex configurations. These networks included not only manufacturers of physical products but also firms playing vital support role in the transportation,

storage, and transformation of these products as well as firms providing the necessary financial, equipment maintenance, and other services (Carter, Rogers, and Choi, 2015). Overall, in Phase 2, I obtained 25*30=750 firm-quarter network representations which included most data on buyer-supplier relations available to analysts in 2003-2010. Firms' supply networks are dynamic entities as firms constantly add new ties and delete existing ones. Our network representations reflect the resulting variability in structural properties which are posited to influence forecasting accuracy.

In Phase 3, I used the adjacency matrix to estimate the hub prominence, clustering coefficient, and small world coefficient for each network in each quarter. The operationalizations for these variables are described in Sections 3.4.1, 3.4.2, and 3.4.3 below. Then I retrieved earnings-per-share (EPS) forecasts and actual values data from the I/B/E/S Detail History database and calculated consensus forecasts made for each of the 25 firms in each quarter. A consensus forecast measure is common in the finance and accounting studies. It is the average of all forecasts made for a particular firm in the given period. In each period, individual analysts commonly make several forecasts for the firms they cover, each forecast having a different horizon. A forecast horizon is the distance in quarters between the quarter *in* which the forecast was made and the quarter *for* which the forecast was made. Consensus forecasts are different for each horizon. For example, if in quarter *t* analysts make forecasts for company *i*'s earnings two and four quarters in the future, there will be two different consensus forecasts: one for the two-quarter forecasts and one for the four-quarter forecasts.

Variables

Dependent variable

Our dependent variable is the accuracy of earnings per share (EPS) forecasts. Earnings per share is the value of payments a shareholder will receive from a share of stock. The EPS value depends

on the firm's revenues and costs. Because risks emanating from the firm's supply network also affect both revenues and costs, changes in EPS reflect the effects of these risks on shareholder value. For example, when an upstream supplier experiences financial distress and its delivery and quality performance suffers, the focal firm may experience a greater amount of lost sales due to unavailability of products or a greater amount of expenses to procure the products from new suppliers. The decrease in sales and the increase in costs will decrease the EPS value.

Following studies of EPS forecast accuracy in the finance and accounting literatures, I operationalize EPS forecast accuracy as the absolute value of the difference between the consensus forecast of a firm's earnings per share and actual earnings per share, divided by the stock price at the time when the forecast was made:

$$Accuracy_{iht} = (-1) * \left(\frac{|Forecast_{iht} - Actual|}{Price_{it}} \right)$$

Multiplying the forecast error, which is measured by the difference between the forecast and the actual EPS values, by (-1) gives a measure that increases with greater forecast accuracy. Thus, a network property that is positively associated with the accuracy measure signals that the property facilitates more accurate analysts' forecasts.

Independent variables

Using the adjacency matrix A_t I estimated the following set of independent variables for each network in each quarter in the period under investigation. All variables were estimated using MATLAB.

Hub prominence

In this research, I argue that more prominent hubs will be both more noticeable and more influential in the network. The concept of network hubs is based on the measure of a node degree

defined as the number of connections the node has with other nodes in the network. Hubs are defined as nodes with degrees that are very high relative to other nodes in the network. Our measure of hub prominence is operationalized as the ratio between the average degree of all nodes in the network and the average degree of those nodes whose degrees are in the top ten percent of all degrees in the network:

$$Hub\ Prominence_{it} = \frac{Average\ degree\ of\ hubs_{it}}{Average\ degree\ of\ all\ nodes_{it}}$$

This measure shows the extent to which the average degree of hubs exceeds that of an average node in the network of company *i* in quarter *t*. A greater value of this measure means that hubs are more recognizable and that more nodes are grouped around hubs.

Clustering coefficient

In network theory, clustering coefficient is defined as the ratio of closed to open triads in a network (Newman, 2003; Borgatti and Everett, 2006):

$$C_{it} = \frac{Closed\ triads_{it}}{Open\ triads_{it}}$$

An open triad consists of three nodes connected by two ties. A closed triad consists of three nodes which are fully connected. Clustering coefficient shows what percent of a firm's direct partners are connected to each other.

Small World Coefficient

In network theory, a small-world network is defined as one having a much larger clustering coefficient than the random network of the same size and a characteristic path length approximately equal to that of the random network of the same size (Watts and Strogatz, 1998; Newman, 2003). Using this definition, I calculated the small world coefficient for each network

using the random network baseline method, a staple approach in network studies. To obtain a random network baseline, I randomized the entries of the adjacency matrices representing the connectivity of each of the actual networks in our sample and calculated the clustering coefficients and characteristic path lengths of the obtained random networks. This procedure was repeated 10 times for each quarter of the period under investigation, after which I calculated the average clustering coefficient and characteristic path length of the 10 random networks. Then I calculated the clustering coefficient and characteristic path length of each of the real network in each quarter. The clustering coefficients of these networks were calculated using the formula described above. The characteristic path lengths were calculated using the following formula (Borgatti et al., 2018):

$$L_{it} = \frac{1}{N(N-1)} \sum d_{mn} ,$$

Where *N* is the number of nodes in the network of firm *i* in quarter *t* and d_{mn} is the length of the shortest path between nodes *m* and *n*. Finally, the small world coefficient for each network at quarter t was obtained using the following formula:

$$Small\ World\ Coefficient = (C_{actual}/C_{random})/(L_{actual}/L_{random}).$$

where C_{actual} is the clustering coefficient of the actual network, C_{random} is the average clustering coefficient of the set of 10 random networks, L_{actual} is the characteristic path length of the actual network and L_{random} is the average characteristic path length of the set of random networks which I generated.

Control variables

a.) Uncertainty

An important factor that affects the forecasting accuracy is the degree of uncertainty related to the firm. To estimate the overall uncertainty around a firm, scholars in finance and accounting use the

volatility of the firm's stock returns. Because stock returns are affected by both firm-specific and market-wide factors affecting the firm, the volatility of a firm's stock returns is a comprehensive measure of the overall uncertainty related to the firm. An increase in stock returns volatility is an easily observed measure which analysts may use in their forecasts. Following extant studies, I operationalize the quarterly volatility of stock returns as the standard deviation of daily stock returns over each quarter. To estimate the volatility of a firm's stock returns, I use the daily stock return data from CRSP database.

b.) Forecast attributes

Other factors that affect forecasting accuracy include forecast horizon and the number of analysts following the firm. Longer forecast horizons are associated with lower accuracy of analysts' earnings forecasts (Brown et al., 1987; O'Brien and Bhushan, 1990; Brown, 1993). I operationalize forecast horizon as the number of quarters between the quarter in which the forecast was made and the quarter for which the forecast was made using the data from the I/B/E/S database. According to previous research, analyst following increases forecast accuracy because analysts can learn from each other's forecasts. Further, I operationalize analyst following as the number of analysts whose forecasts are included in the I/B/E/S database. Also, because forecasting difficulty may vary across industries and across time, I include year and industry dummy variables. The industry dummies are based on 4-digit SIC codes.

Model specification

To test our hypotheses, I use multiple regression and estimate the following equation:

$$Accuracy_{it} = \beta_0 + \beta_1 Hub\_Prominence_{it-1} + \beta_2 Clustering_{it-1} + \beta_3 Small\_World_{it-1} + \beta_4 Volatility_{it-1} + \beta_5 Coverage_{it} + \beta_6 Horizon + \beta_7 Industry + \beta_8 Year + \varepsilon_{it} \quad (1)$$

Accuracy$_{it}$ is the accuracy of the consensus EPS forecasts provided by analysts for firm i in quarter t. $Hub\_Prominence_{it-1}$ is the measure of hub prominence in firm i's supply network in the quarter preceding the quarter when the forecast was made. I use the measure of the preceding quarter because analysts mainly observe records of buyer-supplier relations from previous periods. $Clustering_{it-1}$ and $Small\_World_{it-1}$ are, respectively, the clustering coefficient and the small world coefficient of firm i's supply network in the quarter preceding the quarter when the forecast was made. $Volatility_{it-1}$ is the volatility of firm i's stock returns in the quarter preceding the quarter when the forecast was made. $Coverage_{it}$ is the number of analysts following firm i in quarter t. $Horizon$ is the forecast horizon and $Industry$ and $Year$ are the dummies controlling for the differences in forecasting difficulty across industries and time.

Results

Descriptive Statistics

Table 1 presents means, standard deviations, and correlations between the variables in the model. The correlation results indicate some preliminary support for the hypothesized relationships between structural properties of supply networks and the accuracy of analysts' forecasts. The correlation between hub prominence and the accuracy of analysts' forecasts is positive and significant ($r = 0.1535$, $p < 0.05$), as expected. The correlation between the clustering coefficient and the forecasting accuracy is also positive and significant ($r = 0.0453$, $p < 0.05$). The correlation between the small world coefficient and the forecasting accuracy is negative and significant ($r = 0.0992$, $p < 0.05$).

I performed the analyses in STATA 15. Before estimating the specified model, I accounted for multicollinearity by mean centering all explanatory variables and ensured that the variance inflating factor (VIF) values for each explanatory variable were below 10.

== Insert Table 1==

Main results

In this study, I am interested in effects of supply network structure on the accuracy of equity analysts' forecasts. Model 1 in Table 2 tests the effects of each structural property covered in this research on the forecast accuracy. In Model 2, I add the interaction between the measure of hub prominence and the small world coefficient to examine the hypothesized moderating effects of prominent hubs on the accuracy of analysts' forecasts when the firm's supply network has a small world structure.

== Insert Table 2==

Hypothesis 1 predicts a positive influence of the presence of prominent hubs in a firm's supply network on the accuracy of analysts' EPS forecasts. The respective regression result in Model 1 supports this prediction ($\beta = 0.0044$, $p<0.01$). Hub prominence has a small but significant effect on forecasting accuracy. Hypothesis 2 predicts a positive influence of clustering in a firm's supply network on the accuracy of forecasts provided by analysts covering the firm. The regression result in Model 1 support this hypothesis ($\beta = 0.1948$, $p<0.01$). Among the three structural properties covered in this study, clustering has the strongest positive influence on the forecast accuracy. This suggests that grouping and chunking heuristics have a strong impact on analysts' perception of supply networks. They encode and store network information in terms of groups of ties.

Hypothesis 3a predicts a negative effect of small world connectivity on the accuracy of analysts' forecasts. The respective regression result in Model 1 provides support for this prediction ($\beta = -0.0686$, $p<0.01$). Small world structures appear to hinder forecast accuracy. Hypothesis 3b predicts a moderating effect of the presence of prominent hubs in a firm's supply network on the

impact of small world connectivity on the forecasting accuracy. Hypothesis 3b is also supported: the coefficient of the interaction term in Model 2 is 0.0554 and $p < 0.01$. The interaction plot in Figure 3 can enrich the interpretation of this moderating effect. In Figure 3, I plot the predicted effects of small world structures on analysts' predictive accuracy against the changes in the small world property and hub prominence. I use high and low values of each of these variables as one standard deviation above and below the mean, respectively.

The "Lower small world coefficient" line depicts the slope of the effect of small world structure on forecasting accuracy when the value of the small world coefficient is set to one standard deviation below its mean. The "High small world coefficient" line depicts the slope of the effect of small world structure on forecasting accuracy when the value of the small world coefficient is set to one standard deviation above its mean. Similarly, the "More prominent hubs" mark refers to the value of hub prominence set one standard deviation above its mean and the "Less prominent hubs" mark corresponds to the value of hub prominence set one standard deviation below the mean. When hubs are more prominent, the negative effects of small world structures are weaker, more so when the small world property is higher.

The overall picture painted by these results is that the structure of firms' supply networks affects the accuracy of analysts' forecasts. Equity analysts tend to produce more accurate forecasts for firms with more clustered supply networks. Moreover, the presence of prominent hubs in a firm supply network leads to slightly better accuracy. The influence of hubs on facilitating higher forecast accuracy becomes stronger in networks with small world structures. While small world networks tend to lower the accuracy of forecasts, prominent hubs in such networks attenuate this impact. These results also suggest that grouping heuristics play an important role in analysts' perceptions of actual supply network structures.

Discussion

In this research, I leveraged a novel source of extensive data on buyer-supplier relations to examine the relationship between the structure of a firm's supply network and the accuracy of earnings forecasts made by equity analysts following the firm. Our main finding is that analysts tend to more accurately predict the earnings of firms with more clustered supply networks and networks where hub nodes are more prominent. In contrast, analysts' forecasting accuracy decreases when the firm's supply network has a small world structure Overall, our findings contribute to theory and practice in several ways.

Theoretical implications

In this research, I find that supply network structure affects the accuracy of analysts' forecasts. Supply networks of many large firms have complex structures that present a cognitive challenge for an analyst attempting to follow along a firm's supply chain to obtain more information relevant to his or her forecasts of the firm's performance. Our study identifies some of the ways in which analysts' mind perceives, encodes, and represents these structures. Because analysts make forecasts based on their perception of the network, not the actual structure, it is important to identify which structures are relatively easier for analysts to perceive. I find that hubs and clusters are associated with higher accuracy of analysts' forecasts. Therefore, they are likely to be more cognitively accessible for analysts.

Networks are becoming increasingly important for economic and social life. Scholars in various disciplines have developed theoretical perspectives of interfirm network formation and evolution as well as provided accounts of the numerous ways in which interfirm networks influence organizational outcomes. In this study, I am exploring how interfirm networks influence the outcomes of outside stakeholders such as equity analysts. In order to achieve superior forecast

accuracy, analysts must perceive the complex network structures accurately. Identifying and exploring the effects of structural elements which enhance or hinder individuals' perceptions of networked realities add new insights to our knowledge of how we can understand our social and economic environments.

Managerial implications

Our research has implications for equity analysts and for managers of the firms which these analysts cover. Our findings indicate that in their perception of supply networks, equity analysts follow a certain set of heuristic rules. For example, they tend to become attuned to grouping patterns of ties constituting supply network structure. Following this grouping heuristic, they perceive some elements better than others. I find that the presence of prominent hubs and large clusters in supply networks facilitates higher forecasting accuracy. This suggests that in the process of seeking order in a complex system, analysts are predisposed to focus on dominant structural elements. This makes sense because most ties in networks are grouped around prominent hubs or in clusters. Focusing on dominant structural elements allows analysts to perceive complex supply networks parsimoniously. At the same time, focusing on dominant elements, analysts fail to notice important dynamics associated with less discernible elements. For example, the rapid dynamic of risk diffusion in small world networks is based on the relatively few inter-cluster ties which may elude analysts' attention.

Managers of the firms covered by analysts should be aware of the special role which dominant elements in the firm's supply networks play in increasing the accuracy of analysts' forecasts. Because analysts' forecasting accuracy affects the firm's financial position and standing on capital markets, managers should engage analysts into discussions of the structural complexities inherent in their firms' supply networks. Our fieldwork shows that analysts are interested in

learning more about supply networks because knowledge of firms' supply networks allows them to produce superior forecasts and compete for investor attention more effectively. In this regard, managers may consider supplying analysts with specific information about supplier development programs, relationships with critical or dominant suppliers, and other activities aimed at making the firm's supply base more stable. If a firm's supply network is very complex, managers may consider mapping the relationships among the supplier firms as an important step to increasing analysts' awareness and understanding of the patterns and structures of ties in the network. Such visualizations would help managers to communicate more data about their firms' supply networks in order to aid analysts in overcoming their cognitive limitations and increasing forecast accuracy.

Limitations and directions for future research

Our study offers new insights for a range of research streams. At the same time, it has certain limitations which suggest promising areas for future research. First, answering the call for deeper analysis of firms' structural embeddedness in supply networks, I solely focus on the structural characteristics of supply networks. Future research may extend our analysis by including other variables. For example, links between firms in supply networks may be assigned weights reflecting the volume, strength, or criticality of the supplier-customer relations. Some suppliers may provide components that are much more critical for the firm than others, and therefore should be more closely followed by equity analysts exploring the firm's supply chain. It is important to learn more about how analysts encode strong or critical ties in their minds. In this study, I posited that analysts' perception of networks is based to an important extent on grouping heuristics. They tend to attune to ties grouped in certain patterns rather than individual dyads. However, in the case of strong or critical ties, dyadic representation may be the optimal way to perceive complex networks. While in this study I focused on the most widely studied heuristic which individual follow to make sense

of complex patterns of relations, identification of other heuristics central to analysts' perception of networks will provide important insights allowing managers maximize the shareholder value of their firms.

Appendix

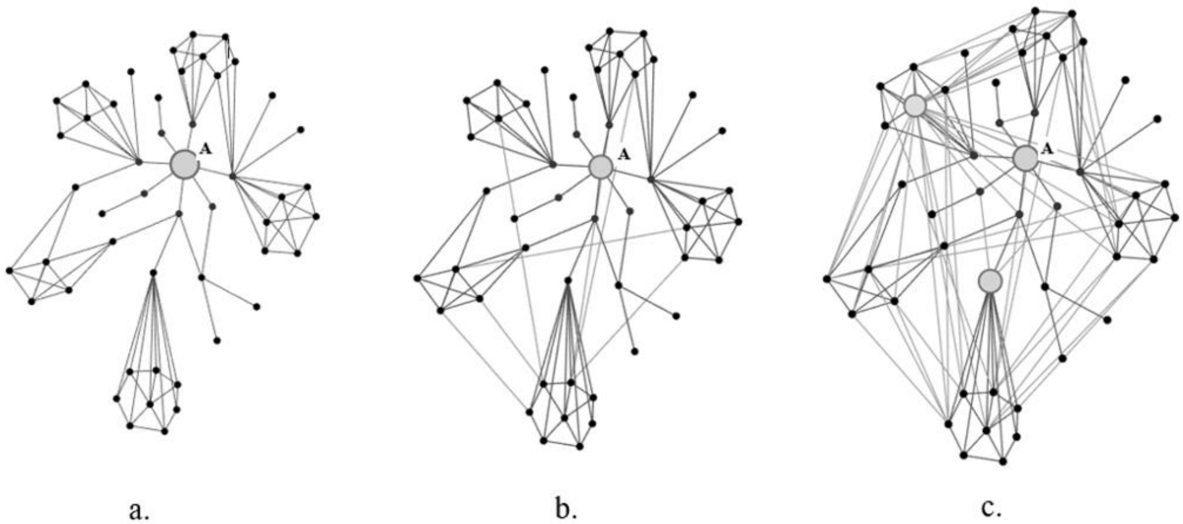

Figure 1. Supply network of Firm A with clusters in Tiers Two and Three (a); supply network of Firm A with moderate small world coefficient (b); supply network of Firm A with high small world coefficient and two prominent hubs (c).

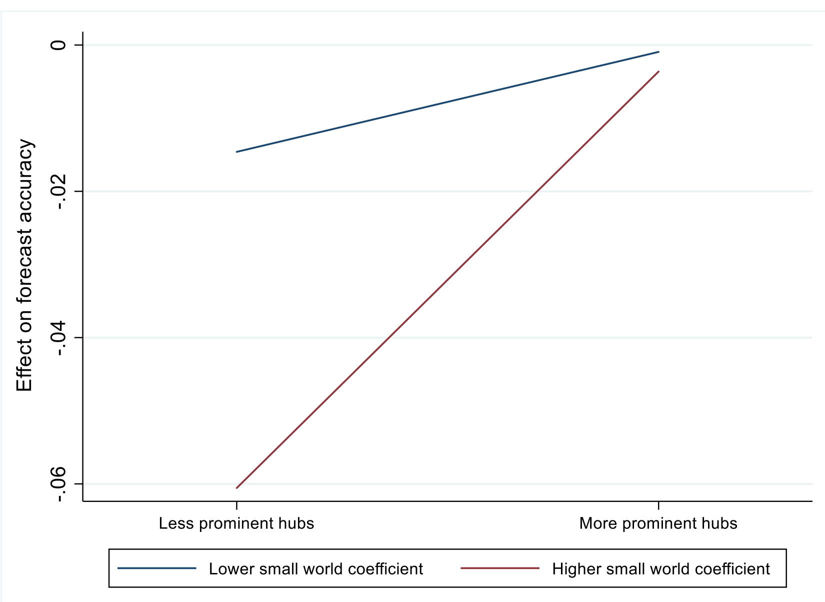

Figure 2. The moderating effect of hub prominence on the impact of small world supply networks on the accuracy of forecasts

Table 1. Descriptive statistics and correlations

Variable	Mean	Std. Dev.	Min	Max	1	2	3	4	5	6	7
Accuracy	-0.0063	0.0229	-0.5178	0	1						
Hub Prominence	3.6111	0.4091	1.4145	4.6422	0.1535*	1					
Clustering	0.0477	0.0098	0.0333	0.1271	0.0453*	-0.6109*	1				
Small world	0.0861	0.0226	0.0693	0.3381	-0.0992*	-0.2704*	0.5327*	1			
Volatility	0.0181	0.0109	0.0048	0.1227	-0.5285*	-0.2096*	0.0787*	0.1415*	1		
Horizon	4.2054	2.1929	1	8	-0.0812*	-0.0009	-0.0108	0.0053	0.0149	1	
Coverage	15.8565	7.7032	1	44	0.0249	0.2029*	-0.1745*	0.0877*	0.0571*	0.0564*	1

Table 2. The Relationships Between Supply Network Structural Properties and Forecast Accuracy

Dependent Variable = Accuracy

	Model 1	Model 2
Hub prominence	0.0044*** (0.0009)	0.0051*** (0.0009)
Clustering coefficient	0.1948*** (0.0432)	0.2705*** (0.0526)
Small world coefficient	-0.0686*** (0.0156)	-0.0658*** (0.0157)
Hub prominence X Small world		0.0554*** (0.022)
Firm-specific uncertainty	-1.1071*** (0.0276)	-1.1082*** (0.0276)
Forecast horizon	-0.0008*** (0.0001)	-0.0008*** (0.0001)
Firm coverage by analysts	0.00018*** (0.00004)	0.00018*** (0.00004)
Industry dummy	0.00019 0.0002	0.00019 0.0002
Year	0.0001*** (0.00003)	0.0002*** (0.00003)
Constant	-0.0089*** (0.0014)	-0.0089*** (0.0014)
R^2	0.2846	0.2956
N forecasts	4,663	4,663

Standard errors in parentheses,
*** p<0.01

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ESSAY 2. THE ROLE OF PARTNER-SPECIFIC UNCERTAINTY IN SUPPLY NETWORK CHANGE

Introduction

How do interfirm networks change when exchanges between firms become less predictable? Interfirm exchange networks, for instance, supply networks, often become arenas of dynamic tensions between partners. Business news media are quick to pick up a situation in which a powerful buyer experiencing difficulties decides to take advantage of its suppliers. When Tesla's cash position dwindled in 2018 due to a high level of debt and struggles with launching mass-market vehicles, the cash-strapped auto maker pressed its suppliers to reduce prices and refund a part of what it had already spent (Higgins, 2018; Higgins *et al.*, 2018). It may also be a factor beyond a large buyer's control that exposes the dependent suppliers' to uncertainty or risk. For example, when the U.S.–China trade war lowered the demand for iPhones in China, Apple experienced a considerable revenue shortfall and was forced to slash production orders, thus letting the shock to reverberate across its supply network (Grocer, 2019).

For the dependent suppliers in such situations, the stakes are high and stress can build up quickly. In Emerson's (1962) view, if a dependent exchange partner has potentially useful resources, the powerful partner will increase the use of power and cut deeper into the dependent partner's resources. As unanticipated and undesired changes in a major buyer's conditions lead to the pileup of additional demands on the dependent suppliers, the suppliers may start seeking to change their dependence status quo. Frequently, such change involves forming ties with alternative buyers (Emerson, 1962; Cook and Emerson, 1978; Pfeffer and Salancik, 2003). This resource dependence-based logic implies that a shift in uncertainty specific to a powerful exchange partner's

conditions may spur a flurry of new tie formation activity in the network as each dependent partner seeks a new alternative. The new ties, in turn, can significantly alter the structure of the network.

The literature on interfirm network evolution, on the other hand, emphasizes the embeddedness or reinforcing nature of existing network ties. Firms view embedded exchange ties as instruments of uncertainty reduction, and thus tend to repeat ties with past partners (Podolny, 1994; Gulati, 1995a; Uzzi, 1997), to form new ties with partners of their existing partners (Baker, 1990; Uzzi, 1996; Gulati and Gargiulo, 1999), or to pair up with partners similar to themselves (Lincoln *et al.*, 1992; Podolny, 1994; Ahuja *et al.*, 2009). An underlying assumption on which this logic rests is that organizations tend to avoid forming uncertain ties. Pairing up with an unfamiliar partner entails considerable uncertainty, while homophily, transitivity, and repeated tie formation, which this stream of research considers to be the primary mechanisms of interfirm network evolution, generate ties that are relatively more certain. In contrast to the resource dependence logic, the embeddedness logic implies that the structure of the exchange network would not undergo a significant change when exchange relations between partners become less predictable. Newly formed ties will be predominantly local, contributing only to the density and stability of the powerful partner's cluster.

The purpose of this study is to reconcile these two views of network evolution and gain a deeper empirical understanding of how interfirm networks alter their structure when exchange between firms becomes less predictable. Many empirically observed networks have dynamic architectures with pockets of densely interconnected local ties between similar actors, which are sparsely linked together by ties that cut across the organizational space connecting dissimilar actors who often have no history of prior relationships (Sorenson and Stuart, 2008; Baum *et al.*, 2005). These architectures are radically different from the dense, stable clusters of firms with similar

characteristics and ties infused with a higher degree of trust, which would form if homophily, transitivity, and tie repeating were the only tie formation mechanisms at work. This suggests that firms attempting to form alternative ties to alleviate an increase in partner-specific uncertainty consider a wider set of potential alternative partners than that implied by the logic of embeddedness. Yet, many important questions remain unanswered – we do not know how firms choose alternative partners, whether they prefer partners located in their close proximity to more distant prospects, and which prospective partners – close or more distant – choose to reciprocate their offer of a new tie. These choices, in turn, have direct implications for the network structure. Choosing partners located in the firm's own cluster increases the network density while choosing more distant partners makes the network more small-worldly.

To explore the choices firms make when their major partners experience a change in uncertainty, we focus our analytical lens on the changes in the rates of new tie formation and existing tie deletion among firms with a common key exchange partner. Specifically, we focus on tie formation and deletion rates of suppliers of large manufacturing firms. We examine how the dynamics of new ties, which these suppliers form with partners located both within and beyond the boundaries of their own clusters, change when the uncertainty specific to their large buyers increases. Using a novel dataset offering an extensive coverage of buyer-supplier relations, we probe deep into supply networks of large U.S. manufacturing firms to track the numbers of newly formed and deleted ties over a seven-year period. A significant relationship between an increase in uncertainty specific to a major actor and changes in the rates of new tie formation and deletion among its dependent partners would support our contention that such uncertainty affects the structures of interfirm networks in predictable ways. In this light, we seek to contribute to the

progress in organizational scholars' on-going quest for a comprehensive theoretical model of interfirm network evolution.

Theory and hypotheses

Beckman *et al.* (2004) distinguish between firm-specific uncertainty and market uncertainty. Firm-specific uncertainty stems from sources that are unique to the firm. For instance, firms may experience unique uncertainty when their business models become outdated (Beckman *et al.*, 2004). Other firms may have viable business models but carry excessive debt or suffer from management problems (Opler and Titman, 1994). On the one hand, firms are compelled to take action to reduce the new uncertainty they face. However, the rising uncertainty diminishes the resources available for firms to act on this imperative. Cutting into the dependent partners' resources becomes a tempting option. When Tesla carried a considerable amount of debt and struggled with the launch of mass-market vehicles, its stock returns had a very high volatility reflecting the uncertainty around the car maker. This, in turn, increased Tesla's cost of capital. As it became increasingly more difficult for Tesla to obtain liquidity from capital markets, the car maker decided to squeeze its suppliers demanding to extend additional credit, refund a portion of the earlier payments, and cut future prices (Higgins, 2018; Higgins *et al*., 2018). Moreover, Tesla needed to hold on to cash longer and delayed the short-term payments.

Tesla's actions increased the suppliers' uncertainty. In general, a supplier's ability to operate efficiently depends on whether it can receive stable cash flows from its buyers (Hendricks and Singhal, 2005). Unstable cash flows could prevent the suppliers from financing their own capital or labor, thereby impacting their profitability. In fact, cash-strapped firms frequently use their dependent suppliers as sources of liquidity. Suppliers often borrow to finance additional trade credit for their major buyers (Cunat, 2006; Garcia-Appendini and Montiorol-Garriga, 2013).

Besides borrowing, they may pinch funds used for hiring or investments, or raise prices to squeeze other firms along the supply chain in order to accommodate the demands of the major buyer. Other ways in which dependent suppliers frequently support their distressed buyers include allowing retrospective or late payments, offering extra discounts (Cunat, 2006) or an opportunity to return unsold products (Gerchak and Wang, 2004).

In extreme cases, suppliers may lose a large percent of their revenue at once. In less extreme cases, the suppliers' stock returns are likely to experience a higher volatility because returns of economically linked firms such as supply chain partners are correlated due to related fundamentals (Hong, Torous, and Valkanov, 2007; Cohen and Frazzini, 2008) and profits (Menzly and Ozbas, 2010). The finance literature shows that stock markets often react negatively when suppliers commit into significant relationship-specific investments serving the needs of a particular buyer and having limited resale options outside of the troubled exchange relationship (Banerjee, Dasgupta, and Kim, 2008; Kale and Shahrur, 2007; Titman and Wessels, 1988). While dependence on a powerful buyer may be unproblematic when conditions are certain (Pfeffer and Salancik, 2003; Pennings, 1981), the accumulation of uncertainty presses dependent firms to respond. However, predictions regarding the nature of such response vary across theories.

The resource dependence logic of network change

The resource dependence logic (e.g., Pfeffer and Salancik, 2003) predicts a collective response among firms in structurally equivalent, dependent positions. Emerson (1962) distinguished between two forms of structural responses. One is adding alternative exchange ties to diversifying cash flow risk across multiple buyers and thus reduce the impact of an increase in uncertainty specific to one particular buyer. For example, in response to the increase in Tesla's unique uncertainty, Panasonic formed a new tie with Toyota to jointly market its batteries to new buyers (Mochizuki, 2018). The other form is uniting the disadvantaged positions into a coalition to

increase the power of each individual actor. In this case, the dependent suppliers create and reinforce ties among themselves. For instance, several direct suppliers of Tesla united efforts to raise concern about the car maker's actions by filing a record number of claims.

The resource dependence logic predicts that a shift in partner-specific uncertainty sets into motion a coping process prompting its direct partners to balance their dependence on the source of uncertainty. These partners begin altering the patterns of relations in the network by creating new ties, thereby changing the network structure, sometimes in profound ways. This perspective emphasizes an individualistic approach centered on actors who have rational-choice incentives to exchange. Because the survival of an actor depends on exchange with other actors in the network, a change in the conditions of exchange entail a threat to the actor's survival. In this context, the stakes are high and there is a strain to change the dependence status quo.

The embeddedness logic of network change

In contrast, the network perspective emphasizes a less strained world in which exchange is embedded within a structural or relational framework that promotes cooperation and reduces opportunism. The logic of embeddedness (Gulati, 1995a; Uzzi, 1997) implies that structurally and relationally embedded firms prefer to accommodate their exchange partners' demands rather than balance the power differential by creating ties with alternative partners. Mutual familiarity and understanding which breed in close clusters enable and facilitate trust among exchange partners. Moreover, such clusters are infused with rich background information about capacities, needs, and reliability of other actors (Larson, 1992; Gulati, 1995b; Chung, Singh, and Lee, 2000; Gulati and Garguilo, 1999; Li and Rowley, 2002). Furthermore, clusters of close ties provide such benefits as the reduction of opportunism through collective sanctions for noncooperative behavior (Greif, 1993) and thus become safe havens for firms. This increases the comparative costs and risks of

forming new relationships with outsider actors (Garguilo and Benassi, 1999; Li and Rowley, 2002).

New tie formation entails considerable uncertainty stemming from imperfect information about potential partners' capabilities, resources, needs, and willingness to cooperate (Kogut, 1988; Podolny, 1994; Gulati, 1995a; Oxley, 1997; Gulati and Gargiulo, 1999). The range of tie formation mechanisms considered in the literature on interfirm networks is predominantly limited to homophilous pairing with similar actors (Lincoln, Gerlach, and Takahashi, 1992; Podolny, 1994), or pairing with the partners of existing partners (Gulati and Gargiulo, 1999), or repeating ties with past partners (Podolny, 1994; Gulati, 1995a; Uzzi, 1997). These mechanisms underscore a strong effect of social proximity and shared third parties on new tie formation and the tendency of firms to rely on heuristic-based decisions in partnering (Uzzi and Gillespie, 1999). To economize on partner search, firms tend to create ties with partners who are close and available (Gulati and Garguilo, 1999; Shipilov and Li, 2012; Zaheer, Gözübüyük, and Milanov, 2010). Firms also tend to select partners with whom they have some familiarity, either directly or indirectly, or through prior partnerships (e.g., Gulati and Gargiulo 1999, Shipilov and Li 2012, Zaheer *et al.* 2010). This preference favors local ties because firms can tap into a pool of referrals and background information which a network of close ties can generate on prospective partners. The embeddedness logic further implies that firms respond to an increase in partner-specific uncertainty by either accommodating the partner's demands or balancing by forming ties with close and familiar partners, thus changing the network structure only marginally.

Framing network change

Research views network change as a process of interaction between two evolutionary elements, new tie formation and existing tie deletion (Koka *et al.*, 2006). Ties are the fundamental building blocks of networks. Tie creation and deletion, therefore, are the fundamental units of analysis in

network transformation. A marginal analysis of changes in tie formation and deletion rates, therefore, can provide a comprehensive picture of network change. The additional amounts of novel ties and deleted existing ties following a change in the uncertainty specific to an exchange partner can explain the effects of this change on the structure of the network.

Insert Figure 3

Figure 1 provides an illustration. Firms B, C, D, E, F, G, H, and I are immediate, or Tier-one, suppliers of the focal firm A. Each one of these immediate suppliers have their own suppliers, which constitute the Tier-two echelon of the focal firm's suppliers. The Tier-two suppliers, in turn, also have suppliers, which constitute the Tier-three echelon, and so on. For example, firm J is a Tier-four supplier of the focal firm. In contrast to alliances, supply networks have directionality as the product or service is transferred from suppliers to their buyers. Therefore, firm A's supply network is represented as a directed graph. All suppliers are located at a certain distance from the focal firm. The shortest distance from the focal firm to each direct or indirect supplier is equal to the supplier's tier number. The path length between the focal firm and its immediate, Tier-one suppliers is equal to one. The path length between the focal firm and the suppliers of its immediate suppliers – the Tier-two suppliers – is equal to two.

When the focal firm A in Figure 1 (a) experiences an increase in unique uncertainty and its Tier-one suppliers observe shifts in the rhythm of exchange, they begin considering changing their dependence status quo. Finding alternative buyers is a direct way to make such change (Emerson, 1962; Cook and Emerson, 1978). These suppliers can find alternative buyers among their closest neighbors, other Tier-one suppliers, thus benefitting from a greater circulation of background and reputational information facilitated by proximity. They can also find new buyers among Tier-two or Tier-three suppliers and even reach out to Tier-four or Tier-five suppliers. At the same time,

they may consider terminating ties with some of their existing partners to redirect resources to either accommodate A's increasing demands or to cultivate new buyer ties. The Tier-one suppliers consider all these actions simultaneously, and their final choice may include creating or deleting one or more ties in their close proximity or at a more distant range. Figure 1 (b) illustrates the choice of firm G. In response to an increase in the focal firm's unique uncertainty, G has severed its existing ties with F and I and established new ties with distant partners K, L, and M. Firm H formed a new tie with firm F.

In making their choices, Tier-one firms face several constraints. First, there is uncertainty and risk associated with entering a new partnership. In general, the farther the prospective new partner is located, the less information the firm has about the prospect's capacities, resources, standards, or willingness to engage in opportunism. Second, there are structural constraints. Because the number of exchange relationships a firm can feasibly form and maintain is limited, it is harder to find a partner in close proximity if the neighborhood is already densely interconnected. A large number of connections means that most firms in the neighborhood have an adequate number of suppliers, and the value of adding a new tie may be limited or even negative. Clustering may make potential partners less accessible as well. Clustering, or closure around a third party, enhances stability of existing relationships by reducing opportunism (Coleman, 1990; Granovetter, 1985; Uzzi, 1997) and conflict (Krackhardt and Handcock, 2007). A substantial degree of triad closure around a firm may limit its ability to form transitive ties because most potential transitive ties are already realized. At the same time, it can contribute to a growing self-containment of a cluster making it increasingly impenetrable for outsiders (Sytch *et al.*, 2012).

Perhaps the most critical constraint is the extent to which resources available to firms are plentiful or scarce. In their theoretical account of interfirm network transformation, Koka *et al.*

(2006) use the concept of munificence to represent the availability of resources. In general, munificence is the capacity of the environment to support the firm and its strategies (Dess and Beard, 1984). Greater munificence indicates that firms have greater resources available for building new partnerships. In contrast, lower munificence indicates that firms are limited in their ability to create new ties or reciprocate a tie offer. In environments with lower munificence, firms tend to reinforce their existing relationships rather than create ties with new partners (Galaskiewicz and Shatin, 1981; Gulati, 1995a). Moreover, lower munificence may spur a higher dissolution of weaker existing relationships to redirect the resources to stronger, more viable relationships. Thus, strategic action and environmental munificence act in tandem in influencing structural changes in interfirm networks. The individual effect of either uncertainty or munificence on network change, therefore, is ambiguous. They shape the course of network transformation simultaneously and interactively.

In our view, the resource dependence logic and the embeddedness logic are both essential for an accurate account of structural changes occurring in interfirm networks. These logics are not mutually exclusive. Rather, they coexist and jointly shape the trajectories of interfirm networks transformation. We admit to both perspectives because firms' individual self-interest, patterns of relationships that connect these firms together, and the uncertainty which they face are often intertwined in influencing the rates at which these firms form new ties and delete existing ones. We further contend that the coexistence of the two logics can at times be marked by shifts in dominance in guiding the processes of tie formation and deletion.

For instance, when exchange in a network is predictable, the relations among the firms may be rather harmonious and firms may not experience a pressure to change the rates at which they form new ties or delete existing ones. An increase in partner-related uncertainty, however, triggers

stress toward balancing the power status quo. As exchange in the network becomes less certain, firms are compelled to take steps to a new balance. In such context, forming more alternative exchange ties becomes instrumental and the dominance in guiding tie formation shifts to the resource dependence logic. Because the coexistence of the two logics implies their joint impact on the structure of the network, we consider the relationship between them to be cooperative and synergistic rather than competitive. The increasing influence of one logic does not reduce the influence of the other. To balance their dependence on a partner experiencing an increase in unique uncertainty, firms can form new alternative exchange ties or increase exchange with the existing partners embedded in the same cluster. Therefore, both an increase in new tie formation consistent with the resource dependence logic and a higher focus on preserving existing tie consistent with the embeddedness logic are likely to take place. In light of this reasoning, we hypothesize that:

Hypothesis 1. In response to an increase in uncertainty specific to a powerful exchange partner, firms form more new ties and delete fewer existing ties in their networks.

The two coexisting logics are likely to exert differential influence on the rates of new tie formation in different regions of the firms' networks. Many empirically observed interfirm networks have structures that are dynamic and far-reaching. These structures consist of clusters of dense close connections, which are linked together by more distant, cross-cluster ties cutting across the organizational space to connect dissimilar actors who often have no history of prior relationships (Sorenson and Stuart, 2008; Baum et al., 2005). Such ties are relatively costlier and more uncertain to form and maintain as they don't entail the structural and relational benefits and protections of close ties. Distant tie formation may be triggered by firms' attempts to obtain non-

redundant, unique knowledge and skill sets to promote survival in highly dynamic and knowledge-intensive settings such as microelectronics and telecommunications industries (Sytch et al., 2012). Baum et al. (2005) found that low levels of performance relative to social or historical baselines prompt investment banks to form ties with distant partners to increase their chances to uncover new ideas and explore new options. Sorenson and Stuart (2008) show that organizations at times form distant ties to seize fads and fashions' time-sensitive opportunities for supra-normal profits.

Such structures provide an opportunity for firms to form new alternative ties both within and beyond the boundaries of their own clusters. When a major buyer experiences an increase in unique uncertainty, its entire Tier-one echelon of suppliers is likely to be affected. When a Tier-one supplier attempts to balance the dependence status quo by forming a new tie with another Tier-one supplier or its partner, it exposes itself to a new partner that is equally affected by an increase in the uncertainty specific to the major buyer. Because the Tier-one firms and their direct partners may all be in the same predicament facing uncertain cash flows, balancing will be effective when new relationships are developed with partners located beyond the bounds of the Tier-one proximity. Resources, knowledge, information, and uncertainty are heterogeneous between network communities. Alternative partners in other parts of the network may not be impaired by the focal firm's actions at all or may experience their negative effects only indirectly and to a much lower extent. As the increase in uncertainty specific to a major immediate partner shifts the dominance in guiding new tie formation to the resource dependence logic, firms shift the emphasis of their tie formation activity towards more distant partners. Therefore, we hypothesize that:

Hypothesis 2. In response to an increase in uncertainty specific to a powerful exchange partner, firms form new close ties at a lower rate and new distant ties at a higher rate.

Changes in the rates of new tie formation in more distant parts of firms' networks consistent with the resource dependence logic can encourage concurrent changes in tie deletion rates consistent with the embeddedness logic. Establishing new ties requires resources. A less predictable future due to increasingly uncertain conditions of a major exchange partner, on the other hand, requires tighter spending. In such times, firms are compelled to review their portfolio of network ties in order to identify and reinforce the highly contributing ties and eliminate the weakly contributing or non-essential ones. The elimination of non-essential or weakly contributing ties allows firms to redirect the resources they use to maintain these ties to reinforce the stronger ones or buffer themselves by holding more cash to continue operating when payments from the focal buyer become uncertain.

Such strategy of deliberate reinforcement of the vital contributors and elimination of non-essential ties does not necessarily mean narrowing the size or scope of firms' networks. A firm may eliminate one existing tie to free up resources to create one or more new ties, thus keeping the size of its network the same or even increasing it. This strategy would increase the overall rate of tie deletion, and this increase would occur primarily in more distant parts of the network. Close ties tend to be stronger, owing in part to greater information exchange and the development of enforceable behavioral norms (Granovetter, 1985; Koka and Prescott, 2002, Koka et al., 2006). They have stood the test of time and are likely to be of greater assistance when a need arises. Distant ties, in contrast, tend to be weak. Thus, in their pruning efforts, firms will target distant ties to a greater extent. In this light, the increasing influence of the resource dependence logic in more distant parts of the network strengthens the impact of the embeddedness logic in closer proximities.

Hypothesis 3. In response to an increase in uncertainty specific to a more powerful exchange partner, firms delete existing close ties at a lower rate and existing distant ties at a higher rate.

Overall, our hypotheses suggest an increase in tie formation and tie deletion dynamics following an increase in partner-related uncertainty. A shift in uncertainty provides an impulse to change the dependence status quo, and firms increase their rates of tie formation and tie deletion. However, we predict that firms form more new ties and delete more existing ties in more distant parts of their networks than in their close proximity. At the same time, they reinforce their existing ties with close partners, thus building more tightly connected clique-like clusters to stabilize their close proximity. The concomitant formation of distant ties increases the connectivity and integration among clusters in the larger network making the network more small-worldly.

Empirical Context, Sample and Data

From a longitudinal perspective, testing our hypotheses requires tracking the numbers of ties firms form and delete within successive intervals. In this research, we do so in the context of large-scale supply networks. Specifically, we focus on how Tier-one suppliers of large manufacturing firms change their rates of tie formation and deletion as these large manufacturers experience a change in unique uncertainty. Our sample includes supply networks of 30 U.S. firms in aircraft, electronics, heavy machinery, and machine tools industries. These industries require multiple different inputs, thus the 30 focal firms must interact with a large number of various partners. In fact, when we probe five tiers deep into their supply networks, the average number of firms in these networks reaches 3,020. Our period of our interest is from April 2003 through September 2010 (30 quarters). This period includes stretches of economic growth and recession, which allows

testing the effects of partner-specific uncertainty on firms' tie formation and deletion dynamics under both high and low munificence.

We mapped the supply networks using data on buyer-supplier relationships from the FactSet Revere database. The unit of observation in the FactSet Revere database is a buyer-supplier link between two firms. FactSet Revere collects information on firms' supplier and customer relationships from multiple sources. First, it captures supplier-customer relationships reported by firms in accordance with Regulation SFAS 131 which requires firms to identify customers accounting for 10 or more percent of their sales. Further, FactSet Revere complements this information with additional data from SEC 10-K filings, corporate websites, press releases, investor presentations, analyst reports, executive interviews, and other sources.

Using FactSet Revere data, we identified the entire set of buyer-supplier ties in the vicinities of each of the 30 firms in our sample in each quarter. The 30 vicinities were bounded at Tier five. The set includes both vertical (cross-tier) and horizontal (within-tier) buyer-supplier ties. We further use this set to construct directed binary adjacency matrices A_t reflecting the recorded ties in quarter t, where t=1, 2…30, representing the 30 quarters in the period under investigation. In our directed binary adjacency matrices, the entry in each cell a_{ijt} is one if firm i is a supplier of firm j in quarter t, and zero otherwise. Using the adjacency matrices, we estimated the following range of dependent variables for each of the 30 networks in each quarter in the period under investigation. All variables were estimated using MATLAB (the code is provided in the Supplementary Materials).

Dependent variables

a.) New close ties

Our first dependent variable is the total number of new close ties formed by Tier-one suppliers of the 30 focal firms in quarter t. We operationalize a new close tie as a tie connecting a Tier-one

firm with a new buyer which was originally separated from the Tier-one firm by a distance less than or equal to two. According to extant literature, a path length of two constitutes the bounds of the observability horizon beyond which the uncertainty associated with the capacity and reliability of potential partners drastically increases significantly lowering the likelihood of tie formation (Baum *et al.*, 2005, Li and Rowley, 2002). Close ties connect Tier-one suppliers with buyers located in Tier-one, Tier-two, and Tier-three. Firms located in these tiers form the set of the most likely potential partners for Tier-one firms searching for an alternative buyer to balance their dependence on the focal firm.

b.) New distant ties

Our second dependent variable is the total number of new ties formed by Tier-one suppliers with buyers in Tiers four and five. Firms in these tiers are less likely to become alternative buyers of Tier-one firms than those located in Tiers one, two, and three. At the same time, they are less likely to be affected by uncertainty specific to the focal firm due to considerable distance. Thus, they represent attractive alternative options for Tier-one firms seeking to reduce the uncertainty stemming from the focal firm.

c.) Total new ties

Our third dependent variable is the overall number of new ties formed by Tier-one firms in quarter t. It is operationalized as the sum of new close ties and new distant ties.

d.) Close ties deleted

Our fourth dependent variable is the number of existing ties between Tier-one firms and buyers located in Tiers one, two, and three, which are terminated in quarter t.

e.) *Distant ties deleted*

Similarly, our fifth dependent variable is the count of existing ties between Tier-one firms and buyers located in Tiers four and five, which are terminated in quarter t.

f.) *Total ties deleted*

The sixth dependent variable is the overall number of existing ties deleted by Tier-one firms in quarter t. It is operationalized as the sum of terminated close and distant ties.

Independent variables

a.) Partner-specific uncertainty

Beckman *et al.* (2004) use the volatility of a firm's stock returns as a proxy for the uncertainty facing that firm. An increase in stock returns volatility is an easily observed measure which the firm's stakeholders may use to make judgments about the uncertainty specific to the firm. However, this volatility may be caused by both firm-specific factors and market-wide factors. In order to make the measure of firm-specific uncertainty more precise, we decompose the volatility into firm-specific and market-wide elements. The firm-specific element is measured by the firm's idiosyncratic risk. The market-wide element is measured by the systematic component of the total volatility of a firm's stock returns. This distinction is important because firms may be exposed to systematic, market-wide factors to a different extent, and this may obscure the firm-specific uncertainty.

To estimate the total volatility of a firm's stock returns, we use daily stock return data from CRSP for the 30 firms in our sample. We measure the total volatility using the Fama-French four-factor model, a staple approach in the finance literature. This model suggests that a firm's stock return is a function of four common factors and the idiosyncratic residual:

$$r_{i,d} - rf_d = \propto_i + \beta_i^{MKT} r_d^{MKT} + \beta_i^{SMB} r_d^{SMB} + \beta_i^{HML} r_d^{HML} + \beta_i^{UMD} r_d^{UMD} + u_{i,d} \quad (1)$$

The four common factors include the market return (r_d^{MKT}), the difference in returns between small and big stocks (r_d^{SMB}), the difference of returns between high and low book-to-market stocks (r_d^{HML}), and the return momentum (r_d^{UMD}) which reflects the difference in returns between highly performing and stocks and those with low performance. The residual $u_{i,d}$ is a measure of firm-specific excess return. Our estimates of daily returns are excessive to the risk-free Treasury bill rate (rf_d).

Using the daily stock price data from CRSP, we match the daily stock returns of the 30 firms in our sample with daily data for the four factors available from Ken French's web site at Dartmouth (http://mba.tuck.dartmouth.edu/ pages/faculty/ken.french/data_library.html). Then we estimate Equation 1 for each of the 30 firms. The standard deviation of the daily residuals $u_{i,d}$ over each of the 30 quarters in the period under investigation measures the idiosyncratic component,$\sigma_{\varepsilon,i}$, of the total quarterly stock return volatility. This idiosyncratic component is our proxy for firm-specific uncertainty.

b.) Munificence

The systematic component of the volatility of a stock price volatility – the firm's systematic risk – reflects the extent to which the firm is impacted by market or industry-wide factors, such as downturns due to overall economic conditions, changes in government policy, adjustments in interest or exchange rates, changes in energy prices, and the like (Brealey *et al.*, 2008). We use the average systematic risk for all firms in the CRSP database as a proxy for the munificence of the larger environment in which the 30 firms in our sample and their suppliers operate. Because the total stock price volatility is the sum of the idiosyncratic and systematic components, we calculate the systematic component of the total variance, $\sigma_{sys,i}^2$, by subtracting the quarterly squared standard deviation of the residuals $u_{i,d}$ from the quarterly squared standard deviation of

stock returns. The square root of $\sigma^2_{sys,i}$ is the systematic risk for each firm in each quarter. To obtain the value of munificence, we calculate the average systematic risk for all firms in the CRSP database (10,284 firms) in each quarter and take its inverse, $\frac{1}{\sigma_{sys,t}}$. This measure characterizes the munificence of the larger environment. A higher average systematic risk σ_{sys} in the economy means that firms are less likely to experiment with new partners, and thus the capacity of the environment to support new tie creation is lower.

Because the firms' ability to form new ties is affected by the structure of the network in which they and their potential partners are located, we included several independent variables reflecting structural characteristics salient for new tie formation.

c.) Path length

In a network with a greater average path length, firms have fewer close partners. Therefore, they have more opportunities to form close ties which are preferable to distant ties. At the same time, a greater path length means that the information exchange between firms in the network is less rich (Schilling and Phelps, 2007). This may also affect the dynamics of distant tie formation relative to the rate of close tie formation. Therefore, we include this variable in our analyses. We calculated the directed average path lengths for the 30 networks in each quarter using the formula:

$$\textit{Path length}_t = \frac{1}{n}\sum_{i\in N}\frac{\sum_{j\in N, j\neq i} d_{ijt}}{n-1},$$

where N is the set of all firms in the network; n is the number of firms in the network; d_{ijt} is the shortest directed path from organization *i* to organization *j* in quarter *t.*

d.) Clustering coefficient

Based on extant studies of interfirm network dynamics (e.g., Greve *et al.*, 2013), we expect that higher clustering would make it harder for firms to establish distant ties. A higher clustering coefficient indicates a greater degree of embeddedness. A firm that is structurally embedded in

closed triads is less likely to reciprocate an offer of a tie from an outsider. Operationally, we define clustering coefficient as the ratio of open to closed triads for the whole network (Borgatti and Everett, 2006). In other words, clustering shows what percent of an organization's partners are connected to each other. Because supply networks have directionality, we calculate the directed clustering coefficient using the Fagiolo (2007) formula:

$$Clustering_t = \frac{1}{n} \sum_{i \in N} \frac{\frac{1}{2} \sum_{j,h \in N} (a_{ijt} + a_{jit})(a_{iht} + a_{hit})(a_{jht} + a_{hjt})}{(k_{it}^{out} + k_{it}^{in})(k_{it}^{out} + k_{it}^{in} - 1) - 2 \sum_{j \in N} a_{ijt} a_{ji} t},$$

where N is the set of all organizations in the network; a_{ijt} is the status of a buyer-supplier link between organization *i* and *j*: $a_{ijt} = 1$ when organization *i* is a supplier of *j* in quarter *t* and zero otherwise; k_{it}^{out} is the out-degree of organization *i* in quarter *t*, indicating the number of its buyers; k_{it}^{in} is the in-degree of organization *i* in quarter *t*, indicating the number of its suppliers.

e.) Density

Because the relationship with a supplier entails certain costs, each organization has a limit in the number of suppliers it can feasibly manage. Thus, network density indicates how close each firm is to this limit. The higher the network density, the harder it is for firms to find a new customer. We operationalize network density as the ratio of ties present in the network to the number of ties possible. We estimate density in each quarter using the following formula:

$$Density_t = \frac{2T_t}{n_t(n_t - 1)},$$

where T_t is the number of ties and n_t is the number of organizations in the network in quarter *t.*

Our dependent variables are count variables (the number of new or deleted ties). Thus, in our analyses we use negative binomial fixed-effects models. Negative binomial models correct for overdispersion present in our data. They have been used in other studies of overdispersed counts (Barnett 1997, Haunschild and Beckman 1998, Beckman *et al.*, 2004).

Results

Before estimating our models, we took several measures to mitigate multicollinearity. First, we used the grand mean-centered values of all predictor variables. 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. Each of the VIF scores for our dataset met this requirement (mean score of 1.56) after we mean-centered the predictor variables. We first report the descriptive statistics and simple correlations in Table 1.

Insert Table 1

The odd-numbered models presented in Tables 2, 4, and 6 test the direct effects of changes in partner-specific uncertainty on the rates of various types of tie formation and deletion. Model 1 in Table 2 tests the direct effects of changes in partner-specific uncertainty on the total number of new ties formed in the networks. Previous research (e.g., Nohria, 1992) argues for the path-dependency of network transformation: the rate at which firms form new ties in the current period depends on the rate of new tie formation in the previous period. Similarly, the rate of new tie formation may depend on the contemporaneous rate of tie deletion as firms may need to replace the ties they delete with new ones. To control for these effects, Model 1 includes the net change in the count of ties in the previous quarter and the number of ties deleted in the current quarter. Model 3 tests the direct effects of changes in partner-specific uncertainty on the total number of ties deleted in the networks. Model 3 controls for the effects of the rate of tie formation in the previous quarter and the contemporaneous rate of tie formation because the number of ties deleted may depend on the number of new ties formed.

Models 5, 7, 9, and 11 presented in Tables 4 and 6 test the direct effects of changes in partner-specific uncertainty on the number of close ties formed, the number of close ties deleted, the number of distant ties formed, and the number of distant ties deleted, respectively. Model 5

controls for the effects of the previous and contemporaneous rates of tie formation and deletion by including the number of close ties formed in the previous quarter and the number of close ties deleted in the current quarter. Model 7 does so by including the numbers of close ties deleted in the previous quarter and formed in the current quarter. The rate of distant tie formation depends on the rates of close tie formation, close tie deletion, and distant deletion in the current quarter as well as the rate of distant tie formation in the previous quarter. Model 9 includes these variables as controls. The rate of distant tie deletion, in turn, depends on the rates of close tie formation, close tie deletion, and distant tie formation in the current quarter as well as the rate of distant tie deletion in the previous quarter. Model 11 includes these variables as controls.

Insert Tables 2-7

The results of models 1, 3, 5, 7, 9, and 11 show that the direct effects of changes in partner-specific uncertainty on the changes in the rates of tie creation and deletion are significant. However, according to Koka *et al.* (2006), these direct effects may have ambiguous interpretations. They must be estimated in interaction with environmental munificence. Models 2, 4, 6, 8, 10, and 12 include the interaction term. The results show that the interactions are significant in all models. To unpack the interactions, we performed marginal analyses of the impacts of changes in partner-specific uncertainty on tie formation and deletion dynamics in environments with high and low levels of munificence. The high level of munificence was set at one standard deviation above its (mean-centered) mean and the low level of munificence was at one standard deviation below its mean.

Hypothesis 1 predicted that firms respond to an increase in uncertainty specific to their major buyer by forming more new buyer ties and deleting fewer existing buyer ties. The results of the marginal analyses of the effect of changes in partner-specific uncertainty on the conditional

means of newly formed ties and deleted ties (Table 3) reveal that firms' responses differ considerably between the high and low levels of munificence. Thus, a one-unit change in partner-specific uncertainty is associated, on average, with 16.44 more new ties formed when the munificence is high and 9.61 fewer new ties formed when the munificence is low. Similarly, a one-unit change in partner-specific uncertainty is estimated to increase the average number of deleted ties by 22.46 when munificence is high and decrease this number by 15.72 when munificence is low. These results provide partial support for Hypothesis 1 and reveal that firms' responses to shifts in partner-specific uncertainty change drastically between the high and low levels of environmental munificence.

Hypothesis 2 predicted that firms respond to an increase in uncertainty specific to a powerful exchange partner by forming fewer close ties but more distant ties. Our results show that firms do form more distant ties in response to an increase in partner-specific uncertainty when munificence is high (Table 7). However, our results show no effect of changes in partner-specific uncertainty on close tie formation in high munificence conditions (Table 5, Model 6, $p>0.05$). When munificence is low, firms decrease both close and distant tie formation. Hypothesis 3, in turn, predicted that firms delete fewer existing close ties and more existing distant ties in response to an increase in partner-specific uncertainty. The results of our marginal analyses of the interaction terms in Models 8 and 12 (Table 5 and 7) show that when munificence is high firms delete more of both close and distant ties. When munificence is low, however, firms delete fewer close and distant ties. Overall, these results partially support Hypotheses 2 and 3 and provide further evidence that firms can employ both the resource dependence logic and the embeddedness logic in their responses to changes in partner-specific uncertainty, depending on the level of environmental munificence.

Furthermore, the results we obtained provide interesting insights about the enabling and constraining effects of network structure on the rates of tie formation and deletion. Network density powerfully constrains the rates of close tie formation and deletion but does not affect distant tie formation rates. Clustering, on the other hand, increases the rates of close and distant tie deletion but does not significantly influence their formation. Path length facilitates the rates of both close and distant tie formation and deletion.

Discussion

To obtain a deeper understanding of how interfirm networks change, our research leveraged the context of practical dilemmas which firms face when uncertainty specific to their major exchange partners increases and exchange becomes less predictable. The choices firms make to resolve such dilemmas expose several key processes relevant for our understanding of interfirm network transformation that may remain invisible during more stable periods. Our results reveal shifts in the dominant logic guiding tie formation and dissolution as the munificence of the larger environment changes.

When munificence is high, firms' responses to an increase in partner-specific uncertainty are guided primarily by the resource dependence logic. We observe that in such conditions firms respond by forming more ties with new alternative buyers. The majority of these new ties are with distant partners. Because these partners are far enough from the source of uncertainty, they are unlikely to be affected by its changes. An alternative tie with a distant partner, therefore, has a higher utility as an instrument of uncertainty reduction than a tie with a closer partner. At the same time, we observe an increase in the rate of close tie deletion, and this suggests that firms are attempting to reduce their embeddedness in the cluster around the focal firm experiencing an increase in uncertainty. This suggests that in such contexts firms emphasize their connections with

distant buyers. As new distant ties are formed at a higher rate, the network becomes more small-worldly increasing the integration among tiers.

When munificence is low, however, the dominance shifts to the embeddedness logic. Firms slow down their rates of new tie formation and existing tie deletion. While the declining rates may in some instances be viewed as a threat-rigidity effect (Staw *et al*., 1981), we consider them to be a result of a deliberate change in strategy. Lower environmental munificence makes forming new ties to change the dependence status quo less appealing. First, firms have fewer resources available to form new ties. Second, because firms are less prone to experimentation with new partners when munificence is low, the chances that an offer of a new tie will be reciprocated are lower. These two considerations suggest that the opportunity costs and the difficulty of forming new ties in environments with lower munificence are higher. Third, while the magnitudes of the increase in partner-specific uncertainty in our sample were sufficiently large to make the exchange less predictable, they were not large enough to threaten the short-term survival of focal firms and thereby lead to threat rigidity. Thus, our research provides evidence that when munificence is low firms cope with increases in partner-related uncertainty by relying more on their embedded ties.

Furthermore, our results show that the rates of close tie deletion slow down faster than do the rates of close tie formation. This leads to an increase in the density of the firms' proximate networks. At the same time, a different dynamic unfolds in more distant parts of their networks. Firms delete more existing distant ties than they form new distant ties. This makes the Tier-one group of firms less connected with firms in Tiers four and five. Structurally, this implies that the network becomes less small worldly. The concomitant increase in the density of the Tier-one firms' close proximity increases the degree of these firms' structural embeddedness. While higher levels of environmental munificence activate deliberate, creative organizational action aimed at

changing the dependence status quo, lower levels of munificence suppress the firms' motivation to restructure their networks. Firms prefer to stay in the comfort zone and relative certainty of their existing ties and to form new ties predominantly with close neighbors or partners of their existing partners.

Implications for interfirm network research

Our findings indicate that firms' propensity to change the dependence status quo by restructuring their networks varies with characteristics of the larger environment. In this light, our research alerts scholars that the path of interfirm network evolution is likely to be nonlinear. In order to be able to explain and predict structural transformations of interfirm networks, future studies of network evolution must consider the effects of various contextual variables on the rates of tie formations and deletions in interfirm networks. Extending the approach and theory developed in the literature on interfirm networks into untested realms of such salient contexts as emerging uncertainty are likely to yield new valuable knowledge. The literature on interfirm networks has considered interfirm ties mostly as sources of benefits or opportunities. The role of ties as sources of uncertainty or difficulties has not received concerted consideration. We show that when uncertainty emerges within major exchange ties, a new dynamic of tie formation and deletion unfolds in the network changing its structure. Due to the ubiquity of relational uncertainty across organizational contexts (Singha and Van de Ven, 2005), its effects on the structure of interfirm networks should not be assumed away in further research.

Our research provides insights about the ways in which existing structural properties of interfirm networks influence the extent of their transformation. We found that, on average, firms form more new ties and delete more existing ties in response to an increase in partner-specific uncertainty in networks with greater path lengths. This suggests that networks in which partners are, on average, farther away from each other undergo a larger structural change as a result of an

increase in endogenous uncertainty. On the other hand, we found that the degree of clustering significantly affects the rate of tie deletion and has no effect on tie creation. A higher clustering may indicate a greater degree of solidarity among close partners, which may become a source of collective pressure constraining firms from modifying of their dependence by forming alternative ties and motivating them instead to drop weaker existing ties to redirect resources to accommodate the demands of a major buyer which the cluster views as a common good.

Next, our research contributes to the small literature on the origins of distant ties. The literature on distant ties shows that their formation is motivated by factors other than those triggering the formation of the majority of organizational ties which are local (Rosenkopf and Padula, 2008). The factors leading firms to create distant ties are relatively less known. At the same time, distant ties are fundamental for network change because a handful of such ties can transform the structure of a network turning it into a small-world (Watts and Strogatz, 1998). We identify a new origin of distant ties. Our results show that such contextually ubiquitous phenomena as an increase in uncertainty specific to a major exchange partner and the concomitant need to balance the dependence may prompt firms to form new distant ties.

Practical implications

Our research provides managers with important caveats regarding power and its use in interorganizational relations. Pfeffer (1981) argued that power is predominantly a structural phenomenon: the existing structure of relationships in a network defines which actor is more powerful. At the same time, a less powerful actor may increase its power relative to a more powerful actor through finding alternatives outside the exchange relationship (Emerson, 1962). The resource dependence logic rests on the assumption that a firm is always motivated to lessen dependence on its present exchange partners. An increase in the uncertainty unique to a more powerful firm may give its managers an impression that its suppliers will necessarily search for

alternative partners and start developing new ties if they observe a change in the rhythm of exchange. Such impression may lead the powerful firm to take actions to counter the suppliers' gains in power.

While the impulse to balance may always be there, our research shows that firms do not always act on this motivation. They do so when the larger environment is munificent enough to support new tie formation, most new buyer ties are formed in more distant parts of the network. Such ties are usually weaker, more uncertain, and costlier to maintain. They may be short-term, short-lived options. In this light, while such restructuring may be beneficial for the focal firm's suppliers, it is not a serious threat to the focal firm's power. Moreover, these new distant ties make the network more efficient in circulating information and knowledge from more distant parts to the focal firm. In a way, these new distant ties may even benefit the focal firm through an increased inflow of new ideas and knowledge from other communities in the network.

When the environment's munificence is lower, suppliers actually lower their rates of tie formation, thereby relying on existing ties to cope with the shifts in the rhythm of exchange. These shifts in tie formation emphasize the switch towards mostly heuristic-based decisions accentuating homophilous pairing, engaging old partners, and forming ties with partners of existing partners as major mechanisms of new tie formation. Suppliers prefer the comfort zone and relative certainty of their existing ego-networks to forming ties with unknown partners. The structure of the network solidifies the power of the focal firm.

Appendix

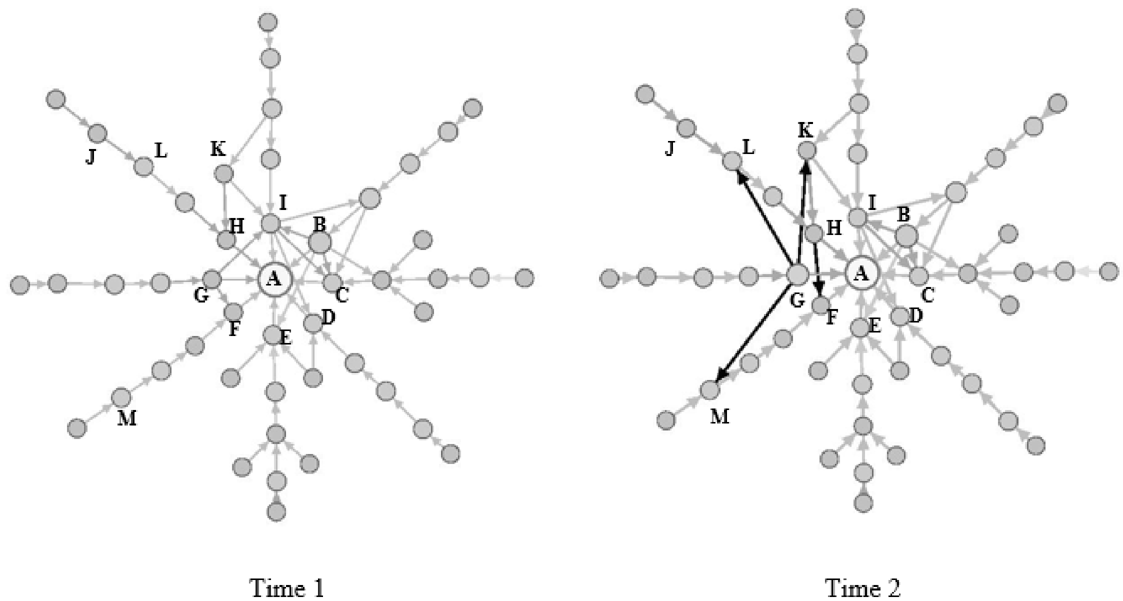

Figure 3. Firm A's supply network undergoes a structural change from Time 1 to Time 2 as supplier G deletes its ties with firms F and I, and establishes ties with K, L, and M. At the same time, supplier H establishes a new tie with F.

Table 1. Descriptive statistics and correlations

Variable	Mean	S.D.	1	2	3	4	5
Dependent Variables:							
New close ties	26.61	65.11					
New distant ties	10.24	17.11					
Total new ties	36.85	82.20					
Close ties deleted	22.85	55.29					
Distant ties deleted	7.91	12.87					
Total ties deleted	30.76	68.17					
Independent Variables:							
Partner-specific uncertainty	0.02	0.01	1.000				
Munificence	304.18	139.43	-0.408	1.000			
Path length	2.62	0.16	-0.142	0.274	1.000		
Density	0.002	0.001	-0.029	-0.011	-0.690	1.000	
Clustering	0.05	0.009	0.043	-0.057	-0.676	0.635	1.000

Table 2. Fixed-effects negative binomial regression models for the effects of partner-specific uncertainty on total tie formation and deletion

Variable	Total new ties formed at t				Total ties deleted at t			
	Model 1		Model 2		Model 3		Model 4	
Partner-specific uncertainty	-8.588	[0.007]	3.4132	[0.422]	-13.2593	[0.000]	3.3709	[0.465]
	(3.2008)		(4.252)		(3.5853)		(4.613)	
Munificence	0.0003	[0.211]	0.0004	[0.062]	0.0004	[0.19]	0.0005	[0.05]
	(0.0002)		(0.0002)		(0.0003)		(0.0002)	
Partner-specific uncertainty X Munificence			0.0868	[0.000]			0.1272	[0.000]
			(0.0207)				(0.0231)	
Path length	3.4425	[0.000]	3.694	[0.000]	1.8591	[0.000]	2.2833	[0.000]
	(0.3608)		(0.3604)		(0.3874)		(0.3879)	
Clustering	9.9766	[0.414]	8.2701	[0.497]	62.356	[0.000]	55.8358	[0.000]
	(12.2197)		(12.1748)		(13.0237)		(13.047)	
Total new ties formed at t					0.0033	[0.000]	0.0033	[0.000]
					(0.0002)		(0.0002)	
Total ties deleted at t	0.0042	[0.000]	0.0041	[0.000]				
	(0.0002)		(0.0002)					
N (network-quarters)	869		869		869		869	

p-values are in brackets; standard errors are in parentheses

Table 3. Average marginal effects of partner-specific uncertainty on total tie formation and deletion

	Total new ties formed		**Total ties deleted**	
	Model 2		Model 4	
High munificence	16.4397	[0.013]	22.4645	[0.002]
Low munificence	-9.6131	[0.006]	-15.7226	[0.001]

p-values are in brackets.

Table 4. Fixed-effects negative binomial regression models for the effects of partner-specific uncertainty on close tie formation and deletion

	New close ties formed at quarter t				Close ties deleted at quarter t			
Variable	Model 5		Model 6		Model 7		Model 8	
Partner-specific uncertainty	-9.3862	[0.008]	0.9155	[0.84]	-11.0491	[0.003]	4.3287	[0.363]
	(3.5111)		(4.4925)		3.7094		(4.7552)	
Partner-specific uncertainty X Munificence			0.0801	[0.000]			0.1209	[0.000]
			(0.022)				(0.0239)	
Path length	3.1639	[0.000]	3.404	[0.000]	1.7136	[0.000]	2.1532	[0.000]
	(0.3777)		(0.3786)		(0.3933)		(0.3975)	
Clustering	14.8869	[0.252]	12.52	[0.33]	56.0825	[0.000]	48.8911	[0.001]
	(12.9938)		(12.954)		(13.9811)		(14.0511)	
New close ties formed at t-1	0.0007	[0.017]	0.0008	[0.01]				
	(0.0003)		(0.0003)					
Close ties deleted at t-1					0.0004	[0.288]	0.0003	[0.404]
					(0.0004)		(0.0004)	
New close ties formed at t					0.0038	[0.000]	0.0037	[0.000]
					(0.0002)		(0.0002)	
Close ties deleted at t	0.0049	[0.000]	0.0048	[0.000]				
	(0.0002)		(0.0002)					
Constant	-0.2905	[0.000]	-0.2202	[0.000]	-0.5627	[0.000]	-0.4636	[0.000]
	(0.0653)		(0.0671)		(0.0696)		(0.0709)	
N (network-quarters)	869		869		869		869	

p-values are in brackets; standard errors are in parentheses.

Table 5. Average marginal effects of partner-specific uncertainty on close tie formation and deletion

	Close ties formed		**Close ties deleted**	
	Model 6		Model 8	
High munificence	12.9438	[0.061]	22.4736	[0.002]
Low munificence	-11.1127	[0.004]	-13.816	[0.001]

p-values are in brackets

Table 6. Fixed-effects negative binomial regression models for the effects of partner-specific uncertainty on distant tie formation and deletion

	New distant ties formed at quarter t				Existing distant ties deleted at quarter t			
	Model 9		Model 10		Model 11		Model 12	
Partner-specific uncertainty	-7.2735	[0.043]	5.0906	[0.286]	-10.3205	[0.007]	5.702	[0.239]
	(3.5896)		(4.7678)		(3.8501)		(4.8454)	
Partner-specific uncertainty X Munificence			0.0925	[0.000]			0.1344	[0.000]
			(0.023)				(0.0254)	
Path length	3.0225	[0.000]	3.3264	[0.000]	1.2918	[0.001]	1.7399	[0.000]
	(0.3698)		(0.3741)		(0.3893)		(0.3911)	
Clustering	6.8375	[0.601]	8.4364	[0.514]	49.0948	[0.000]	47.4227	[0.000]
	(13.0301)		(12.9343)		(13.7143)		(13.5671)	
Distant ties formed at t-1	0.0006	[0.649]	0.0017	[0.231]				
	(0.0013)		(0.0014)					
Distant ties deleted at t-1					0.0079	[0.000]	0.008	[0.000]
					(0.0021)		(0.002)	
Close ties formed at t	0.0063	[0.000]	0.001	[0.011]	-0.0119	[0.000]	-0.0115	[0.000]
	(0.0007)		(0.0003)		(0.0013)		(0.0012)	
Close ties deleted at t	-0.0099	[0.000]	-0.0098	[0.000]	0.0111	[0.000]	0.0109	[0.000]
	(0.0013)		(0.0013)		(0.0011)		(0.0011)	
Distant ties formed at t					0.0289	[0.000]	0.0281	[0.000]
Distant ties deleted at t	0.0401	[0.000]	0.0225	[0.000]				
	(0.0033)		(0.0023)					
N (network-quarters)	869		869		869		869	

p-values are in brackets; standard errors are in parentheses.

Table 7. Average marginal effects of partner-specific uncertainty on distant tie formation and deletion

	Distant ties formed		Distant ties deleted	
	Model 10		Model 12	
High munificence	18.9711	[0.01]	27.2596	[0.001]
Low munificence	-8.7898	[0.025]	-15.5473	[0.001]

p-values are in brackets.

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ESSAY 3. FIRMS' INNOVATION AND SUPPLY NETWORK STRUCTURE: THE DYNAMIC INTERPLAY

Introduction

When we think of where organizations obtain innovative solutions we usually think of exceptionally creative leaders or teams of engineers armed with cutting-edge technology. Since Schumpeter (1911), innovation has been understood as an effort and achievement of an individual economic entity. A growing body of sociological literature and organizational studies indicates that innovative breakthroughs often come from complex interaction among several interdependent entities (Powell et al., 1996; Porter and Stern, 2001). In a similar vein, supply chain scholars increasingly view a firm's direct suppliers or buyers as sources of innovative ideas. This view of innovation as a systemic phenomenon implicitly suggests that innovative firms reside in the systems which are in some ways different from those where less innovative firms are located. However, two firms with essentially the same set of suppliers may radically differ in terms of innovativeness: take Amazon and Walmart as an example. Such contradiction shifts the focus back to the individual firm and the individual qualities such as absorptive capacity, business model or strategic orientation. On what grounds, then, do supply networks matter and how supply networks of innovative companies differ from those of the less innovative ones?

Supply chain literature, where we might expect to find answers, mostly treats the network concept as a metaphor and largely focuses on the ways firms engage their direct suppliers in innovative projects or "pull" innovations from their suppliers (Wagner and Bode, 2014). As products become more complex, manufacturers outsource more components and thus are exposed to a wider knowledge base. Tapping this knowledge allows firms to focus more on their core competencies and to economize on internal research costs (McIvor and Humphreys, 2004; Ragatz

et al., 1997; Swink, 1999). Further, many direct suppliers have a first-hand knowledge of their customers' demands and therefore can offer innovative solutions that fit these demands particularly well (Kohli and Jaworski, 1990; Ulaga and Eggert, 2006; Ellis et al., 2012; Wagner and Bode, 2014). While supply chain scholarship recognizes supply networks as important sources of innovative ideas, its focus on the actions of the focal firm and its direct suppliers provides only a partial answer to the central questions of this study.

On the other hand, several studies in organization science shift the analytic lens from the individual firm and its immediate surroundings toward the structure of the larger inter-firm network and explore its enabling and constraining effects on the firm's innovation output. For example, Schilling and Phelps (2007) networks characterized by dense clustering enable a relatively more efficient transmission capacity for information diffusion. At the same time, nonredundant connections increase the reach within the network by shortening the distance between firms. Therefore, firms embedded in interorganizational networks with both high clustering and short average path lengths are likely to have a greater innovative output than firms in networks that do not exhibit these characteristics. Bellamy et al. (2014) employ a similar perspective to explore the relationship between such structural properties of supply networks as accessibility and interconnectedness and the innovation performance of firms embedded in these networks.

However, viewing firms' outcomes primarily as a function of the structure of their supply networks provides an incomplete and potentially misleading perspective because supply networks are themselves shaped through organizational action: structural properties of supply networks co-evolve with firms' behavior. The Rowley et al. (2000) study, for example, shows that in slow-paced industries, such as steel industry, firms tend to form relatively closed networks. The tempo

of innovation in the slow-paced industries is usually lower relative to that in the fast-paced industries (Eisenhardt and Schoonhoven, 1996; Orsenigo et al., 2001; Powell et al., 2005). In the slow-paced industries, firms' needs for information, knowledge or external skill sets are different from those of firms in the more dynamic industries. Firms in the slow-paced industries have lower incentives to seek access to complementary assets and knowledge of others in their networks, and thus tend to form closed networks.

Therefore, to explore the central questions of this research, we combine both perspectives and explore the dynamic interplay between a firm's innovative agency and the structure of the firm's supply network. We adopt an open system view of supply networks. We also follow Schumpeter (1934), Hargadon and Sutton (1997), Rogers (2003), and many other studies which conceptualize innovation as the process of recombining such inputs as knowledge, information, capabilities, or resources. This process is particularly effective when it involves multiple heterogeneous inputs. As knowledge, information, skills and resources are often more heterogeneous across network clusters than within them, firms pursuing innovation are likely to form new cross-cluster ties, thus changing the structure of their supply networks.

We start in this direction by building upon Swindler's (1986) distinction between "settled" and "unsettled" times. During stable, "settled" periods, most firms may unproblematically employ established practices and exploit existing competencies and other sources of competitive advantage (Mudambi and Swift, 2014). However, with time, these resources wane in value, and firms' innovative agency enters the stage. During these periods of upheaval, firms may seek access to supplier innovations and technologies to update their product portfolios (Gianiodis et al., 2010), improve the product design (Primo and Amundson, 2002), or reduce costs (Cooper and

Yoshikawa, 1994). These periods of exploration may bring about considerable changes in the structures of the firms' supply networks as they are driven to build ties with new partners.

We anticipate that our examination of changes in the structure of firms' supply networks during periods when these firms ramp up their innovative activity will advance existing knowledge in two major ways. First, the insights into the processes taking place in supply networks as a result of innovative exploration of an individual agent will show whether and to what extent firms' actions help explain the dynamics of their supply networks. Second, if buyer-supplier relations indeed generate knowledge-sharing benefits, then it is important to understand why we observe such heterogeneity in the ways these relations are structured. A deeper understanding of how supply networks evolve and what factors contribute to systematic variation in their evolution will allow connecting the emergent network structures to individual outcomes in a more compelling way.

The remainder of this article is organized as follows. In Section 2, we discuss supply networks as complex systems, theorize individual innovative agency of a firm, and develop hypotheses relating innovative agency to structural properties of supply networks. We describe our method in Section 3 and our empirical findings in Section 4. In section 5 we discuss our results and their implications for theory and practitioners.

Theoretical background and hypothesis development

Systems terminology has become commonplace in defining supply networks. In an early conceptualization, Choi et al. (2001) view supply networks as complex adaptive systems situated in and interacting with dynamic environments. In this perspective, supply networks are comprised of a large number of interdependent agents linked together by buyer-supplier relations. However, they are not simply the sum of these agents. Their structure to a large extent depends on the nature

of interactions among the agents. For example, in a tightly coupled complex system, the components are strongly interdependent, while a loosely coupled complex system can be divided into subsets of tightly coupled components that are loosely connected to one another. Complex feedback loops leading to self-reinforcing cascades of changes affect tightly and loosely coupled systems in different ways (Poole, 2014). This leads to nonlinear relationship between causes and effects in such systems as well as to adaptivity manifested in self-organization and emergence. A supply network emerges with no one firm deliberately organizing and controlling it (Choi et al., 2001).

However, supply networks do not evolve in a random way. There are common patterns of behavior among the agents comprising them leading to common structural properties. As systems, supply networks are likely to evolve to optimize a specific set of competitive criteria, which regularly includes a high efficiency of product and information transfer and low cost of transactions and connection among firms. If minimization of transaction costs was the exclusive priority, supply networks' structures would resemble a regular lattice because this structure has minimal number of links between the interconnected components and each link entails a cost of establishing and maintaining. If global efficiency was the only criterion, the networks would be close to the random network archetype which maximizes the number of long-range links connecting distant parts of the network. Because supply networks are likely to evolve to optimize both criteria, they can be expected to have relatively short path lengths, which are necessary for global efficiency of product transformation and information transfer.

At the same time, we can expect supply networks to exhibit a relatively high degree of clustering. The high clustering is necessary for achieving cost efficiencies through specialization. Moreover, we can expect supply networks to be sparsely connected, especially between clusters.

Their dense local clustering and short path lengths minimize the costs related to establishing and maintaining network ties and at the same time support the complexity required to produce modern multicomponent products. Such locally clustered and at the same time extensive configurations can effectively support production and distribution systems is paired with relatively low connection and transfer costs.

Although supply networks are systems comprised of interdependent agents (Choi et al., 2001), the concept of agency in such systems has not yet received a concerted attention. Systems theories are primarily founded on the premise that processes are causally influenced by outside factors including the structure of the system in which the company operates (Poole, 2014). In fact, most studies applying network perspective examine the influence of structure on operational outcomes. Outside the literature on agent-based modeling, the nature and systemic consequences of intentions and actions of individual components has not been explored. Agency theory applies to situations in which an agent is acting for a principal, not to the context of interdependent relations among components of a system. Agency is a unique construct that has always been a part of inter-firm networks. Yet, it remains undertheorized and is often assumed away or becomes merged into other concepts.

We argue that individual agency and actions are important for understanding what supply networks are and how they come into existence and what structural properties they have. Ultimately, supply networks are the outcomes of strategic, deliberate actions of multiple firms. These firms form ties with partners to address specific needs. As these needs shape the partnering behavior of firms in a network, different network structures emerge. We contend that at the core of firms' choices of partners is the fundamental tradeoff between the benefits and costs of new network ties. For example, reliable, continuous collaboration is often a primary objective for firms

seeking exchange partners. Therefore, the moral hazard stemming from a new relationship is a key factor shaping such firms' ties (Gulati, 1995a). The costs of search for a reliable partner, however, are high as information about potential partners is distributed unevenly throughout the network. Thus, firms seeking reliable, continuous collaboration will tend to pair with those about whom they can obtain private information in a cost-effective way such as through shared third-party ties (Gulati, 1995b). Because a shared third party may also intervene in conflict situations and act to reduce opportunistic pursuits (Larson, 1992), such partners are especially attractive for many firms. Such firms, therefore, will tend to form dense and rather closed networks with the partners of existing partners or past partners. This tendency is further reinforced by a relatively faster diffusion of reputational insights in close networks which reduces opportunistic behavior (Greif, 1989; Ahuja, 2000) as well as precludes releasing confidential information and technology to outsiders or leakage of skills, experiences, and competencies that may form the basis of the firm's competitiveness.

Following Poole (2014), we conceptualize agency from a systems perspective by focusing on responsiveness and meaningfulness of an agent's actions. Agency is an issue of responsiveness to external and internal cues – changes in the larger environment, actions of exchange partners or own pressing needs. Another important feature of agency is the degree to which an agent reflexively accounts for and monitors its actions relative to the processes taking place in the system (Poole, 2014; Brummans, 2017). For example, deliberative problem solving processes in which the agent compares alternative solutions involve such reflexivity and monitoring. Agency is to a large extent defined an agent awareness of other agents and their resources (Poole, 2014). The agent displays a higher degree of agency if it sees other firms in a supply network not just as nodes or objects but as agents in and of themselves.

Overall, in the context of a supply network, individual agency means a deliberate and meaningful action based on an interpretation of the larger environment as well as actions of other agents comprising the network. Such actions usually have a problem-solving dimension which includes drawing on previous experiences in determining how choices fit the agent's goals (Poole, 2014). Most importantly, to exercise agency, the agent is aware of being an agent, an autonomous entity that is able to act within the system's structural constraints (Poole, 2014; Brummans, 2017). For example, the agent must be aware that it can undertake a network action – form a new tie or set of ties – to reconfigure the surrounding structure to ease its constraints. Agency is about intent, not about final results. The complexity of supply networks introduces a probability of unintended and unanticipated consequences these creative interventions may result in (Choi et al., 2001).

Innovation is often viewed as a process of recombinatory search (Fleming, 2001; Schilling and Phelps, 2007), a problem-solving activity in which innovators discover new solutions by searching for and recombining existing solutions or knowledge (Nelson and Winter, 1982; Schilling and Phelps, 2007) or finding new ways to combine existing knowledge elements (Henderson and Clark, 1990). The competitive advantage of an innovative firm critically depends on access to and recombination of novel inputs. When building network ties, innovative firms, therefore, act with a goal to obtain continuous access to new and diverse information, knowledge, or skill sets. As a firm's supply network may become a source of such resources, innovative firms see the links with their direct or indirect partners as channels of information and knowledge. In this sense, the need to innovate provides a generative capacity – the potential to engage with the existing supply network structure in a certain way. For example, innovative firms may be motivated to form ties with companies outside their own cluster. These distant ties are more uncertain and riskier than close ties but they can benefit innovative firms by providing fresh

information or knowledge (Baum et al., 2005). Thus, the need to innovate activates a different type of agential dynamic which may in turn produce a network with specific properties.

Reaching out beyond the boundaries of their own cluster and building ties with new partners not connected to any firm in the cluster, innovative firms are able to tap diverse pools of technical knowledge and information (Sytch and Tatarynowicz, 2014). This agential dynamic relies on a distinct level of situational awareness. Innovative firms frequently other firms' innovation activities, including new product announcements and patent grants. Since innovation depends on new and unique information, innovative firms are actively seeking to form ties with new partners. These new ties are weak ties but they work to channel unique, novel information and knowledge. This is especially important when firms are unable to solve the problems they face with resources in their existing network.

However, this may be true only for very innovative firms. Most firms are unlikely to build risky new ties during periods of stability when they can exploit the existing competencies. The innovative agential dynamic rarely enters the stage during stable and predictable times as firms seek to maximize the current value of their existing resource endowments and refine and improve their methods of production and execution (Benner and Tushman, 2003). During stable times, therefore, the structure persists and constrains agency permitting only incremental adjustments. The periods of stability are often followed by intervals of change as existing resources eventually wane in value (Gilsing and Nooteboom, 2006; Miller and Friesen, 1984; Romanelli and Tushman, 1994) or competitors come up with superior products (Klepper, 1996). During these unstable times, most firms are compelled to pursue innovations in order to adapt to changes in the value of their competitive advantage and regain stability. This is when their innovative agency assumes a prominent role and drives risk-taking, experimentation, and innovative search.

As firms move from exploitation mode to exploration mode as the value of their extant sources of competitive advantage begins to wane, their new agentic orientation may generate several structural changes in their supply networks. The most likely change is an increase in network size.

Focused on seeking new information, new knowledge, or skill sets firms form new ties bringing new partners into their networks. Such new partners may be specialist firms contracted to provide their specific expertise to solve problems. They may also be alternative suppliers if firms are seeking to improve the lead times or reduce product costs. If firms are focusing on developing new product offering, the new partners become main suppliers. In any case, the size of the supply network is expected to increase. At the same time, firms that have been more focused on exploiting their existing resource base rather than on developing new solutions face a more formidable challenge as they move into exploration mode because more innovative firms are likely to already have a broader access to a more diverse knowledge base in their supply network. Therefore, we expect less innovative firms to increase the size of their supply networks to a larger extent as a result of innovation. More formally:

Hypothesis 1. An increase in a firm's innovative activity leads to an increase in the size of its supply network, and this increase is larger for firms that are generally less innovative.

We also expect other structural changes to emerge. Besides bringing in new firms into the network, firms may form ties with suppliers of their current partners in order to cooperatively seek innovative solutions to technological problems or develop new products. The firms are more familiar with partners of their current partners than with firms outside of their networks. Moreover, such cooperation may work to loop in their current direct suppliers in innovative triads. The new

denser connectivity creates transmission capacity to share large amounts of information (Burt, 2001; Schilling and Phelps, 2007).

As firms in the network become interconnected via multiple paths, both the volume and reliability of diffused information increase enabling richer information and knowledge exchange and integration. Firms can compare the inputs coming from multiple sources and choose the best option or identify and remove distortions (Schilling and Phelps, 2007). This also leads to a more effective collective problem solving (Powell et al., 1996). A higher density couples a deeper collective understanding of the problem with a higher degree of mutual trust which develops in densely interconnected clusters based on shared group identity (Coleman, 1988, Granovetter, 1992) and reciprocity norms (Dyer and Singh, 1998). Connecting with the partners' partners is also effective because it ensues a higher willingness to exchange information and knowledge. Thus, building connections with the deeper-tier suppliers may provide access to tacit knowledge (Hansen, 1999, Zander and Kogut, 1995). While innovative companies constantly tap the knowledge stored in their supply networks, less innovative companies may quickly get access to a considerable pool of new knowledge by connecting with their suppliers' suppliers. For less innovative companies, this pool is largely untapped, and they may benefit by increasing the density of the connections in their network. In light of this reasoning, we hypothesize that:

Hypothesis 2. An increase in a firm's innovative activity leads to an increase in the density of its supply network, and this increase is larger for firms that are generally less innovative.

While an increase in density provides a greater information access and deeper collective understanding of the problem, it often makes information and knowledge in the network homogeneous and redundant (Burt, 2004; Granovetter, 1973). The new paths connect actors who are close to each other and source their information from the same sources. An increase in density

may therefore stifle the diversity of information and knowledge required for effective recombination. The norms, standards, and conventions adopted in dense clusters of partners tend to homogenize the available knowledge. Katz and Allen (1982) describe the Not-Invented-Here syndrome as an example of such homogenization. To increase the diversity of inputs, firms facing the need to innovate reach out and create ties with partners located in more distant clusters. The formation of such spanning ties is likely to create shorter path lengths among firms in the network and increase its global interconnectivity. Shorter path lengths to a wider range of firms ensures a greater diversity of available information, knowledge, or skill sets. Schilling and Phelps (2007) show that networks combining high within-cluster density and short path lengths may significantly enhance the creative output of member firms.

The average number of links that separates each pair of firms in the network also impacts information diffusion. The speed of information transfer as well as the degree of information distortion are directly related to the path length separating two firms. Watts (1999) shows that in networks with shorter average path lengths, the diffusion of information and knowledge occurs more rapidly and with more integrity. Thus, creating ties with partners located in distant parts of a firm's supply network benefits the firm as it can reach more information that is more diverse. At the same time, it reduces the path lengths in the network thus enabling the firm to reach more diverse information quicker and with less risk of distortion. Firms that are more innovative are likely to have such spanning ties already established. The less innovative firms, however, have the knowledge potential of distant regions of their networks largely untapped and therefore would benefit more from such ties. As they introduce such cross-cluster ties into their network, they may reduce the path lengths to a larger extent than the more innovative firms which are likely to already have many of these ties established. Therefore, we hypothesize that:

Hypothesis 3. An increase in a firm's innovative activity leads to a decrease in the average path length in its supply network, and this decrease is larger for firms that are generally less innovative.

The concomitant formation of ties with the partners' partners in the same cluster and more distant cluster-spanning ties may create a change in the structure of the entire network making its clusters more interconnected globally as firms are able to reach one another through relatively shorter paths. The new within-cluster ties will keep the network clustering at the pre-innovation level but now they will work to facilitate information and knowledge exchange between organizations located in the same cluster. In contrast, the new cluster-spanning ties provide efficient access to nonredundant information and novel resources that are typically unavailable through within-cluster ties (Burt 2005). As firms engage in a broader search for information and knowledge derived from otherwise disconnected groups of actors, these otherwise risky and uncertain ties spanning distant clusters will endure and the network will become more small-worldly. A small-world network combines a relatively high degree of clustering with relatively short path lengths: any two actors in such network are connected by a surprisingly small number of intermediaries.

The incentives to pursue cross-cluster ties are always significant for highly innovative firms, whose competitive advantage rests on the ability to continuously access and recombine diverse information, knowledge, and other resources. To survive, such firms must be connected to clusters containing unique knowledge via distant ties enabling effective knowledge transmission. In general, their networks are more small-worldly than those of less innovative firms. Thus, we expect the formation of new ties will change the small-worldliness of less innovative firms to a larger extent as they move into exploration mode. More formally:

Hypothesis 4. An increase in a firm's innovative activity leads to an increase in the small world coefficient of its supply network, and this increase is larger for firms that are generally less innovative.

Empirical setting and sample

We test our hypotheses in the context of large-scale, global supply networks. In such networks, the nodes are organizations engaged in industrial production and distribution of goods and services. The links are the buyer-supplier relationships among these organizations. Every organization in such networks has direct suppliers or buyers. These immediate partners have their suppliers who, in turn, procure from their own suppliers. In this regard, supply networks interconnect firms with multiple tiers of suppliers. The structural and relational interactions among the firms form dyadic, triadic and more complex configurations which jointly constitute the global network structure. Many global companies are embedded in supply networks connecting several tiers consisting of thousands of firms in various industries. Such networks include not only manufacturers of physical products but also firms playing vital support role in the transportation, storage, and transformation of these products as well as firms providing the necessary financial, equipment maintenance, and other services (Carter et al., 2015).

Supply networks are directed networks as the product or service is transferred from suppliers to their buyers. Therefore, in this study we represent them as directed graphs centered on a firm of interest, the focal firm. All supplier firms in these graphs are located at a certain distance from the focal firm. The shortest distance from the focal firm to each direct or indirect supplier represents the supplier's tier. The path length between the focal firm and its immediate, Tier-1 suppliers is equal to one. The path length between the focal firm and the suppliers of its immediate

suppliers is equal to two. The Tier-1 suppliers and connections among them constitute the focal firm's ego network. Firms located in Tier 2 are direct suppliers of Tier-1 firms, and firms located in Tier 3 are these suppliers' suppliers.

To test our hypotheses, we selected 45 firms with vastly global supply networks and operating arena. These firms are in industries where suppliers can become sources of technology, product, or process innovations. The industries include heavy machinery, automobile and aircraft manufacturing, electronics, medical device and equipment production as well as food and consumer goods. Such industries are interesting because they often experience market unpredictability and put a greater pressure on member firms to collaborate with partners and use the flow of information and knowledge in their supply networks to innovate.

The period of our interest is 30 quarters from April (Quarter 2) 2003 to September (Quarter 3) 2010. This period is interesting because it includes both the boom and bust cycles and may include a range of innovative behaviors.

Using the patent data from the United States Patent and Trademark Office (USPTO), we divided the 45 firms in our sample into three categories based on the count of patents each firm applied for in the period under investigation. We labeled the bottom 15 firms by patent applications count as Type 1 firms. They are the least innovative in our sample. We further labeled the middle 15 firms by patent applications count as Type 2 firms. They are more innovative than Type 1 firms but less innovative than Type 1 firms, the top 15 firms by patent application count. According to Bellamy et al. (2014) logic, inventions can be used to track back a firm's knowledge creation activity. Inventions instantiate the accumulation of knowledge used to generate novel solutions from a given set of resources.

We obtained data on buyer-supplier relationships of the 45 firms in our sample from the FactSet Revere database. The FactSet Revere database provides an extensive coverage of buyer-supplier links for a period from April 2003 to present. The unit of observation in the FactSet Revere database is a buyer-supplier link between two firms. FactSet Revere collects information on firms' supplier and customer relationships from multiple sources. First, it captures supplier-customer relationships reported by firms in accordance with Regulation SFAS 131 which requires firms to identify customers accounting for 10 or more percent of their sales. Further, FactSet Revere complements this information with additional data from SEC 10-K filings, corporate websites, press releases, investor presentations, analyst reports, executive interviews, and other sources.

Variables and dataset construction

Using FactSet Revere data, we identified the entire set of buyer-supplier ties in the vicinities of each of the 45 firms in our sample. The 45 vicinities were bounded at Tier 5. The set includes both vertical (cross-tier) and horizontal (within-tier) buyer-supplier ties. We further use this set to construct a directed binary adjacency matrix A_t reflecting the recorded ties in quarter t, where t=1, 2…30, representing the 30 quarters in the period under investigation. In our directed binary adjacency matrix A_t, the entry in each cell a_{ijt} is one if firm i is a supplier of firm j in quarter t, and zero otherwise. Our multi-step analytical procedure is rooted in graph theory and matrix algebra.

Step 1: Using the adjacency matrix A_t we estimated the following properties for each of the 45 networks in each quarter in the period under investigation. All variables were estimated using MATLAB.

a.) *Network density.* We operationalize network density as the ratio of ties present in the network to the number of ties possible. We estimate density in each quarter using the following formula:

$$Density_t = \frac{2T_t}{n_t(n_t - 1)} ,$$

where T_t is the number of ties and n_t is the number of organizations in the network in quarter t.

b.) *The directed characteristic path length* for each network was calculated using the following formula:

$$\mathrm{L}_t = \frac{1}{n} \sum_{i \in N} \frac{\sum_{j \in N, j \neq i} d_{ijt}}{n-1} ,$$

where:

N is the set of all organizations in the network;

n is the number of organizations in the network;

d_{ijt} is the shortest directed path from organization i to organization j in quarter t.

c.) *Small World Coefficient.* Following Kogut and Walker (2001) and Baum et al. (2003), we define a small-world network as one having a much larger clustering coefficient than the random network of the same size ($C_{actual} > C_{random}$) , and a characteristic path length approximately equal to that of the random graph of the same size ($L_{actual} \sim L_{random}$). Using this definition, we calculated the small world coefficient for each network using the random network baseline method. To obtain a random network baseline, we randomized the entries of the adjacency matrices representing the connectivity of each of the actual networks in our sample and calculated the clustering coefficient and characteristic path length of the obtained random network. This procedure was repeated 10 times for each quarter of the period under investigation, after which we calculated the average clustering coefficient and characteristic path length of the 10 random

networks. Then we calculated the clustering coefficient and characteristic path length of each of the real network in each quarter. Finally, the small world coefficient for each network at quarter t was obtained using the following formula:

$$\text{Small World Coefficient} = (C_{actual}/C_{random})/(L_{actual}/L_{random}).$$

The directed clustering coefficients for actual and random networks were calculated using Fagiolo (2007) formula:

$$C_t = \frac{1}{n} \sum_{i \in N} \frac{\frac{1}{2}\sum_{j,h \in N}(a_{ijt} + a_{jit})(a_{iht} + a_{hit})(a_{jht} + a_{hjt})}{(k_{it}^{out} + k_{it}^{in})(k_{it}^{out} + k_{it}^{in} - 1) - 2\sum_{j \in N} a_{ijt} a_{jit}},$$

where:

N is the set of all organizations in the network;

a_{ijt} is the status of a buyer-supplier link between organization *i* and *j*: a_{ijt} = 1 when organization *i* is a supplier of *j* in quarter *t* and zero otherwise;

k_{it}^{out} is the out-degree of organization *i* in quarter *t*, indicating the number of its buyers;

k_{it}^{in} is the in-degree of organization *i* in quarter *t*, indicating the number of its suppliers.

The directed characteristic path lengths for actual and random networks were calculated using the formula described in part b above.

Step 2: Based on the results of Step 1, we constructed a separate matrix for each of our three categories of firms. As each category consists of 15 firms, we obtained a separate 30x15 matrix for each network property in each category.

Step 3: Using matrices obtained in Step 2, we calculated the change in each network property ΔX^i from quarter to quarter during the period under investigation:

$$X_{t+1}^i - X_t^i = \Delta X^i$$

where *X* is either network size, density, characteristic path length, or small world coefficient and *i* is either Type 1, Type 2 or Type 3 category.

Step 4: In this step, we calculated the mean of each network property over the period of 30 quarters:

$$< X^i >_t = \frac{\sum_{t=1}^{30} X_t^i}{30}$$

and then normalized ΔX^i by dividing it by the mean property:

$$\widetilde{\boldsymbol{X}} = \frac{\Delta X^i}{< X^i >_t}$$

Step 5: In this step, we identified quarters in which firms in our sample moved from exploitation mode to exploration mode. We identified these quarters based on Mudambi and Swift (2014) finding that changes in R&D expenditures away from a firm's historic trend indicate transitions between exploitation mode and exploratory innovation mode. To identify these periods, we first obtained data on each firm's quarterly R&D expenditures and sales from Compustat. Then we normalized R&D expenditure values by dividing them by sales. To get the historic trend, we used the smoothing spline. Quarters in which the ratio of R&D expenditures to sales was above the historic trend obtained using smoothing spline were periods when firms started exploratory innovation. Figures 4-6 illustrate the results for Type 1-3 firms respectively.

= Insert Figure 4=
= Insert Figure 5=
= Insert Figure 6=

Further, for each of the three categories of firms we constructed innovation period matrices using the following rule:

$$\begin{cases} innovation = 1 \; if \; \left(\frac{R\&D}{Sales}\right)_t > \left(\frac{R\&D}{Sales}\right)_{fit} \\ innovation = 0 \; otherwise \end{cases}$$

Thus, for each category of firms we obtained a 30x15 innovation period matrix **I** containing zeros and ones.

Step 6: In this step, we multiplied matrices $\tilde{\boldsymbol{X}}$ and $\boldsymbol{I}$ and analyzed the distribution of the nonzero entries in the resultant matrices.

These six steps allowed us to measure the changes in network properties in quarters immediately following the start of an exploratory innovation period.

Results

Our main analytical objective in this research is to compare the changes in the structural properties of supply network of firms with different levels of innovativeness as they unfold an innovation project. To achieve this objective, we measure these changes and compare the distributions of their values in each of the three categories of firms. Comparing the distributions allows to identify a bias toward decreasing or increasing a property among firms as they begin an exploratory innovation. Figures 7 and 8 provide visual representations of the dynamics of the changes in the characteristic path length and density in the supply networks of Type 1 (least innovative) firms. Figures 9 and 10 do so for Type 2 (mid-innovative) firms and Figures 11 and 12 provide the representations for Type 3 (most innovative) firms in our sample. These are descriptive representations for the dynamics occurring as a result of an innovation effort.

= Insert Figures 7 – 12 =

Our Hypothesis 1 predicts that an increase in a firm's innovative activity leads to an increase in the size of its supply network, and this increase is larger for firms that are generally less innovative. The distributions of the changes in network size for the three types of firms in our sample are shown in Figure 13. We observe a bias toward increasing the network size among Type

1 (least innovative firms). The mean increase for this category is 1.3%. We also observe a bias toward decreasing the network size among Type 2 (mid-innovative firms): the mean decrease is 1.8%. Type 3 (most innovative) firms do not display a bias. Their mean increase is, however, 0.8%. We used t-test to examine whether the differences in mean changes of network size among these categories are significant. The results of the t-test at 10%-confidence level suggest a significant difference between Type 2 and Type 3 firms ($p = 0.048$). However, the direction of changes is opposite to what Hypothesis 1 predicts. The differences in mean changes of network size between Type 1 and Type 3 firms as well as between Type 1 and Type 2 firms are not significant ($p = 0.146$ and 0.821, respectively). Therefore, our results do not support Hypothesis 1.

=Insert Figure 13=

Hypothesis 2 predicts that an increase in a firm's innovative activity leads to an increase in the density of its supply network, and this increase is larger for firms that are generally less innovative. The distributions of the changes in network density for the three types of firms in our sample are shown in Figure 14. We observe a bias toward increasing the network density among Type 2 firms. At the same time, we observe a decrease in network density among Type 1 and Type 3 firms. The mean increase for Type 2 firms is 1.7%. The mean decrease among Type 1 and Type 3 firms is 3.9% and 1.8% respectively. The t-test results suggest that the difference in means between Type 1 and Type 2 firms is significant at 10%-confidence level ($p=0.064$). The difference in means between Type 2 and Type 3 firms is also significant at 10%-confidence level ($p=0.068$). The difference in means between Type 1 and Type 3 firms is not significant ($p=0.35$). Overall, these results provide a partial support for Hypothesis 2. In many cases, the network density increases and it increases more for relatively less innovative firms.

=Insert Figure 14=

Hypothesis 3 predicts that an increase in a firm's innovative activity leads to a decrease in the characteristic path length in its supply network, and this decrease is larger for firms that are generally less innovative. The distributions of the changes in the characteristic path length in supply networks of the three types of firms in our sample are shown in Figure 15. We observe a bias toward decreasing the characteristic path length among Type 2 firms and a bias toward an increase of the characteristic path length among Type 1 and Type 3 firms. The results of the t-test suggest that the difference in mean changes of the characteristic path length between Type 1 and Type 2 firms and Type 1 and Type 3 firms are not significant (p= 0.158 and 0.581, respectfully). The difference in means between Type 2 and Type 3 is significant at 10%-confidence level (p=0.072). These results provide a partial support for Hypothesis 3. In many cases, the less innovative firms decrease the characteristic path length in their network to a larger extent than the more innovative firms. This is evident in the difference in the changes of the characteristic path length between Type 2 and Type 3 firms.

=Insert Figure 15=

Our Hypothesis 4 predicts that an increase in a firm's innovative activity leads to an increase in the small world coefficient of its supply network, and this increase is larger for firms that are generally less innovative. The distributions of the changes in the small world coefficient of the three types of supply networks are shown in Figure 16. We observe a greater bias toward increasing the small worldliness of the supply network among Type 2 firms than among Type 3 firms. The results of the t-test suggest that difference in the mean increase of small world coefficient between Type 2 and Type 3 firms is also significant (p=0.045). Type 1 firms, however, display a bias toward decreasing the small world coefficient. The differences in means between

Type 1 and Type 2 and Type 1 and Type 3 firms, however, are not significant (p=0.244 and 0.329) respectively. These results provide support for Hypothesis 4.

=Insert Figure 16=

To gain a deeper understanding of the processes taking place in supply networks as focal firms engage in innovative activities and to explain the surprising findings, we analyzed the dynamics of the population in each of the five tiers of the supply networks under investigation. We observe different patterns in partnering behavior among the three types of firms. Thus, the least innovative (Type 1) firms increase the size of their immediate partners (Figure 17). This suggests that as they unfold an innovative project, they tend to partner with an outsider firm, most likely a specialist able to provide specific expertise. The specialist firm brings into the supply network its own partners and the partners' partners, thus increasing the size of the focal firm's Tier 2 and Tier 3. On average, the distant tiers of Type 1 supply networks, such as Tier 4 and 5 do not change much.

=Insert Figure 17=

Very innovative firms (Type 3) act differently. On average, they do not choose to partner with newcomers. Moreover, they tend to drop some of their direct partners as they embark on an innovative project. Instead, they rely on their distant partners to form new ties, thus increasing the size of Tier 4 and 5. This increases the size of their network. It also slightly increases the characteristic path length because the structural changes occur away from the majority of the existing connections. This explains the surprising finding that the characteristic path in the supply network of Type 3 firms actually increases, on average, as they engage in innovation.

This also provides an additional insight into why the small-world coefficient does not increase much for Type 3 firms. The small-worldliness of a network critically depends on the

presence of long-range ties spanning the tiers. Instead of creating long-range ties themselves, Type 3 firms rely on their indirect partners to do so. This suggests that very innovative firms not only actively engage the structure in which they are embedded but also rely upon their relational embeddedness to motivate distant partners to form additional ties in order to obtain the needed expertise or skill sets.

Discussion

The overall picture painted by our results is one of deliberate innovative behavior shaping the structure of firms' supply networks. We theorize that partnering behaviors of innovative firms differ from those of less innovative firms and that this difference engenders different changes in the structure of their supply networks. Our results trace the changes in supply network size, density, characteristic path length, and small-worldliness to differences in inherent innovativeness of the focal firm.

We observe that when less innovative firms undertake a significant innovation project, they tend to connect with new partners in order to source new knowledge or skill sets. Doing so, they tend to form direct, strong ties which are usually based on legal arrangements, such as nondisclosure agreements or exclusive licensing contracts (Owen-Smith and Powell, 2004). More innovative firms tend to tap the potential of their weak and indirect ties by inducing their suppliers to partner with outsiders in order to source the needed knowledge and resources. Innovative firms, therefore, have supply networks with a wider reach. When faced with a need to mount up innovation efforts, innovative firms turn to sources other than their suppliers or the suppliers of their suppliers. Less innovative firms, in contrast, prefer to keep a narrower knowledge-transmitting reach of their supply networks. This suggests that less innovative firms have the knowledge potential of their supply networks tapped to a much less extent.

Theoretical contributions

Our main point is that the structure of supply networks is influenced by deliberative, agential dynamic stemming from an individual actor. We show that agency is not just constrained by the structure in which the agent is embedded but can also change the structure to make it more conducive for certain desired outcomes. We provide evidence of such dynamic interplay between agency and structure in which one constitutes the other. Our results suggest that firms often act as customers in the market of buyer-supplier partnerships choosing partners based on pressing needs. Thus, innovative firms tend to complement their proximate networks with relational arrangements with more distant partners. Less innovative firms prefer to bring new partners into the bounds of their proximate networks.

Our primary insight is that the variation in firms' innovative agency explains certain changes in the macro-level properties of their supply networks. Thus, we find that supply networks may exhibit different patterns of change depending on how innovative the focal firm is. We relate these differences to the varying agential dispositions of firms. For firms depending on innovation for survival, tapping supply network for knowledge is not an ad hoc activity but a continuous, deliberate and directed process. While all firms are sometimes compelled to innovate in response to unexpected circumstances such as adverse competitive actions, market shifts, or the emergence of new technology, for less innovative firms tapping the knowledge base of their supply networks is the exception rather than the rule. Their innovative agency is different from that of more innovative firms, and therefore engenders different changes in the structure of their supply networks.

Furthermore, we contribute to the growing body of research on the dynamics of supply network evolution. Our results show that supply network structure should not be viewed as a static

determinant of firms' actions, but rather as a dynamic set of opportunities and constraints. An emerging need to innovate may punctuate the equilibrium in a supply network forcing it to undergo structural changes. Our findings also suggest that the complex evolutionary dynamics of supply network structures is likely to be deeply intertwined over both micro and macro levels of analysis. Finally, we contribute to studies of supply networks as complex systems by showing that supply networks and their evolution can be better understood as open systems exhibiting nonlinear patterns of change that cannot be fully explained by existing theoretical accounts.

Managerial insights

Can managers purposefully restructure supply networks to increase their efficiency or change one or several structural properties? Our research provides evidence that supply networks are malleable and can be made more or less fit for innovation diffusion. However, restructuring a complex network is a challenging task. First, because networks are formed for different reasons of individual companies, there is relational inertia and concomitant resistance to changes. Research on supply network dynamics has shown that supply networks evolve in both predictable and unpredictable ways. Second, few firms have adequate data on their supply networks to discern and fill structural gaps. Third, operations management literature provides managers with minimal guidance on how to reorganize supply networks to make them more efficient. Moreover, most extant guidelines assume a static network and ignore network dynamics. In contrast, our research is based on the dynamic nature of supply networks and can offer several important insights for organizing a supply network to accelerate innovation.

First, collecting supply network data is necessary for a firm to tap the true potential of its supply network. Network data will show where the network is fragmented or too clumpy. Further, new organizations can be added to the network to improve its connectivity. For example,

consultants can be placed as an additional bridge between very sparsely connected clusters. This strategy will allow firms to know the resources available across the network, not just within their own cluster. Firms generally tend to rely on partners within their own clusters for information and prefer to avoid dependence on distant partners, because local partners provide advice that is more sensitive to local conditions and norms. However, distant partners are important because they might have more diverse knowledge than close sources.

Most guidance in the operations management literature is limited to working with immediate suppliers. For example, Wagner and Bode (2014) show that integrating suppliers early in the process of new product development enhances the project's success. Our research suggests that supplier engagement should reach out to deeper tiers of suppliers. A strategically placed consulting firm or a new supplier in a certain important cluster may provide the necessary connectivity or become a path around clusters that may dominate or control information diffusion. Modern information technologies may dramatically enhance firms' ability to connect with distant and indirect partners and thus enhance their knowledge of the structure and dynamics of their supply networks. For example, blockchain technology may enable network knowledge and structural awareness to truly go "to scale" and facilitate structural action well beyond the bounds of a firm's proximate network.

Appendix

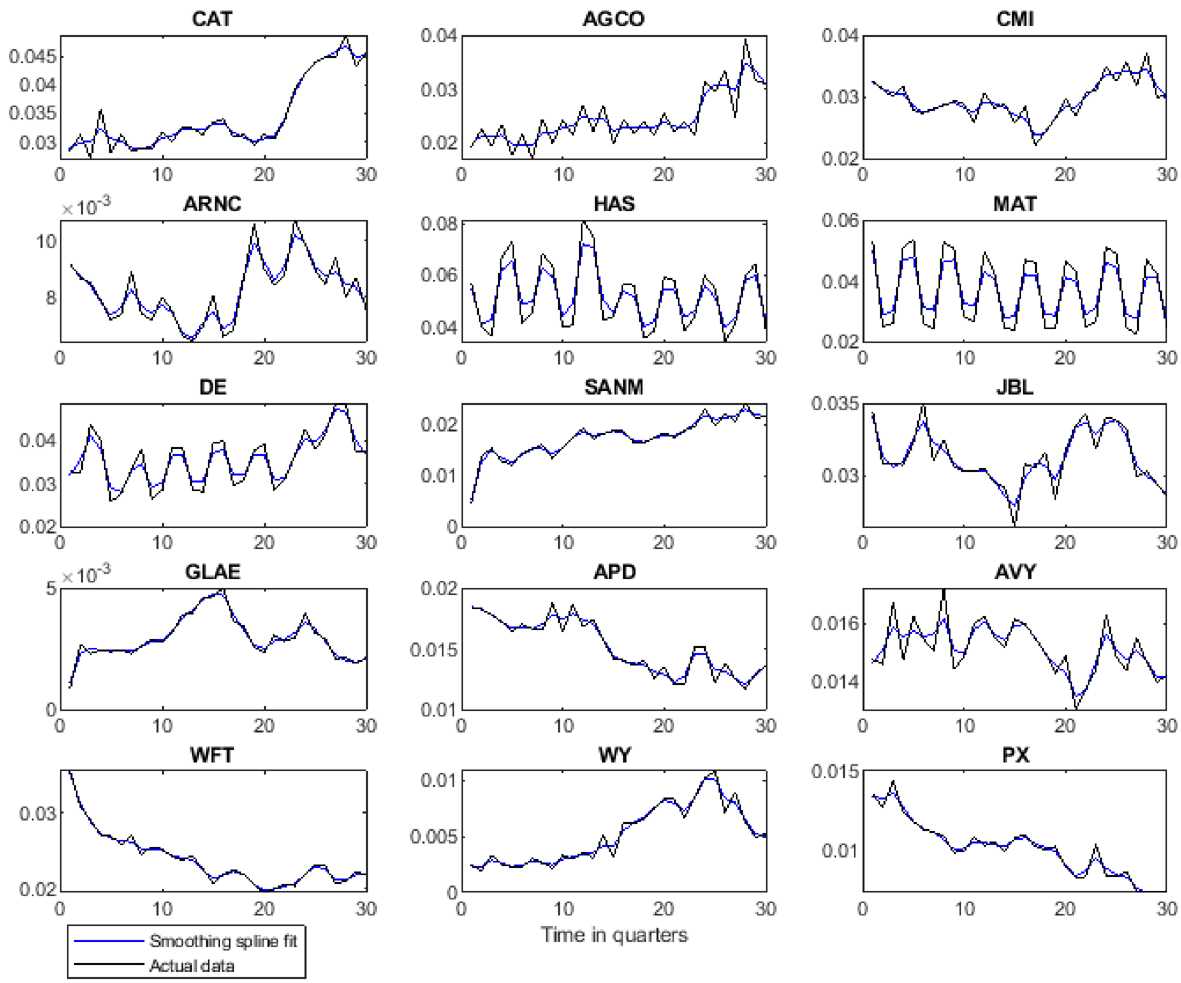

Figure 4. The dynamics of the R&D expenses to sales ratio for Type 1 firms, April 2003 – September 2010.

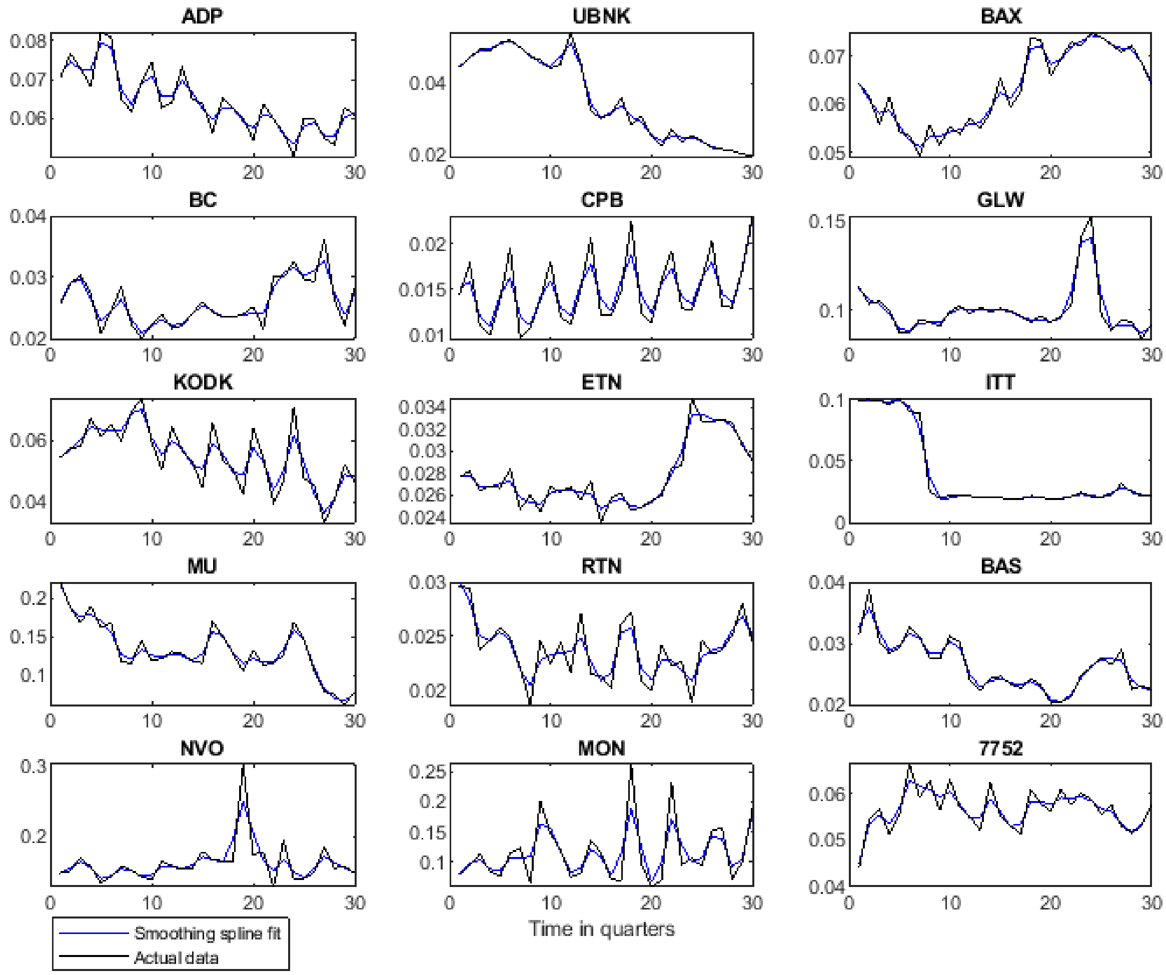

Figure 5. The dynamics of the R&D expenses to sales ratio for Type 2 firms, April 2003 – September 2010.

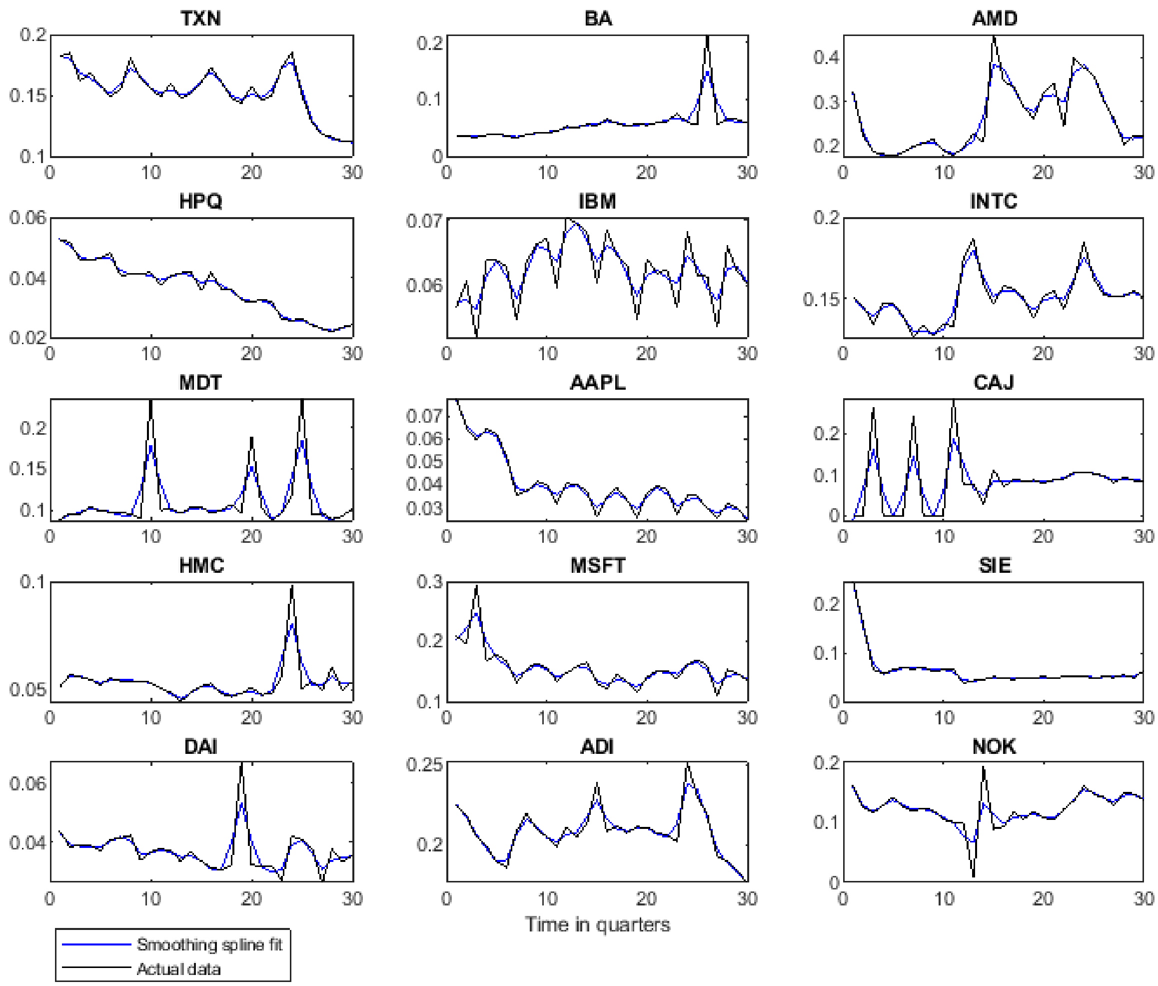

Figure 6. The dynamics of the R&D expenses to sales ratio for Type 3 firms, April 2003 – September 2010.

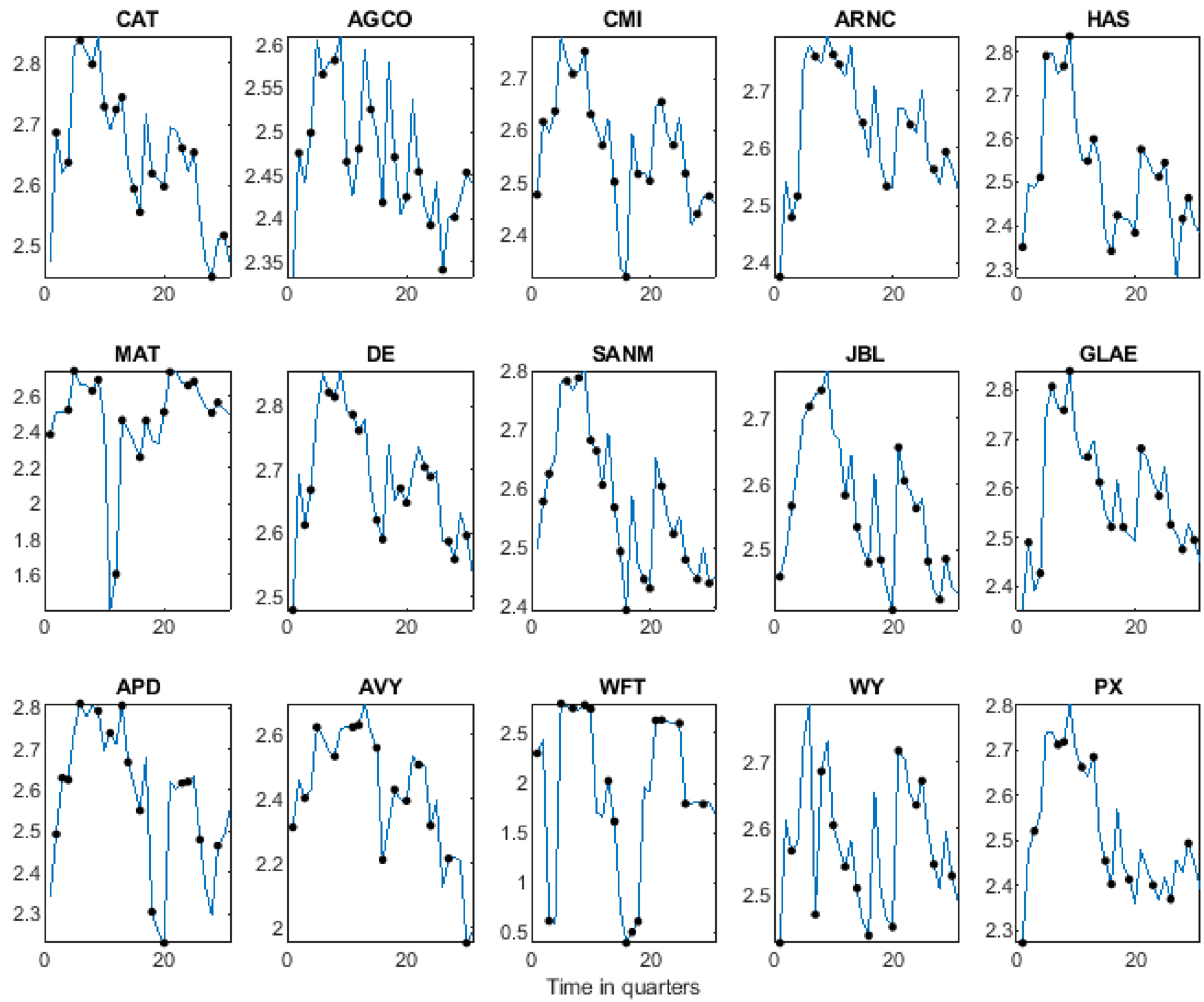

Figure 7. The dynamics of the characteristic path lengths of Type 1 firms' supply networks in April 2003-September 2010 (black dots denote quarters in which compact, significant increases in the ratio of R&D expenses to sales are observed).

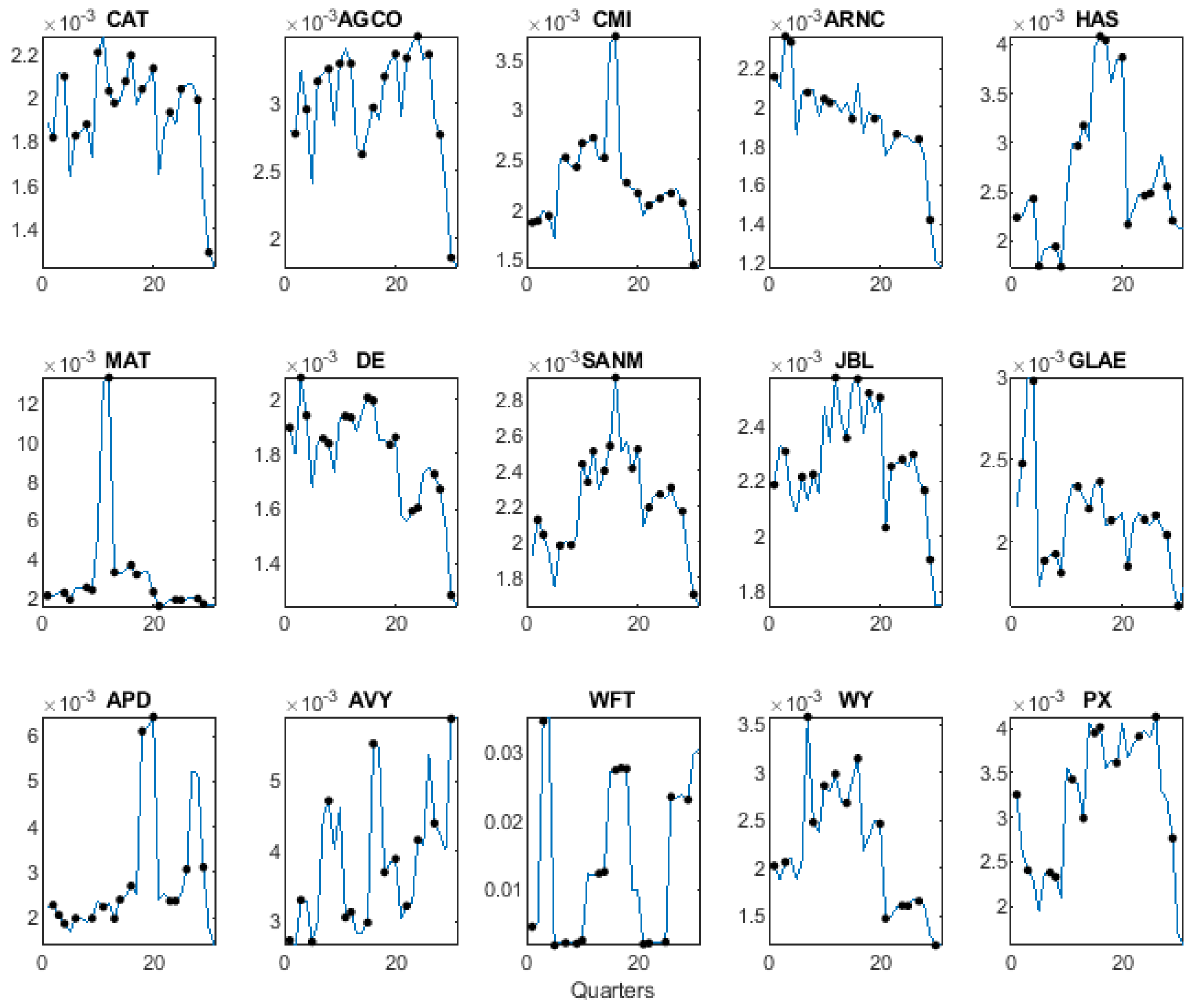

Figure 8. The dynamics of the Type 1 firms' supply network density in April 2003-September 2010 (black dots denote quarters in which compact, significant increases in the ratio of R&D expenses to sales are observed).

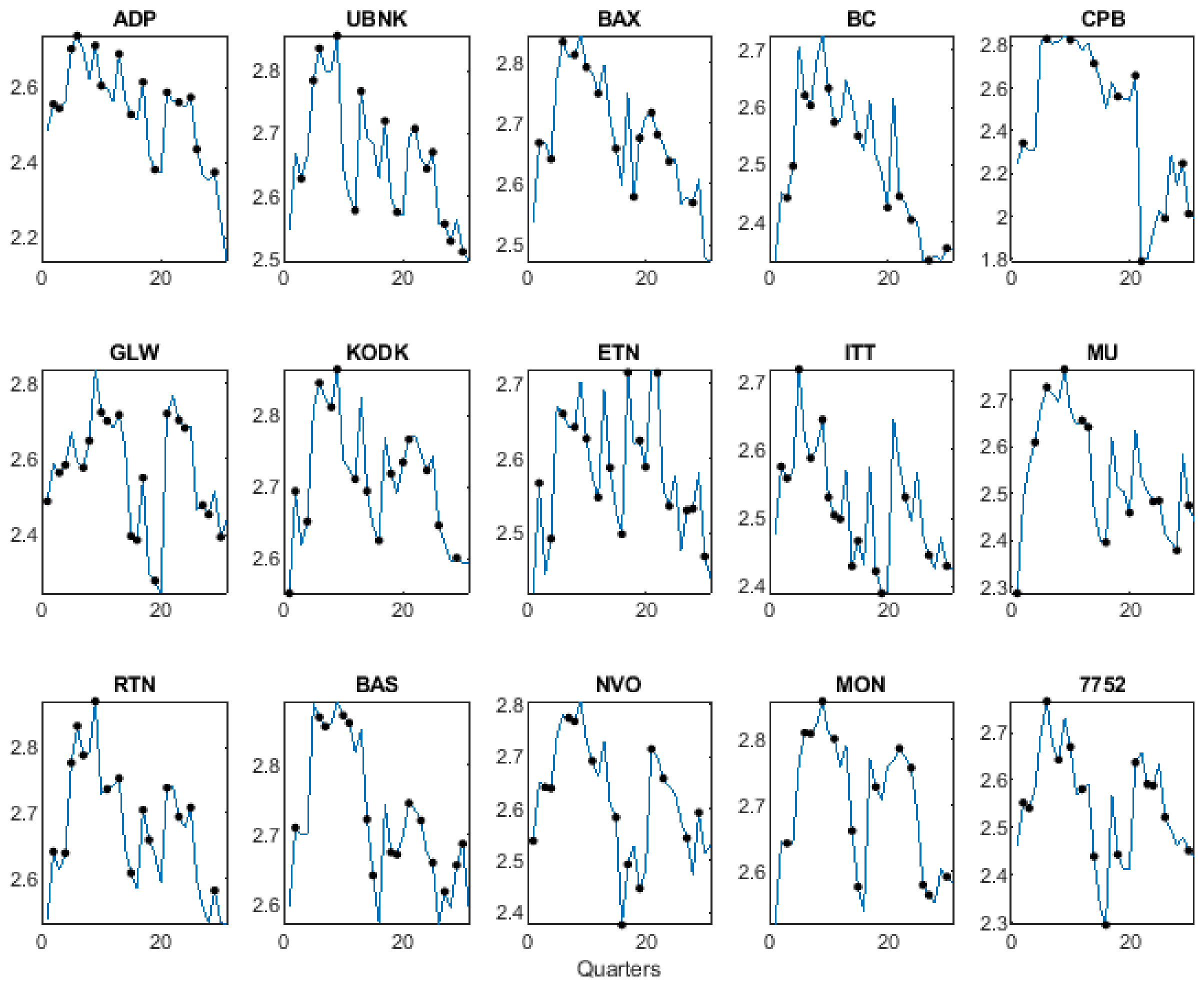

Figure 9. The dynamics of the characteristic path lengths of Type 2 firms' supply networks in April 2003-September 2010 (black dots denote quarters in which compact, significant increases in the ratio of R&D expenses to sales are observed).

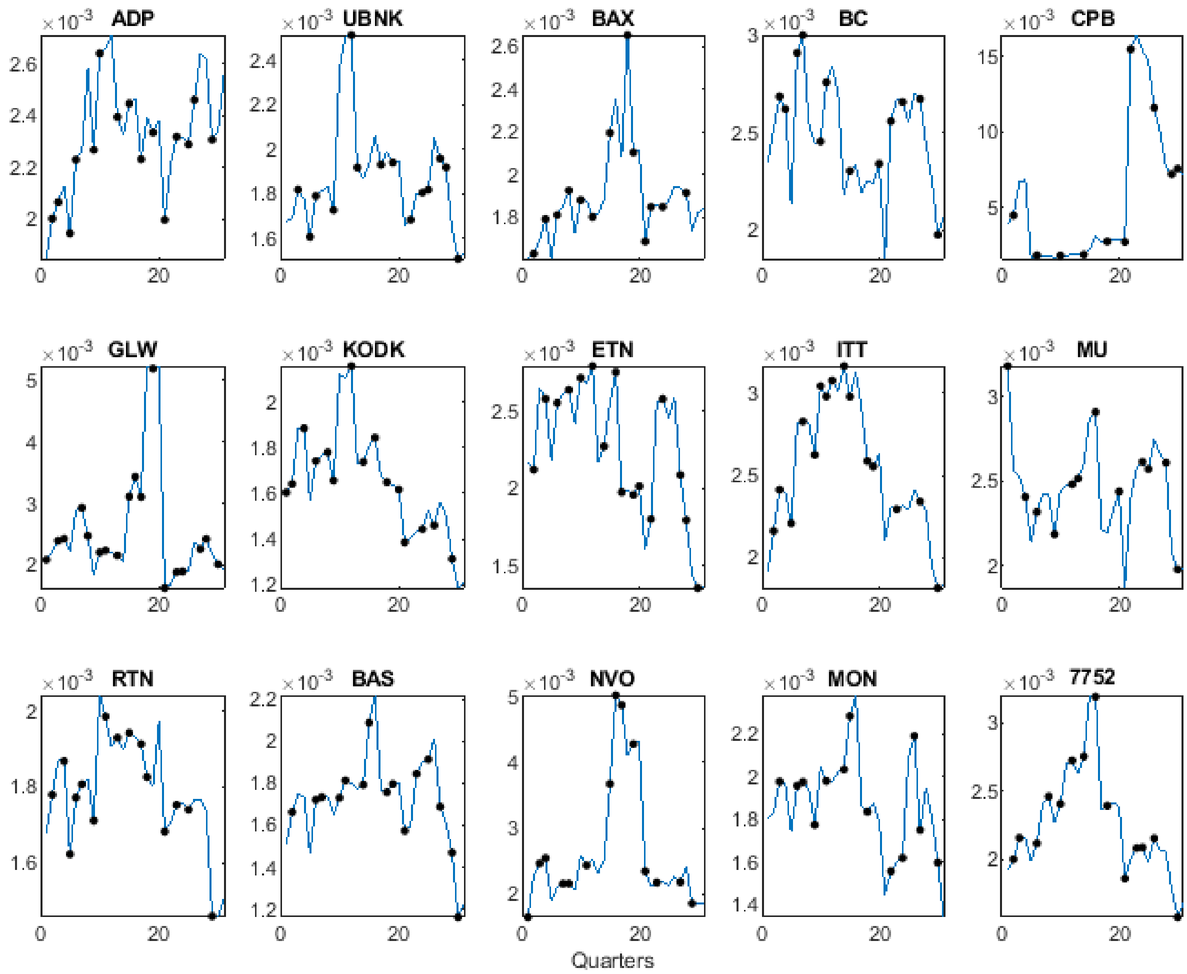

Figure 10. The dynamics of the Type 2 firms' supply network density in April 2003-September 2010 (black dots denote quarters in which compact, significant increases in the ratio of R&D expenses to sales are observed).

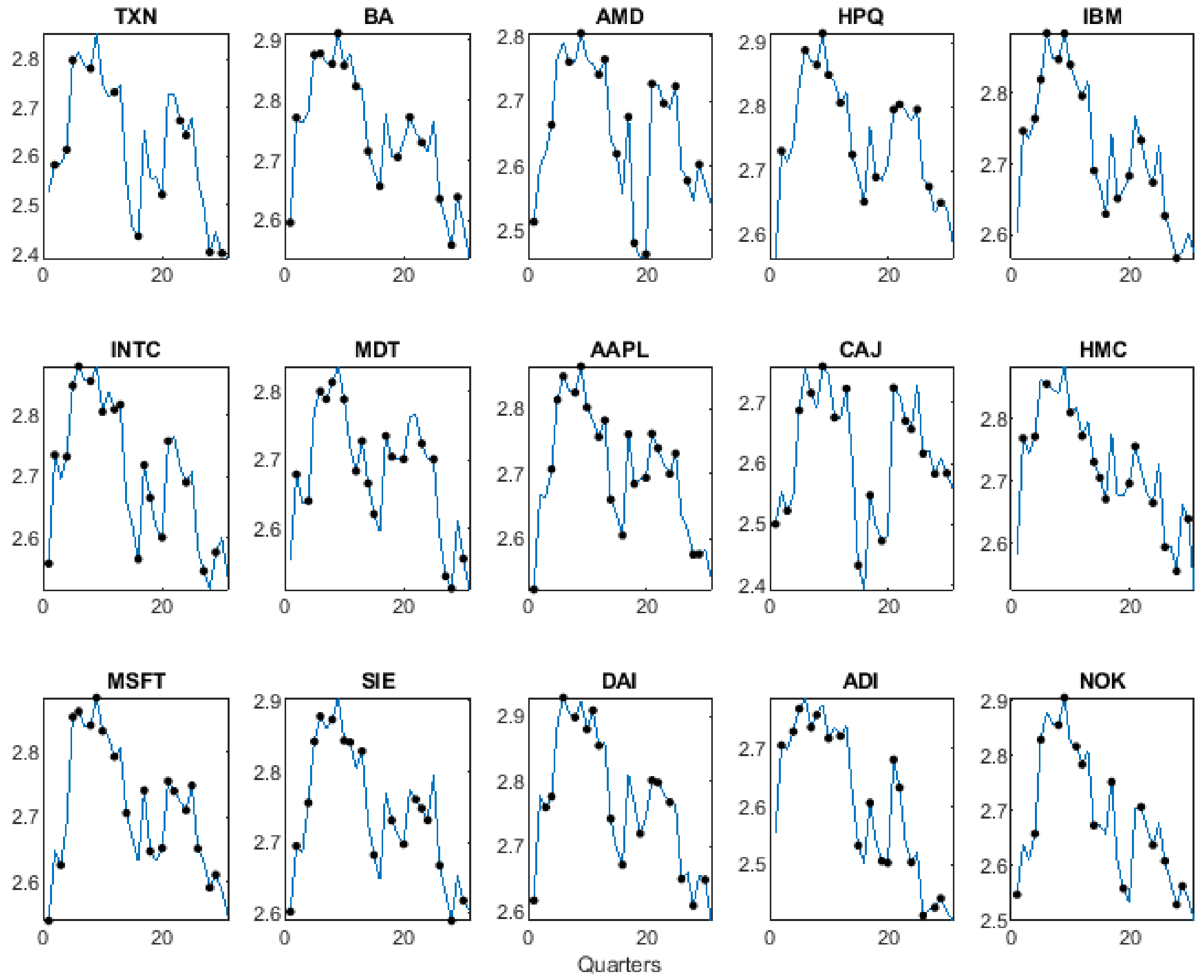

Figure 11. The dynamics of the characteristic path lengths of Type 3 firms' supply networks in April 2003-September 2010 (black dots denote quarters in which compact, significant increases in the ratio of R&D expenses to sales are observed).

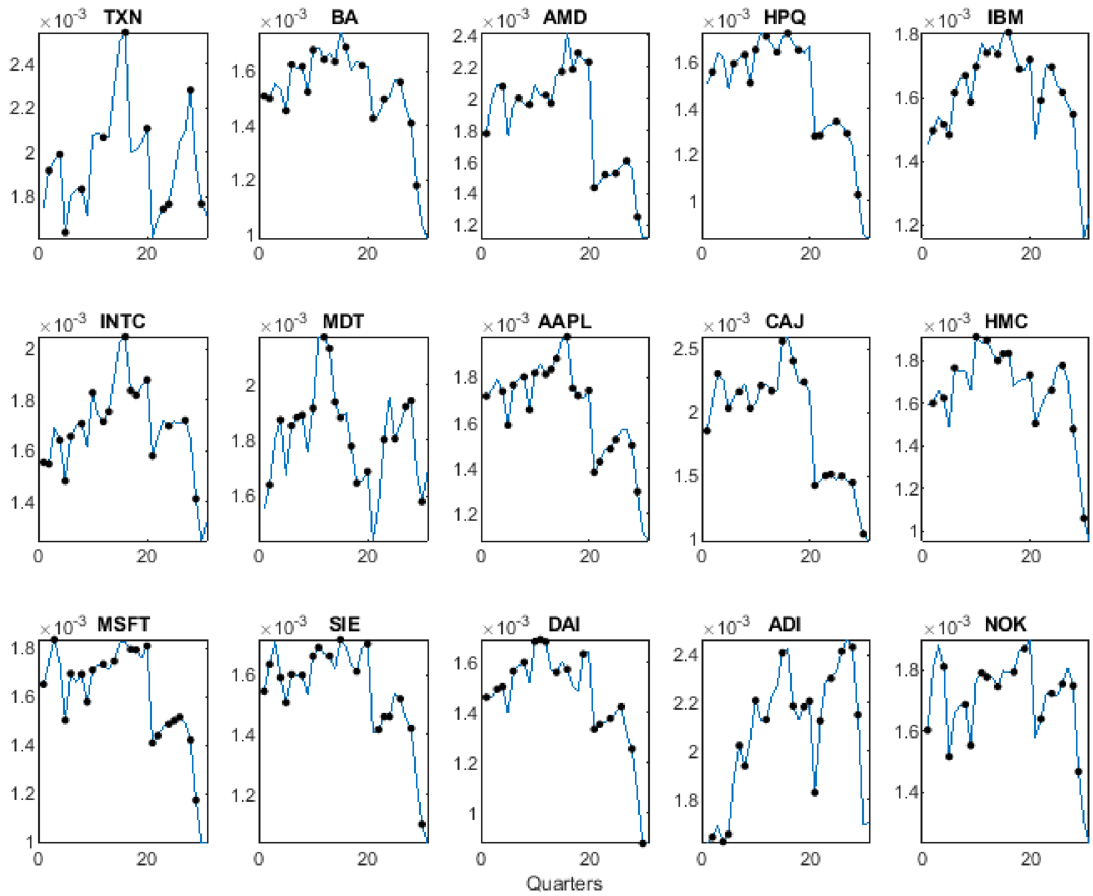

Figure 12. The dynamics of the Type 3 firms' supply network density in April 2003-September 2010 (black dots denote quarters in which compact, significant increases in the ratio of R&D expenses to sales are observed).

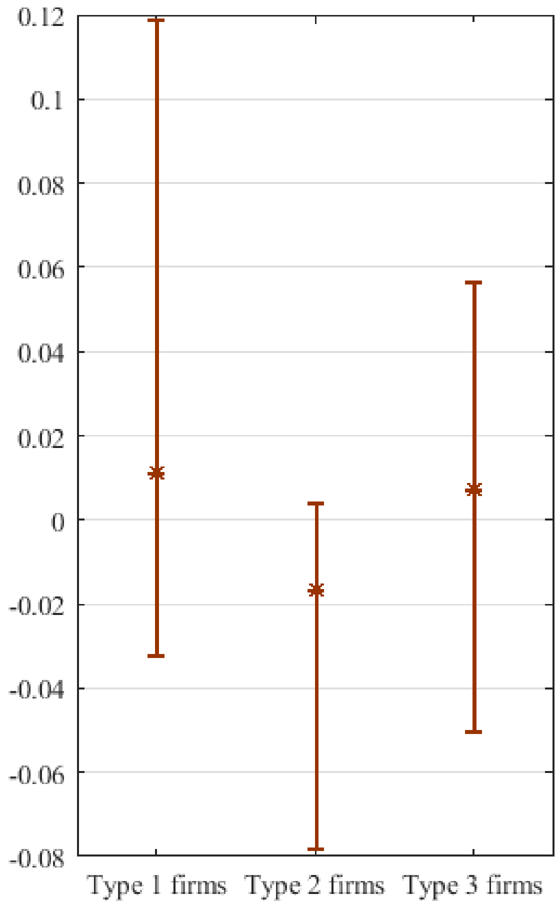

Figure 13. The dynamics of the total number of suppliers in the quarters immediately following compact, significant increases in the ratio of R&D expenses to sales (25^{th} -75^{th} percentile; star denotes the mean).

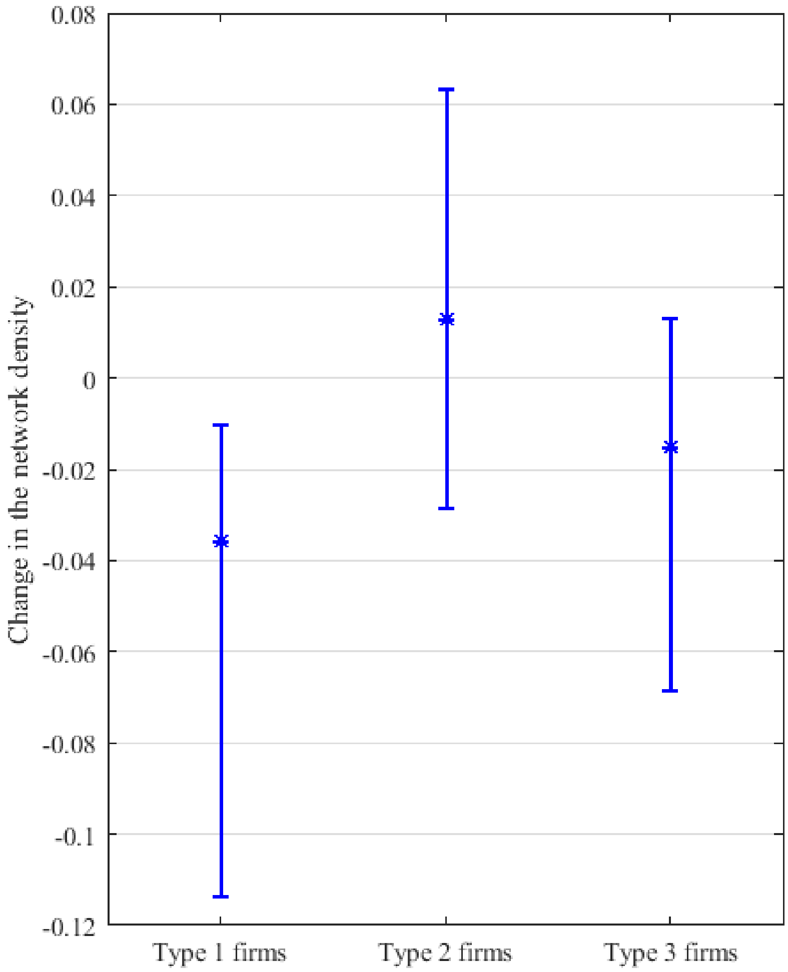

Figure 14. The dynamics of network density in the quarters immediately following compact, significant increases in the ratio of R&D expenses to sales (25^{th} -75^{th} percentile; star denotes the mean).

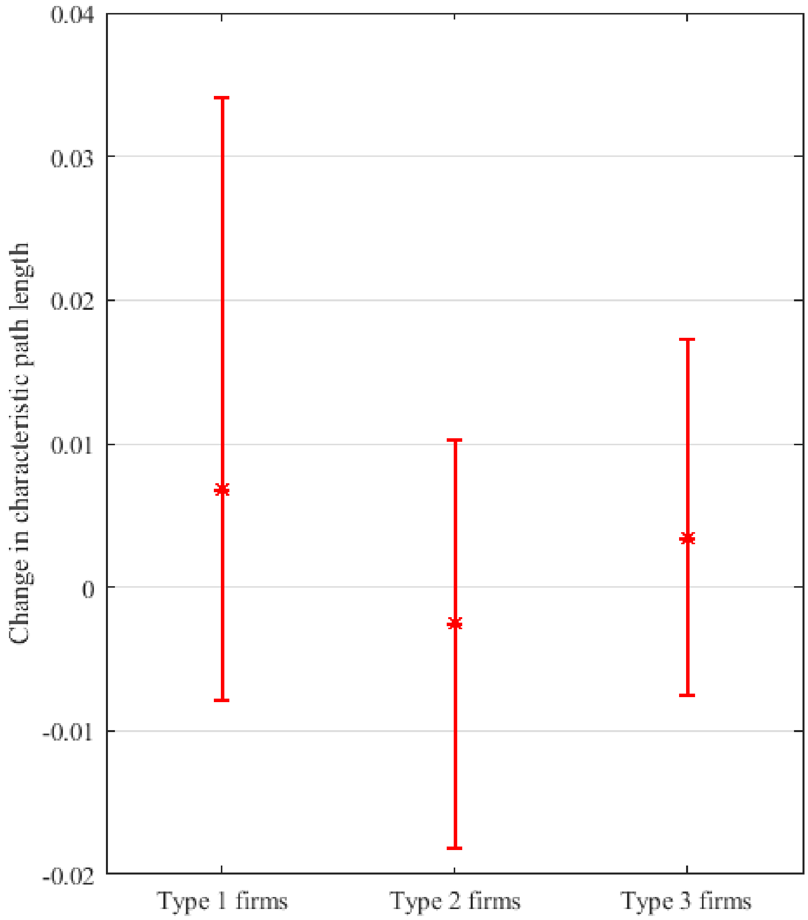

Figure 15. The dynamics of characteristic path length in the quarters immediately following compact, significant increases in the ratio of R&D expenses to sales (25^{th} -75^{th} percentile; star denotes the mean).

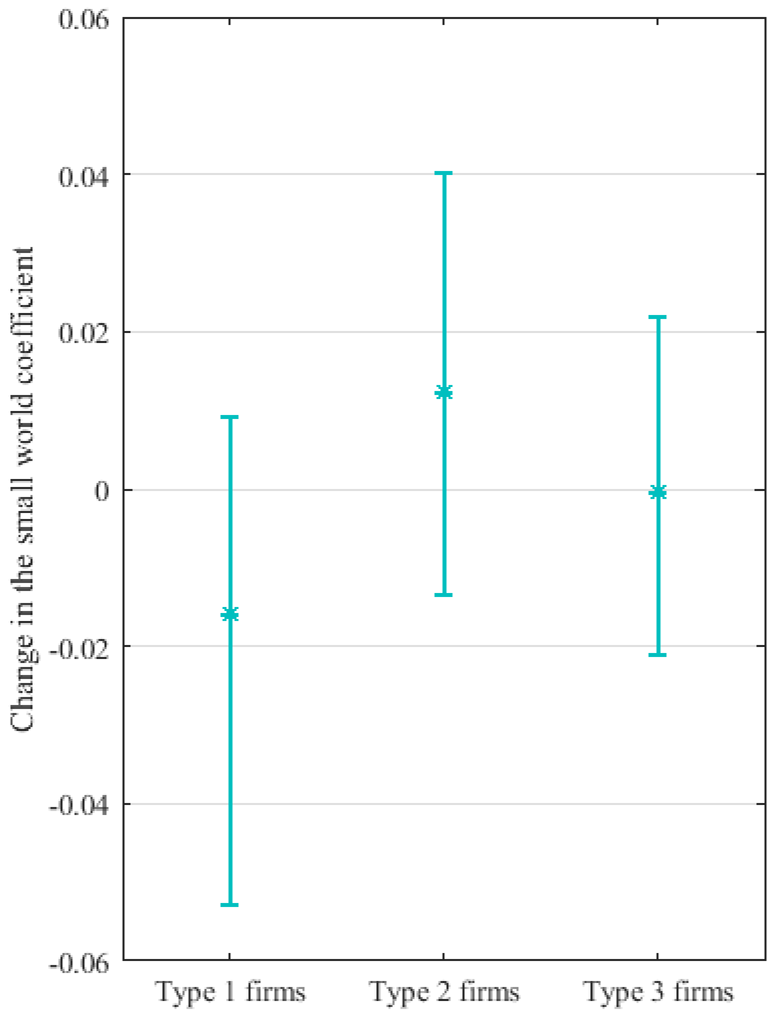

Figure 16. The dynamics of the small world coefficient in the quarters immediately following compact, significant increases in the ratio of R&D expenses to sales (25th -75th percentile; star denotes the mean).

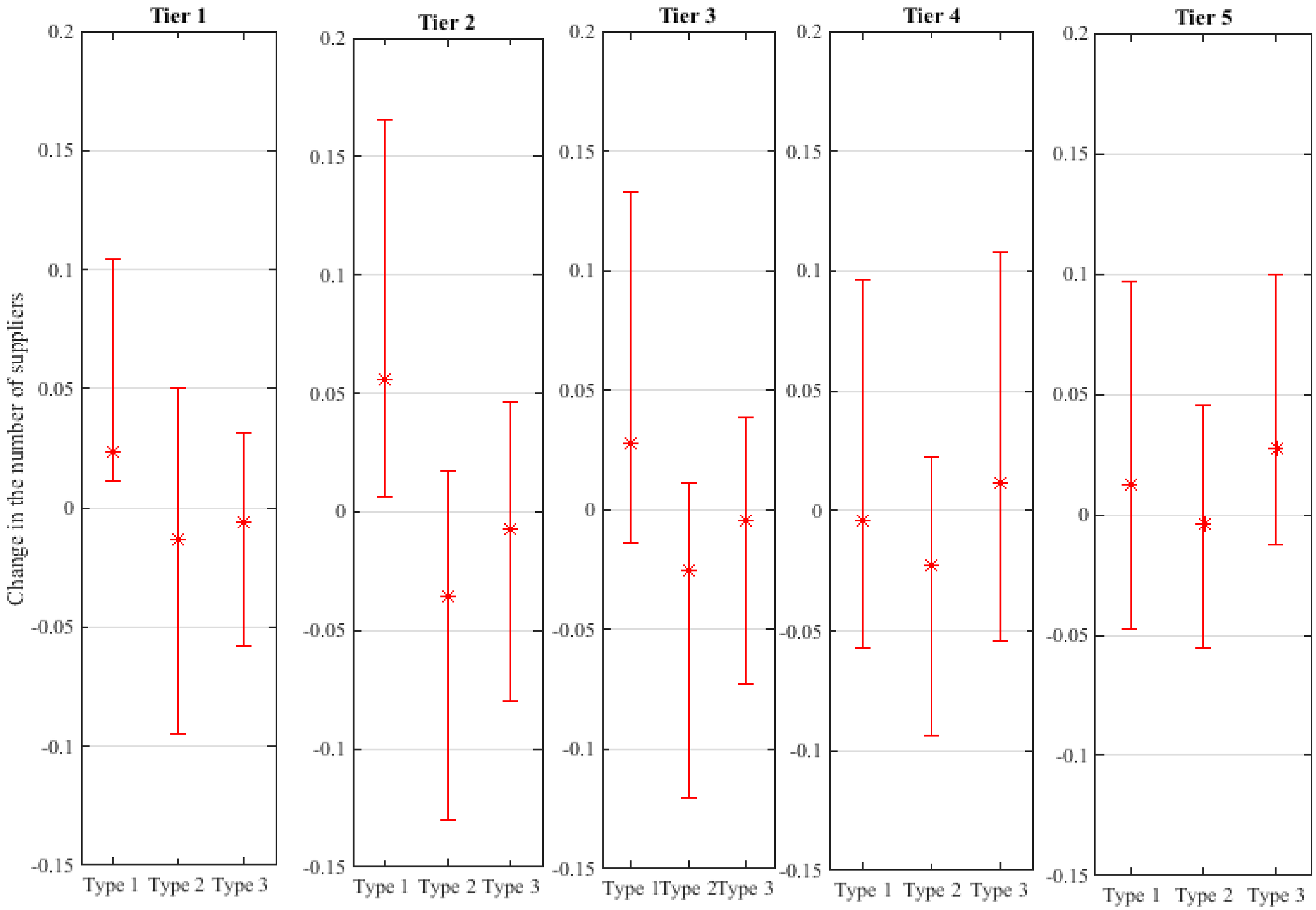

Figure 17. The tierwise dynamics of the number of suppliers in the quarters immediately following compact, significant increases in the ratio of R&D expenses to sales (25^{th} -75^{th} percentile; star denotes the mean).

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CONCLUSION

Networks are becoming increasingly important for economic and social life. Scholars in various disciplines have developed theoretical perspectives of interfirm network formation and evolution as well as provided accounts of the numerous ways in which interfirm networks influence organizational outcomes. This dissertation brings the network perspective to supply chain management research and illustrates some of the ways it can be applied to study various firm actions and phenomena in more depth. Essay 1, for instance, applies network theory to examine some of the effects of interfirm networks on the the outcomes of outside stakeholders such as equity analysts. This method offers a practical insight for analysts: in order to achieve superior forecast accuracy, they must be aware that some features of networks that they study may be too complex for them to perceive accurately.

Furthermore, this dissertation illuminates some of the aspects of the dynamics of supply network evolution. The results show that supply network structure should not be viewed as a static determinant of firms' actions, but rather as a dynamic set of opportunities and constraints. An emerging need to innovate may punctuate the equilibrium in a supply network forcing it to undergo structural changes. The findings also suggest that the complex evolutionary dynamics of supply network structures is likely to be deeply intertwined over both micro and macro levels of analysis. Besides, this dissertation contributes to studies of supply networks as complex systems by showing that supply networks and their evolution can be better understood as open systems exhibiting nonlinear patterns of change that cannot be fully explained by existing theoretical accounts.

The fact that supply networks are malleable is practically important. If networks are malleable, they can be made more or less fit for innovation diffusion. Restructuring a complex network is, of course, a challenging task. First, because networks are formed for different reasons

of individual companies, there is relational inertia and concomitant resistance to changes. Research on supply network dynamics has shown that supply networks evolve in both predictable and unpredictable ways. Second, few firms have adequate data on their supply networks to discern and fill structural gaps. Third, operations management literature provides managers with minimal guidance on how to reorganize supply networks to make them more efficient. Moreover, most extant guidelines assume a static network and ignore network dynamics.

This dissertation provides some remedies to these drawbacks. It offers insights about the ways in which existing structural properties of interfirm networks influence the extent of their transformation. For instance, firms form more new ties and delete more existing ties in response to an increase in partner-specific uncertainty in networks with greater path lengths. This suggests that networks in which partners are, on average, farther away from each other undergo a larger structural change as a result of an increase in endogenous uncertainty. Moreover, the degree of clustering significantly affects the rate of tie deletion and has no effect on tie creation. A higher clustering may indicate a greater degree of solidarity among close partners, which may become a source of collective pressure constraining firms from modifying of their dependence by forming alternative ties and motivating them instead to drop weaker existing ties to redirect resources to accommodate the demands of a major buyer which the cluster views as a common good.

Next, this dissertation aims to contribute to the small literature on the origins of distant ties. The literature on distant ties shows that their formation is motivated by factors other than those triggering the formation of the majority of organizational ties which are local (Rosenkopf and Padula, 2008). The factors leading firms to create distant ties are relatively less known. At the same time, distant ties are fundamental for network change because a handful of such ties can transform the structure of a network turning it into a small-world (Watts and Strogatz, 1998). We

identify a new origin of distant ties. The results of this dissertation results show that such contextually ubiquitous phenomena as an increase in uncertainty specific to a major exchange partner and the concomitant need to balance the dependence may prompt firms to form new distant ties.

This provides managers with important caveats regarding power and its use in interorganizational relations. The literature on organizational power dynamics argues that power is predominantly a structural phenomenon: the existing structure of relationships in a network defines which actor is more powerful. At the same time, a less powerful actor may increase its power relative to a more powerful actor through finding alternatives outside the exchange relationship. The resource dependence logic rests on the assumption that a firm is always motivated to lessen dependence on its present exchange partners. An increase in the uncertainty unique to a more powerful firm may give its managers an impression that its suppliers will necessarily search for alternative partners and start developing new ties if they observe a change in the rhythm of exchange. Such impression may lead the powerful firm to take actions to counter the suppliers' gains in power.

I show that this is not always the case. Firms do not always act on this motivation. They do so when the larger environment is munificent enough to support new tie formation, most new buyer ties are formed in more distant parts of the network. Such ties are usually weaker, more uncertain, and costlier to maintain. They may be short-term, short-lived options. In this light, while such restructuring may be beneficial for the focal firm's suppliers, it is not a serious threat to the focal firm's power. Moreover, these new distant ties make the network more efficient in circulating information and knowledge from more distant parts to the focal firm. In a way, these new distant

ties may even benefit the focal firm through an increased inflow of new ideas and knowledge from other communities in the network.

When the environment's munificence is lower, suppliers actually lower their rates of tie formation, thereby relying on existing ties to cope with the shifts in the rhythm of exchange. These shifts in tie formation emphasize the switch towards mostly heuristic-based decisions accentuating homophilous pairing, engaging old partners, and forming ties with partners of existing partners as major mechanisms of new tie formation. Suppliers prefer the comfort zone and relative certainty of their existing ego-networks to forming ties with unknown partners. In this regard, the structure of the network solidifies the power of the focal firm.