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Supply Chain Risk Propagation and Canonical Supply Network Structure: A Multi-Level Analysis

(Authors' names blinded for peer review)

It has been suggested that supply chain risk and disruption possess inherent theoretical distinctions. Recent studies have also suggested that there is a need to incorporate risk-interdependencies that extend beyond firm boundaries. Such interdependencies are referred to as ”risk propagation”, and has been suggested to be theoretically distinct from ”risk”. Much of this research has focused on risk propagation measurement frameworks, but has lacked an exploration into it's nature, drivers, and definition. One critical driver that has been omitted from the literature around risk propagation is that of canonical network structure. In this study, we explore the nature of this association across different network levels of analysis, as well as cross-level associations by leveraging a mixed-methods approach of simulation using Bayesian Networks and empirical analysis on simulated network and risk data leveraging a Seemingly Unrelated Regression (SUR). The findings of the study distinguish between supply chain disruption propagation and supply chain risk propagation. Additionally, the study advances a new notion of the *k-ego network* as a modeling and measurement tool in supply networks.

Key words: Supply Chain Structure; Supply Chain Risk Management; Supply Chain Risk Propagation; Supply Network Structure

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1. Introduction

In April of 2016, a deadly 6.5 magnitude earthquake struck Japan, leaving nine dead as a result. It was reported that Sony, Toyota, Honda, and Nissan were affected from the disturbance. Toyota initiated a shut down of country-wide assembly lines (Kubota 2016), while GM had only initiated a more targeted and refined shutdown of it's facilities (Nagesh 2016). Due to the structural and process designs of Toyota's and GM's respective supply networks, the consequences of this disruption greatly differed for each firm. This anecdote illustrates that supply networks are inherently risk-prone, and the disruptions that occur are complex, costly, and inevitable.

Accordingly, efforts to understand the roots of these disruptions have been extensively addressed in the literature (Craighead et al. 2007, Osadchiy et al. 2015, Peck 2005), particularly focusing on managing supply chain disruptions at the organizational level via proactive/reactive strategies. A significant advancement to this body of literature involved theoretically distinguishing between supply chain disruptions and supply chain risks, where the former are physical manifestations of the latter (DuHadway et al. 2017, Garvey et al. 2015). As a result of highlighting this distinction, the research pertaining to planning and mitigating disruptions has significantly advanced (Ho et al. 2015), especially as a result of stochastic modeling (Tomlin 2006). Likewise, some scholars have recently argued that there is also a theoretical distinction between supply chain risk and supply chain risk propagation (Shin et al. 2012, Garvey et al. 2015).

Most studies on supply chain risk refine the level of analysis to the firm-level (Heckmann et al. 2015). However, much of this research does not capture the inter-dependencies between risks extending beyond firm boundaries (Garvey et al. 2015), and moving outward from the firm-level or dyadic level will greatly enhance our understanding of risk (Osadchiy et al. 2015). While there have been early attempts to recognize this theoretical distinction by constructing measurement frameworks (Garvey et al. 2015), such attempts have failed to ascertain the nature and drivers of supply chain risk propagation, let alone formally define it. Recent attempts to measure risk inter-dependency (i.e. supply chain risk propagation) (Kim et al. 2015) have not yet explored it's connection to supply network structure, overall, which has been shown to be related with other types of risk such as those of exchange rates (Huchzermeier and Cohen 1996). Though recent work from a lens of classification has made great strides (Kim et al. 2015), questions pertaining to this connection across different levels within networks still remain.

We argue that this is an important consideration since as the structure of the supply network changes, it can inadvertently affect the canonical structure of the network, which may not be reflected within existing classification-based frameworks. In addition, these two concepts are commonly analyzed within an isolated network level of analysis. To the best of our knowledge, we have yet to understand the nature of this association across different network levels, as well as cross-level effects of risk propagation. Such an exploration can highlight any trade offs between groups and individuals, which can lead to better operational planning and a reduction in supply risk, which can lead to the potential of increased investment into the firm (Babich and Kouvelis 2018). Accordingly, we employ a mixed-methods approach by first designing a simulation study which samples supply networks. We subsequently generate Bayesian Networks to model risk propagation in each supply network. This is followed by an empirical study in order to address the following research questions:

1. How does canonical network structure impact supply chain risk propagation within different structural levels of analysis of the supply network?
2. How does risk propagation within a "high" network level affect risk propagation within a "low" network level?

2. Literature Review

2.1. Supply Chain Disruptions

A *supply chain disruption* (SCD) is an "unplanned and unanticipated event that disrupts the normal flow of goods and materials within a supply chain" (Craighead et al. 2007, Kleindorfer and Saad 2005). The extant literature has given special attention to SCDs due to the rise of global sourcing and the level of perceived importance from practitioners (Craighead et al. 2007). SCDs have a significant impact on a firm's manufacturing and inventory performance (Tomlin 2006), which has led firms to consider mitigation strategies such as leveraging business interruption insurance (Dong and Tomlin 2012). Some have proposed other mitigation strategies such as the use of primary suppliers, pre-positioned warehouses, or duel sourcing (Yang et al. 2012). In addition, there have been many attempts to optimize decision making within supply chain risk management (SCRM) and SCD management via analytical models (Saghafian and Van Oyen 2016).

2.2. Supply Chain Risk and Risk Management

Distinct from a SCD, a *supply chain risk* (SCR) is often considered to be the antecedent of a SCD (DuHadway et al. 2017). There is, however, much debate over a precise definition of "supply chain risk". Some authors characterize it in terms of a consequence (Hendricks and Singhal 2005), whereas others characterize it as a likelihood (Kleindorfer and Saad 2005), although these two dimensions are often used together to measure risk (Tang and Tomlin 2008). Regardless of their definition, SCRs have been shown to have impacts on firm performance, contingent on detection efforts, perception, and implemented mitigation strategies (Garvey et al. 2015, Kleindorfer and Saad 2005, Zsidisin and Wagner 2010). This impact on performance is an important consideration since performance often serves as a foundation for financial arrangements of suppliers (Tang et al. 2017) . The extant literature views *Supply Chain Risk Management (SCRM)* as both a strategic (Chopra and Sodhi 2004) and tactical (Ho et al. 2015) activity, which lies at the intersection of Supply Chain Management and Risk Management (Khojasteh-Ghamari and Irohara 2018). Furthermore, many have proposed managerial frameworks that include many dimensions and related concepts, including assessment, measurement (Kleindorfer and Saad 2005), mitigation strategies (Tang and Tomlin 2008), risk classification (Ho et al. 2015), as well as drivers and consequences due to various firm characteristics and decisions (Ang et al. 2016).

2.3. Supply Chain Risk Propagation

A recent trend in the literature has been the emergence of the construct of *risk propagation*. Unlike traditional risk management, which views risk as the potential to directly manifest into a disruption, risk propagation is the sequence of inter-dependent risks that lead to changes in others risks or the manifestation of them (Garvey et al. 2015). Much of the extant literature currently conflates the constructs of "disruption", "risk", and "propagation", and some have proposed to disentangle these constructs (DuHadway et al. 2017, Garvey et al. 2015). Disruption propagation involves the sequence of events, derived from a known systematic structure, that occur due to a disruption itself, whereas *supply chain risk propagation* involves the sequence of inter-related risks that *could* occur, which may (or may not), lead to a disruption propagation or a different risk propagation (Garvey et al. 2015).

Recent advancements in this area primarily lie within the modeling of measuring the extent of the potential damage of such propagations using Bayesian Networks (Shin et al. 2012, Garvey et al.

2015), it's impact on facility location decisions (Lu et al. 2015), and simulations (Osadchiy et al. 2015). As a result of these prior studies, two primary methods of analysis have emerged. The first approach involves event-based modeling to measure the deterministic impacts of propagation based on the known design of systems (Dolgui et al. 2018), whereas the second approach has applied Bayesian Networks to incorporate uncertainty and inter-dependencies of risk, where potential events are identified, but "paths" of the risk are not necessarily known (Shin et al. 2012, Garvey et al. 2015). Bayesian-based methods rest on having an initial belief regarding a parameter's probability distribution. This distribution is subsequently updated upon the presence of evidence (Pearl 2014). This approach of modeling has been applied to sourcing (Tomlin 2009), inventory (DeHoratius et al. 2008, Chen and Plambeck 2008), and dynamic pricing (Afèche and Ata 2013) strategies.

2.4. Supply Chain Structure

There are three streams in the literature that have discussed the characterization of "network structure": structure characterization based on supply-chain constructs, mathematical graph theory, and classification, respectively.

2.4.1. Context-Based Characterization Context-based characterizations of network structure depend on the specific contextual attributes of the nodes and edges within the network. Lambert et al. (1998) proposed that supply networks can be characterized along the dimensions of *horizontal structure*, *vertical structure*, and the *horizontal position* of a focal firm. Others have suggested that such dimensions be based on the product (Fisher 1997), firm attributes, and inter-firm relationship attributes (Choi and Krause 2006). Other characterizations are based on network embeddeness (Choi and Wu 2009), number of echelons (Klosterhalfen et al. 2014), and industry-specific attributes (Ho et al. 2015).

2.4.2. Context-Free Characterization Graph-theory provides a mathematical tool box to objectively understand a network's "structure" within multiple contexts. The motivation for the theory is rooted within Leonhard Euler's now popular Seven Bridges of Königsberg Problem (Euler

1736). Since then, various measures of network structure have been proposed, which can be categorized into local-level metrics and group-level metrics.

Local-Level Measures

Local-level measures of a network involve characterizing how a single node or edge is in relation to the remainder of the network. The following are common measures used to gain an understanding of the local attributes within the graph: Betweenness, Closeness, Eigenvector, and Degree Centrality, Eccentricity, Min and Max Distance from the Center, Average Shortest Path, Density, Number of Triads, Number of structural holes, coreness, and the clustering coefficient (Borgatti and Li 2009, Freeman 1978, Carnovale and Yeniyurt 2014). Most of these were developed for the use in social network theory (Burt 1982). However, the same equations for these measures have mainly been developed and applied as operationalizations for various constructs within several different fields of study (Carnovale and Yeniyurt 2014, Burt 1982). It should be emphasized that these measures have been just that, measures, with no underlying theory relating to the network itself, but rather mostly depending on social science constructs.

Group-Level Measures

Researchers may also study networks from a group-level of analysis. That is, they can identify a well-defined group of nodes or edges in a network, and consider these groups as the unit of analysis. These can range from groups as small as dyads and triads (Choi and Wu 2009) to as large as ego-networks (Carnovale and Yeniyurt 2014) and entire networks (Borgatti and Li 2009). Group level metrics are commonly computed by combining the local-level metrics of individual nodes and edges within each well defined "unit". The extant literature currently employs two commonplace methods to combine the local metrics: describe the distribution of the local-level metrics, or leverage an equation to arithmetically combine them into a single metric (Kim et al. 2015, Borgatti and Li 2009). The latter approach is often employed either by centralizing the local metrics (Freeman 1978) or by finding the arithmetic mean of the local-level measures (Kim et al. 2015).

2.4.3. Classification-Based Characterization Classification of objects can distinguish between individuals under study, and are often dependent on the purpose for which they are implemented (Sneath 1957, pg. 184). This would explain the vast number of Supply Chain Structure Taxonomies in the extant literature, which views classification from two perspectives: graph-theoretic based and construct-based classification. Strogatz (2001) introduced the category of "small-world networks" and a method of classification based on criteria defined in terms of graph-theoretic metrics. Supply chain scholars have extended this work and defined different categories of networks including but not limited to centralized, linear, flat, hierarchical, federated, starburst, scale-free-like, and diagonal (Pathak et al. 2009, Kim et al. 2011, Rivkin and Siggelkow 2007). A second stream of literature for supply network classification is one that originates from Lambert et al. (1998), where the identification and differentiation of supply network structure is dependent on supply chain constructs such as network complexity, embeddeness, triads (Choi and Wu 2009), and ego-networks (Carnovale and Yeniyurt 2014). Bellamy and Basole (2013) offers an extensive review of approaches to characterize supply chain structure.

2.5. Network Levels of Analysis

The extant literature currently characterizes the "level of analysis" for supply networks in one of two ways: context-specific levels of analysis and structure-based levels of analysis. The former is based on the idea that supply chains are complex adaptive systems that comprise of actors (Carter et al. 2015), and hence, one must properly define the actors under study by identifying the types of "nodes" and "links". Peck (2005) developed a system of levels for the supply chain whereby the nodes can be anything from firms to physical assets, while the links represent physical material, information, or financial flows. Yet, even if the nodes and edges are contextually defined, the researcher must be clear as to which units of the network are under consideration. Provan et al. (2007) had synthesized much of the organizational network literature from this perspective, and argues that there are two fundamental types of units: the individual node level (the "organization") and the collective level ("the whole network"). They were careful to explain that the latter can include structures such as dyads, triads, ego-networks, and entire networks.

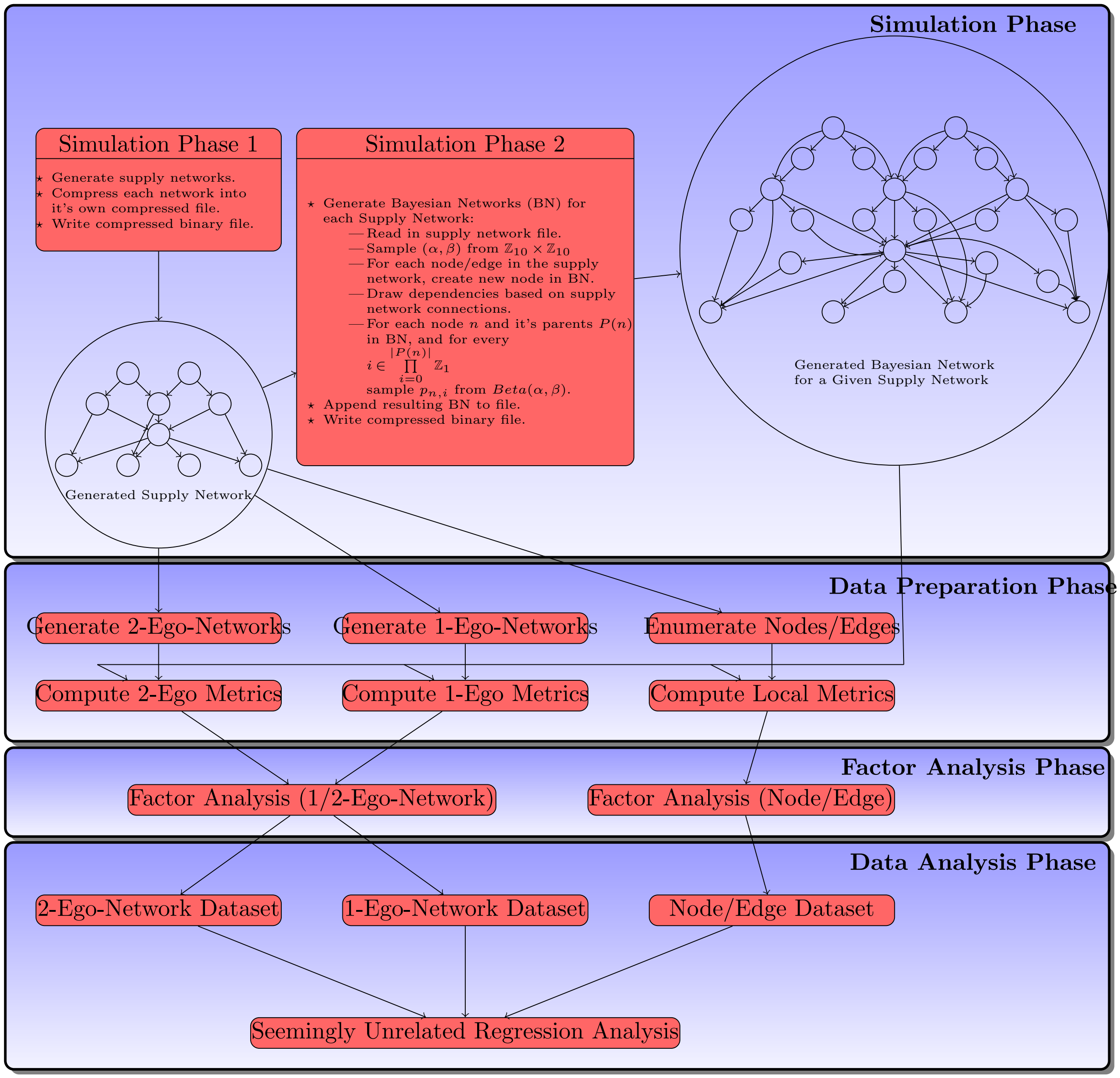


Figure 1 **Our Research Design**

3. Simulation Design

3.1. Phase 1: Network Generation

We generate a data set of supply networks in this phase which will later be used to generate the risk components in the second phase of the simulation. We first sampled different supply networks of varying sizes so that we had enough heterogeneity to isolate possible relationships. The simulation operated on the assumptions of generating networks that had a minimum of 100 nodes, in a hierarchical manner with the number of layers as few as 5, and such that every node in the network had at most 10 parent nodes. We conducted this first phase by writing algorithms in R which ran on a single Amazon m5.24xlarge instance (96 VPUs, 384 Gib RAM) which was launched with Ubuntu 18 Server and R as well as R-Studio Server. A total of 600 unique networks were generated leveraging R's *igraph* package, which allows for the creation of networks and mathematical graphs without the need to store network information within an adjacency matrix or a data structure.

3.2. Phase 2: Risk Graph Generation

The second phase involved simulating different risks at every location in a given network, for all of the networks generated from Phase 1. To do so, we generated a Bayesian Network for each supply network, as is outlined in Garvey et al. (2015). This involved iterating through every node and link in a supply network, and for each element, identifying a collection of risks, drawing the dependencies between the risks within a single location, as well as the dependencies between the risks in adjacent locations (node and edge). Last, we computed the conditional probability distributions for each risk for each instance of the parent-risks.

Since we are simulating the risks and the conditional probability distributions, most of our simulation design was based on simplifying assumptions regarding the risks within the supply networks. First, we made the assumption that each location (node or edge) in every network was associated with a single general risk of "disruption", modeled by a binary random variable. We argue that while understanding the intricacies of the dependencies of risk within a single location is important for strategic decision making, we determined that modeling beyond a single generic risk of disruption (for each node/edge in each network) in our simulation would not add any additional value to the current research. Furthermore, this simplifying assumption allowed us to ignore the context of a "risk" so as to allow for greater external validity of our results.

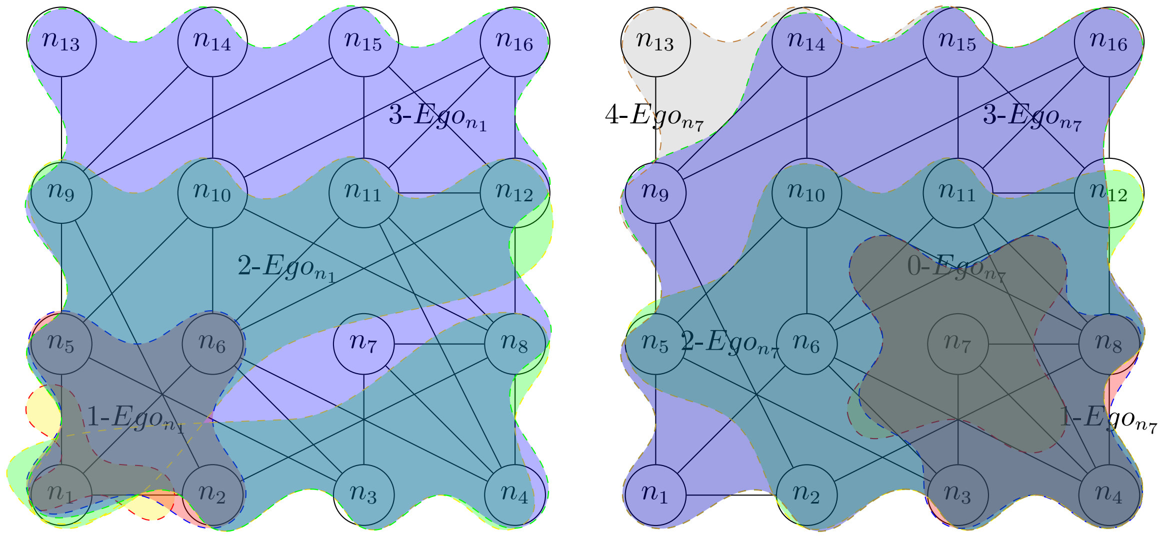
Second, the conditional probability distributions (that is, the conditional probabilities for each risk manifesting into a disruption given information of disruption/no disruption in the parent nodes) were sampled from a Beta Distribution. The Beta Distribution has been used in prior models to describe the distribution of probabilities of discrete events (Heckerman et al. 1995), and encapsulates an infinite number of possible distributions of the probabilities by altering two shape parameters. To allow for enough heterogeneity in the conditional probabilities of disruption, we uniformly sampled the (α, β) parameters from $\mathbb{Z}_{10} \times \mathbb{Z}_{10}$ for each individual supply network. Last, we assumed that decisions within supply networks were fixed, and that any potential consequences of a disruption as a result of those decisions were reflected within the probabilities of disruption as well as the cost functions. That is, by randomly sampling conditional probabilities, we are in effect sampling the possible consequences of decision making within the network. Phase 2 of the simulation was implemented in R as a separate script. The networks that were generated from phase 1 were stored within individual compressed R binary files. This collection of files was split onto 3 different Amazon EC2 instances to allow for parallel generation of Bayesian Networks. On each instance, the script would read in the supply network data from the file, and for each individual network, executed an algorithm to generate the risk graph (i.e. the Bayesian Network). Each binary file was appended with the generated Bayesian Network, which contained the structural information of the risk dependencies, as well as the conditional probabilities. The details of both phases can be found in the supplement to this manuscript.

4. Framework Development

4.1. Levels of Analysis of a Network: Defining the *k-ego-network*

Generally, in the network context, a "level" can be defined as either the node, link, triad, ego-network, or entire network level. Many in the literature have already explored various dynamics of supply chain management and risk within some of these levels. We argue, however, that this taxonomy of levels of analysis is somewhat incomplete. Despite there being no "gaps" between the levels of nodes/edges, dyads, and triads, there is a gap between triads, ego networks, and the entire network. We argue that most of these levels of analysis are actually special cases of a more general taxonomy which can be generated with a structure which we define as the k-ego network. This structure is defined recursively:

Definition 1. *The 0-Ego-Network of a node or an edge is the node or edge itself.*



(a) The 0-Ego-Network (in yellow area), 1-Ego-Network (in red area), 2-Ego-Network (in green area), and 3-Ego-Network (in blue area) of node n_1.

(b) The 0-Ego-Network (in yellow area), 1-Ego-Network (in red area), 2-Ego-Network (in green area), 3-Ego-Network (in blue area), and the 4-Ego-Network (in gray area) of node n_7.

Figure 2 Different k-Ego Network structures, relative to different nodes, on the same network.

Definition 2. *The k-Ego-Network of an element n in a network is the induced subgraph of all nodes in the (k-1)-Ego-Network of n and all of the nodes in each 1-Ego-Network of each node in the (k-1)-Ego-Network of n.*

Figures 2a and 2b illustrate that k-Ego-Networks are *relative* constructs with respect to a given node in the graph (or edge, where the "ego network" of the edge would be the union of the Ego-Network of each respective node in the dyadic relationship). We contend that this new tool of a structural level of analysis allows the researcher of supply networks and more generally of any field of study that leverages network theory, an easy to use method which clearly specifies the level of analysis. The specification of the level of analysis is only dependent on the number of "levels up" from a given node or edge. Furthermore, the construction of this framework allows for the preservation of current theory that rests on certain levels of analysis, which can be shown to be special cases of this framework.

4.2. A Framework of Constructs for Canonical Network Structure

We illustrated in the literature review that supply network structure can be characterized either by context, graph theory, or classification. The focal point of our study is to understand *canonical* network structure and it's association with risk propagation, where the definitions of nodes/edges, as well as contextual properties of them, are irrelevant. While classification systems currently exist to distinguish between networks, we argue that the study of analytical topics such as risk propagation requires a more granular level of information, much of which is "thrown away" as a result of the classification process. We hence decided to characterize our "canonical structure" with graph theoretic metrics. However, we argue that directly leveraging existing metrics would be too cumbersome for a few reasons. First, there are a large number of these metrics, all of which measure something about the canonical structure, but were originally designed for use within sociological theories. That is, we argue they measure something about the canonical structure, but no one has identified what specifically they measure about said structure. Second, the vast number of these metrics would not allow us to "see the forest through the trees", so to speak. That is, we have information overload, and intuition would be lost in trying to decipher through these metrics. Last, the number of these metrics would greatly increase the number of dimensions in our empirical analysis, which could lead us to risk entering into a curse of dimensionality. Hence, as a result of a thorough literature review, we identified 28 group-level and 14 local-level graph metrics to compute within each level of every generated network, and subsequently reduce the dimensions via Exploratory Factor Analysis (EFA) to extract more intuitive constructs which characterize a network's canonical structure.

4.2.1. Data Preparation We leveraged the new k-Ego-Network structure with $k \leq 2$, a decision rooted within practical considerations, since a firm's visibility is rarely beyond the second tier supplier (Carter et al. 2015). We again leveraged the *igraph* package on the same machine described earlier to compute group and local graph theoretic metrics. For every node/edge in every network, we generated the 1 and 2-Ego-Networks and computed group-level metrics based on the nodes/edges within each 1/2-Ego-Network, which yielded two data sets, respectively. We subsequently combined these observations together to form a single data set. Next, we computed the local-level graph metrics for every node in every network, and enumerated these results into a different dataset. The edge level metrics were computed by converting each network into it's line graph (Detti et al. 2007) and computing node-level metrics on this network. The data for all nodes and edges for every network were combined to form the second data set.

4.2.2. Factor Analysis We conducted an exploratory factor analysis (EFA) on all of the variables in our 1/2-Ego-Network dataset as well as the local node/edge dataset. Initial results indicated that the optimal number of factors was 5. We ran a final version of the EFA using the Minimum Residual Method with a Varimax Rotation in R using the *psych* package. The final loadings for both data sets are shown in Table 1, with the highest loadings highlighted in gray.

4.2.3. Construct Development Given the results of the EFA, meaning can be extracted from each factor. We do so by observing common attributes across the variables that loaded onto each respective factor for both data sets. First, we notice from Table 1 that the first factor had similar types of measures loaded, overwhelmingly those of "centrality". In light of this observation, we identify the first factor in both data sets, MR1, as a "Centrality" construct, which we define as the network's overall ability to associate with others within the network. We notice that in the 1/2-Ego-Network loadings, diameter, radius, density, shortest path distance and eccentricity reflected the same underlying construct, MR3. On the node level, eccentricity, min/max center distance, and average shortest path distances all loaded on the same factor as well, MR2. The common theme across these variables is that of "Distance", and we define this as the overall size of the network's landscape. Moving to MR4 in the 1/2-Ego-Network loadings, we see that clique number and size, the number of triads, and the average constraint and degree loaded on the same construct, while the closeness centrality at the node/arc level loaded on MR4. At the local level, our results indicate that closeness centrality would be a better indicator of "clustering" than it would be at the global level, where it is a better indicator of either centrality or distance, depending on if the average or Freeman's centralization is leveraged.

Graph Metric	MR1	MR3	MR4	MR2	MR5
eNNodes	0.84	0.47	0.23	0.11	-0.01
eNArcs	0.82	0.27	0.49	0.12	0.01
eNSH	0.89	0.25	0.29	0.03	-0.01
eConstraintCen	0.84	0.37	0.32	0.09	-0.12
eAvgBetweeness	0.89	0.42	0.03	0.04	-0.02
eCenBetweeness	0.87	0.11	0.02	0.01	0.01
eCenEigen	0.88	0.44	0.12	0.06	-0.04
eCenCloseness	0.74	0.51	0.29	0.11	-0.07
eCenDegree	0.91	0.28	0.23	0.04	-0.03
eEccentricityCen	0.77	0.44	0.17	0.06	-0.06
eDiameter	0.39	0.86	0.11	0.07	-0.15
eRadius	0.42	0.75	0.10	0.06	-0.12
eNumOfLargestCliques	0.22	0.39	0.04	-0.25	0.10
eDensity	-0.29	-0.90	-0.14	-0.04	0.21
eAvgShortestPathDis	0.51	0.83	0.01	0.03	-0.12
eAvgCloseness	-0.06	-0.77	-0.28	-0.37	-0.02
eAvgEV	-0.41	-0.84	-0.16	-0.09	0.17
eAvgEccentricity	0.42	0.86	0.10	0.08	-0.16
eCliqueNum	0.35	0.15	0.76	0.47	0.04
eAvCliqueSize	0.30	0.11	0.85	0.38	0.10
eNTriads	0.65	0.04	0.67	0.08	0.02
eAvgConstraint	-0.19	-0.62	-0.68	-0.07	-0.02
eAvgDegree	0.27	0.26	0.81	0.40	0.18
eGirth	0.10	0.35	0.14	0.86	0.05
eClusterCoeff	0.04	-0.07	0.33	0.89	0.24
eClusterCoeffAv	0.09	0.03	0.32	0.85	0.29
eEdgeConnectivity	-0.09	-0.14	0.23	0.21	0.87
eNodeConnectivity	-0.03	-0.24	-0.03	0.21	0.72

Graph Metric	MR1	MR2	MR4	MR3	MR5
nBetweenness	0.35	-0.20	0.10	-0.16	-0.30
nEigen	0.62	-0.27	0.37	-0.02	-0.05
nDegree	0.92	-0.26	-0.07	0.21	-0.17
nDensity	0.83	-0.24	0.23	0.23	-0.38
nCoreness	0.86	-0.25	-0.07	0.42	0.02
nTriads	0.96	-0.21	-0.00	0.06	0.15
nSH	0.96	-0.20	-0.01	-0.13	0.01
nEccentricity	-0.23	0.88	-0.09	-0.10	0.08
nMinCenterDistance	-0.25	0.91	-0.14	-0.05	0.16
nMaxCenterDistance	-0.25	0.91	-0.16	-0.04	0.17
nAvgSPathDis	-0.38	0.81	-0.15	-0.19	0.18
nCloseness	-0.01	-0.52	0.72	-0.15	-0.25
nClusterCoeff	0.10	-0.10	-0.05	0.56	0.11
nEgoConnectivity	0.01	0.14	-0.06	0.08	0.47

Table 1 **EFA Loading Table for the 1/2-Ego-Network (Left) and the Node/Edge Level (Right).**

This result is logical, since if a node has a high level of closeness centrality, it's distance to other nodes is much lower, which would be more indicative of a "clustering" or "cliqueness" property than that of a centrality property. Hence, we identify MR4 as a construct that describes the network's level of "Clustering", which we define as the networks tendency to form cliques. Next, the girth and average/centralized clustering coefficient (CCC) loaded on factor MR2 in the 1/2-Ego-Network loadings, while the clustering coefficient loaded on MR3 in the local loadings. Girth measures the smallest cycle length in the network, while CCC is computed by the number of triads within the network for it's computation. We argue that these loadings are reflective of a property that represents a certain level of "feedback", level of "rigidity", or the network's level of "thickness". We will call this construct "Feedback". Last, we notice on MR5 for both data sets that our connectivity variables loaded on the same construct, which should be expected, and so we define "Connectedness" in the network as the ability of the network to remain accessible after actions of "removing" elements of the network, which is indicative of the networks "strength".

4.3. Risk Propagation Constructs

We define *supply chain risk* as the *interaction* between the likelihood and the potential consequence of an event that could manifest into a supply chain disruption. As we have stated in the literature review above, many still conflate supply chain risk and supply chain risk propagation. These two constructs, we argue, are distinct. We can view supply chain risk as a specific event that could manifest into a disruption, while a supply chain risk propagation is a sequence of events that have the potential to manifest into one or more supply chain disruptions, disruption propagations, or other risk propagations.

To the best of our knowledge, only Garvey et al. (2015) have proposed metrics to measure the extent of supply chain risk propagations. A limitation in Garvey et al. (2015) is the lack of a characterization of risk propagation constructs. We argue that there are three fundamental risk propagation constructs. Risk Significance (Diagnostic) is the level of potential damage or cost "upstream" in a supply network relative to a focal node upon the observation of evidence at the focal node. Risk Contribution (Causal) is the level of potential damage or cost ”downstream” in a supply network relative to a focal node upon the observation of evidence at the focal node. Last, Risk Kinematics (Change) are the various quantities of change between ”upstream” damage and ”downstream” damage as a result of risk ”flowing” through a focal node, upon the observation of evidence at the focal node. In this research, we consider only one such kinematic, namely, that of velocity, which we define as the relative change in damage with respect to a location in the supply network.

5. Empirical Study

5.1. Design

5.1.1. Population and Levels of Analysis We constructed a hierarchical-based research design, where we study the potential association between the aforementioned constructs within and across the aforementioned three levels of analysis. Ideally, we sought to understand these connections for all possible networks, which would be our intended population of interest. As such, we constructed three data sets, one for each level, with the variables described in each section below.

5.1.2. Dependent Variables The primary dependent variables in this research were the 2-Ego Network Risk Propagation, 1-Ego-Network Risk Propagation and Node/Arc Risk Propagation. Risk was characterized by using the three constructs developed earlier (contribution, significance, and velocity), and they were all operationalized by computing the equations described below. To design these equations, we leveraged the Garvey et al. (2015) model, which uses Bayesian Networks (BN) to model the inter-dependencies of risk within a supply network. Within each BN, a node represents a single risk, which is linked to parent nodes that describe the risk's dependencies on other risks. For each node in the BN, the entire collection of possible assignments to the parent nodes $\{0,1\}$ is enumerated. If a node has k parents, then there are a total of 2^k possible instances. For each instance in this enumeration, a conditional probability of occurrence for the specified node is assigned to a specific node-parent-instance permutation. Therefore, a BN is ”fully specified” once we have identified (1) the risks (nodes), (2) the directed links between the risks, and (3) the conditional probability distributions for each node-instance permutation.

Once the BN for a given supply network is fully specified, we can leverage the BN to compute propagation metrics. Each node is assigned a cost function $U(n)$, which indicates some form of loss if the specific risk n were to manifest(denoted by $n = 1$, $n = 0$ for non-manifestation). In our study, we define the cost function to be $U(n) = n$. This is a counting cost function. If a risk were to manifest at a node n, then $U(n) = 1$. Hence, if we consider different scenarios in different portions of the BN relative to a given node, we can construct metrics to reflect the "expected number of disruptions" either upstream or downstream relative to information of occurrence for the given node.

To construct the definitions of our measures used for the dependent variables, we used Garvey et al. (2015) definition of the Expected Location Risk Contribution Factor (ELRCF) as a basis to construct the other measures. First, we designed The Expected Location Risk Significance Factor (ELRSF), which computes the expected cost of the ancestors of a given risk in the BN:

$$ELRSF(n) = (1 + ERSF(n|n = 1))P(n = 1) + ERSF(n|n = 0)P(n = 0)$$

where ERSF is the Expected Risk Significance Factor, which we define for a node n assigned to a value $a \in \{0, 1\}$ and n has a set of ancestors $A(n)$ in the BN, and the cost $U(n) = n$:

$$ERSF(n = a) = E\left[\sum_{n_i \in A(n)} U(n_i)|n = a\right]$$

Next, we operationalized contribution by using the Expected Location Risk Contribution Factor (ELRCF), which computes the expected cost of the descendants of a given risk in the BN and is defined as follows:

$$ELRCF(n) = (1 + ERCF(n|n = 1))P(n = 1) + ERCF(n|n = 0)P(n = 0)$$

where ERCF is the Expected Risk Contribution Factor, which we define for a node n assigned to a value $a \in \{0, 1\}$ and n has a set of descendants $D(n)$ in the BN:

$$ERCF(n = a) = E\left[\sum_{n_i \in D(n)} U(n_i)|n = a\right]$$

We measure the last dependent variable by using the Expected Location Risk Velocity (ELRV), which computes the expected percentage change between total downstream cost relative to total upstream cost, and is defined mathematically as:

$$ELRV(n) = ERV(n|n=1)P(n=1) + ERV(n|n=0)P(n=0)$$

where ERV is the Expected Risk Velocity, which is defined for a node n assigned to a value $a \in \{0, 1\}$

$$ERV(n=a) = E\left[\frac{\sum_{n_i \in D(n)} U(n_i) - \sum_{n_i \in A(n)} U(n_i)}{\sum_{n_i \in A(n)} U(n_i)} | n = a\right]$$

5.1.3. Control Variables The study controlled for three primary variables of interest, namely the α parameter, the β parameter, and a dummy variable indicating if a data point in the local data was a node or an edge. The α and β are critical to control for, as they significantly impact the calculation of the risks. However, controlling for all probabilities would be cumbersome. Hence, one way to control for the probabilities simulated is to simply use the parameters of the distribution from which the probabilities were sampled, as a regressor in the primary model, so that proper structural effects can be isolated and omitted variable bias can be reduced.

5.1.4. Independent Variables We had seen from our EFA that all of the graph-theoretic variables had loaded onto one of five constructs: Centrality, Distance, Clustering, Feedback or Connectivity. We want to determine how each of these impacts risk. There is some precedent in the extant literature for this association being that of a quadratic nature (Choi and Krause 2006). Hence, our independent variables in the empirical model will not only include the factor scores for each structural construct, but also the squares of each score to reflect this possible quadratic association. In addition, for the "lower" empirical models, we included the risk propagation measures from the "higher" levels as IVs, since we would like to determine if risk propagation in higher levels of analysis impact risk propagation in lower levels of analysis.

5.2. Empirical Model

Our independent variables are denoted as C for Centrality, N for Connectivity, L for Clustering, F for Feedback, D for Distance, I for Risk Contribution, S is Risk Significance, V for Risk Velocity, and E for a Dummy Variable to denote if the observation is a Node(1) or an Edge(0). Given that we have 3 measures each for 3 different risk constructs at the 1/2-Ego-Network levels that share the same regressors, it is highly likely that the error terms in each model, across the models, will be correlated. As such, we leveraged a Seemingly Unrelated Regression (SUR) model. In this case, because we have three different levels of analysis, of which are connected via 3 variables each (namely, the risk confidence, significance, and velocity, respectively), we estimated the SUR separately. Thus, there will be three systems of equations. The first will be the system of equations for the 2-Ego-Network risk model, the second for the 1-Ego-Network risk model, and the third for the local-network risk model. The models, given their length, are displayed on the following page.

5.3. Data Preparation

Using the generated network data from the EFA and the simulations, we constructed three different data sets: one at the 2-Ego-Network level, 1-Ego-Network level, and local (node/edge) level, respectively. The 2-Ego-Network data set was found by using the factor scores from the EFA and labeling them according to the identified structural construct (i.e. Centrality, Distance, etc). In addition, an overall risk propagation measure was computed for the dependent variable. The 2-Ego-Network data set contained 9 dependent variables, since there were three measures for each propagation construct. Each variable was computed by taking the corresponding risk metric for the nodes and edges in each individual 2-Ego-Network and computing the average, standard deviation, and coefficient of variation. The same process was conducted for the 1-Ego-Network data, but we also appended the risk metrics from the 2-Ego-Network level as IVs. We did so by conducting a CFA on the propagation metrics at the 2-Ego-Network level, computing three factor scores (one for each construct). Last, the local level data set was constructed from the factor scores from the local-level EFA. For the dependent variables, each risk metric for each node/edge was computed. Again, a CFA was conducted on the 1-Ego-Network risk metrics to reduce the dimensions of the operationalizations from 9 measures down to 3. These were included as independent variables for the local level data set, analogous to our procedure for including 2-Ego-Network risk in the 1-Ego-Network data set. A final dataset was then assembled and cleaned for further pre-processing. To ensure the data was clean and free of outliers for analysis, we removed the lower and

$$\mu_c^{ego2} = \beta_{0,1} + \beta_{1,1}\alpha_i + \beta_{2,1}\beta_i + \beta_{3,1}C_i + \beta_{4,1}C_i^2 + \beta_{5,1}N_i + \beta_{6,1}N_i + \beta_{7,1}L_i + \beta_{8,1}L_i^2 + \beta_{9,1}F_i + \beta_{10,1}F_i^2 + \beta_{11,1}D_i + \beta_{12,1}D_i^2 + \epsilon_{i,1}^{ego2}$$
$$\mu_s^{ego2} = \beta_{0,2} + \beta_{1,2}\alpha_i + \beta_{2,2}\beta_i + \beta_{3,2}C_i + \beta_{4,2}C_i^2 + \beta_{5,2}N_i + \beta_{6,2}N_i + \beta_{7,2}L_i + \beta_{8,2}L_i^2 + \beta_{9,2}F_i + \beta_{10,2}F_i^2 + \beta_{11,2}D_i + \beta_{12,2}D_i^2 + \epsilon_{i,2}^{ego2}$$
$$\mu_v^{ego2} = \beta_{0,3} + \beta_{1,3}\alpha_i + \beta_{2,3}\beta_i + \beta_{3,3}C_i + \beta_{4,3}C_i^2 + \beta_{5,3}N_i + \beta_{6,3}N_i + \beta_{7,3}L_i + \beta_{8,3}L_i^2 + \beta_{9,3}F_i + \beta_{10,3}F_i^2 + \beta_{11,3}D_i + \beta_{12,3}D_i^2 + \epsilon_{i,3}^{ego2}$$
$$\sigma_c^{ego2} = \beta_{0,4} + \beta_{1,4}\alpha_i + \beta_{2,4}\beta_i + \beta_{3,4}C_i + \beta_{4,4}C_i^2 + \beta_{5,4}N_i + \beta_{6,4}N_i + \beta_{7,4}L_i + \beta_{8,4}L_i^2 + \beta_{9,4}F_i + \beta_{10,4}F_i^2 + \beta_{11,4}D_i + \beta_{12,4}D_i^2 + \epsilon_{i,4}^{ego2}$$
$$\sigma_s^{ego2} = \beta_{0,5} + \beta_{1,5}\alpha_i + \beta_{2,5}\beta_i + \beta_{3,5}C_i + \beta_{4,5}C_i^2 + \beta_{5,5}N_i + \beta_{6,5}N_i + \beta_{7,5}L_i + \beta_{8,5}L_i^2 + \beta_{9,5}F_i + \beta_{10,5}F_i^2 + \beta_{11,5}D_i + \beta_{12,5}D_i^2 + \epsilon_{i,5}^{ego2}$$
$$\sigma_v^{ego2} = \beta_{0,6} + \beta_{1,6}\alpha_i + \beta_{2,6}\beta_i + \beta_{3,6}C_i + \beta_{4,6}C_i^2 + \beta_{5,6}N_i + \beta_{6,6}N_i + \beta_{7,6}L_i + \beta_{8,6}L_i^2 + \beta_{9,6}F_i + \beta_{10,6}F_i^2 + \beta_{11,6}D_i + \beta_{12,6}D_i^2 + \epsilon_{i,6}^{ego2}$$
$$cv_c^{ego2} = \beta_{0,7} + \beta_{1,7}\alpha_i + \beta_{2,7}\beta_i + \beta_{3,7}C_i + \beta_{4,7}C_i^2 + \beta_{5,7}N_i + \beta_{6,7}N_i + \beta_{7,7}L_i + \beta_{8,7}L_i^2 + \beta_{9,7}F_i + \beta_{10,7}F_i^2 + \beta_{11,7}D_i + \beta_{12,7}D_i^2 + \epsilon_{i,7}^{ego2}$$
$$cv_s^{ego2} = \beta_{0,8} + \beta_{1,8}\alpha_i + \beta_{2,8}\beta_i + \beta_{3,8}C_i + \beta_{4,8}C_i^2 + \beta_{5,8}N_i + \beta_{6,8}N_i + \beta_{7,8}L_i + \beta_{8,8}L_i^2 + \beta_{9,8}F_i + \beta_{10,8}F_i^2 + \beta_{11,8}D_i + \beta_{12,8}D_i^2 + \epsilon_{i,8}^{ego2}$$
$$cv_v^{ego2} = \beta_{0,9} + \beta_{1,9}\alpha_i + \beta_{2,9}\beta_i + \beta_{3,9}C_i + \beta_{4,9}C_i^2 + \beta_{5,9}N_i + \beta_{6,9}N_i + \beta_{7,9}L_i + \beta_{8,9}L_i^2 + \beta_{9,9}F_i + \beta_{10,9}F_i^2 + \beta_{11,9}D_i + \beta_{12,9}D_i^2 + \epsilon_{i,9}^{ego2}$$

$$\mu_c^{ego1} = \beta_{0,1}^{ego1} + \beta_{1,1}^{ego1}\alpha_i + \beta_{2,1}^{ego1}\beta_i^{ego1} + \beta_{3,1}^{ego1}C_i + \beta_{4,1}^{ego1}C_i^2 + \beta_{5,1}^{ego1}N_i + \beta_{6,1}^{ego1}N_i + \beta_{7,1}^{ego1}L_i + \beta_{8,1}^{ego1}L_i^2 + \beta_{9,1}^{ego1}F_i + \beta_{10,1}^{ego1}F_i^2 + \beta_{11,1}^{ego1}D_i + \beta_{12,1}^{ego1}D_i^2 + \beta_{13,1}^{ego1}I_i + \beta_{14,1}^{ego1}S_i + \beta_{15,1}^{ego1}V_i + \epsilon_{i,1}^{ego1}$$
$$\mu_s^{ego1} = \beta_{0,2}^{ego1} + \beta_{1,2}^{ego1}\alpha_i + \beta_{2,2}^{ego1}\beta_i^{ego1} + \beta_{3,2}^{ego1}C_i + \beta_{4,2}^{ego1}C_i^2 + \beta_{5,2}^{ego1}N_i + \beta_{6,2}^{ego1}N_i + \beta_{7,2}^{ego1}L_i + \beta_{8,2}^{ego1}L_i^2 + \beta_{9,2}^{ego1}F_i + \beta_{10,2}^{ego1}F_i^2 + \beta_{11,2}^{ego1}D_i + \beta_{12,2}^{ego1}D_i^2 + \beta_{13,2}^{ego1}I_i + \beta_{14,2}^{ego1}S_i + \beta_{15,2}^{ego1}V_i + \epsilon_{i,2}^{ego1}$$
$$\mu_v^{ego1} = \beta_{0,3}^{ego1} + \beta_{1,3}^{ego1}\alpha_i + \beta_{2,3}^{ego1}\beta_i^{ego1} + \beta_{3,3}^{ego1}C_i + \beta_{4,3}^{ego1}C_i^2 + \beta_{5,3}^{ego1}N_i + \beta_{6,3}^{ego1}N_i + \beta_{7,3}^{ego1}L_i + \beta_{8,3}^{ego1}L_i^2 + \beta_{9,3}^{ego1}F_i + \beta_{10,3}^{ego1}F_i^2 + \beta_{11,3}^{ego1}D_i + \beta_{12,3}^{ego1}D_i^2 + \beta_{13,3}^{ego1}I_i + \beta_{14,3}^{ego1}S_i + \beta_{15,3}^{ego1}V_i + \epsilon_{i,3}^{ego1}$$
$$\sigma_c^{ego1} = \beta_{0,4}^{ego1} + \beta_{1,4}^{ego1}\alpha_i + \beta_{2,4}^{ego1}\beta_i^{ego1} + \beta_{3,4}^{ego1}C_i + \beta_{4,4}^{ego1}C_i^2 + \beta_{5,4}^{ego1}N_i + \beta_{6,4}^{ego1}N_i + \beta_{7,4}^{ego1}L_i + \beta_{8,4}^{ego1}L_i^2 + \beta_{9,4}^{ego1}F_i + \beta_{10,4}^{ego1}F_i^2 + \beta_{11,4}^{ego1}D_i + \beta_{12,4}^{ego1}D_i^2 + \beta_{13,4}^{ego1}I_i + \beta_{14,4}^{ego1}S_i + \beta_{15,4}^{ego1}V_i + \epsilon_{i,4}^{ego1}$$
$$\sigma_s^{ego1} = \beta_{0,5}^{ego1} + \beta_{1,5}^{ego1}\alpha_i + \beta_{2,5}^{ego1}\beta_i^{ego1} + \beta_{3,5}^{ego1}C_i + \beta_{4,5}^{ego1}C_i^2 + \beta_{5,5}^{ego1}N_i + \beta_{6,5}^{ego1}N_i + \beta_{7,5}^{ego1}L_i + \beta_{8,5}^{ego1}L_i^2 + \beta_{9,5}^{ego1}F_i + \beta_{10,5}^{ego1}F_i^2 + \beta_{11,5}^{ego1}D_i + \beta_{12,5}^{ego1}D_i^2 + \beta_{13,5}^{ego1}I_i + \beta_{14,5}^{ego1}S_i + \beta_{15,5}^{ego1}V_i + \epsilon_{i,5}^{ego1}$$
$$\sigma_v^{ego1} = \beta_{0,6}^{ego1} + \beta_{1,6}^{ego1}\alpha_i + \beta_{2,6}^{ego1}\beta_i^{ego1} + \beta_{3,6}^{ego1}C_i + \beta_{4,6}^{ego1}C_i^2 + \beta_{5,6}^{ego1}N_i + \beta_{6,6}^{ego1}N_i + \beta_{7,6}^{ego1}L_i + \beta_{8,6}^{ego1}L_i^2 + \beta_{9,6}^{ego1}F_i + \beta_{10,6}^{ego1}F_i^2 + \beta_{11,6}^{ego1}D_i + \beta_{12,6}^{ego1}D_i^2 + \beta_{13,6}^{ego1}I_i + \beta_{14,6}^{ego1}S_i + \beta_{15,6}^{ego1}V_i + \epsilon_{i,6}^{ego1}$$
$$cv_c^{ego1} = \beta_{0,7}^{ego1} + \beta_{1,7}^{ego1}\alpha_i + \beta_{2,7}^{ego1}\beta_i^{ego1} + \beta_{3,7}^{ego1}C_i + \beta_{4,7}^{ego1}C_i^2 + \beta_{5,7}^{ego1}N_i + \beta_{6,7}^{ego1}N_i + \beta_{7,7}^{ego1}L_i + \beta_{8,7}^{ego1}L_i^2 + \beta_{9,7}^{ego1}F_i + \beta_{10,7}^{ego1}F_i^2 + \beta_{11,7}^{ego1}D_i + \beta_{12,7}^{ego1}D_i^2 + \beta_{13,7}^{ego1}I_i + \beta_{14,7}^{ego1}S_i + \beta_{15,7}^{ego1}V_i + \epsilon_{i,7}^{ego1}$$
$$cv_s^{ego1} = \beta_{0,8}^{ego1} + \beta_{1,8}^{ego1}\alpha_i + \beta_{2,8}^{ego1}\beta_i^{ego1} + \beta_{3,8}^{ego1}C_i + \beta_{4,8}^{ego1}C_i^2 + \beta_{5,8}^{ego1}N_i + \beta_{6,8}^{ego1}N_i + \beta_{7,8}^{ego1}L_i + \beta_{8,8}^{ego1}L_i^2 + \beta_{9,8}^{ego1}F_i + \beta_{10,8}^{ego1}F_i^2 + \beta_{11,8}^{ego1}D_i + \beta_{12,8}^{ego1}D_i^2 + \beta_{13,8}^{ego1}I_i + \beta_{14,8}^{ego1}S_i + \beta_{15,8}^{ego1}V_i + \epsilon_{i,8}^{ego1}$$
$$cv_v^{ego1} = \beta_{0,9}^{ego1} + \beta_{1,9}^{ego1}\alpha_i + \beta_{2,9}^{ego1}\beta_i^{ego1} + \beta_{3,9}^{ego1}C_i + \beta_{4,9}^{ego1}C_i^2 + \beta_{5,9}^{ego1}N_i + \beta_{6,9}^{ego1}N_i + \beta_{7,9}^{ego1}L_i + \beta_{8,9}^{ego1}L_i^2 + \beta_{9,9}^{ego1}F_i + \beta_{10,9}^{ego1}F_i^2 + \beta_{11,9}^{ego1}D_i + \beta_{12,9}^{ego1}D_i^2 + \beta_{13,9}^{ego1}I_i + \beta_{14,9}^{ego1}S_i + \beta_{15,9}^{ego1}V_i + \epsilon_{i,9}^{ego1}$$

$$c^{local} = \beta_{0,7}^{loc} + \beta_{1,7}^{loc}\alpha_i + \beta_{2,7}^{loc}\beta_i^{loc} + \beta_{3,7}^{loc}C_i + \beta_{4,7}^{loc}C_i^2 + \beta_{5,7}^{loc}N_i + \beta_{6,7}^{loc}N_i + \beta_{7,7}^{loc}L_i + \beta_{8,7}^{loc}L_i^2 + \beta_{9,7}^{loc}F_i + \beta_{10,7}^{loc}F_i^2 + \beta_{11,7}^{loc}D_i + \beta_{12,7}^{loc}D_i^2 + \beta_{13,7}^{loc}I_i + \beta_{14,7}^{loc}S_i + \beta_{15,7}^{loc}V_i + \beta_{16,7}^{loc}E_i + \epsilon_{i,1}^{loc}$$
$$s^{local} = \beta_{0,8}^{loc} + \beta_{1,8}^{loc}\alpha_i + \beta_{2,8}^{loc}\beta_i^{loc} + \beta_{3,8}^{loc}C_i + \beta_{4,8}^{loc}C_i^2 + \beta_{5,8}^{loc}N_i + \beta_{6,8}^{loc}N_i + \beta_{7,8}^{loc}L_i + \beta_{8,8}^{loc}L_i^2 + \beta_{9,8}^{loc}F_i + \beta_{10,8}^{loc}F_i^2 + \beta_{11,8}^{loc}D_i + \beta_{12,8}^{loc}D_i^2 + \beta_{13,8}^{loc}I_i + \beta_{14,8}^{loc}S_i + \beta_{15,8}^{loc}V_i + \beta_{16,8}^{loc}E_i + \epsilon_{i,2}^{loc}$$
$$v^{lo} = \beta_{0,9}^{loc} + \beta_{1,9}^{loc}\alpha_i + \beta_{2,9}^{loc}\beta_i^{loc} + \beta_{3,9}^{loc}C_i + \beta_{4,9}^{loc}C_i^2 + \beta_{5,9}^{loc}N_i + \beta_{6,9}^{loc}N_i + \beta_{7,9}^{loc}L_i + \beta_{8,9}^{loc}L_i^2 + \beta_{9,9}^{loc}F_i + \beta_{10,9}^{loc}F_i^2 + \beta_{11,9}^{loc}D_i + \beta_{12,9}^{loc}D_i^2 + \beta_{13,9}^{loc}I_i + \beta_{14,9}^{loc}S_i + \beta_{15,9}^{loc}V_i + \beta_{16,9}^{loc}E_i + \epsilon_{i,3}^{loc}$$

upper 2.5% of the data. In the 1-Ego-Network and 2-Ego-Network data sets, it was possible that duplicate networks were generated, since two nodes or edges in a network can share the same exact ego or 2-ego networks. We thus removed duplicates from the data. After cleaning, we had three different data sets that were ready for our analysis.

6. Analysis and Results

The raw network dataset that was generated by the simulation comprised of 600 distinct networks. The average number of nodes was 215.25, with a standard deviation of 10.066, while the average number of arcs was 321.417, with a standard deviation of 63.484. The 2-Ego-Network data set had 90,442 distinct observations, the 1-Ego-Network data set had a total of 101,035 distinct observations, and the dataset for the nodes and edges comprised of 205,327 observations. We ran three separate Seemingly Unrelated Regression (SUR) models using R *systemfit* package. Before doing so, we had levered R's *usdm* package to conduct a step-wise VIF on all the independent variables for the three datasets. For each VIF belonging to each individual dataset, we found that all regressors were less than 10, indicating that multicollinearity would not be of a concern in the final fitting of any of the models.

6.0.1. 2-Ego-Network Risk The overall model fit of 8 out of the 9 equations in the 2-Ego-Network system had an R^2 of over 0.22, with the standard deviation of the risk significance being the best fit, as judged by R^2, at 0.66. A Wald χ^2-Test was conducted on the entire system with the restriction of $\beta_{i_1,j_1} = 0$. The result was significant ($p < 0.05$), indicating an overall good fit of the system. In addition, a second restriction χ^2-Test was conducted on the squared terms, individually set to 0. Results suggested that the curvi-linear model was an adequate fit to the data ($p < 0.05$). In addition, most of the coefficients were found to be statistically significant ($p < 0.05$). Results suggest that higher levels of the α parameter for the Beta distribution indicated higher levels of overall risk across most of the models. Higher levels of the β parameter for the Beta distribution indicated lower levels of risk. With respect to the Coefficient of Variation for the Risk Velocity, nearly all coefficients were found significant, although the R^2 was very low at a value of 0.04. The

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max	Data Set
alpha	90,442	3.077	1.152	1	2	4	7	2-Ego-Network
beta	90,442	5.741	2.743	1	4	8	10	2-Ego-Network
Centrality	90,442	0.135	1.103	−1.010	−0.550	0.421	4.617	2-Ego-Network
Distance	90,442	0.881	0.734	−0.923	0.358	1.507	2.020	2-Ego-Network
Clustering	90,442	−0.137	0.706	−1.710	−0.562	0.123	2.517	2-Ego-Network
Feedback	90,442	0.117	0.712	−1.864	−0.230	0.594	1.419	2-Ego-Network
Connectivity	90,442	−0.210	0.470	−1.255	−0.565	0.138	1.022	2-Ego-Network
avg_elrcf	90,442	8.883	6.321	1.105	3.998	12.312	40.029	2-Ego-Network
avg_elrsf	90,442	5.707	2.808	1.593	3.601	7.205	16.264	2-Ego-Network
avg_elrv	90,442	3.357	4.550	−0.787	0.131	5.206	21.328	2-Ego-Network
sd_elrcf	90,442	15.488	12.606	1.237	5.359	23.036	59.365	2-Ego-Network
sd_elrsf	90,442	1.595	0.785	0.462	0.994	2.029	4.205	2-Ego-Network
sd_elrv	90,442	10.199	11.481	0.342	1.765	15.110	45.107	2-Ego-Network
cv_elrcf	90,442	1.618	0.460	0.784	1.249	1.945	2.836	2-Ego-Network
cv_elrsf	90,442	0.309	0.140	0.104	0.197	0.397	0.688	2-Ego-Network
cv_elrv	90,442	2.405	4.728	−18.453	1.803	3.950	24.609	2-Ego-Network
alpha	101,035	3.090	1.166	1	2	4	7	1-Ego-Network
beta	101,035	5.616	2.753	1	3	8	10	1-Ego-Network
contribution	101,035	−0.543	11.118	−39.659	−7.587	2.877	216.320	1-Ego-Network
significance	101,035	0.097	2.900	−33.277	−1.198	1.850	16.741	1-Ego-Network
velocity	101,035	−0.404	6.814	−34.872	−4.538	2.072	45.083	1-Ego-Network
Centrality	101,035	−0.360	0.211	−0.818	−0.526	−0.200	0.313	1-Ego-Network
Distance	101,035	−0.138	0.589	−1.715	−0.822	0.350	0.942	1-Ego-Network
Clustering	101,035	−0.032	0.712	−0.775	−0.491	0.133	3.480	1-Ego-Network
Feedback	101,035	0.410	0.804	−1.805	0.128	0.906	1.485	1-Ego-Network
Connectivity	101,035	−0.139	0.783	−1.140	−0.677	0.083	3.192	1-Ego-Network
avg_elrcf	101,035	7.052	6.386	0.867	2.724	9.104	49.182	1-Ego-Network
avg_elrsf	101,035	6.240	3.123	1.511	3.908	7.865	17.797	1-Ego-Network
avg_elrv	101,035	1.612	3.546	−0.860	−0.474	2.046	26.660	1-Ego-Network
sd_elrcf	101,035	9.539	9.755	0.744	2.761	12.511	54.381	1-Ego-Network
sd_elrsf	101,035	1.288	0.672	0.387	0.781	1.629	3.711	1-Ego-Network
sd_elrv	101,035	4.606	6.861	0.184	0.686	5.149	39.536	1-Ego-Network
cv_elrcf	101,035	1.244	0.400	0.558	0.939	1.489	2.453	1-Ego-Network
cv_elrsf	101,035	0.231	0.116	0.077	0.141	0.295	0.614	1-Ego-Network
cv_elrv	101,035	1.063	4.466	−18.669	−0.996	2.975	21.160	1-Ego-Network
alpha	205,327	3.067	1.175	1	2	4	7	Node/Edge
beta	205,327	5.680	2.785	1	3	8	10	Node/Edge
isNode	205,327	0.337	0.473	0	0	1	1	Node/Edge
contribution	205,327	−1.261	12.097	−52.568	−6.823	−1.431	242.254	Node/Edge
significance	205,327	0.119	2.501	−24.919	−0.576	1.561	23.822	Node/Edge
velocity	205,327	−0.772	8.015	−24.950	−3.709	−2.304	88.491	Node/Edge
Centrality	205,327	−0.193	0.583	−0.924	−0.567	−0.026	2.908	Node/Edge
Distance	205,327	0.090	0.844	−1.593	−0.557	0.689	2.170	Node/Edge
Clustering	205,327	−0.151	0.758	−1.945	−0.678	0.354	2.199	Node/Edge
Feedback	205,327	0.099	0.775	−1.332	−0.494	0.657	1.948	Node/Edge
Connectivity	205,327	−0.037	0.676	−1.790	−0.485	0.608	1.087	Node/Edge
elrsf	205,327	6.549	3.494	1.322	3.958	8.335	18.874	Node/Edge
elrcf	205,327	2.520	3.087	0.202	0.703	3.009	23.032	Node/Edge
elrv	205,327	−0.480	0.767	−1.000	−0.923	−0.398	3.641	Node/Edge

Table 2 Summary Statistics for the Final Three Data-Sets.

resulting model indicated that there is a positive curvi-linear association between Distance and Connectedness with risk propagation, respectively ($p < 0.05$). Feedback, Centrality, and Clustering were also identified to be statistically significant ($p < 0.05$) and in a negative curvi-linear association with risk propagation, respectively.

6.0.2. 1-Ego-Network Risk The 1-Ego-Network results also had similar R^2 values to those of the 2-Ego-Network, with most above 0.22. Overall, the fit of the model seemed to be adequate. We also ran a restricted Wald χ^2-Test with all of the parameters set equal to 0, which again indicated an adequate fit ($p < 0.05$). A second restricted Wald χ^2-Test was conducted on only the parameters of the squared terms which indicated another adequate fit ($p < 0.05$). The effect that α and β had on the risk were analogous to the effects found in the 2-Ego-Network analysis. α was found to be positively associated with risk while β was the opposite. Connectivity was found to be neither significant in the linear nor quadratic term ($p > 0.05$). Interestingly, Centrality and Distance were respectively found to be in a statistically significant, positive curvi-linear relationship with risk propagation ($p < 0.05$). The Clustering and Feedback constructs were found to be in a statistically significant negative quadratic association with risk, respectively ($p < 0.05$).

6.0.3. Local Risk The last data set comprised of the node and edge level data. The model was estimated, but different from the prior two systems. This system did still have the three measures of risk for 1-Ego-Network as the independent variables, respectively, but it also only had three dependent variables. The overall fit of the model seemed to be better than the prior two systems, as the smallest R^2 value was only 0.36. Again, a Wald χ^2-Test was conducted on the parameters with the restriction of them set all to 0 individually. The results showed that the model was an overall adequate fit ($p < 0.05$). A second restriction test was conducted on the parameters but only those of the squared terms, which indicated an adequate fit to the data ($p < 0.05$). The three control variables of α, β, and isNode, were all found to be statistically significant ($p < 0.05$). α and β once again were shown to have a pattern consistent across all the models. The results indicate that there is a statistically significant relationship between Centrality, Distance, and Connectedness

	μ_c	μ_s	μ_v	σ_c	σ_s	σ_v	c_c	c_s	c_v
(Intercept)	8.21(0.07)*	13.28(0.14)*	1.49(0.01)*	6.17(0.03)*	1.57(0.01)*	0.28(0)*	2.25(0.05)*	7.16(0.13)*	2.01(0.06)*
alpha	1.26(0.02)*	2.11(0.03)*	0(0)	0.94(0.01)*	0.24(0)*	0(0)*	0.09(0.01)*	0.51(0.03)*	0.02(0.01)
beta	-0.77(0.01)*	-1.24(0.01)*	0(0)*	-0.63(0)*	-0.17(0)*	0(0)*	0.03(0)*	-0.14(0.01)*	-0.04(0.01)*
Centrality	3.68(0.03)*	8.53(0.07)*	0.29(0)*	-0.35(0.01)*	0.36(0)*	0.09(0)*	2.7(0.03)*	7.52(0.06)*	1.09(0.03)*
Distance	2(0.05)*	4(0.1)*	0.12(0)*	0.34(0.02)*	0.32(0)*	0.05(0)*	1.07(0.04)*	2.96(0.09)*	0.71(0.04)*
Clustering	1.62(0.03)*	2.82(0.06)*	0.04(0)*	0.68(0.01)*	0.46(0)*	0.05(0)*	0.48(0.02)*	1.29(0.05)*	0.35(0.03)*
Feedback	1.23(0.03)*	2.09(0.06)*	0.01(0)*	1.23(0.01)*	0.48(0)*	0.03(0)*	0.04(0.02)	0.36(0.06)*	-0.07(0.03)*
Connectivity	0.57(0.06)*	0.79(0.11)*	-0.01(0)*	0.36(0.02)*	0.18(0)*	0.02(0)*	0.14(0.04)*	0.33(0.1)*	-0.01(0.05)
Centrality2	-0.45(0.01)*	-1(0.02)*	-0.04(0)*	0.08(0)*	-0.02(0)*	-0.01(0)*	-0.3(0.01)*	-0.72(0.02)*	-0.24(0.01)*
Distance2	-0.39(0.03)*	-0.56(0.06)*	0.01(0)*	0(0.01)	-0.02(0)*	-0.01(0)*	-0.27(0.02)*	-0.54(0.06)*	0.08(0.03)*
Clustering2	-0.02(0.02)	0.04(0.05)	0(0)*	0.01(0.01)	0.02(0)*	0(0)*	0.04(0.02)*	0.12(0.04)*	-0.08(0.02)*
Feedback2	0.06(0.03)*	0.36(0.05)*	0.02(0)*	0.18(0.01)*	0.06(0)*	0(0)	-0.03(0.02)	0.11(0.05)*	-0.1(0.02)*
Connectivity2	0.67(0.07)*	0.92(0.13)*	0.02(0.01)*	-0.49(0.03)*	-0.12(0.01)*	0(0)*	0.6(0.05)*	1.13(0.12)*	0.39(0.06)*
σ	5.13	9.94	0.4	1.96	0.45	0.1	3.87	9.28	4.64
R^2	0.34	0.38	0.26	0.51	0.67	0.48	0.28	0.35	0.04
Adjusted R^2	0.34	0.38	0.26	0.51	0.67	0.48	0.28	0.35	0.04

Table 3 Results from SUR Estimation of 2-Ego-Network System

	μ_c	μ_s	μ_v	σ_c	σ_s	σ_v	c_c	c_s	c_v
(Intercept)	9.45(0.08)*	13.76(0.12)*	1.38(0.01)*	6.11(0.03)*	1.43(0.01)*	0.27(0)*	3.04(0.04)*	7.79(0.08)*	1.68(0.07)*
alpha	0.81(0.01)*	0.95(0.02)*	-0.01(0)*	0.93(0.01)*	0.19(0)*	0(0)*	0(0.01)	0.07(0.02)*	-0.06(0.01)*
beta	-0.5(0.01)*	-0.51(0.01)*	0.01(0)*	-0.64(0)*	-0.13(0)*	0(0)*	0.05(0)*	0.06(0.01)*	0.04(0.01)*
Centrality	6.88(0.24)*	14.08(0.35)*	0.5(0.02)*	-1.67(0.09)*	0.21(0.02)*	0.12(0)*	5.26(0.13)*	11.78(0.24)*	1.13(0.2)*
Distance	2.53(0.05)*	4.5(0.07)*	0.14(0)*	0.24(0.02)*	0.27(0)*	0.04(0)*	1.27(0.03)*	2.98(0.05)*	0.63(0.04)*
Clustering	2.43(0.04)*	3.73(0.06)*	0.12(0)*	0.56(0.02)*	0.49(0)*	0.06(0)*	0.75(0.02)*	1.61(0.04)*	0.63(0.03)*
Feedback	0.92(0.03)*	1.21(0.04)*	0(0)*	0.95(0.01)*	0.33(0)*	0.02(0)*	0.05(0.01)*	0.21(0.03)*	-0.05(0.02)*
Connectivity	0.08(0.03)*	-0.02(0.04)	-0.01(0)*	0.4(0.01)*	0.14(0)*	0.01(0)*	-0.24(0.02)*	-0.47(0.03)*	-0.04(0.03)
contribution	0.09(0)*	0.18(0)*	0.01(0)*	0.03(0)*	0.01(0)*	0(0)*	-0.01(0)*	-0.01(0)*	0.01(0)*
significance	-0.25(0.01)*	-0.52(0.01)*	-0.03(0)*	0.13(0)*	-0.01(0)*	-0.02(0)*	-0.39(0)*	-0.75(0.01)*	-0.15(0.01)*
velocity	0.23(0)*	0.4(0)*	0.01(0)*	-0.17(0)*	0(0)	0.01(0)*	0.23(0)*	0.45(0)*	0.1(0)*
Centrality2	5.31(0.33)*	9.29(0.49)*	0.32(0.02)*	-1.94(0.13)*	0.09(0.03)*	0.1(0)*	3.78(0.18)*	7.34(0.34)*	0.89(0.28)*
Distance2	-0.1(0.06)	-0.05(0.08)	0.01(0)*	-0.02(0.02)	0.05(0)*	0.01(0)*	-0.06(0.03)	-0.09(0.06)	0.11(0.05)*
Clustering2	-0.32(0.02)*	-0.51(0.03)*	-0.03(0)*	0.06(0.01)*	0(0)	0(0)*	-0.15(0.01)*	-0.28(0.02)*	-0.18(0.02)*
Feedback2	-0.15(0.02)*	-0.07(0.04)	-0.01(0)*	0.34(0.01)*	0.06(0)*	0(0)*	-0.13(0.01)*	-0.12(0.02)*	-0.2(0.02)*
Connectivity2	-0.01(0.02)	0.04(0.03)	0(0)*	-0.09(0.01)*	-0.05(0)*	0(0)*	0.06(0.01)*	0.13(0.02)*	0(0.02)
σ	5.12	7.54	0.35	2.05	0.39	0.07	2.82	5.29	4.32
R^2	0.36	0.4	0.22	0.57	0.66	0.58	0.37	0.4	0.06
Adjusted R^2	0.36	0.4	0.22	0.57	0.66	0.58	0.37	0.4	0.06

Table 4 Results from SUR Estimation of 1-Ego-Network System

	(Intercept)	alpha	beta	isNode	Centrality	Distance	Clustering	Feedback	Connectivity	contribution	significance	velocity	Centrality2	Distance2	Clustering2	Feedback2	Connectivity2	σ	R^2	Adjusted R^2
Contribution	2.2(0.03)*	0.38(0)*	-0.28(0)*	1.02(0.02)*	0.39(0.02)*	-0.28(0.01)*	-0.04(0.01)*	0.27(0.01)*	-1.87(0.01)*	0.02(0)*	0.01(0)*	0(0)*	0.47(0.02)*	-0.02(0.01)*	0.18(0.01)*	-0.27(0.01)*	0.68(0.01)*	2.37	0.41	0.41
Significance	5.18(0.03)*	0.95(0)*	-0.63*	2.25(0.03)*	-1.91(0.03)*	1.04(0.01)*	-1.46(0.01)*	1.55(0.01)*	-0.24(0.01)*	0.03(0)*	0.04(0)*	-0.04*	0.92(0.02)*	0.12(0.01)*	0.32(0.01)*	-0.3(0.01)*	0.04(0.01)*	2.57	0.46	0.46
Velocity	-0.43(0.01)*	-0.02(0)*	0.01(0)*	-0.04(0)*	0.29(0.01)*	-0.18(0)*	0.14(0)*	-0.09*	-0.42(0)*	0(0)*	-0.02(0)*	0.01(0)*	0.02(0)*	0.01(0)*	0(0)*	-0.03(0)*	0.16(0)*	0.61	0.36	0.36

Table 5 Results from SUR Estimation of Node/Edge System

with Risk, respectively ($p < 0.05$). Feedback was found to be in a negative association with risk ($p < 0.05$), while Clustering was not found to be statistically significant at this level of analysis ($p > 0.05$).

7. Discussion

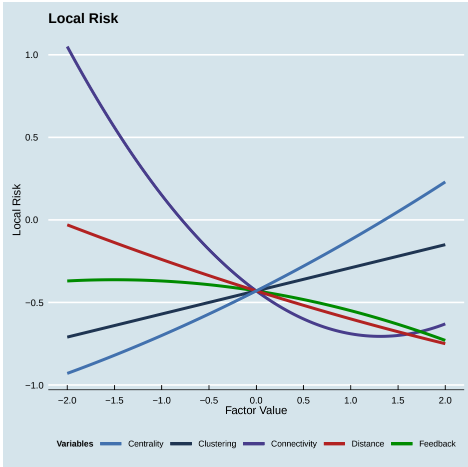
The core motivation underpinning this research was to explore the gap between the study of canonical supply chain risk propagation and supply network structure. In order to do so, this manuscript combined a simulation approach with an empirical analysis. In this process, we also advanced the idea of the k-Ego-Network structure, as a way to more concretely ground different "levels" of network analysis, as well as to comprehensively analyze the dynamics of risk propagation. Our study revealed several key findings of note. First, we found that increasing the distance in the 2-Ego-Network will result in a decrease of risk propagation. Contrarily, increasing the distance in the 1-Ego-Network results in an increase of risk propagation. Additionally, the results suggest that increasing distance at the node level will decrease risk propagation. Our findings also revealed that increasing centrality at the 2-Ego-Network level will increase risk propagation. However, this risk appears to exhibit non-monotonicity in its relationship, where it either reaches a carrying capacity or reverses direction entirely. Effectively, this result suggests that the 2-Ego-Network's risk has an upper-bound, with respect to centrality. Once the 2-Ego-Network reaches a certain centrality level, then the marginal effects on risk for incremental additions to centrality are negligible. Though, at the 1-Ego-Network level, we notice that increased centrality, initially, will result in a reduction of risk. However, once it reaches past a certain point, it will accelerate. That is, the relationship between centrality and risk differs between the 2-Ego-Network and the 1-Ego-Network levels.

Of all the effects of centrality, we see that at the local level, centrality is the worst offender. There is no gain in regards to risk by increasing centrality locally, since doing so will always result in an increase in risk. This finding comes in contradiction to some extant research on the relationship between complexity and risk (Choi and Krause 2006). It has been suggested that firms that increase their inter-relationships should experience lower levels of risk. This may be true for inner-firm, or single location risk, but as the results in this manuscript illustrate, risk propagation itself would be accelerated with increased levels of such increases to centrality. This indicates that firms need to be careful in weighing the benefits of reducing within-firm risk while increasing risk propagation as a result. Shifting our focus to clustering, the results indicate that clustering exhibits the same effect across all dimensional levels. It appears that clustering impacts risk in similar ways that other dimensions do. This suggests that clustering is the most "stable" dimension. Furthermore, in the 2-Ego-Network level, clustering reaches a carrying capacity much sooner than centrality. This suggests that 2-Ego-Networks are much more robust to risk when changes to clustering occur. Connectivity appears to be a "wolf in sheep's clothing". Across nearly all the dimensions, a familiar pattern emerges. Once the connectivity increases, the entity enjoys an initial reduction in risk. However, if the entity becomes too-connected, risk appears to return. That is, the results suggest a cautionary advisement where in levels should be scrupulously managed for this dimension, as heightened levels of connectivity rise rapidly, risk levels can also escalate.

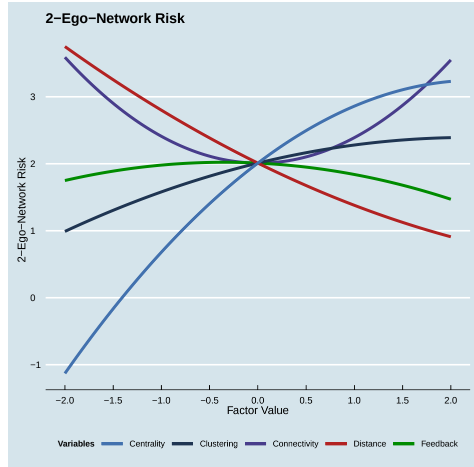
Finally, across all the dimensions, feedback appears to be the dimension that aids in supply chain risk management. Increasing the feedback at any level of the network appears to always result in reduction of risk. Furthermore, a pattern across the levels of analysis emerges with respect to the "flows" of risk to the lower levels of analysis (e.g. 2-Ego-Network to 1-Ego-Network). We also notice that as the risk significance increases in a higher dimension, the lower dimension will experience a drop in their own risk. We also notice that as risk velocity increases in the higher dimension, risk in the lower dimension also increases. Contribution seems to have little impact on lower dimensional risks. Essentially, we contend that the conceptual framework of network structure developed, and empirically tested, in this manuscript helps scholars simplify and synthesize the vast number of characterizations of structure. Furthermore, the results of this manuscript allow for a formalized framework within which to understand, and identify, supply chain risk propagation. Inherently, there are trade-offs in the efforts to minimize risk propagation at higher-levels of analysis, as reductions to the 2-Ego-Network or 1-Ego-Network risk propagations, may inadvertently increase such risk propagation at lower levels (or vice versa). This leads us to new questions regarding supply chain design and strategies for mitigating risk propagation that future research will need to address.

8. Limitations & Future Research

To the best of our knowledge, this is the first major study to distinguish between supply chain disruption propagation and supply chain risk propagation. Furthermore, the conceptual development of canonical network structure is the first of it's kind, as far as we are aware. Another contribution of our research is our introduction of the *k-ego-network* framing, which allows the supply chain researcher a more comprehensive method to understand supply chain structure and visibility, topics that have been of extreme importance within the recent literature (Kraft et al. 2018). In addition, we have contributed to the relatively new area of supply chain risk propagation by constructing a framework for the constructs of *contribution*, *significance*, and *velocity*, as well as defining their respective operationalizations. Last, we have contributed to an area of research that is currently very scarce of publication: the intersection between supply network structure and supply network risk propagation. Though this study has made significant in-roads, there are several limitations to note. First, the networks we generated were not based on real-world supply network data. Next, the framework for risk measurement had assumed that a "consequence" was defined as the number of nodes that either were affected or could be affected due to a disruption in the network. Hence, our results may very well change if different cost functions are considered. The simulation of this study was designed to randomly sample conditional probabilities from a Beta Distribution of a given α and β parameter, and we have not studied the impact of probabilities on risk from other distributions. Another limitation of our study is the lack of consideration of time. We sought to understand the connection between structure and risk in a static environment, however, our result may change in dynamic environments. All of the above should be investigated in future research.



(a)



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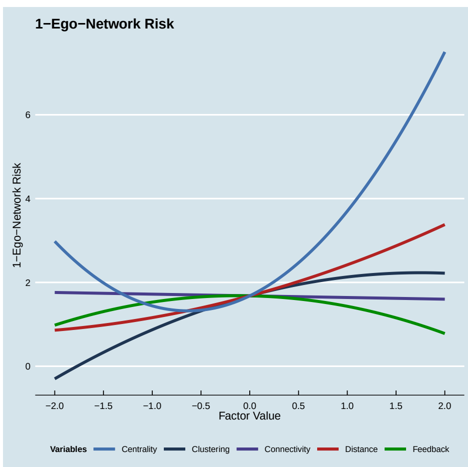

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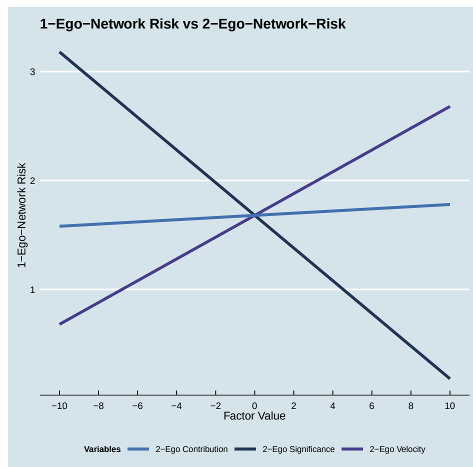

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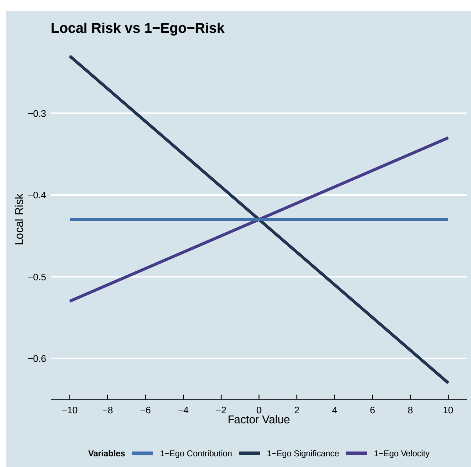

(e)

Figure 3 The Effects of Canonical Network Structure Constructs on Risk Propagation in the Local, 2-Ego-Network, 1-Ego-Network Levels, as well as the Cross-Effects of Higher Risk Propagation on Lower Risk Propagation

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