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Supply Network Structure, Visibility, and Risk Diffusion: A Computational Approach*

Rahul C. Basole†
School of Interactive Computing & Tennenbaum Institute, Georgia Institute of Technology, Atlanta, GA 30332, e-mail: basole@gatech.edu

Marcus A. Bellamy
Scheller School of Business & Tennenbaum Institute, Georgia Institute of Technology, Atlanta, GA 30332, e-mail: marcus.bellamy@gatech.edu

ABSTRACT

Understanding and managing supply chain risks is a critical functional competency for today's global enterprises. A lack of this competency can have significant negative outcomes, including costly production and delivery delays, loss of future sales, and a tarnished corporate image. The ability to identify and mitigate risks, however, is complicated as supply chains are becoming increasingly global, complex, and interconnected. Drawing on the complex systems and epidemiology literature, and using a computational modeling and network analysis approach, we examine the impact of global supply network structure on risk diffusion and supply network health and demonstrate the importance of supply network visibility. Our results show a significant association between network structure and both risk diffusion and supply network health. In particular, our results indicate that small-world supply network topologies consistently outperform supply networks with scale-free characteristics. Theoretically, our study contributes to our understanding of risk management and supply networks as complex networked systems using a computational approach. Managerially, our study illustrates how decision makers can benefit from a network analytic approach to develop a more holistic understanding of system-wide risk diffusion and to guide network governance policies for more favorable health level outcomes. The article concludes by highlighting the main findings and discussing possibilities of future research directions.[Submitted: June 14, 2012. Revised: January 20, 2013. Accepted: March 7, 2013.]

Subject Areas: Agent-Based Models, Computational Modeling, Network Structure, Risk Diffusion, Supply Chain Management, Supply Networks, and Visibility.

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The order of authorship is alphabetical, and authors contributed equally to the manuscript.

†Corresponding author.

INTRODUCTION

Today's global supply chains are dynamic, complex systems consisting of a multitude of heterogeneous and autonomous supply chain entities, many of which have conflicting goals and behavior. Global supply chains often exhibit nonlinear, multiscale behavior, where the evolution of behavior and performance is driven by a complex interaction of structure and function. The scope and magnitude of these interactions can cause the poor performance of one or a few suppliers to rapidly propagate into the entire supply chain system, leading to major supply disruptions (Nair & Vidal, 2011) and detrimental performance of other supply chain entities (Hua, Sun, & Xu, 2011). Effective supply chain management (SCM) consequently requires focal firms to develop the capabilities to manage a series of multitier, interconnected relationships between multiple suppliers, manufacturers, assemblers, distributors, and retailers spanning a wide variety of industries. At the same time, firms are faced with the challenge of continuously adapting their strategy to remain relevant and profitable in a highly dynamic business environment.

Conventional SCM strategies often do not account for risks emanating beyond first-tier relationships. However, recent events illustrate the enormous risks associated with neglecting to identify issues at the perspective subtiers that could amplify through the entire system. In the aerospace industry, Boeing's 787 Dreamliner has faced significant delays in production and delivery due to unexpected supply chain issues. Shortcomings stemming from some of the smallest suppliers caused a ripple effect that led to massive delays in production ramp-up and delivery (Tang, Zimmerman, & Nelson, 2009; Hendricks & Singhal, 2011). In the consumer electronics industry, Apple has faced significant product shortages due to supply chain issues with key manufacturing partners (Fink, 2008). Similar issues have plagued the automotive industry (Trkman & McCormack, 2009).

At the same time, there is an increasing spectrum of risks that supply chains are exposed to, especially as businesses are becoming ever more globalized, are subjected to different tax and regulatory regimes, disparate business cultures, and varying levels of economic development, all requiring greater integration and collaboration among supply chain partners. Risks such as poor supplier health, suppliers' distortion of abilities, and conflicting goals and behavior can therefore cause significant supply and inventory disruptions as well as quality and performance issues (Bellamy & Basole, 2013). In order to better identify and manage the risk, complexity, and dynamics driving global supply chain systems, it is necessary to move beyond traditional linear, dyadic views. An interdisciplinary approach is needed to understand, prepare for, and manage how supply networks behave and evolve (Pathak, Day, Sawaya, & Kristal, 2007).

Adopting a complex systems lens has been shown to be particularly useful in characterizing, understanding, and managing today's global supply networks (Choi, Dooley, & Rungtusanatham, 2001; Pathak, Day et al., 2007). Grounded in principles from network theory (Borgatti & Li, 2009; Kim, Choi, Yan, & Dooley, 2011) as well as complexity, evolutionary economic, and systems theory (Surana, Kumara, Greaves, & Raghavan, 2005), complex systems models of supply networks assist managers in identifying linkages between patterns of behavior of individual entities in the supply network, the level of interconnectivity between these entities, and the overall supply network evolution and performance. These dynamic models are frequently instantiated through agent-based (AB) and computational modeling approaches to examine real-world supply network structure and dynamics, thereby accounting for complex cause and effect, nonlinearity, entity heterogeneity, and supply network phenomena over an extended time horizon (Martinez, Fouletier, Park, & Favrel, 2001; Thadakamaila, Raghavan, Kumara, & Albert, 2004; Nair & Vidal, 2011). The advantage of these models is that they can be designed to capture phenomena at multiple enterprise levels (Basole, Rouse, McGinnis, Bodner, & Kessler, 2011), such as firm-level (e.g., financial and operational health), network-level (e.g., density, centralization, clustering, and complexity), and sustainability-based metrics (e.g., robustness, responsiveness, and resilience) over time (Pathak, Day et al., 2007). Given the proprietary and sensitive nature of divulging supply network data, these computational models can also serve as a valuable proxy in understanding possible risk diffusion patterns using complex designs that mimic real-world supply networks. Risk diffusion refers to the propagation of both endogenous or exogenous risks from one organization to other organizations through the supply network (Pai, Kallepalli, Caudill, & Zhou, 2003; Wu, Blackhurst, & O'Grady, 2007; Narasimhan & Talluri, 2009). For instance, if the supplier has an operational failure that leads to a delay in part availability, this can negatively affect the focal firm's (e.g., buyer's) performance. The risk from the supplier is then said to have propagated to impact the focal firm.

This research combines complex systems, epidemiology, and AB modeling approaches to model and analyze risk diffusion in global supply networks. The two objectives of this study are to: (i) examine the impact of network structure on risk diffusion and ultimately supply network health (e.g., system performance) and (ii) explore how structural visibility into lower tiers of supply networks can reduce and potentially mitigate cascading risks. We pursue these objectives using a computational modeling and network analysis approach.

The remainder of this article is organized as follows. First, we discuss the theoretical foundations and hypotheses for this research. Next, we describe our research design and methodology. Following that, we present the analysis, results, and implications of our findings. Finally, we summarize our main conclusions and highlight promising avenues for future research.

THEORETICAL FOUNDATION

Supply Chains as Complex Networks

Risk management of large-scale supply chain systems requires a macroscopic approach that captures and portrays the complexity inherent in these systems (Choi & Hong, 2002; Nair, Narasimhan, & Choi, 2009). The emerging field of "network science" offers a promising interdisciplinary lens to study supply chains as complex networked systems, in which nodes represent supply chain entities (e.g., firms) and links depict relationships between these entities (Bellamy & Basole, 2013). A complex network lens is particularly applicable as supply networks are growing in scale, interconnectedness, geographic dispersion, and nonlinear behavior (Pathak, Day et al., 2007). The complex network lens enables researchers to describe supply networks with well-established structural properties (e.g., degree, path length, clustering) based on a series of unifying principles and statistical distributions (e.g., Poisson, power-law) from mathematical graph theory (Hasan & Ukkusuri, 2011). It also allows researchers to include attributes unique to each entity in the system while also incorporating the complex web of interactions that define the overall network structure as well as each entity's level of power, control, and embeddedness in the network (Bellamy & Basole, 2013). This is in contrast to more common quantitative supply chain analysis approaches on firm competition and cooperation, which draw on optimization, game theory, and microeconomics, but suffer from limitations in failing to account for nonlinear dynamics, scaling-up to multifirm systems, as well as firm interactions, heterogeneity, and autonomy (Ge, Zhang, Lü, Zhou, & Xi, 2011).

A complex network analysis approach also allows for a more holistic assessment of factors that cause supply disruptions and how poor (strong) supplier performance propagates through the supply network over time. For example, this approach can be used to investigate how the structure and interactions between supply network entities affect the propagation of delays, shortages, information, and technological innovation throughout the entire supply network. Structural characteristics of supply networks unquestionably have a significant influence on the performance and health of firms (Bellamy & Basole, 2013). It should be noted that while there is a symbiotic relationship between structure and behavior, the focus of this study is exclusively on the impact of supply network structure on risk diffusion.

Risk Diffusion in Supply Networks

Epidemiological and evolutionary biology models present a formidable foundation for the study of risk diffusion in complex networks (Eubank et al., 2004). Indeed, previous research has applied epidemiological models to understand risk diffusion in a wide range of complex network contexts. Examples include the transmission of infectious diseases through communities in biological systems, the global spread of Internet-based computer viruses, and power grid failures in electricity systems (Martínez-Jaramillo, Pérez, Embriz, & Dey, 2010; Hasan & Ukkusuri, 2011). The finance literature is particularly rich in using epidemiological models to study the diffusion of risks, as exemplified by research on contagion stemming from unexpected shocks in complex financial networks (Gai & Kapadia, 2010), bankruptcy propagation in large-scale production networks (Battiston, Delli Gatti, Gallegati, Greenwald, & Stiglitz, 2007) and supply chains (Hertzel, Li, Officer, & Rodgers, 2008), and impact of different forms of systemic risk on financial collapse (stability) of the banking system (Gai & Kapadia, 2010).

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

As risks spread through a supply network and infect firms, the health of a supply network deteriorates. Similar to the biological theory of an ecosystem, the health of a supply network is highly dependent on the health of each entity within the network and vice versa. A detailed discussion of supply network health is beyond the scope of this study. Interested readers are referred to Basole & Bellamy (2012). The health of a supply network can be defined as the system's ability to be productive, agile, and resilient. This ability is influenced by a range of factors including operational, financial, collaboration, and strategic aspects (Basole & Bellamy, 2012). Each of these represents a source of risks. Supply chain-related risks are exacerbated through the increasing interdependency among firms. Efficiency-driven SCM and extensive outsourcing of research and development (R&D) and manufacturing activities are very prevalent in today's supply networks, leading to greater dependence on supplier capabilities (Wagner, Bode, & Koziol, 2009). Previous research has shown that poor financial and operational health of individual suppliers in a focal firm's supplier portfolio can lead to increased supply chain risk and diminished firm performance (Wagner & Neshat, 2010; Blome & Schoenherr, 2011; Thun & Hoenig, 2011). The supply network health level is thus a function of the rate at which risks spread through the network and is influenced by the rate at which individual firms can recover. A conceptual representation of supply network infection and recovery is shown in Figure 1.

Drawing on these theoretical foundations, we argue that network structure influences the rate at which risk propagates through the supply network and in turn determines the level of supply network health. This association is influenced by the initial health level of the supply network and the level of visibility into the supply network. The conceptual model is shown in Figure 2. Specific hypotheses are developed next.

HYPOTHESES DEVELOPMENT

Supply Network Structure

The extent of supply network risk diffusion is not only dependent on infection and recovery rates, but also on the nature of interconnectivity between supply network entities. An examination of supply network structure is therefore essential. Our

Figure 1: Cascading risk: (a) infection-only, (b) infection and recovery.

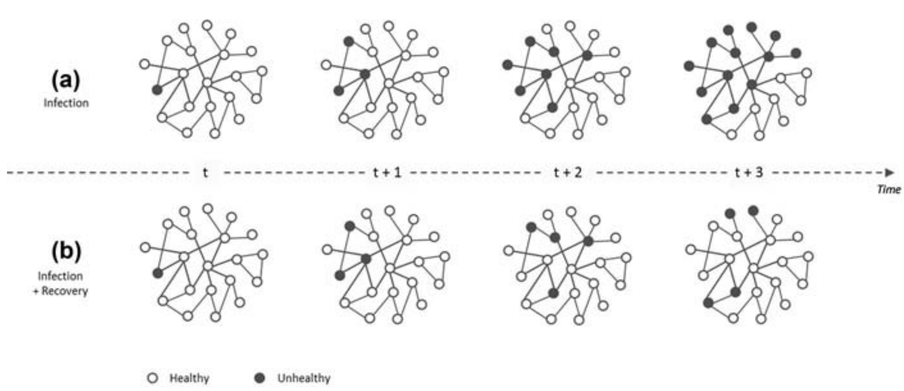
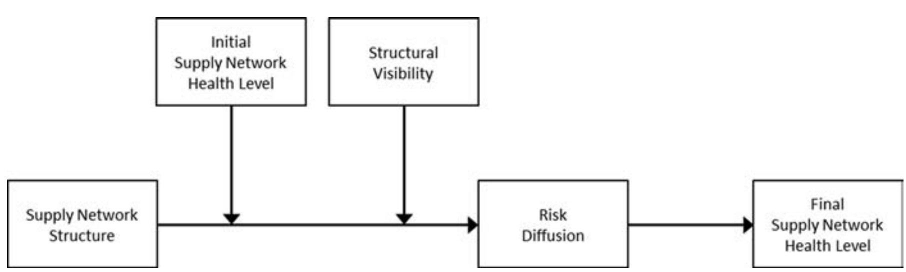


Figure 2: Conceptual model.



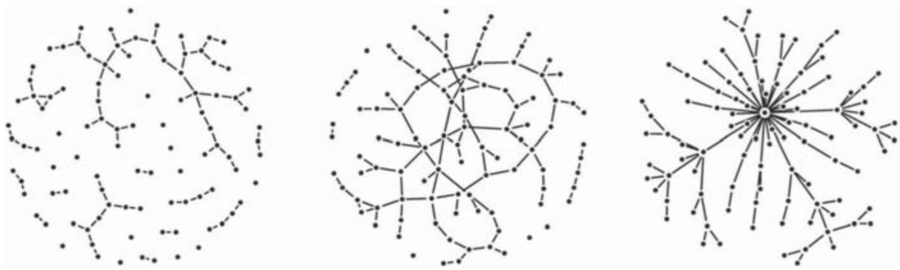
study examines risk diffusion in three complex network topologies: random, small-world, and scale-free (Strogatz, 2001; Airoldi, Bai, & Carley, 2011). Previous research has shown that these three network topologies commonly characterize real-world networks (Strogatz, 2001), including supply networks (Nair & Vidal, 2011).

Random networks are constructed by placing n nodes (which we refer to synonymously as entities) on a plane, then joining their pairs together at random. A total of $\frac{k \times n}{2}$ of the $\frac{n \times (n-1)}{2}$ possible links are selected randomly, leading to a bell-shaped Poisson degree distribution for the number of links across the nodes (Gilbert, 1959)

$$P(k) = \binom{n}{k} p^k (1-p)^{n-k} \simeq \frac{k^k e^{-k}}{k!} \tag{1}$$

where $P(k)$ is the probability of an entity having degree k and k is the average degree. Given the low clustering among entities, random networks are not very realistic for industry supply networks. However, as it has been the most widely used topology in modeling and empirical studies on complex networks, we include

Figure 3: Common supply network topologies (adapted from Airoldi et al., 2011).



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

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

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

it for purposes of a comparison benchmark (Callaway, Newman, Strogatz, & Watts, 2000).

Small-world networks have characteristics of high clustering and small average path length between nodes. The model starts with a ring lattice of n nodes, with each node connected only to its nearest neighbors. Then, with probability p_n, links are detached from one end and rewired to another random node in the population, with duplicate links not allowed (Watts & Strogatz, 1998).

Scale-free networks are characteristic of hub nodes that are highly connected and follow a power-law degree distribution, $P(k) \sim k^{-\alpha}$. This results in networks with a heavy tailed degree distribution among nodes. They are formed based on a preferential attachment algorithm. In our model, scale-free networks start with m individuals connected to each other in a ring, where the rest of the n - m individuals are added to the structure by attaching new nodes at random to previously existing nodes. The probability of attachment is proportional to the degree of the target node, with well-connected nodes picked more often than sparsely connected nodes. Outside of the well-connected hubs, the majority of nodes tend to have very few connections (Albert & Barabási, 2002). The applicability of these network topologies for modeling real-world industry supply networks is exemplified by characterization of the large-scale supply networks of the electronics and automotive industry (Appendix A). Figure 3 gives a visual depiction of each of the three network topologies.

Very few authors have explicitly factored supply network topological characteristics into their studies. Pathak, Dills, and Biswas (2007) and Pathak, Dills, and Mahadevan (2009) examine the impact of firm behavioral dynamics and environmental conditions on the evolution of a wide variety of supply network topologies over a very long (80 year) horizon. Nair & Vidal (2011) develop an AB model to examine the effect of random and scale-free topologies on robustness in the presence of random failures and targeted attacks.

The structural properties of a supply network are based on the series of interactions that exist among supply network entities. These interactions are what characterize the level of dependency in the supply network—such as a buyer who single-sources for a particular resource—making them more dependent on a single supplier to deliver the resource in the right quantity, quality, and time. They also determine the distribution of centrality and power among supply network entities. Hence, the structural make-up of a supply network should have a significant impact on its vulnerability to cascading delays, shortages, and informational failures. For example, a firm's sourcing strategy (e.g., sole-sourcing and outsourcing decisions) will result in different types of supply network structures, and the network structure will impact that firm's level of flexibility (dependency) to avoid (suffer) supply shortages and delays, and hence will lower the firm's service levels (Pathak, Day et al., 2007; Trkman & McCormack, 2009). By sole sourcing for a particular component, a firm establishes one additional link in the supply network, while multiple sourcing adds more flexibility as it allows the firm multiple ports of access to that resource in the network (Li & Amini, 2012). Consequently, greater reachability for a focal firm leads to faster access to resources and information in the supply network. As mentioned earlier, supply networks with small-world characteristics have high levels of clustering and low average path lengths. Focal firms in a small-world environment can therefore benefit from the faster spreading of resources through the supply network. Scale-free networks, however, may suffer from higher dependencies on a small number of central entities in the core and fewer backup sources to shield against unintended disruptions. In this case, several of the central entities have the ability to avoid a major disruption. However, a supply network with scale-free characteristics can lead to a decrease in each entity's ability to help others recover and perform well. This view on scale-free networks is counterintuitive to many findings in previous studies. However, the study by Barthélemy, Barrat, Pastor-Satorras, & Vespignani (2005) finds that complex networks with scale-free characteristics promote epidemic spreading by both suppressing the epidemic threshold and accelerating its propagation through the network. One extension that our model brings, as conceptualized in Figure 1, is the inclusion of a recovery rate working to mitigate the effects of the infection rate. In reality, suppliers, manufacturers, assemblers, distributors, and retailers all have the capability to improve performance or recover from a disruption. Hence, the impact of a supply network's structural properties on performance and sustainability should be based not only on their vulnerability, but also on their ability to recover from or avoid a disruption. Based on the considerations mentioned, we hypothesize the following:

H1a: A supply network with small-world characteristics decelerates risk propagation, resulting in more favorable network health level outcomes.

H1b: A supply network with scale-free characteristics accelerates risk propagation, resulting in less favorable network health level outcomes.

Structural Visibility

Past researchers have defined visibility as the ability to access information across the supply chain, visibility of customer and supplier operational activities (e.g., point of sale data, customer levels of inventory), and the extent and quality of exchanged information (Swaminathan & Tayur, 2003; Barratt & Oke, 2007). More recent work has suggested distinguishing between asset and behavioral visibility in the supply chain (Shu & Barton, 2012). Though no universal definition of visibility exists in SCM literature, greater supply chain visibility has been suggested by numerous authors to help improve operational performance, responsiveness, planning and replenishment capabilities, and improved decision making (Caridi, Crippa, Perego, Sianesi, & Tumino, 2010; Barratt & Barratt, 2011).

In the context of supply network risk, we propose that different levels of visibility will impact the degree of structural insight into the supply network a particular firm has. We further argue that increased visibility in turn enables faster risk identification. The importance of visibility is best exemplified when a firm focuses solely on directly connected suppliers, and does not realize the potential ripple effect of any source of risk in lower tiers (Tang et al., 2009). Furthermore, simplified, dyadic supply chains ignore much of the complexity in supply network environments and do not consider the many dimensions of visibility (Caridi et al., 2010). This limited view into what is happening in lower tiers can lead to a snowball effect of substantial delays and ultimately greater probability of experiencing a major disruption. Increased visibility, and in turn more timely and effective risk identification, enables firms to incorporate protection mechanisms to better insulate themselves from risk.

Examples of lack of structural visibility are provided in Basole & Bellamy (2012) where a facility failure in a focal firm's lower tier is not realized until it cascades through the supply network. After some period, this oversight eventually impairs the performance of multiple entities which the focal firm relies on to sustain its own performance. Choi & Kim (2008) use a series of real-world examples to further demonstrate how lack of visibility into second-tier suppliers or its supplier's vulnerabilities can lead to significant quality and supply risk issues. For example, they illustrate how an aerospace company experienced serious quality issues that stemmed from a new electronics parts (sub) supplier of one of its direct suppliers. Another example involves an automaker facing supply risk issues due to financial and operational burdens of one of its major suppliers, which had actually originated from an entirely different automaker.

Caridi et al. (2010) provide an excellent quantification of supply chain visibility and explain the variables that impact its level, while considering the context of complex supply networks. However, they focus primarily on operational-based (e.g., transactions, inventory status information, distribution, and production plan) and a few financial-based (volume of sales dedicated to the focal firm) dimensions. A more holistic representation of structural visibility would still incorporate the multitude of supply network interactions yet would benefit from considering significant aspects beyond the operational or financial. An elaboration of alternative representations, however, is beyond the scope of this article. A review of appropriate financial, operational, collaborative, and strategic dimensions is provided in Basole & Bellamy (2012).

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

$$adj\_inf_i = inf_i \times e^{-\gamma \times vis_i} \tag{2}$$

$$adj\_rec_i = rec_i \cdot \left(1 - e^{-\gamma \times vis_i}\right) \tag{3}$$

where inf_i is the probabilistic rate of infection, rec_i is the probabilistic rate of recovery, γ is the parameter that impacts the rate of growth or decay in infection (recovery) levels, and vis_i is the visibility level. The model parameter settings are discussed further in the section on experimental design. Based on these considerations, we hypothesize that visibility will significantly improve or sustain the overall performance of a supply network, regardless of its structural properties.

H2a: Firms with high visibility in supply networks exhibiting small-world characteristics will help decelerate risk propagation in the supply network, resulting in more favorable network health level outcomes.

H2b: Firms with high visibility in supply networks exhibiting scale-free characteristics will help decelerate risk propagation in the supply network, resulting in more favorable network health level outcomes.

Initial Health Level

The nonlinear behavior of a complex system, such as a supply network, is a result of the complex interactions of many entities. Nonlinearity of a system implies that a change of a given magnitude in the input of a system is not matched in a linear fashion to a corresponding change in output (Choi et al., 2001). Large changes in input may lead to small changes in outcome, and small changes in input may lead to large changes in outcome (Guastello, 1995). Chaos theory refers to this phenomenon as the "butterfly effect," where simple adaptive responses and corrective actions can lead to possible catastrophic outcomes (Lorenz, 1963). Complex supply networks are therefore hypersensitive to small changes in their environment. Initial conditions therefore can play an important role in the outcomes of complex supply networks.

Furthermore, research in the medical sciences has shown that future health outcomes (of individuals) often depend in part on the initial health status (Korotkov & Hannah, 2004). Individuals in poor physical health are—in absence of an intervention—more likely to progress to a weaker health state in comparison to their healthier counterparts due to lower immunity levels and higher potential for comorbidities, which together can accelerate the well-documented downward spiral of disease where the sick get sicker, or the weak get weaker.

Based on these considerations, it is therefore important to consider the initial health distribution levels of the supply network. Companies that are connected to firms in poorer health are more likely to become affected negatively than those that are in good health ceteris paribus. An illustrative recent example is the rapid deterioration of the automotive industry, where over 200 key suppliers of major manufacturers faced insolvency (Blome & Schoenherr, 2011). Similarly, good health levels can also spillover to connected firms as it may promote support, collaboration, and recovery and encourage joint risk identification and mitigation.

Given the structural characteristics of short path length and high clustering, we therefore argue that small-world supply networks will provide greater opportunity to enhance the recovery of each supply network entity. The greater access a focal entity has to healthier entities, the greater its probability of enhancing its own health levels. We postulate that, given an initially low number of healthy entities, supply networks characteristic of small worlds will recover significantly quicker than supply networks exhibiting either random or scale-free characteristics. This leads to the following two hypotheses:

H3a: A supply network exhibiting small-world characteristics and low initial levels of healthy entities recovers at a faster rate than a supply network exhibiting random characteristics, resulting in more favorable network health level outcomes.

H3b: A supply network exhibiting small-world characteristics and low initial levels of healthy entities recovers at a faster rate than a supply network exhibiting scale-free characteristics, resulting in more favorable network health level outcomes.

MODEL DESCRIPTION

AB Model

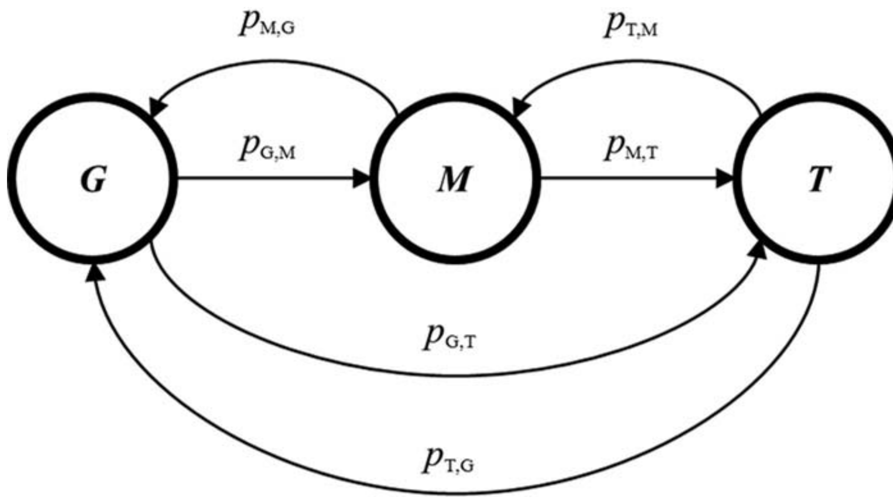
We develop an AB model to gain a better understanding of the risk diffusion process in complex supply networks. We create various simulated supply network structures to mimic actual industry supply networks and track their performance over time. Traditionally, researchers have leveraged computer-based simulations for studies on interorganizational supply networks to obtain results about larger-scale systemic behavior, using techniques that are analytically intractable (Pathak, Day et al., 2007). Simulations can be used to examine the steady state as well as dynamic behavior of complex systems. One limitation of many of the conventional simulation approaches (e.g., object-oriented, discrete event) is their limited or lack of ability to reflect the heterogeneity and autonomy of each entity, or to capture the complex interactions among entities. AB models allow users to develop a system that captures the dynamic, complex internal behaviors of each entity in the system (Pathak, Day et al., 2007; Gibbons & Samaddar, 2009; Hua et al., 2011). These entities have the ability to make decisions and adapt to changes in their environment, as opposed to conventional models that often standardize the behavioral effects of the population of interest. AB models can enable researchers to better understand emergent behavior within a complex system comprising heterogeneous, autonomous, and interactive entities, as individual behaviors combine to form the system's behavior (Wu, Huang, Blackhurst, Zhang, & Wang, 2012). AB models have been applied to a very wide range of domains such as biology, sociology, ecology, epidemiology, economics, and supply chain modeling (Barthélemy et al., 2005; Christley et al., 2005; Rahmandad & Sterman, 2008; Ge et al., 2011; Hua et al., 2011; Nair & Vidal, 2011).

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

Risk Diffusion

For the risk diffusion and health, we create parameters for probability of infection, rate of recovery, initial health states, and visibility level. In our model, we assign a level of health to all supply network entities randomly using an initial health distribution. For this particular study, health levels are assumed to be equally weighted across all health dimensions. Clearly, there are interdependencies within and across each health dimension. However, the primary focus of this study is to examine the overall effects of network structure on supply network health and risk

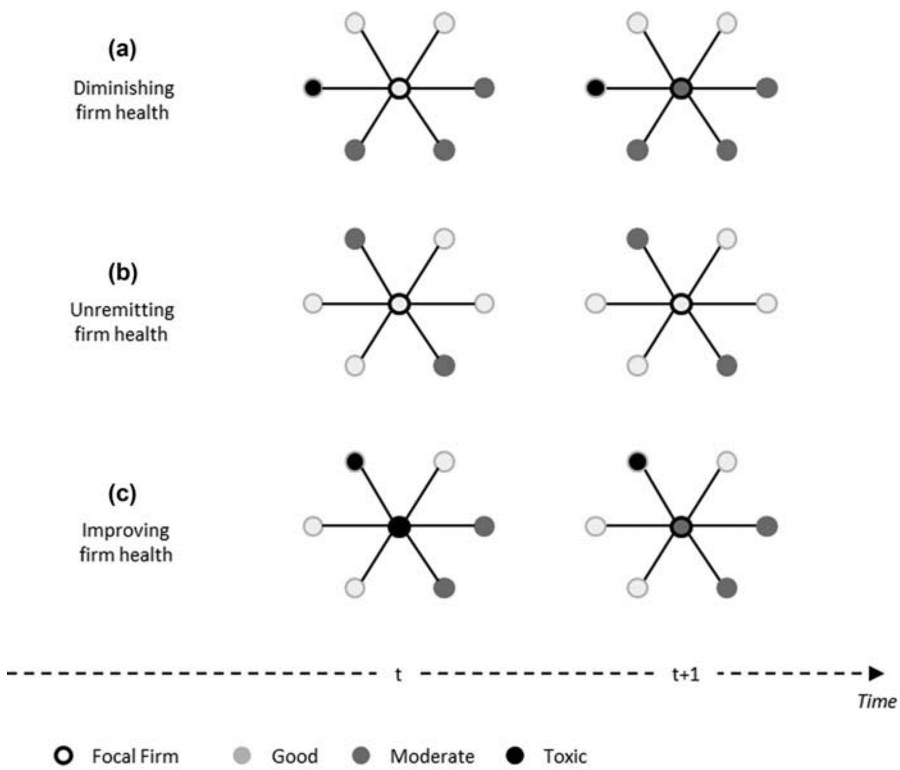
Figure 4: Health state transition.



diffusion, not on specific effects of each health dimension, which is a feat requiring a separate study on its own. It should be noted that AB models do not necessarily require initial health distributions or equally weighted health levels; our model could be easily adapted to accommodate these modifications.

Following suit with the SIR model (Anderson & May, 1992), we incorporate three health states for each supply network entity as follows: G, M, and T. Thus, we have an MTG model (analogous to the SIR model), where firms are not completely immune once recovered, but have the potential to be reinfected. The SIR model can be viewed as a unique Markov chain for each entity in the system (Aleman, 2012). An entity in the supply chain system has a unique probability of transitioning from their current state *i* into state *j* at each time step. A particular entity currently in a good state of health can remain in the same state, transition to a moderate state, or transition to a dire toxic state, each with a certain probability. In similar fashion, an entity in either a moderate or toxic state will be in one of the three states each with a certain probability. The resulting transition diagram is shown in Figure 4. It is important to note that our model takes a much more holistic approach to the traditional SIR model by computing the level of health of each supply network entity as a function of the health of its corresponding neighbors. This is an important differentiation from previous approaches as it helps to account for the negative (positive) effects of being connected to others who are currently under (over)performing. In doing so, we capture inherent interdependency in supply networks and address the call for and value in more modeling approaches that consider the systemic impact of supply network disruptions (Blackhurst et al., 2005). Figure 5 conceptually illustrates how the health of a focal firm's neighbors

Figure 5: Illustration of health dependencies.



can negatively (positively) affect its own state of health. The resulting transition probabilities are as follows:

$$p_{i,j} = w \propto_i \left[1 + \left(\frac{\sum_{j \neq i} Ego_j}{\sum_j Ego_j}\right)\right] \forall i, j, i \notin [Moderate] \tag{4}$$

$$p_{i,j} = w \propto_i \left[1 + \left(\frac{Ego_j}{\sum_j Ego_j}\right)\right] \forall i, j, i \notin [Good, Toxic] \tag{5}$$

where

$$\propto_i \in [adj\_inf_i, adj\_rec_i], \; w = \begin{cases} 1 \; if \; j \; 1 \; state \; away \; from \; i \\ 0.5 \; if \; j \; 2 \; states \; away \; from \; i \end{cases} \tag{6}$$

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

Experimental Design

The experimental design of our network model parameters is motivated by the previous body of work examining evolution and risk diffusion in complex networks as well as characteristics of real-world supply networks. Christley et al. (2005), adopt an SIR model to estimate individuals' risk of infection and time to infection in small-world and randomly mixing networks, using a network size (n) of 100 and an average degree (k) of 20. Barthélemy et al. (2005) examine dynamical patterns of epidemic outbreaks in complex random and scale-free networks, using $n = 1{,}000$, values of k ranging from 4 to 50, and initial hub values ($m = m_0$) ranging from 4 to 20. The authors also adopt the idea of varying the percent of entities that are initially infected (referred to as $health_{G-M-T}$ in our study) to study the changes in infection propagation. Rahmandad & Sterman (2008) compare AB and differential equation models to examine the impact of individual heterogeneity and different network topologies, including fully connected, random, small-world, scale-free, and lattice networks. Network diffusion dynamics are examined in their study using an $n = 200$, $k = 10$, a neighbor link fraction (p) of 0.05, 10 initial hubs ($m = m_0$), and additional parameter values for sensitivity analysis ($n = 50$, $k = 6$ and $n = 800$, $k = 18$). Buzna, Peters, and Helbing (2006) investigate the dynamic spreading of failures in random, small-world, scale-free topologies, and grid networks. Zhao, Kumar, Harrison, and Yen (2011) examine the resilience of supply networks against disruptions using random, scale-free, hierarchy, and degree- and locality-based attachment topologies, using a network size of 1,000 and average degree of 3.6.

Tables 1–4 provide a description of our complete research design. In an effort to reflect prior parameter considerations for diffusion in complex networks, we decided to range network size from 100 to 1,000, average degree from 2 to 20, neighbor link fraction from 0.25 to 0.75, and initial hub ranges from 5 to 50 (Table 1). Also, our choice of the three topologies (random, small-world, and scale-free) are all very common in the body of literature studying network evolution and diffusion. As reflected in Table 2, we modeled the risk diffusion to vary in infection and recovery rates, percentage of entities initially in each health state, and visibility levels. We fixed degree of visibility's impact on the rate of growth or decay in infection and recovery levels (γ) to equal 2 based on the premise that increased visibility mitigates risk spread and improves recovery, but at a diminishing rate. This was done to represent the high costs associated with building the technology and infrastructure to integrate all information eventually outweighing the savings in improved knowledge of current and impending risks.

ANALYSIS, RESULTS, AND DISCUSSION

Analysis

We simulated the model for a total period of 10 years (or 40 quarters) of supply chain risk diffusion. Previous studies have not been explicit arguing their choice of simulation length. In the epidemiology literature, it has been argued that the simulation length should be equal to the time it takes for the outbreak to end (i.e., the time until no latent or infectious individual remains). In general, studies have

Table 1: Design of experiments for supply network.

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

Table 2: Design of experiments for risk diffusion and health

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

Table 3: Correlation matrix.

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
(1)	Δ Good	1											
(2)	Δ Moderate	−0.22	1										
(3)	Δ Toxic	−0.96	−0.06	1									
(4)	inf_i	−0.37	0.25	0.31	1								
(5)	rec_i	0.37	−0.17	−0.33	0.00	1							
(6)	Random	0.01	−0.01	0.00	0.00	0.00	1						
(7)	Small-world	0.01	−0.02	−0.01	0.00	0.00	−0.56	1					
(8)	Scale-free	−0.02	0.03	0.01	0.00	0.00	−0.27	−0.65	1				
(9)	Health Dist. 1	−0.37	0.33	0.28	0.00	0.00	0.00	0.00	0.00	1			
(10)	Health Dist. 2	−0.17	−0.48	0.31	0.00	0.00	0.00	0.00	0.00	−0.50	1		
(11)	Health Dist. 3	0.53	0.15	−0.59	0.00	0.00	0.00	0.00	0.00	−0.50	−0.50	1	
(12)	vis_i	0.38	−0.19	−0.34	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1

Note: All correlations with an absolute value greater than 0.03 are significant at the .05 level.

Table 4: OLS regression results: Supply network structure, visibility, and risk diffusion.

	Δ Good		
	(1.1)	(1.2)	(1.3)
inf_{i}	−50.579***	−50.581***	−52.020***
	(1.500)	(1.500)	(1.480)
rec_{i}	41.568***	41.570***	43.141***
	(1.531)	(1.532)	(1.516)
Δ toxic	−0.865***	−0.865***	−0.855***
	(0.005)	(0.005)	(0.005)
Small-world	0.318*	0.318*	0.321*
	(0.146)	(0.146)	(0.141)
Scale-free	−0.629***	−0.629***	−0.635***
	(0.176)	(0.176)	(0.170)
$vis_{\text{i}} = 0.5$	3.094***		3.300***
	(0.283)		(0.277)
$vis_{\text{i}} = 0.75$	7.390***		7.604***
	(0.252)		(0.248)
HealthII	5.004***	5.004***	
	(0.173)	(0.173)	
HealthIII	1.854***	1.854***	
	(0.219)	(0.219)	
$vis_{\text{i}} = 0.5 \times$ random		3.110***	
		(0.615)	
$vis_{\text{i}} = 0.5 \times$ small-world		3.097***	
		(0.364)	
$vis_{\text{i}} = 0.5 \times$ scale-free		3.076***	
		(0.552)	
$vis_{\text{i}} = 0.75 \times$ random		7.302***	
		(0.536)	
$vis_{\text{i}} = 0.75 \times$ small-world		7.341***	
		(0.321)	
$vis_{\text{i}} = 0.75 \times$ scale-free		7.578***	
		(0.482)	
HealthII × random			8.064***
			(0.346)
HealthII × small-world			2.417***
			(0.218)
HealthII × scale-free			8.066***
			(0.311)
HealthIII × random			0.809*
			(0.404)
HealthIII × small-world			3.217***
			(0.231)
HealthIII × scale-free			0.762*
			(0.375)
Constant	−8.019***	−8.019***	−7.942***
	(0.308)	(0.308)	(0.298)
Observations	5,103	5,103	5,103
Adjusted R^2	0.958	0.958	0.960

***$p < .001$, **$p < .01$, *$p < .05$, +p < .10.
Standard errors in parentheses.

Table 5: Summary of findings

Hypothesis	Factor(s)	Impact on Risk Propagation	Impact on Desired Health Level Outcome	Support?
H1a	Small-world	(−)	(+)	Yes
H1b	Scale-free	(+)	(−)	Yes
H2a	Small-world, high visibility	(−)	(+)	Yes
H2b	Scale-free, high visibility	(−)	(+)	Yes

chosen time horizons that allow the contagion/diffusion/risk spread to peak and stabilize or die out. The length also represents two five-year Chapter 11 bankruptcy repayment and recovery periods. For example, we calculated the standard deviation and variance for the last five to six periods, and both stayed below 1. This would signify that we considered a stable network when the variance (or percent change in health states) remained below 1% for at least five consecutive periods.

Every simulation was repeated 100 times for the entire parameter space to average out stochastic effects. We systematically explored the variation in supply network health levels over the parameter space by using ordinary least squares (OLS) regression analysis. For our base regression model, we estimated the effects of network structure, visibility, and initial supply network health distribution on risk diffusion and supply network health. We then reran the analysis incorporating any interaction effects corresponding to our hypotheses. The use of regression analysis for the evaluation of simulation results is particularly applicable as it enables analyzing high-dimensional empirical data whose underlying model is uncertain (Hanaki, Peterhansl, Dodds, & Watts, 2007). In fact, previous research has utilized OLS totest the impact of network structure on diffusion level, speed, and breadth over a variety of network topologies in AB and computational models (Gibbons, 2004, 2007). We also studied and cross-examined the resulting time-series plots as an additional check to verify our hypothesized supply network phenomena over the entire time horizon. As a robustness check, we tested for several of the key model assumptions that coincide with using an OLS regression (e.g., homoskedasticity, nonlinearity). We ran all analyses in STATA Version 11. The piecewise correlations are presented in Table 3.

Key Findings

The simulation results are presented and discussed in this section. The results of the OLS regression analyses are shown in Table 4. Figures 6–8 depict the evolution of the health state distributions for the random, small-world, and scale-free supply network topologies. We included the grand mean centered network type and initial health distribution measures in the models. For visibility, we used the reverse helmet coding scheme in STATA to compare levels of visibility with the mean of its previous levels, as this comparison is more meaningful for ordinal variables (Ender & Mitchell, 2003; Edillo, Touré, Lanzaro, Dolo, & Taylor, 2004). Model 1.1 includes the network type, visibility, and initial health distribution measures along with control variables. The results indicate that the number of supply network

Table 6: Summary of findings.

Hypothesis	Factors	Promotes Slower Recovery than Small-World and High Initial Distribution?	Relative Unit of (+) Impact on Desired Health Level Outcome	Support?
H3a	Random, high initial health distribution	Yes	<1/3	Yes
H3b	Scale-free, high initial health distribution	Yes	<1/3	Yes

Figure 6: Evolution of health state distribution (random supply network topology).

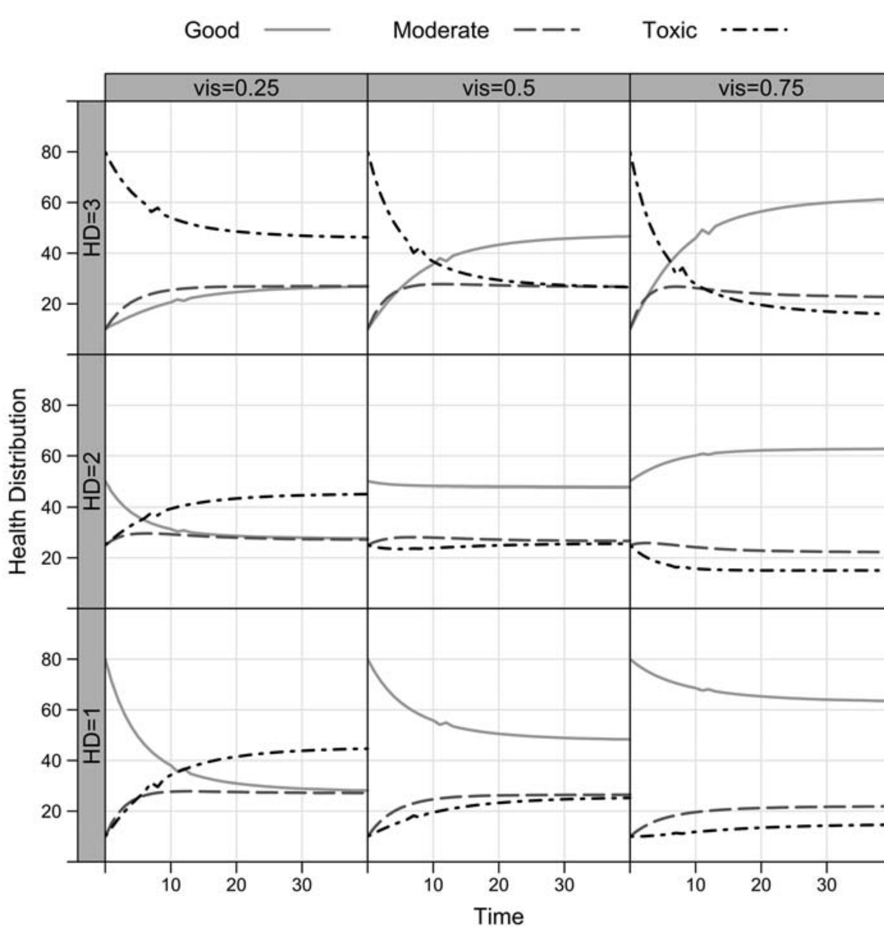
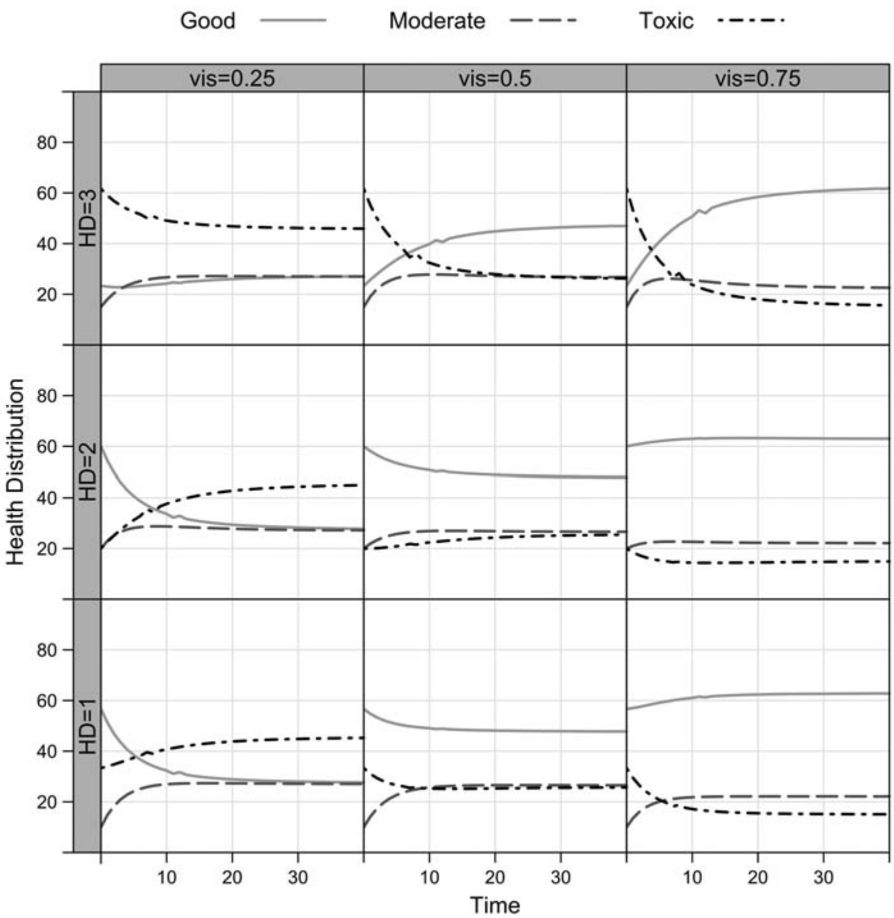


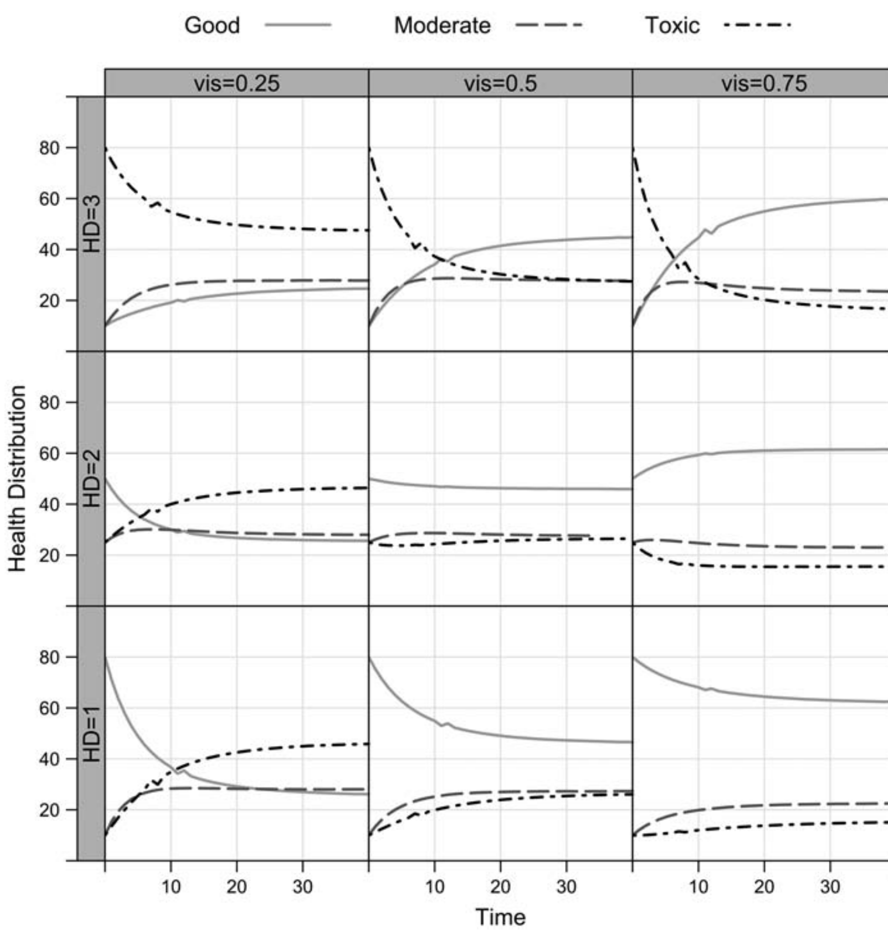
Figure 7: Evolution of health state distribution (small-world supply network topology).



entities in a good state of health increased with an increase in recovery rate, small-world network structures, and visibility levels. The number of supply network entities in a good state of health decreased with an increase in infection rate, the number of supply network entities in a toxic state of health, and in scale-free network structures. These results support H1a and H1b.

Next, we tested for the main effects of network type and the corresponding simple effects used in our hypotheses, which were also found to be statistically significant ($F = 6.94$, $p < .05$). Model 1.2 incorporates the interaction effects between network type and visibility levels. The results indicate that each of these interaction terms is significant and in the direction expected (H2a and H2b). Model 1.3 includes the interaction effect terms for network type and initial health distribution. Given an initially low number of healthy entities, the results show an increase in the number of supply network entities in a good state of health with an

Figure 8: Evolution of health state distribution (scale-free supply network topology).



increase in structures mimicking random, small-world, and scale-free networks. However, while all interactions were significant ($p < .05$), the small-world supply network structure resulted in the most significant increase ($p < .001$) with the largest effect size of the three. This result supports H3a and H3b.

Our results have important supply network system performance implications related to: (i) the supply network structure, (ii) supply network visibility, and (iii) the initial distribution of supply network health levels. These are discussed next.

Implications of Supply Network Structure

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

Implications of Visibility

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

Implications of Initial Health Level

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

CONCLUSIONS AND FUTURE RESEARCH

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

Our computational study of supply network structure and risk diffusion was motivated by the significant challenges supply chain executives face when managing large, complex global supply networks. We did not model a specific firm's supply network, in part because complete network data are hard to obtain, but more importantly because our primary aim was to illustrate the types of risk diffusion patterns that emerge for typical real-world supply network configurations. Future research could examine risk diffusion patterns in supply networks of actual firms through in-depth case studies and comparing and contrasting supply networks with multiplex, weighted relationships, and different product characteristics and industry clock speeds.

Our study also focused on a single (integrated) form of risk. Our discussion highlighted that there are many different types of risk areas (i.e., operational, financial, collaborative, strategic, etc.) with varying levels of importance. Future studies need to evaluate the relative importance of each risk area, the interaction among these areas, and investigate how this multiform of risk impacts diffusion in supply networks.

Our study presented a simplified view of visibility. An interesting future research opportunity includes testing multiple models and forms of structural visibility (e.g., inverted-U) and whether structural visibility could also have negative impacts, perhaps through (over)reactive strategies. Similarly, we did not distinguish between different "types" of and "extents" of supply network visibility, such as differing levels of insight into operational aspects (such as inventory, shortage, production or work-order, shipment, quality, schedule, order, lead-time, and cost) or differentiation between asset visibility and behavioral visibility (Shu & Barton, 2012).

Our study also did not evaluate targeted failures or alternative risk mitigation strategies (Ellis, Henry, & Shockley, 2010). A valuable future research direction includes the examination of the impact of these strategies on the probability of supply disruption and overall supply disruption risk. Our experience suggests that some supply networks can be managed by past methods of command and control but at some level of complexity, the governance approach has to dramatically change. Additionally, when transitioning from command and control methods to a network scale that is too large to manage by traditional methods, firms must compartmentalize sections of the network and rely on "self-regulating networks" for the sections that have high complexity. This implies that supplier and network contract types, incentives, and visibility are crucial and it demands an evaluation of alternative risk mitigation approaches such as insurance against failure.

Last, our study focuses on understanding risk diffusion patterns in static supply networks. Supply networks, however, are dynamic, evolving systems, in which there is a symbiotic relationship between structure and behavior. An important extension of our study thus includes the specification of behavioral aspects of individual firms in a supply network, including fitness functions and interaction rules, as well as the growth and shrinkage of supply networks as new players emerge and existing players leave (either by choice or by organizational death). Each of these limitations presents exciting opportunities for future research.

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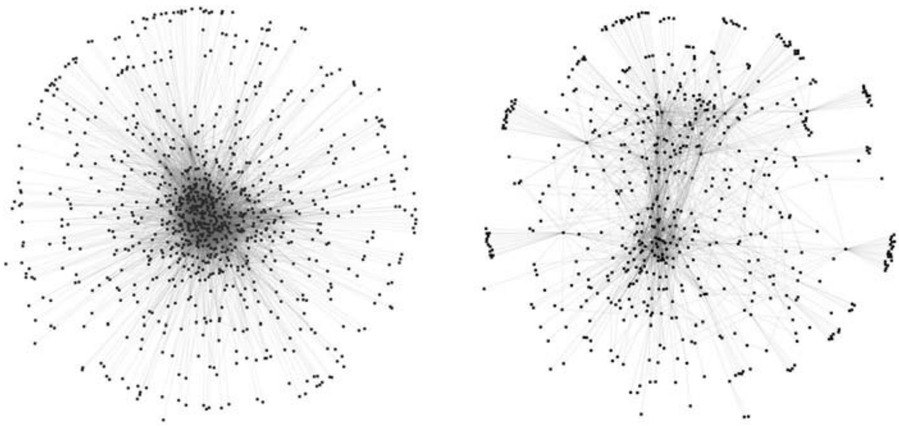
APPENDIX A: REPRESENTATIVE EXAMPLES OF SUPPLY NETWORKS

Based on a comprehensive data set of global supplier and customer relationships by Connexiti (Basole, 2009) and strategic supply alliances from the SDC Platinum database, we mapped the supply networks of the electronics and automotive industries and computed relevant network metrics. The electronics industry supply network (Figure A1a) consists of 911 firms and 7,311 supplier and customer relationships among all supply network entities. The automotive industry supply network (Figure A1b) consists of 600 firms and 1,997 supplier and customer relationships. The electronics industry supply network is more characteristic of a small-world, which is characterized by a low average path length but relatively high clustering coefficient when compared to random networks with the same number of firms and average number of supplier and customer relationships (Watts & Strogatz, 1998; Strogatz, 2001). We generated a random network with 911 nodes and 7,311 links using Gephi (Bastian, Heymann, & Jacomy, 2009) to compare with the electronics network. While the two networks had a nearly identical average number of neighbors (16.05 in the random versus 16.02 in the small-world) and average path length (2.74 in the random versus 2.73 in the small-world), the small-world network had a significantly higher clustering coefficient (0.018 in the random versus 0.175 in the small-world). This finding provided further validation that the electronics supply network is characteristic of a small-world network. In contrast, the automotive industry supply network bears greater resemblance to a scale-free network. Scale-free networks follow a power-law degree distribution and high network heterogeneity, reflecting a network with hub nodes. As a check for evidence of a power-law distribution, researchers often plot the degree distributions of complex networks on a double logarithmic (log-log) scale and look for evidence of a linear curve using the log-transformed data (Strogatz, 2001; Newman, 2003). The results of the log-log degree distribution plot in Figure A2 reveal that the automotive industry supply network highly resembles a power-law degree distribution, as indicated by its approximately straight-line form on the log-transformed plot.

APPENDIX B: DESCRIPTION AND VALIDATION OF AB MODEL

This appendix describes how our AB model was built, verified, and validated. The steps in this section follow the best practice modeling guidelines suggested by Rand and Rust (2011).

Figure A1: Representative industry supply network topologies.



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

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

Guidelines for Model Development

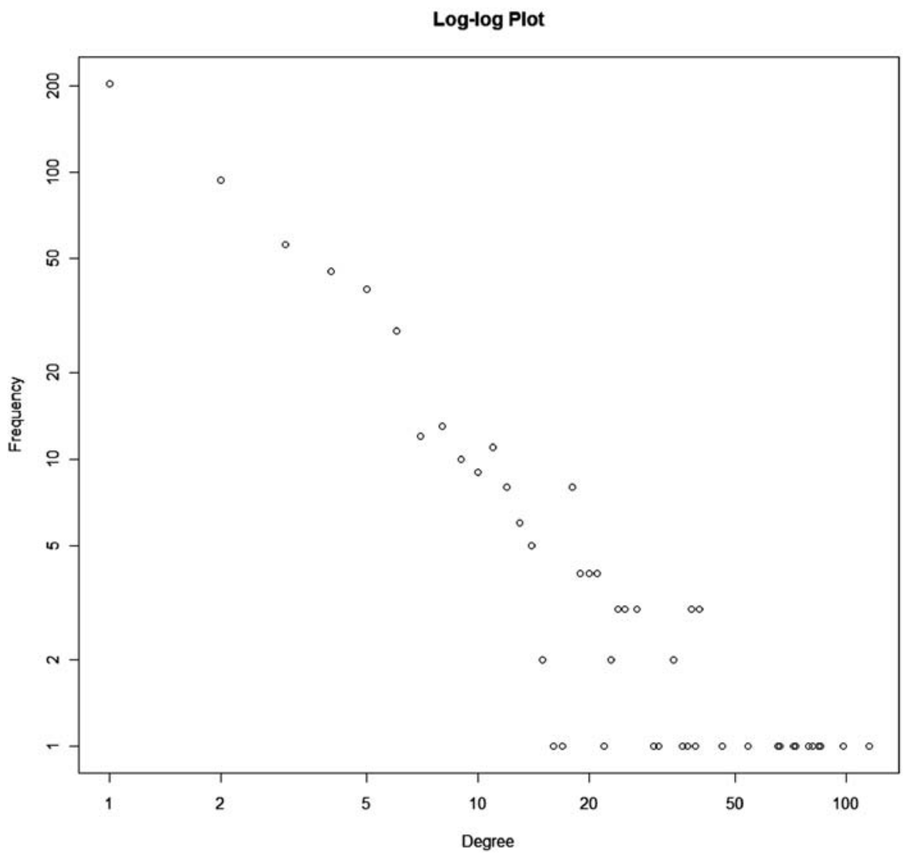
Step I: Decide if an AB Model is appropriate

We find that an AB model is appropriate because our modeling context has components that are both indicative (heterogeneity, complex interactions, and rich and dynamic environments) and necessary (temporal aspects).

Step II: Design the AB model

i. *Scope of the model.* The model scope was defined based on the susceptible, infectious, and recovered (SIR) model (Anderson & May, 1992), where we preserve the two standard assumptions of three stages and a fixed population. However, we relax the assumption of permanent immunity so that supply network entities stay in the system and do not simply disappear from the supply network once they have recovered. We incorporate three health states for each supply network entity: G, M, and T. Thus, we have an MTG model (analogous to the SIR model), where firms are not completely immune once recovered, but have the potential to be reinfected. We also incorporate network structure into the model, which allows each agent to have a social network that it interacts with. Items falling outside of the scope were noted in the article (e.g., targeted failures, different risk types, nature of the product, multiplexity).

Figure A2: Log-log plot of degree distribution for automotive supply network.



ii. *Agents.* The agents in our model represent firm-level entities in the supply network, such as customers and suppliers. We do not define separate agent classes based on agent type.

iii. *Properties.* Each agent has its own infection rate (inf_i) and recovery rate (rec_i) as well as a set of neighboring agents. Both of these rates are adjusted according to the level of visibility (vis_i) that they have (see Equations (2) and (3)). Incorporation of the supply network gives each agent a set of neighboring agents.

iv. *Behaviors.* Each agent moves from a state of health with a certain probability ($p_{i,j}$) based on network, risk diffusion, and initial health parameters (see Equations (4)-(6)). These behaviors are explained in detail in the study.

v. *Environment.* The external forces acting on each agent come from the supply network environment within which that agent operates.

vi. *Input and output.* The model inputs are the network structure, risk diffusion, and initial health parameters. The outputs collected by the model are the final health outcomes. The inputs and outputs are all explained in detail in the study.

vii. *Time step.* Our iteration time step is a quarter-year. We simulated the model for a total period of 10 years (or 40 quarters) of supply chain risk diffusion.

Step III: Construct the model

We used a combination of Java programming and AnyLogic® AB modeling language/library commands for our model implementation.

i. *Initialization.* The number of agents is created according to the input parameter n. Each agent is given an infection rate (inf_i) and recovery rate (rec_i) value, according to the input parameters. The agents are then connected to each other according to the random, small-world, and scale-free network topologies, and their associated input parameters. Last, the initial health parameter determines the number of agents starting in a particular health state.

ii. *Health transition.* The probabilistic nature of the health transition behaviors is explained in detail in the study.

iii. *Statistics collection.* The number of agents in each health state at a particular time step is recorded.

iv. *Repeat.* The process continues until the last time step of 40, which changes in infection rate, recovery rate, visibility, and the random, small-world, and scale-free network structures affecting the final health outcomes.

Step IV: Analyze the model

We analyzed and evaluated the results using multiple regression analysis in STATA.

Guidelines for a Rigorous Model

Verification: Determines how well the implemented model corresponds to the conceptual model

i. *Documentation.* The authors continually recorded and saved written correspondences and discussion notes related to the model design. As a safety measure and for convenience, all relevant documents were backed up, uploaded, and shared via Dropbox cloud storage. In line with programming best practices, we have created detailed documentations and have included extensive comments throughout the AB code to allow programmers at any level to follow our programming logic. An example of our code is attached in Appendix C.

ii. *Programmatic testing.* The process of programmatic testing proved to be very fruitful as the authors were able to fix several bugs in custom coding and AnyLogic® functions, by sharing and discussing the intended purpose for each element in the model. This helped to mitigate several issues before moving beyond preliminary modeling and analysis stages.

- *Unit*: Due to the various individual- and network-based parameters, we carefully inspected each line of code to ensure that it was executing as intended. We carried this out by using the built-in variable values (optionally listed in the output screen), statistics, bar charts, and time plot functions in AnyLogic®.
- *Code*: Both authors are experienced programmers and obtained any necessary coding advice from the AnyLogic® support team, development forums, and colleagues. Together (and with colleagues when possible), the authors walked through and discussed each coding step to ensure that the logic used expressed the concept that they had intended.
- *Debugging*: The debugging process was similar to the "Unit" subsection above, leveraging built-in capabilities and evaluating relevant metrics and graphs in AnyLogic®.
- *Formal testing*: Due to the sufficiently complicated nature of our AB models, the authors did not use an extensive formal logic to verify the code. The models were presented to and evaluated by simulation and domain experts.

iii Test cases and scenarios.

Corner cases: We ran independent models using zero infection rate (inf_i), zero recovery rate (rec_i), and zero interaction effects—stemming from agent ties to other entities in the supply network—as these results were more easily predictable. For example, we knew that for our model, if agents have zero probability of being infected (recovering) then absolutely no agents should be transitioning to a worse (better) state of health. Our intuition and expected model outcomes held up under these changes.

Relative value: We kept all parameter values constant while increasing only rec_i to examine whether the number of agents in a good state of health due to recovery speed increased relative to the number of agents in a good state of health due to any other effect. We also tested similar cases for other parameters of interest, increasing inf_i, vis_i, n, and k, separately while holding all other effects constant. Based on this, our implemented model was shown to correspond very well to the conceptual model.

Validation: Relates to the process of determining how well the implemented model corresponds to reality

i. *Microface validation.* The authors have addressed this issue based on the theoretical motivation in the article on firm behavior and interdependence in actual supply networks. We have also presented this model at various leading scholarly conferences, incorporating the feedback received from researchers that enhanced insight gained from the model.

ii. *Macroface validation.* Again, we have tried to address this issue in the study by conducting a series of extensive literature reviews on complex systems, epidemiology, and supply chains and reflecting this in the design of our model. As mentioned in the microcase, we integrated feedback received from experts and senior scholars into revised versions of the model.

iii. *Empirical input validation.* We use data from two real-world, large-scale supply networks. The main purpose was to show that real-world supply networks share many of the same characteristics as those in small-world and scale-free networks. We validated this with our data set, providing support for our use of the random (as a baseline), small-world, and scale-free networks to reflect real-world supply networks.

iv. *Empirical output validation.* Due to the lack of available dynamic data on supply networks, the authors were not able to do much in this category.

APPENDIX C: SAMPLE CODE FOR ANYLOGIC® MODEL

Our AB model was implemented in a multimethod simulation software platform AnyLogic®. A sample code is shown below:

```
// separate agents into Good, Moderate, and Toxic based on initial health distribution
applyNetwork();
if(Health_Dist = = 1) {
Initial_Good = (Health_Dist_1_1 * Nodes) / 100;
Initial_Moderate = (Health_Dist_1_2 * Nodes) / 100;
Initial_Toxic = (Health_Dist_1_3 * Nodes) / 100;
} else
if(Health_Dist = = 2) {
Initial_Good = (Health_Dist_2_1 * Nodes) / 100;
Initial_Moderate = (Health_Dist_2_2 * Nodes) / 100;
Initial_Toxic = (Health_Dist_2_3 * Nodes) / 100;
} else
if(Health_Dist = = 3) {
Initial_Good = (Health_Dist_3_1 * Nodes) / 100;
Initial_Moderate = (Health_Dist_3_2 * Nodes) / 100;
Initial_Toxic = (Health_Dist_3_3 * Nodes) / 100;
}
// turn agents into Moderate based on initial conditions
for (int i = 0; i < Initial_Moderate; i++){
people.get(i).statechart.fireEvent("Moderate");
}
// turn agents into Toxic based on initial conditions
for (int i = Initial_Moderate; i < Initial_Moderate + Initial_Toxic; i++){
people.get(i).statechart.fireEvent("Toxic");
}
```

Rahul C. Basole is an associate professor in the School of Interactive Computing and the associate director of the Tennenbaum Institute at Georgia Tech, where he is also an affiliated faculty member in the Graphics, Visualization, and Usability (GVU) Center. His research integrates systems science and visualization to understand and manage technology, operations, and innovation in complex enterprises.

His current research focuses on the management of transformative IT innovation and the analysis and design of converging ecosystems and extended enterprises in domains such as mobile telecom, future media, healthcare, energy, and biotech. He has received numerous best paper awards, and his work is published in leading engineering, computer science, and management journals. In previous roles, he was the CEO and founder of a Silicon Valley-based wireless research and consulting firm, the director of research and development at a leading mobile software firm, and a senior consultant for a technology strategy firm. He is a member of the Institute for Operations Research and Management Sciences, the Institute of Electrical and Electronics Engineers, and the Association for Information Systems. He currently serves as a director or advisor for several technology and software firms. He received a BS in industrial and systems engineering from Virginia Tech, has completed graduate studies in engineering-economic systems, operations research, and management information systems at Stanford University and the University of Michigan, and received a PhD in industrial and systems engineering from the Georgia Institute of Technology.

Marcus A. Bellamy is a Ph.D. candidate of Operations Management in the Scheller College of Business at the Georgia Institute of Technology. He is also a graduate research fellow at the Tennenbaum Institute. He received his M.S. in Industrial Engineering at Georgia Tech and his B.S. in Mechanical Engineering at the University of New Mexico. Marcus was a Fulbright scholar for a teaching and researching position in Madrid, Spain. He was also the recipient of the 2013 Academy of Management (AOM) Operations Management Division Best Student Paper Award. His research interests include supply chain management as well as supply networks as sources of innovation and risk.