Computational Analysis and Visualization of Global Supply Network Risks

Rahul C. Basole, Marcus A. Bellamy, Hyunwoo Park, and Jagannath Putrevu

***Abstract*—Management of supply network risks is a critical competency for today's global enterprises. Current practices and tools, however, have limited capabilities and do not allow for systemic exploration of alternate risk strategies. We develop a computational model of risk diffusion in global supply networks that is grounded in techniques from complex systems, network analysis, and epidemiological risk modeling. We draw on a unique, curated dataset of firms, their supply networks, and financial risk in the global electronics industry. Specifically, we assess and visualize the impact of network structure on risk diffusion and supply network health, and determine the impact of visibility on reduction and potential mitigation of cascading risks. Our approach enables decision makers to identify risks and determine potential paths of their diffusion. In doing so, we advance our understanding of the design and development of computational risk management tools in a global supply network context.**

***Index Terms*—Computational simulation, electronics industry, network science, supply chain risk, visualization.**

I. Introduction

SUPPLY chains are complex, sociotechnical systems that require significant coordination, collaboration, and monitoring of heterogeneous, autonomous, and interconnected organizational entities [9], [12]. Conflicting goals and incentives by these entities can lead to dynamic, nonlinear, and emergent behavior of the entire supply chain system. Moreover, interdependencies between supply chain entities can cause the poor performance of upstream suppliers to rapidly propagate downstream to trigger severe supply disruptions and negatively impact the performance of other entities [33], [24], [42], [51]. Because of these complex structural interdependencies supply chains are also commonly referred to and conceptualized as supply networks [18].

Given the criticality of healthy supply networks to firm survival and growth, timely identification, assessment, and mitigation of latent risks in the networks is of significant importance [55]. The rapidly growing global complexity and scale of supply networks complicate matters. Yet, existing tools and practices rarely consider the complex interconnected and multidimensional nature of supply network risk beyond the first tier, and there is a lack of prior research on system analysis and decision support models for insight into systemic supply network risk [43], [8]. New risk analysis and assessment tools are thus needed [16], [50], [51].

A computational system modeling lens has been shown to be particularly useful in characterizing, understanding, and managing global supply networks [18], [23], [8]. Grounded in network analysis as well as complexity, evolutionary economics, and systems theory, computational system models of supply networks enable decision makers to study the impact of system topology, identify patterns of system behavior, and evaluate alternate system scenarios [43], [8].

Our study is motivated by a series of multiyear experiences with executives and decision makers in leading manufacturing companies in the defense aerospace, automotive, and electronics industries. As supply network data is often proprietary, sensitive, and resource intensive to collect, there are no large-scale models of risk diffusion in real supply networks. Executives often rely on simplified decision models with synthetic data or conduct context-specific case studies. Computational decision support tools that allow systemic exploration of alternate risk strategies do not exist.

To overcome this limitation, we developed a computational model of risk diffusion in global supply networks. We draw on a unique curated dataset of firms their supply networks, and financial risk in the global electronics industry—built from multiple secondary, validated, and established data sources. The electronics industry is characterized by high levels of collaboration and partnering [40], short product life cycles with new products and services emerging rapidly [21], and highly global operations with most firms residing in North America, Europe, and Asia. Together, these conditions present formidable risk assessment challenges to decision makers.

We fuse complex systems, network analysis, and epidemiological risk modeling approaches into a computational model in order to address two fundamental managerial objectives.

1) Assess and visualize the impact of network structure on risk diffusion and supply network health.

Manuscript received February 10, 2014; revised October 20, 2014, February 7, 2015, March 26, 2015, and May 7, 2015; accepted May 21, 2015. Date of publication March 30, 2016; date of current version June 2, 2016. This work was supported in part by Intel Corporation, in part by General Motors Labs, in part by Lockheed Martin Aeronautics, and in part by the Georgia Tech Manufacturing Institute. Paper no. TII-14-0181.

R. C. Basole is with the School of Interactive Computing and Tennenbaum Institute, Georgia Institute of Technology, Atlanta, GA 30332 USA (e-mail: basole@gatech.edu).

M. A. Bellamy is with the Questrom School of Business, Boston University, Boston, MA 02215-1300 USA (e-mail: marcus.bellamy@gatech.edu).

H. Park is with the Tennenbaum Institute, Georgia Institute of Technology, Atlanta, GA 30332 USA (e-mail: hwpark@gatech.edu).

J. Putrevu is with Instacart, San Francisco, CA 94105 USA (e-mail: jputrevu3@gatech.edu).

Color versions of one or more of the figures in this paper are available online at http://ieeexplore.ieee.org.

Digital Object Identifier 10.1109/TII.2016.2549268

2) Determine the impact of subtier visibility on reduction and potentially mitigation of cascading risks.

In doing so, our study advances our understanding of the design and development of computational risk management tools in a global supply network context.

The remainder of this paper is organized as follows. Section II presents the theoretical foundations. Section III describes our research design and methodology. Section IV presents the analysis, results, and implications of our findings. Section V concludes this paper and discusses opportunities for future research.

II. Theoretical Foundation

A. Computational Models of Supply Networks

Early research conceptualized supply chains as systems consisting of material suppliers, production facilities, distribution services, and customers, all linked together via a feedforward flow of materials and the feedback flow of information [32]. However, today's supply chains are more aptly described as highly complex networks among suppliers, manufacturers, distributors, retailers, and customers, which have transformed the traditional linear supply chain into a geographically dispersed supply network of interactions between system members [18].

Conventional modeling and analysis approaches tend to emphasize a dyadic perspective, focusing on individual pairs of firms [49], [37]. Such approaches, however, fail to account for systemic effects arising from complex structural and behavioral aspects prevalent in supply networks [12]. In order to manage supply networks more effectively, the structure, behavior, and performance of the entire system must be considered [36]. Prior work has suggested that a computational systems and network analytic approach is particularly suitable [33], [12] as it helps account for both technical and social aspects of supply network phenomena and their implications on performance [15].

Bellamy *et al.* [13], for instance, empirically showed that central supply network firms tend to be in more powerful and influential positions, helping them reduce transactional costs and improve operational efficiency, ultimately leading to better operating and business performance. In another study, Yli-Renko *et al.* [53] identified that the strength of network relations positively facilitate knowledge exchange. More recently, in a study of synthetically generated supply networks of different topologies, Basole and Bellamy [8] demonstrated the importance of visibility in the mitigation of risk and improvement in overall system health.

Methodologically, network analysis draws on the well-established field of graph theory. In a supply network context, the graph nodes or vertices represent customers and suppliers, while edges represent relationships between customers and suppliers. Thus, insight into the network topology gives a holistic perspective of the collective ports of passage for material flow and information exchange in the supply network. Real-world supply networks typically assume one of three types of topologies—random, small-world or scale-free—each with its own strengths and weaknesses [33], [1]. Each network topology

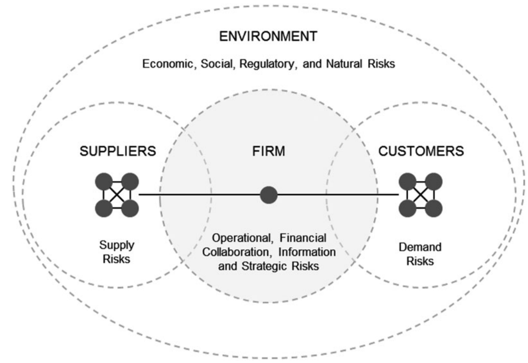

Fig. 1. Conceptual representation of risks in supply networks.

has a unique set of structural characteristics, such as the position and (inter)connectedness of firms within the overall supply network. A network analytic lens enables researchers to incorporate these structural characteristics into their computational model. This provides greater insight into performance, strategy, and governance implications from operating in a particular supply network topology [12].

In this study, we build and extend this prior work by empirically identifying supply networks in the global electronics industry and, through computational analysis and visualization, characterizing their impact on risk diffusion.

B. Risks in Supply Networks

Global supply networks are exposed to a wide range of endogenous and exogenous risks [43]. Fig. 1 provides a conceptual summary of risks prevalent in supply networks. Endogenous risks emerge from inside the supply network, including the firm, supplier, and customer environment [44]. Endogenous risks include supply, demand, operational, financial, collaborative, information, and strategic risks.

Supply risk emanates upstream from suppliers and refers to disruption in supply, inventory, schedules, and technology access, price escalation, quality issues, technological uncertainty, product complexity, and frequent design changes. Demand risk emanates downstream from customers and can arise from new product introductions, variations in demand due to fads, seasonality, and disruptive technologies, and demand distortion and amplification [3], [17].

While several supply and demand risks arise directly from a firm's suppliers and customers, a multitude of endogenous risks arise as a result of a firm's internal environment and its interdependencies with customers and suppliers. Operational risk is one of the most studied types of endogenous risk in the supply chain management literature. Broadly, it relates to events that can lead to lower operational effectiveness and capabilities of a firm and can emanate from issues, such as inadequate manufacturing or processing capability, low-process stability, and changes in technology [17]. Another prominent type of risk, namely financial risk, affects the financial sustainability and growth of a firm. While a firm's own financial state is critical, the financial instability of a firm's suppliers (e.g., from default, insolvency, or bankruptcy) can also affect the health of the focal firm [24], [42]. Collaboration risk is based on a firm's nature and extent of collaborative relationships with its suppliers and customers [7]. Collaboration risks arise from issues such as lack of ability to support the operations or governance mechanisms between a firm and other supply chain entities, contractual obligations constraining firm relationships between supply chain entities, and lack of trust in noncontractual interactions [14]. Besides physical resources, supply network partners also rely on significant information exchange. Information risks, thus, include the level of information accuracy, information system security and disruption, intellectual property, and information outsourcing that a firm has in place [44]. Strategic risks affect a firm's ability to manage and execute change initiatives [7]. This risk includes failing to get supply network entities to understand and be aligned with a focal firm's intents and finding the right balance between a command-and-control or incentive/penalties governance system that results in the desired supply network behavior and performance [14].

Exogenous risks, on the other hand, arise from the uncertainty faced by the supply network that are out of the control of the focal firm or any supply network entity. Exogenous risks include political/country risk, regulatory risk, disaster risk, and foreign exchange rate risk. Political/country risk can arise from political turmoil or terrorist attacks occurring in an area where some part of a focal firm's operations resides [27]. Regulatory risk stems from uncertainty of import/export factors and environmental, health, and safety regulations [31]. Disaster risk arises from catastrophic events, such as earthquakes, hurricanes, fires, and disease outbreaks [19]. Exchange rate risk arises from the fluctuating exchange rates impacting some portion of a firm's operations, and is amplified when a firm is limited in flexibility to colocate to hedge against the volatility in such fluctuations [26]. Examples of real-world supply network disruptions originating from exogenous risk factors are plentiful. Ericsson incurred a $400 million loss in sales after a massive fire destroyed millions of microchips at its semiconductor plant in New Mexico [28]. Compaq, Apple, and Gateway suffered delayed shipments lasting several weeks and, in some cases, months after an earthquake struck Taiwan, leaving these companies unable to receive key computer components for their products [29]. Ford, Toyota, and DaimlerChrysler faced significant indirect consequences from the terrorist attacks of 9/11, particularly major supply disruptions at their North-American assembly plants [39]. A comprehensive review of the literature related to risks in supply networks is beyond the scope of this study. Beyond the literature already mentioned, readers are referred to work such as [41] offering an extensive review on supply chain risk management.

C. Models of Risk Diffusion

Modeling the diffusion of risks in complex networks has been a topic of great interest in both epidemiology and evolutionary biology [20]. 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 [30]. In the managerial and organizational sciences, epidemiological models of risk diffusion are particularly pervasive in finance, such as studies on unexpected shocks in complex financial networks [22], bankruptcy propagation in large-scale production networks [11], and supply chains [25], and systemic risk in banking systems [22], [51].

The underlying framework typically used in these studies is the classic Susceptible-Infected-Removed (SIR) model, in which member entities (e.g., firms) are divided into three risk states: susceptible (S), infectious (I), and recovered (R) [2]. A susceptible entity i that comes into contact with another infectious, one becomes infected itself at a specified probabilistic rate (inf_i). In our study, we build on this classical framework by preserving the three stages and a fixed system size. 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. It is possible that a corporate transformation, such as a merger or acquisition, can potentially remove an entity from the network. However, we characterized our computational model to be more reflective of established supply network contexts, where a disruption may cause a customer or supplier to underperform but not completely dissolve, and eventually recover, at a specified probabilistic rate (rec_i), and once again be susceptible to future risks. As risks propagate through the supply network and infect more entities, the overall health of a supply network deteriorates. Also, there is an inherent cyclical risk effect in the supply network bearing similarity to a biological ecosystem, where the health of a supply network is highly dependent on the health of each entity within the network and vice versa[1].

III. Methodology

A. Data

Our study utilized and integrated multiple public and proprietary data sources. To construct the supply network structure and financial risk score of firms in the electronics industry, we used four well-established sources—Electronics Business (EB) 300, Compustat, Connexiti, and Thomson Reuters Securities Data Company (SDC) Platinum Database. The EB300 is a well-established annual global ranking of the top 300 electronics firms ranked by their respective revenues provided by Electronics Design, Strategy, and News. We seeded our list of focal firms using all firms listed in the EB300 from 2005 to 2009, resulting in an initial dataset of 582 unique firms. However, since the focus of our study was on the supply networks of lead firms in the electronics industry, our dataset reduced to 151 core firms.

The supply network structure of these firms was built using Thomson Reuters SDC Platinum and Connexiti. SDC Platinum database is a commonly used data source for the study of interfirm networks [38]. It contains information on many different types of relationships, including strategic alliances, supply, research and development (R&D), marketing, licensing, and manufacturing. We extracted all active relationships from 2005 to 2009 and excluded relationships that were terminated during

[1] A detailed discussion of supply network health is beyond the scope of this study. Interested readers are referred to [28].

this time period. We cross validated and augmented the SDC Platinum dataset with relationship information from Connexiti. Connexiti is a comprehensive supply network intelligence database that captures both supply and customer relationships for 20 000+ global firms. Financial information on all focal firms and their supply network partners was extracted from Compustat. As some financial data was missing—either due to company type or geographic location—our final set of lead firms reduced to 112. Our complete dataset included nearly 1000 firms and over 8000 supply network relationships.

We constructed a two-tier supply network of each lead firm using a binary adjacency matrix, with cell entries marked as 1 if there is any relationship between two firms and 0 otherwise. Since we were primarily concerned whether a relationship between two firms exists and not with multiplex relationships, multiple relationships between the same pair of firms were treated as a single link (see [35]). Furthermore, as collaborative relationships are considered to be bidirectional, it resulted in an undirected unipartite graph [34].

B. Metrics

1) Supply Network: Following [1], we computed 47 widely adopted network metrics for each firm's supply network. These included degree centrality, betweenness centrality, closeness centrality, eigenvector centrality, clustering coefficient, network size, network constraint, triad count, and average path length. Detailed metric descriptions are provided in [45].

2) Financial Risk: Each firm in a supply network has an associated Altman *Z*-score, a widely used measure of a firm's financial distress [24]. Though the emphasis of this measure is on financial distress, deterioration in supplier financial health will impair its ability to repay debt and can, thus, lead to operational failures in the supply network due to the shutting down of certain supplier plants, facilities, or warehouses[2]. The *Z*-score is calculated according to weighted coefficients on five financial factors as follows:

$$Z_i = 1.2X_{i,1} + 1.4X_{i,2} + 3.3X_{i,3} + 0.6X_{i,4} + 1.0X_{i,5} \quad (1)$$

where $X_{i,1}$ represents working capital/total assets, $X_{i,2}$ represents retained earnings/total assets, $X_{i,3}$ represents earnings before interest and tax/total assets, $X_{i,4}$ represents market value of equity/total liabilities, and $X_{i,5}$ represents sales/total assets for firm *i*. *Z*-scores are calculated using 2008–2009 financial data from the Compustat database[3]. The risk level of firm *i* is then assessed as follows.

1) If $Z_i > 2.99 \Rightarrow$ low risk (L).
2) If $2.99 > Z_i > 1.81 \Rightarrow$ moderate risk (M).
3) If $Z_i < 1.81 \Rightarrow$ high risk (H).

For subsequent analysis, we reverse coded *Z*-scores on a three-point scale, with low risk as "1," moderate risk as "2," and high risk as "3." Supply networks with low *Z*-scores, thus, will have a higher risk score.

[2]Although such an indirect effect on a firm's operations may arise, our focus with this measure is on the financial risk. We leave incorporation of other types of risk to future work

[3]For firms with missing *Z*-Scores due to firm status (i.e. private) or foreign stock exchange listing, we determined risk levels using an iterative estimation approach of risk levels of connected supply network partners..matter

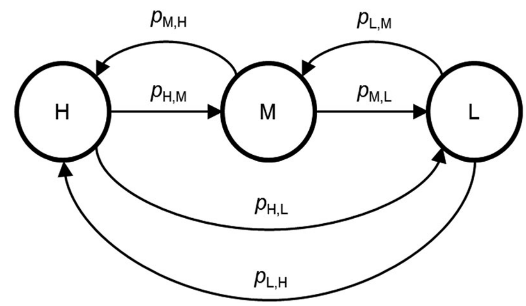

Fig. 2. Markov model of risk state transition.

C. Simulation

1) Approach: We developed a computational agent-based (AB) simulation model to study risk diffusion in each of our 112 supply networks in the global electronics industry. In contrast to traditional simulation paradigms, an AB model allows explicit capture of entity heterogeneity and autonomy and outcomes of their complex dynamic interactions. Agents in our model represent the firms (e.g., lead firms, suppliers, customers). At $t = 0$, each firm as an agent is, thus, assigned its actual *Z*-score and visibility-adjusted infection and recovery rates (see Section III-C3). Agents are connected by their relational supply network structure. An agent's subsequent health levels are dependent on the health levels of each supply chain partner it is connected to. Thus, each agent has a unique probability p_{ij} of transitioning from its current state *i* into state *j* at each time step based on its visibility-adjusted infection and recovery rates as well as the health of its supply chain partners. We designed and executed our AB model using AnyLogic, a multimethod simulation software platform.

2) Risk Diffusion Model: Following the epidemiological SIR model [2], we develop a three-state Markov model of risk transition[4]. Firms have a unique probability of transitioning from their current risk state *k* into state *l*. Each firm can stay in their current risk state or transition to one of the other two states as shown in the transition diagram in Fig. 2.

The resulting transition probabilities are as follows:

$$p_{k,l} = w \times \alpha_k \times \left[1 + \left(\frac{\sum_{s \neq k} P_s}{\sum_s P_s}\right)\right] \forall k \neq l, k \notin \{M\} \quad (2)$$

$$p_{k,l} = w \times \alpha_k \times \left[1 + \left(\frac{P_l}{\sum_s P_s}\right)\right] \forall k \neq l, k \notin \{L, H\} \quad (3)$$

$$p_{k,l} = 1 - \sum\nolimits_{l \neq k} p_{k,l} \quad \forall k = l \quad (4)$$

where $\alpha_k = \mathrm{inf}_i^{\mathrm{adj}}$ (if *l* in lower state than *k*) or $\mathrm{rec}_i^{\mathrm{adj}}$ (if *l* in higher state than *k*) and $w = 1$ (if *l* 1 state away from *k*) or 0.5

[4]By computing the risk level of each firm as a function of the risk of its supply network partners, our model takes a more systemic approach than the traditional SIR model. It accounts for the possible negative (positive) effects of being connected to others who are currently under (over) performing.

(if l 2 states away from k). P_s equals the number of focal firm's supply network partners in risk state s, where $s \in \{L, M, H\}$.

3) Structural Visibility: Visibility has been defined as the ability to access information on customer and supplier operational activities [54]. Visibility helps to improve operational performance, responsiveness, planning and replenishment capabilities, and decision making [16], [54]. Following [8], we operationalize structural visibility as a spectrum-based measure (low 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, and, thereby, enable earlier risk identification.

Using an epidemiological analogy, visibility acts as an immunity measure, enabling firms to identify, protect, and strategize for risks earlier. However, investing in visibility comes with diminishing returns, where the costs of obtaining, monitoring, collecting, and integrating information will begin to outweigh the benefits at some point in time.

We, therefore, model visibility having an exponential effect on both risk infection and recovery; thereby, creating visibility-adjusted infection and recovery rates

$$\mathrm{inf}_i^{\mathrm{adj}} = \mathrm{inf}_i \times e_i^{-\gamma \times \mathrm{vis}} \tag{5}$$

$$\mathrm{rec}_i^{\mathrm{adj}} = \mathrm{rec}_i \times (1 - e_i^{-\gamma \times \mathrm{vis}}) \tag{6}$$

where inf_i is the probabilistic rate of infection, rec_i is the probabilistic rate of recovery, γ is the parameter that impacts the rate of growth or decay in infection (recovery) levels, and vis_i is the visibility level[5].

D. Experimental Design

We estimated the infection (0.09) and recovery rates (0.21) in the global electronics industry using 2008 and 2009 data[6]. Based on previous work [8], we used two levels to reflect low (0.15) and high (0.25) visibility. We used the parameter variation feature in AnyLogic to run full combinatorial experiments of supply networks, infection/recovery rates, and visibility levels. We replicated each experiment 100 times. Simulations were run for a total period of ten years (or 40 quarters) and risk levels were identified at each timestep[7].

E. Visualization

Visualization can provide important novel and complementary insights into the structure, dynamics, and strategy of supply networks [12], [8]. Visualizations can be used to explore, interpret, and communicate data and aid decision makers overcoming cognitive limitations. With the new tsunami of available data, visualization is increasingly recognized as an integral part of the scientific approach and considered a fundamental method of transforming data to knowledge.

There are many examples of network visualizations including biological and ecological networks, social networks, the Internet, and citation networks. Visualizations of industry and supply networks are also quite common and are used as complementary analyses to traditional summaries of network statistics (e.g., [6]). Visualizations are effective when trying to explain substantive differences between network structures. It has also been shown that visualizations are particularly valuable for under-

TABLE I
SUPPLY NETWORK DESCRIPTIVES

	Mean	Standard Deviation	Min	Max
Supply Network Size	464.96	196.07	12	865
#of Direct Partners	30.66	33.78	1	161
Average Initial Risk Level	1.64	0.84	1	3
Average Path Length	2.30	0.18	1.74	2.67
Average Clustering Coefficient	0.26	0.08	0.18	0.62
Average SWQ	0.12	0.05	0.07	0.36

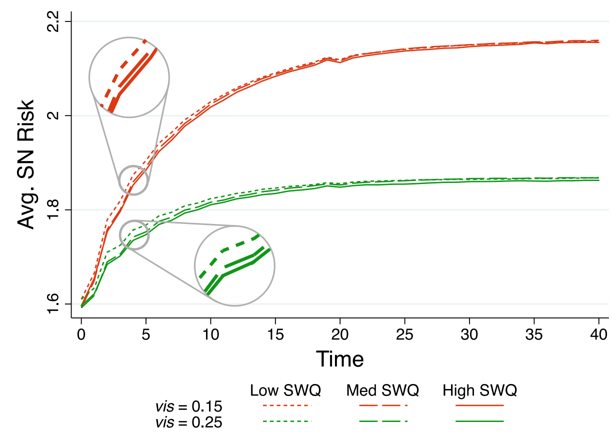

Fig. 3. Evolution of supply network risk.

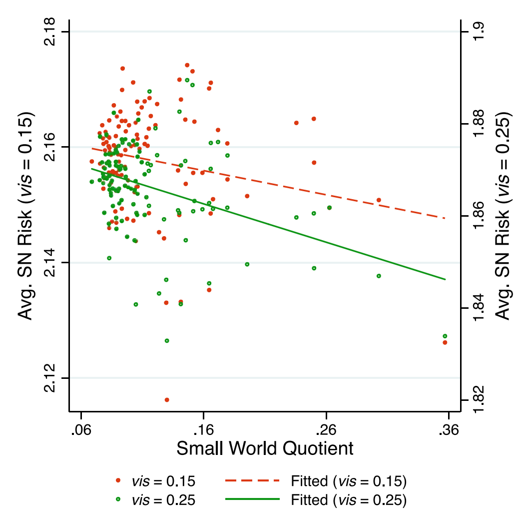

Fig. 4. SWQ and average risk levels.

[5]We fixed γ to equal 2 based on the premise that increased visibility mitigates risk spread and improves recovery, but that the high costs associated with building the technology and infrastructure to integrate all information eventually outweigh the savings in improved knowledge of current and impending risks.

[6]Rate estimation included how many firms moved to a worse/better risk level in 2009 as compared to 2008.

[7]The length of our simulation allows for a peak and stabilizing outcome of typical supply chain risks. The length also represents two 5-year Chapter 11 bankruptcy recovery cycles.

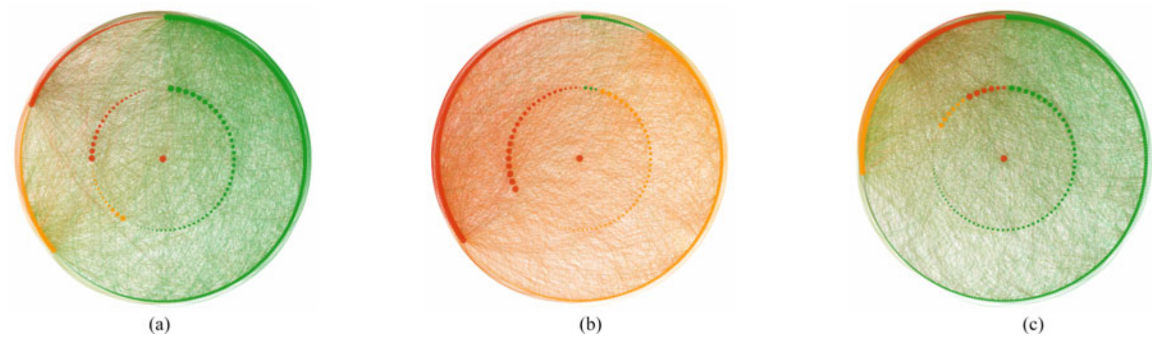

Fig. 5. Illustrative example of risk-encoded supply network visualization. (a) $t = 0$. (b) $t = 40$. vis $= 0.15$. (c) $t = 40$, vis $= 0.25$.

standing and analyzing business issues, including competitive intelligence, strategy, scenario planning, and problem solving [5], [4].

Most prior work has focused primarily on the visualization of entire industries, not on supply networks. Unquestionably, supply network visualizations are challenging and resource intensive. Complete or even comprehensive supply network data is generally not available. At the same time, even if the data are collected and appropriately curated, the amount of information can often be overwhelming to the end user if not presented appropriately. Effective visualizations must, therefore, ensure a careful balance among detail, abstraction, accuracy, efficiency, and aesthetics.

We use Gephi, an open-source software for visualizing and analyzing large network graphs to create graphical representations of supply networks in the electronics industry [10]. We use a concentric layout approach to create visually appealing and insightful supply network representations. The focal firm is placed at the center of the visualization, while firms *n* steps away from the focal firm are placed on the nth circle. Node size is proportional to the firm's importance as measured by betweenness centrality. Node color indicates the firm's distress as measured by its *Z*-score.

IV. Analysis and Results

We first conducted a series of graph identification tests to determine the type and topological characteristics of our 112 supply networks. Our tests revealed that all networks are scale free/small world and none are random, confirming prior observations. Supply networks range in total size from 12 to 865 firms with an average initial health level of 1.64. On average, lead firms had 30.66 direct supply network partners. Table I provides a summary of key supply network characteristics.

A key objective of our study was to determine the influence of supply network visibility on risk diffusion. To group our large set of networks, we computed the small-world quotient (SWQ)—the ratio of average path length and clustering coefficient—and stratified them into three levels. Networks are said to be small world if they have high clustering and short path lengths [46]. Fig. 3 shows a timeline view of the average risk level evolution in supply networks, stratified by low, moderate, and high SWQ and visibility level. Our results show that irrespective of structural characteristic or visibility level, the risk in supply networks increases. However, with higher levels of visibility, the risk level in supply networks is significantly reduced throughout the entire period. This finding, thus, strongly confirms our proposition that supply network visibility is a critical capability for mitigating risks. Although risk implication of different SWQ is much less than that of visibility, persistence difference of risk outcome stems from structural characteristics as shown in the magnified part of Fig. 3, which we examine further.

Our second objective was to determine whether structural differences in supply networks actually matter in risk diffusion. Fig. 4 shows a multiaxis scatterplot chart of the average risk levels of firms by the SWQ of their supply network. We differentiate the results by visibility level. The result is striking. As SWQ increases, risk reduces regardless of visibility level. With higher visibility, however, a higher SWQ reduces risk twice faster[8]. This finding shows that the structure of supply networks matter and that firms with small-world like supply network characteristics maintain topological characteristics particularly favorable for reduced risk diffusion. A potential implication of this finding is that decision makers may want to judiciously select supply network partners and take a proactive approach in "engineering" their supply network structure.

Fig. 5(a)–(c) provides a visual representation of the evolution of supply network risks for an illustrative lead firm. Firms with low risk level are depicted in green, while firms with high risk are shown in red. Firms in orange are associated with intermediate level of risk. Within each risk level, firms are reversely sorted by betweenness centrality. We can see from Fig. 5(a) that, in general, the supply network is healthy, but that there are also a number of well-connected firms at the first and second tier with high risk levels. With low visibility, the supply network has evolved unhealthy, as depicted by the disproportionately more red and orange saturated network [see Fig. 5(b)]. In contrast, the supply network with high visibility is healthier [see Fig. 5(c)]. While these representations are merely static snapshots, they strongly demonstrate the differences in supply network health. When observing the changes in color composition of supply networks dynamically over time, either through animation or an interactive approach, our study further delineates the velocity and nature of risk diffusion in supply networks.

[8]The slopes of SWQ on supply chain risk in low and high visibility are significantly different from each other based on multivariate regression followed by hypothesis testing.

V. Conclusion

Risk identification, analysis, and mitigation have unquestionably become an important capability for supply network executives. A computational analysis and visualization approach provides a powerful way to systemically understand complex supply network interdependencies and identify and evaluate alternate risk mitigation strategies. This study demonstrates the tremendous value of using computational tools for supply network risk management using real supply network and financial data from the electronics industry.

Our study makes several important practical and theoretical contributions. Motivated by our collaboration with supply chain executives, we developed a computational model and visualization framework that provides systemic insights into structure and evolution of multitie supply network risks. Our approach allows mapping and interactive exploration of firms, flow, information, and risk. With the growth in and availability of enterprise data, integration of these new computational capabilities will enable timely identification of peripheral activities and risks in the supply network. Several of our collaborators have already adopted our approach and created entire functional units around it.

Our computational risk analysis approach also allows exploration of "what-if" scenarios. In order to grow and survive, firms must continuously evaluate and benchmark their supply chains. A computational simulation approach allows us to eliminate bad and focus on good ideas quickly. 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 computational analysis and visualization lens provides a more holistic assessment of these risks and helps us to explain the propagation of poor (strong) supplier performance through the supply network over time. Operationally, our results show that there is a significant association between supply network structure, risk diffusion, and supply network health. We also show that greater visibility greatly enhances risk mitigation regardless of the structural properties of the supply network.

In times where resources are limited and decision makers' attention must be focused, a computational visual analysis capability, as presented in this study, can help us to identify points and diffusion of risks and significantly augment enterprise intelligence capabilities. Our study, however, should be seen as an important first step toward computational models of global supply networks. While we discussed multiple types of risks, we focused our analysis on financial risk alone. Future work should incorporate several different risk types and consider the interactions between them [47]. Similarly, supply networks are dynamic entities that may change over time. Furthermore, the assumption of static infection and recovery rates could be relaxed to accommodate time-dependent rates if desired. Subsequent computational models should allow for this dynamism.

References

[1] E. M. Airoldi, X. Bai, and K. M. Carley, "Network sampling and classification: An investigation of network model representations," *Decis. Support Syst.*, vol. 51, no. 3, pp. 506–518, 2011.

[2] R. M. Anderson and R. M. May, *Infectious Diseases of Humans: Dynamics and Control*. Oxford, U.K.: Oxford Univ. Press, 1992.

[3] S. Asian and X. Nie, "Coordination in supply chains with uncertain demand and disruption risks: Existence, analysis, and insights," *IEEE Trans. Syst., Man, Cybern. Syst.*, vol. 44, no. 9, pp. 1139–1154, Sep. 2014.

[4] R. C. Basole, "Visual business ecosystem intelligence: Lessons from the field," *IEEE Comput. Graph. Appl.*, vol. 34, no. 5, pp. 26–34, Sep./Oct. 2014.

[5] R. C. Basole, T. Clear, M. Hu, H. Mehrotra, and J. Stasko, "Understanding interfirm relationships in business ecosystems with interactive visualization," *IEEE Trans. Vis. Comput. Graph.*, vol. 19, no. 12, pp. 2526–2535, Dec. 2013.

[6] R. C. Basole "Visualization of interfirm relations in a converging mobile ecosystem," *J. Inf. Technol.*, vol. 24, no. 2, pp. 144–159, 2009.

[7] Basole, R. C. and M. A. Bellamy, *Global Supply Network Health: Analysis and Visualization* (Tennenbaum Institute Series on Enterprise Systems). Amsterdam, The Netherlands: IOS Press, 2012, sec. 4.

[8] R. C. Basole and M. A. Bellamy, "Supply network structure, visibility, and risk diffusion: A computational approach," *Decis. Sci.*, vol. 45, no. 4, pp. 753–789, 2014.

[9] R. C. Basole and W. B. Rouse, "Complexity of service value networks: Conceptualization and empirical investigation," *IBM Syst. J.*, vol. 47, no. 1, pp. 53–70, 2008.

[10] M. Bastian, S. Heymann, and M. Jacomy, "Gephi: An open source software for exploring and manipulating networks," in *Proc. Conf. Int. AAAI Conf. Weblogs Social Media*, 2009.

[11] S. Battiston, D. Delli Gatti, M. Gallegati, B. Greenwald, and J. E. Stiglitz, "Credit chains and bankruptcy propagation in production networks," *J. Econ. Dyn. Control*, vol. 31, no. 6, pp. 2061–2084, 2007.

[12] M. A. Bellamy and R. C. Basole, "Network analysis of supply chain systems: A systematic review and future research," *Syst. Eng.*, vol. 16, no. 2, pp. 235–249, 2013.

[13] M. A. Bellamy, S. Ghosh, and M. Hora, "The influence of supply network structure on firm innovation," *J. Oper. Manage.*, vol. 32, no. 6, pp. 357–373, 2014.

[14] N. Bennett, W. Kessler, and L. McGinnis, *Enterprise Transformation and Manufacturing in a Global Enterprise* (Tennenbaum Institute Series on Enterprise Systems), vol. 5. Amsterdam, The Netherlands: IOS Press, 2012.

[15] S. P. Borgatti and X. Li, "On social network analysis in a supply chain context," *J. Supply Chain Manage.*, vol. 45, no. 2, pp. 5–22, 2009.

[16] E. Brandon-Jones, B. Squire, C. W. Autry, and K. J. Petersen, "A contingent resource-based perspective of supply chain resilience and robustness," *J. Supply Chain Manage.*, vol. 50, no. 3, pp. 55–73, 2014, doi: 10.1111/jscm.12050.

[17] J. Chen, A. S. Sohal, and D. I. Prajogo, "Supply chain operational risk mitigation: A collaborative approach," *Int. J. Prod. Res.*, vol. 51, no. 7, pp. 2186–2199, 2013, doi: 10.1080/00207543.2012.727490.

[18] T. Y. Choi, K. J. Dooley, and M. Rungtusanatham, "Supply networks and complex adaptive systems: Control versus emergence," *J. Oper. Manage.*, vol. 19, no. 3, pp. 351–366, 2001.

[19] S. Chopra and M. S. Sodhi, "Managing risk to avoid supply-chain breakdown," *MIT Sloan Manage. Rev.*, vol. 46, no. 1, pp. 53–62, 2004.

[20] S. Eubank, H. Guclu, V. S. A. Kumar, M. V. Marathe, A. Srinivasan, Z. Toroczkai, and N. Wang, "Modelling disease outbreaks in realistic urban social networks," *Nature*, vol. 429, no. 6988, pp. 180–184, 2004.

[21] C. H. Fine "Clockspeed-based strategies for supply chain design," *Prod. Oper. Manage.*, vol. 9, no. 3, pp. 213–221, 2000.

[22] P. Gai and S. Kapadia, "Contagion in financial networks," in *Proc. Roy. Soc. A, Math., Phys. Eng. Sci.*, vol. 466, no. 2120, pp. 2401–2423, 2010.

[23] A. Ghadge, S. Dani, M. Chester, and R. Kalawsky, "A systems approach for modelling supply chain risks," *Int. J. Supply Chain Manage.*, vol. 18, no. 5, pp. 523–538, 2013, doi: 10.1108/SCM-11-2012-0366.

[24] V. M. Grötsch, C. Blome, and M. C. Schleper, "Antecedents of proactive supply chain risk management—A contingency theory perspective," *Int. J. Prod. Res.*, vol. 51, no. 10, pp. 2842–2867, 2013, doi: 10.1080/00207543.2012.746796.

[25] M. G. Hertzel, Z. Li, M. S. Officer, and K. J. Rodgers, "Inter-firm linkages and the wealth effects of financial distress along the supply chain," *J. Financial Econ.*, vol. 87, no. 2, pp. 374–387, 2008.

[26] A. Huchzermeier and M. A. Cohen, "Valuing operational flexibility under exchange rate risk," *Oper. Res.*, vol. 44, no. 1, pp. 100–113, 1996.

[27] P. R. Kleindorfer and G. H. Saad, "Managing disruption risks in supply chains," *Prod. Oper. Manage.*, vol. 14, no. 1, pp. 53–68, 2005.
[28] A. Latour "Trial by fire: A blaze in albuquerque sets off major crisis for cell-phone giants," *Wall Street J.*, vol. 1, no. 29, P. A.1, 2001.
[29] H. Lee "The triple-a supply chain," *Harvard Bus. Rev.*, vol. 82, no. 10, pp. 102–112, 2004.
[30] S. Martínez-Jaramillo, O. P. Pérez, F. A. Embriz, and F. L. G. Dey, "Systemic risk, financial contagion and financial fragility," *J. Econ. Dyn. Control*, vol. 34, no. 11, pp. 2358–2374, 2010.
[31] A. Marucheck, N. Greis, C. Mena, and L. Cai, "Product safety and security in the global supply chain: Issues, challenges and research opportunities," *J. Oper. Manage.*, vol. 29, nos. 7/8, pp. 707–720, 2011.
[32] J. T. Mentzer, W. DeWitt, J. S. Keebler, S. Min, N. W. Nix, C. D. Smith, and Z. G. Zacharia, "Defining supply chain management," *J. Bus. Log.*, vol. 22, no. 2, pp. 1–25, 2001, doi: 10.1002/j.2158-1592.2001.tb00001.x.
[33] A. Nair and J. M. Vidal, "Supply network topology and robustness against disruptions—An investigation using multi-agent model," *Int. J. Prod. Res.*, vol. 49, no. 5, pp. 1391–1404, 2010.
[34] M. E. J. Newman, S. H. Strogatz, and D. J. Watts, "Random graphs with arbitrary degree distributions and their applications," *Phys. Rev. E*, vol. 64, no. 2, p. 026118, 2001.
[35] L. Rosenkopf and M. A. Schilling, "Comparing alliance network structure across industries: Observations and explanations," *Strat. Entrep. J.*, vol. 1, nos. 3/4, pp. 191–209, 2008.
[36] W. B. Rouse, "Enterprises as systems: Essential challenges and approaches to transformation," *Syst. Eng.*, vol. 8, no. 2, pp. 138–150, 2005.
[37] T. Sawik, "Selection of resilient supply portfolio under disruption risks," *Omega*, vol. 41, no. 2, pp. 259–269, 2013, [Online] http://dx.doi.org/10.1016/j.omega.2012.05.003
[38] M. A. Schilling "Understanding the alliance data," *Strat. Manage. J.*, vol. 30, no. 3, pp. 233–260, 2009.
[39] Y. Sheffi "Supply chain management under the threat of international terrorism," *Int. J. Log. Manage.*, vol. 12, no. 2, pp. 1–11, 2001.
[40] N. Shin, K. L. Kraemer, and J. Dedrick, "R&D, value chain location and firm performance in the global electronics industry," *Ind. Innov.*, vol. 16, no. 3, pp. 315–330, 2009.
[41] M. S. Sodhi, B.-G. Son, and C. S. Tang, "Researchers' perspectives on supply chain risk management," *Prod. Oper. Manage.*, vol. 21, no. 1, pp. 1–13, 2012.
[42] A. Świerczek "The impact of supply chain integration on the 'snowball effect' in the transmission of disruptions: An empirical evaluation of the model," *Int. J. Prod. Econ.*, vol. 157, pp. 89–104, 2014, doi: http://dx.doi.org/10.1016/j.ijpe.2013.08.010.
[43] O. Tang and S. N. Musa, "Identifying risk issues and research advancements in supply chain risk management," *Int. J. Prod. Econ.*, vol. 133, no. 1, pp. 25–34, 2011.
[44] P. Trkman and K. McCormack, "Supply chain risk in turbulent environments—A conceptual model for managing supply chain network risk," *Int. J. Prod. Econ.*, vol. 119, no. 2, pp. 247–258, 2009.
[45] S. Wasserman and K. Faust, *Social Network Analysis: Methods and Applications*, vol. 8. Cambridge, U.K.: Cambridge Univ. Press, 1994.
[46] D. J. Watts, "Networks, dynamics, and the small-world phenomenon," *Amer. J. Soc.*, vol. 105, no. 2, pp. 493–527, 1999.
[47] A. Wieland and C. M. Wallenburg, "The influence of relational competencies on supply chain resilience: A relational view," *Int. J. Phys. Distrib. Log. Manage.*, vol. 43, no. 4, pp. 300–320, 2013, doi: 10.1108/IJPDLM-08-2012-0243.
[48] D. D. Wu, C. Luo, and D. L. Olson, "Efficiency evaluation for supply chains using maximin decision support," *IEEE Trans. Syst., Man, Cybern. Syst.*, vol. 44, no. 8, pp. 1088–1097, Aug. 2014, doi: 10.1109/TSMC.2013.2291215.
[49] D. D. Wu, "Bargaining in supply chain with price and promotional effort dependent demand," *Math. Comput. Model.*, vol. 58, nos. 9/10, pp. 1659–1669, 2013, doi: http://dx.doi.org/10.1016/j.mcm.2010.12.035.
[50] D. D. Wu and D. L. Olson, "Computational simulation and risk analysis: An introduction of state of the art research," *Math. Comput. Model.*, vol. 58, no. 9, pp. 1581–1587, 2013.
[51] D. D. Wu, S.-H. Chen, and D. L. Olsen, "Business intelligence in risk management: Some recent progresses," *Inf. Sci.*, vol. 256, pp. 1–7, 2014.
[52] D. D. Wu, C. Luo, H. Wang, and J. R. Birge, "Bi-level programing merger evaluation and application to banking operations," *Prod. Oper. Manage.*, vol. 25, pp. 498–515, 2014.
[53] H. Yli-Renko, E. Autio, and H. J. Sapienza, "Social capital, knowledge acquisition, and knowledge exploitation in young technology-based firms," *Strat. Manage. J.*, vol. 22, nos. 6/7, pp. 587–613, 2001.
[54] M.-C. Yu and M. Goh, "A multi-objective approach to supply chain visibility and risk," *Eur. J. Oper. Res.*, vol. 233, no. 1, pp. 125–130, 2014, doi: http://dx.doi.org/10.1016/j.ejor.2013.08.037.
[55] L. Zhao, B. Huo, L. Sun, and X. Zhao, "The impact of supply chain risk on supply chain integration and company performance: A global investigation," *Int. J. Supply Chain Manage.*, vol. 18, no. 2, pp. 115–131, 2013, doi: 10.1108/13598541311318773.

Rahul C. Basole received the B.S. degree in industrial and systems engineering from Virginia Tech, Blacksburg, VA, USA, in 1998; the M.S. degree in industrial and systems engineering from the University of Michigan, Ann Arbor, MI, USA, in 2000; and the Ph.D. degree in industrial and systems engineering from the Georgia Institute of Technology (Georgia Tech), Atlanta, GA, USA, in 2006.

He is currently an Associate Professor with the School of Interactive Computing and is the Associate Director for Enterprise Transformation with the Tennenbaum Institute/Institute for People and Technology (IPaT), Georgia Tech. He is also a Visiting Scholar with the Human-Sciences and Technologies Advanced Research Institute (HSTAR), Stanford University, Stanford, CA, USA, and a Fellow with the Batten Institute, Darden School of Business, Charlottesville, VA. His research and teaching interests include computational enterprise science, information visualization, and strategic decision support.

Dr. Basole is the Editor-in-Chief of the *Journal of Enterprise Transformation* and an Editorial Board Member of *INFORMS Service Science*. His work has received numerous best paper awards; has been recognized by the media, including the *New York Times, Fortune Magazine*, and CNBC; and he has published extensively in leading computing, management, and engineering journals and conferences.

Marcus A. Bellamy received the B.S., M.S., and Ph.D. degrees in operations management from the Scheller College of Business, Georgia Institute of Technology, Atlanta, GA, USA, in 2006, 2010, and 2015, respectively.

He is currently an Assistant Professor of Operations and Technology Management with the Questrom School of Business, Boston University, Boston, MA, USA. His research interests include supply chain management, empirical operations management, supply chains and innovation, supply network risk, and network analytics and visualization. He was a Graduate Fellow at the Tennenbaum Institute, Georgia Institute of Technology, and also a Fulbright Scholar in Madrid, Spain.

Dr. Bellamy is a member of the Academy of Management, the Institute for Operations Research and Management Science, and Production and Operations Management.

Hyunwoo Park received the B.Sc. degree in electrical engineering from Seoul National University, Seoul, South Korea, in 2006; the master's degree in information management and systems from UC Berkeley, Berkeley, CA, USA, in 2010; and the Ph.D. degree in industrial engineering from the Georgia Institute of Technology (Georgia Tech), Atlanta, GA, USA, in 2015.

He is currently a Post-Doctoral Fellow with the Tennenbaum Institue, Georgia Tech. His research interests include technological innovation, platform strategy, new product development, and visual analytics.

Jagannath Putrevu received the bachelor's degree in electrical engineering from the Indian Institute of Technology, Madras, India, in 2011, and the master's degree in operations research from the Georgia Institute of Technology, Atlanta, GA, USA, in 2013.

He is currently a Data Scientist with Instacart, San Francisco, CA, USA. He works on a wide range of problems from search and recommendations to modeling user and shopper behavior. He is currently focusing on optimizing Instacart's logistics fulfillment engine, which is responsible for batching orders together and assigning them to shoppers in an efficient way.