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Decision Support

An analytical framework for supply network risk propagation: A Bayesian network approach

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ABSTRACT

There are numerous examples of supply chain disruptions that have occurred which have had devastating impacts not only on a single firm but also on various other firms in the supply network. We utilize a Bayesian Network (BN) approach and develop a model of risk propagation in a supply network. The model takes into account the inter-dependencies among different risks, as well as the idiosyncrasies of a supply chain network structure. Specific risk measures are derived from this model and a simulation study is utilized to illustrate how these measures can be used in a supply chain setting.

1. Introduction

In 2002, West Coast port employers shut down docks from San Diego all the way up to Seattle as a result of a labor dispute with the ship workers union. The result was delayed cargo for thousands of retailers and manufacturers which, consequently, rendered importers and exporters in fear of long reaching ripple effects to their businesses (Machalaba & Kim, 2002). There are numerous other examples of supply chain disruptions that have occurred which have had devastating impacts not only on a single firm but also on various others in the supply network (Olson & Wu, 2011). Further, it has been suggested that, “Supply chain disruptions and the associated operational and financial risks represent the most pressing concern facing firms that compete in today’s global marketplace” (Craighead, Blackhurst, Rungtusanatham, & Handfield, 2007). Consequently, an important question is: how do the set of risks in a firm’s supply chain relate to each other and subsequently propagate throughout the supply chain in the case of a disruption? A motivating force to this question is that supply chains can be more appropriately viewed as networks (Carnovale & Yeniyurt, 2014; Lambert, Cooper, & Pagh, 1998). As supply networks become increasingly global, not only will their networks grow in length but the level of complexity involved in managing them also grows accordingly. As firms increase the size and complexity of their supply networks the risk of disruption can increase (Blackhurst, Dunn, & Craighead, 2011; Choi & Krause, 2006). Disruptions have cascading effects that can have far reaching impacts on the supply network such as labor disputes leading to operational inefficiency and high turnover rates (Jiang, Baker, & Frazier, 2009). These can lead to impediments to the provision of products and services to end consumers (Zsidisin, 2003). In addition, risky supply chains have been shown to lead to abnormally negative returns on the focal firm’s stock (Hendricks & Singhal, 2005). While research has primarily viewed risk as either logistical or operational, our research abstracts out and rests within the domain of supply chain management taking a network-based perspective (Lambert et al., 1998). It has been suggested that tools need to be developed to measure the relationships, between and among, as well as the propagation of risk (Vakharia & Yenipazarli, 2008). Many frameworks have looked at risk management from a macro perspective and have the common procedure of risk identification, risk assessment, and the development of strategies to mitigate them (Altay & Green, 2006; Kleindorfer & Saad, 2005). These frameworks implicitly require reliable measures of risk. However, existing measurement models only result in local optimality and fall short on the consideration of the structure of the supply network, the effects of propagated risk, and the risk’s implicit casual structure within the supply network. The main objective of this paper is to

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introduce a framework of measures for risk and risk propagation in supply networks. We utilize a Bayesian Network (BN) approach and develop a model of risk propagation in a supply network. The model takes into account the inter-dependencies among different risks, as well as the idiosyncrasies of a supply chain network structure. Specific risk measures are derived from this model and a simulation study is utilized to illustrate how these measures can be used in a supply chain setting. The rest of this paper is structured as follows. We first review the extant literature on supply chain risk management (SCRM) as well as current measurement models. We give a brief review on Bayesian networks and their role in supply chain and risk management. We then construct our model and formulate various measures for risk and risk propagation in supply networks. Utilizing a simulation study, we demonstrate how our model can be used to measure supply chain risk. Finally, we provide the limitations and future research directions.

2. Literature review

2.1. Supply chain risk and supply chain risk management

The ability to foresee potential disruptions allows for firms to create mitigation and contingency plans so as to preserve normal business operations (Yu, Zeng, & Zhao, 2009). While risk has been viewed in the past from a perspective of statistical variance (March & Shapira, 1987), risk tends to proliferate itself within the notion of uncertainty which is defined as the difficulty firms have in predicting the future which comes from a lack of information (Beckman, Haunschild, & Phillips, 2004). This conceptualization of risk allows for its formal definition in the supply network context. Supply chain risk has been defined in many ways, all of which have the common theme of outcomes with a certain likelihood of occurrence and their potentially negative consequences (e.g. Craighead et al., 2007; Gaonkar & Viswanadham, 2007; Vakharia & Yenipazarli, 2008). This is sometimes analyzed by looking at the potential for disruptions, which can be thought of as unforeseen events that disturb the routine operations of a firm (Craighead et al., 2007; Kleindorfer & Saad, 2005). Consequently, we adopt a similar definition of risk: the likelihood of an adverse and unexpected event that can occur and either directly or indirectly result in a supply chain disruption. Given the potentially negative impact that a supply network risk can have on a firm's activities, scholars have articulated an organizational mechanism for the management of risk referred to as supply chain risk management and is viewed as a "strategic management activity in firms" (Kleindorfer & Saad, 2005; Narasimhan & Talluri, 2009; Pettit, Fiksel, & Croxton, 2010). Effectively, planning for risk by implementing a SCRM framework leads to a resilient supply network that can generate a source of competitive advantage for the firm. A common tenet of SCRM is the need to categorize risks that are salient in the firm's supply network, where the common criteria are source and controllability (Dani, 2009; Jüttner, Peck, & Christopher, 2003; Kleindorfer & Saad, 2005; Mason-Jones & Towill, 1998; Wu, Blackhurst, & Chidambaram, 2006). SCRM also comprises of a series of proactive steps in order to identify, assess and mitigate risks (Kleindorfer & Saad, 2005). If we are to achieve fruitful results that ultimately lead to appropriate policies then appropriate measurements of a risk's relationships and propagation must be analytically and formally developed (Vakharia & Yenipazarli, 2008).

2.2. Past models of risk measurement

A variety of measurement models and methodologies have also been proposed to measure risk and uncertainty in a supply chain. Applicable mostly to risk within supplier selection, the analytic hierarchy process (AHP) is used to model the various categories of risk and ultimately lead to a supplier decision (Dai & Blackhurst, 2012; Kull & Talluri, 2008; Levary, 2007). AHP typically is applied to specific decision problems where each decision is given a "risk score" calculated by multiplying the likelihood of a risk category by the consequence of the occurrence (e.g. Chan & Kumar, 2007). Also used for vendor selection and evaluation is the data envelopment analysis (DEA) (Talluri, Narasimhan, & Nair, 2006). This model considers various inputs and outputs and subsequently gives each vendor an efficiency score. Risk is introduced by involving stochastic elements in DEA models. Fuzzy logic has also been incorporated in various operational risk models intended to solve decision problems under the guise of uncertainty (Azadegan, Porobic, Ghazinoory, Samouei, & Kheirkhah, 2011). Interpretive structural modeling has been used on 11 risk categories termed "enablers" which were identified in the literature stream to understand the interdependencies among these categories through the use of dimensions such as "driving power" and "dependency" (Faisal, Banwet, & Shankar, 2006). Some have taken a "Value-at-Risk" perspective (Chen, Shum, & Simchi-Levi, 2014). A von Neumann–Morgenstern utility view was used in measuring risk-aversion in a newsboy model (Eeckhoudt, Gollier, & Schlesinger, 1995). Various other models have incorporated risk by introducing stochastic elements into existing supply chain models (Goh, Lim, & Meng, 2007; Huchzermeier & Cohen, 1996; Tomlin, 2006; Vakharia & Yenipazarli, 2008). An even more recent trend in the extant literature has been to study risk and uncertainty at the higher and more appropriate level of analysis: the supply chain. Some network models have been proposed as possible solutions to the problem of measuring risk in supply networks (e.g. Sawik, 2013). Deane, Ragsdale, Rakes, and Rees (2009) developed a model of risk within a supply chain by developing a mixed integer programming model in the form of a network flow problem (Deane et al., 2009). Other models have taken a more operational perspective by introducing stochastic methods in petri-net models (e.g. Blackhurst, Wu, & Craighead, 2008) by modeling risk as attributes or as simple discrete events without considering the likelihood of an outcome (Blackhurst, Wu, & O'grady, 2004; Wu et al., 2006; Wu, Blackhurst, & O'grady, 2007; Zegordi & Davarzani, 2012). While these network models exist as attempts to solve the problem of measuring risk in supply networks, there are still gaps in the extant literature (Sodhi, Son, & Tang, 2012). Many current risk models are used on a smaller, more local level of analysis for very specific problems leading to locally optimal solutions in supply chain and operational models. Most models do not account for risk propagation. The few network risk models that have been developed only consider risk as a random variable added into existing supply chain models. Another gap in the literature is that most of the models are not embedded in a larger framework to allow for generalizability and additional measures of risk to be further developed for specific situations and interpretations. Risk and uncertainty have been studied in a variety of different fields that model the structure and propagation of risk. Extant literature in the field of supply chain has been incorporating elements of risk into supply chain models rather than adapting current risk models and placing them within a supply chain setting. A common model used for risk analysis generally, is the Bayesian Network (BN). Very few authors, however, have attempted to adapt the BN model to supply chain risk measurement. Pai et al. were one of the first to propose using a BN to model risk and uncertainty in supply chains. Their model (Pai, Kallepalli, Caudill, & Zhou, 2003) sets the foundation for our work in this article, yet requires additions of supply chain risk measures called for in the extant literature (Sodhi et al., 2012; Vakharia & Yenipazarli, 2008).

2.3. Bayesian networks and risk management

Bayesian networks have been in existence for over two decades now, and many fields of study have used them primarily to model risk and knowledge. In its most basic definition, a Bayesian network is an acyclic directed graphical model of a more general probability dependency model where nodes represent random variables and directed edges represent the causal relationships among the variables (Pearl, 1988). Typically, Bayesian networks consist of two primary components: the subjective causal relationships determined either by learning algorithms or expert opinion and the objective conditional probability distributions. Many fields have applied Bayesian networks to a variety of risk models (cf. Nadkarni & Shenoy, 2001). In operations management, risks such as threats to IT infrastructure (e.g. Lauría & Duchessi, 2007), construction project schedules, business lines and due date assignment have all been modeled using BN (Cowell, Verrall, & Yoon, 2007; Luu, Kim, Tuan, & Ogunlana, 2009; Mittnik & Starobinskaya, 2010; Zhang & Wu, 2012). Portfolio and securities analysis also used BN to study risk from a more decision-driven point of view (Demirer, Mau, & Shenoy, 2006). Marketing has seen the use of BN in direct marketing applications (Cui, Wong, & Lui, 2006). Within the services industry, weaknesses in the profit chain have incorporated these models (Anderson, Mackoy, Thompson, & Harrell, 2004). While the uses of BN in other fields of study within business have flourished in regards to risk, supply chain management has only seen a few such models proposed. Many of the models that have been proposed in supply chain management using BN however, have come short of studying specific risks at particular locations in the supply network and their dependencies, propagation and ultimate consequences. Lockamy and others developed a model of risk using BN where the variables under consideration were risk categories (Lockamy, 2011; Lockamy & McCormack, 2012). They failed to see the use of these structures in tools such as scenario and diagnostic analysis as well as the propagation of risk. Some extant literature has attempted to set the groundwork for risk analysis in supply networks using BN where two types of nodes, production and logistics nodes, were used to study risks. However, within each of these types of nodes they modeled risk using a separate BN for each node (Pai et al., 2003). The primary issue with this body of work is that it does not go far enough in carefully defining certain assumptions that needed to be made as well as measures that were flexible and general for future work.

3. Bayesian networks

Bayesian theory is centered on the thought that we hold beliefs in certain events given our prior knowledge on them. If other events occur, however, we have a tendency to change our initial beliefs of the same events. Much of Bayesian theory is based on the notion of conditional probability. If we assume that ξ represents all of our prior knowledge, then we can form a viable theory on probabilities that account for new information which becomes available to us. Bayesian networks leverage Bayesian theory on probabilities by exploiting conditional probabilities as well as a concept called conditional independence. Of even more importance to Bayesian networks is the concept of probabilistic inference and learning. Inference refers to the fact that we have prior beliefs of the world around us structured in the form of a Bayesian network. When we assume that a particular event in our network has occurred, we must update all of our beliefs that are dependent on the event which we assumed to occur; this leads to a posterior belief. Learning on the other hand involves permanently updating our belief network once we have actually observed an event happen. Bayesian networks typically represent the joint probability distribution function of all the variables in the network as a product of the smaller conditional probability distributions of each variable by exploiting the expansion rule:

$$P(X|\xi) = \sum_{i=1}^{n} P(X|Y = y_i, \xi)P(Y = y_i|\xi) \tag{1}$$

3.1. Conditional independence

The notion of conditional independence must be formally defined since the theory of Bayesian networks relies on it. If we assume that we only have our background knowledge ξ, we can usually ascertain whether two events would be independent or dependent. Suppose we have two events, E_1 and E_2 about which we know little of their dependence to each other. Now suppose for the moment that we observed a third event, E_3, with which we can now conclude the first two events as independent. This concept is known as conditional independence, more formally:

$$P(E_1, E_2|E_3, \xi) = P(E_1|E_3, \xi)P(E_2|E_3, \xi) \tag{2}$$

An equivalent and more useful expression would be:

$$P(E_1|E_2, E_3, \xi) = P(E_1|E_3, \xi) \tag{3}$$

In the graphical model of the Bayesian network, theory of d-separations can be referred to in order to determine the conditional independence relationships between nodes.

3.2. Definition of a Bayesian network

We are now in a position to properly define a Bayesian network. For the purposes of this paper, we assume that all of our random variables are binary. Suppose we have a set of binary random variables $X = \{X_1, \ldots, X_n\}$ together with a joint probability distribution function $P(X_1, \ldots, X_n)$ that is possibly unknown or cannot be represented in closed form. Let $N = \{N_1, \ldots, N_n\}$ be a set of nodes where each node represents a random variable. Let $E = \{E_1, \ldots, E_m\}$ be a set of directed edges where each edge has been drawn from some node N_i to a different node N_j and there exists no subset of E in the form $\{N_{i_1}N_{i_2}, \ldots, N_{i_k}N_{i_1}\}$. The resulting acyclic directed graph $G = N \cup E$ represents the probability dependency model of the set X. We call G a Bayesian network, and is shown in Fig. 1 (Heckerman, Geiger, & Chickering, 1995; Hekerman, 1995; Pearl, 1988).

If the dependencies are constructed in such a way that the resulting graph is acyclic, then the designer of the network has implicitly assumed conditional independence among certain variables. That is, if two nodes in the network fail to have a directed edge between them, we can assume a conditional independence between them given a set of other nodes in the network. A more formal discussion on conditional independence relations can be found in Heckerman et al. (1995) and Pearl (1988).

3.3. Conditional probability tables and probabilistic inference

Most of the time, the joint probability distribution function of the Bayesian network is either unknown or intractable. Since we have a subjective causal structure represented by the directed graph, we must also have conditional probability distributions for each node.

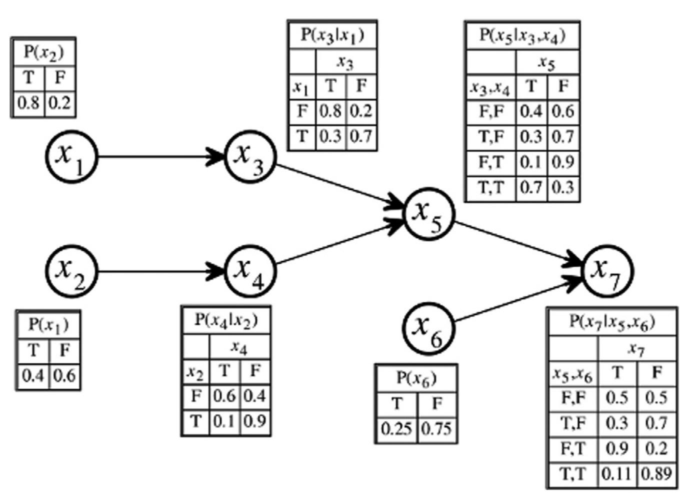

Fig. 1. Example of a general Bayesian network with conditional probability tables.

This allows us to represent the joint probability distribution in a more compact way. Typically, the distribution of any node in N are in the form of conditional probability tables, where each row represents a certain outcome of all the parents. A probability for the event occurring represented by the particular node is then given. As previously mentioned, we can represent the joint probability distribution function using our various tables for each node. If we wish to find the belief in an event D given that events I, E, and F have occurred, such that the structure is D depends on I, and I depends on E and F, then by conditional independence: $P(D|I,E,F) = P(D|I)$ since D, E, and F are separated by I. Let us assume for the moment that we observe both E and F (i.e. $P(E,F) = 1$). Then our belief about D must change. That is,

$$\begin{aligned} P(D|E,F) &= P(D|E,F,I)P(I|E,F) + P(D|E,F,\neg I)P(\neg I|E,F) \\ &= P(D|I)P(I|E,F) + P(D|\neg)P(\neg I|E,F) \end{aligned} \tag{4}$$

By simply acquiring the new information about E and F, our beliefs entirely change about E and F to those above. We use the new beliefs by using the expansion rule. This results in both the beliefs of I and D to be different than before. This is an example of probabilistic inference.

3.4. Probabilities as random variables, beta distributions and basics of learning

In the previous section we discussed the various conditional probability distributions represented by conditional probability tables. While this method is common within Bayesian network models, its form is difficult to update if we wish to "learn" new information. A solution to this is to assume that the probability of an event $X_i \in X$ is a random variable θ. We would then have $P(X_i) = E[\theta]$. Typically θ is assumed to have as its prior distribution the beta distribution $Beta(\alpha_1, \alpha_2)$. When given the new information ξ, we must change our distribution to incorporate the new data. To determine the posterior distribution of θ, Bayes theorem and the likelihood function of binomial sampling are used to find that $\theta|\xi \sim Beta(\alpha_1 + n_1, \alpha_2 + n_2)$, where n_1, n_2 are the number of observations for each outcome. By representing the distribution this way, learning becomes relatively easy. Thus we have our updated belief of X_i as:

$$P(X_i|\xi) = E[\theta|\xi] = \frac{\alpha_1 + n_1}{\alpha_1 + n_1 + \alpha_2 + n_2} \tag{5}$$

We must note that we took advantage of the implicit assumption that X_i had no parents. For a more formal treatment of Bayesian priors, and beta distributions, please refer to Geiger and Heckerman (1995, 1997), Lauritzen (1995) and Winkler (1967).

4. A model for supply chain risk propagation

Now that we have established the basics of Bayesian networks, we are in a position to define the core model of our framework, which takes the structure of a supply network and fuses it with that of Bayesian networks. Once the model is articulated, we then define measures to gauge the supply network's risk profile.

4.1. Core assumptions

Before we begin with the construction of our model, we must speak first to some assumptions that must be made. Assuming the structure of the entire supply network is known is of grave importance, as not knowing will lead to unforeseen risks as well as dependencies. Additionally, assuming that each risk is binary greatly lessons the computational burden. It must be noted that BN are not solely restricted to binary random variables and both discrete multinomial and continuous Gaussian distributions can also be used to model the extent to which an event occurs. Not knowing all the risks at a particular location in a supply network can lead to imprecise risk measures given we have failed to account for all possible threats to the supply chain. Furthermore, many frameworks and procedures exist to determine the whether two risks are casually related or not. Assuming different frameworks for determination of causation can also lead to incorrect measures of risk.

Given that risk flows based upon the structure of the supply network, to assume risk causation dependencies that are not based off of the supply network (i.e. risks at disjoint nodes cannot have direct causal relationships) could lead to statistical anomalies and inappropriate propagation measures. Furthermore, having a complete set of data is required in order to facilitate the estimation of the conditional probability distributions. While missing data could cause issues, so could inference if the BN is of a very large size. In fact, as the network size grows inference becomes NP-Hard. Various learning algorithms exist to acquire the BN from data which use metrics to measure how well the resulting network fits the data (Heckerman et al., 1995; Kass & Raftery, 1995; Spirtes & Meek, 1995). A simplifying assumption would be to assume that the procedure used to determine causality will lead to the "best fit" BN to the data given. Lastly, many operational and logistical risks are dependent upon business decisions that are made (i.e. production,inventory policies, etc.). If we take these into account, then the probability distributions would be functions of these decision levels. Consequently we assume that all decisions have been made and are static. Taking into account all of these possible concerns, we must assume the following:

1. The entire structure of the supply network is known.
2. All risks considered are modeled as a binary random variable.
3. All conceivable risks to a supply network at any location (i.e. at the node or edge level) in the network have been accounted for.
4. Given a set of risks, the causal relationships among the risks are determined in a procedural and objective manner that results in an acyclic directed graph (i.e. given two experts and the same set of risks, they will arrive at the same acyclic, casual structure of the graph).
5. Given a set of risks, the procedure for determining the causal structure of the risks must be based on the structure of the supply network (i.e. given any two locations in the supply network, node or edge, not connected directly in some way, then any risks inherent in one location cannot be causally related to any risks in the other location).
6. The data for all risks and conditional probability tables/distributions can be determined in full (i.e. distributions and parameter estimates for the random variables or the conditional probability tables have already been determined and estimated).
7. The resulting network allows for tractable probabilistic inference.
8. The resulting Bayesian network constructed using the risks inherent in a supply network using the procedure given below is the "best fit" network to the data.
9. All risks that are dependent on business decisions are static and have only a single distribution (i.e. decisions remain static and result in only a single probability distribution for a risk related to the particular decision).

4.2. Risk graph construction

We begin with the supply network itself. A supply network consists of two primary elements: the locations and the material/information flow (Lambert et al., 1998). The result is a directed graph, as shown in Fig. 2.

We can model the supply network as follows. Let $N_S = \{n^s_1, \ldots, n^s_{N(N_S)}\}$ be the nodes representing locations in the supply network. Let $E_S = \{e^s_1, \ldots, e^s_{N(E_S)}\}$ be the set of directed edges representing the

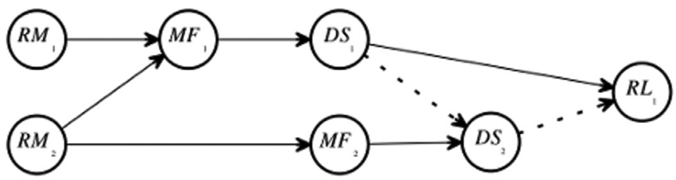

Fig. 2. An example of a general supply network with a raw materials source (RM), a distributor (DS), a manufacturer (MF) and a retailer (RL).

materials/information flow in the supply network. The entire directed graph $S = N_S \cup E_S$ is called the supply network. If an edge is solely an information flow, then risks in one node can be dependent on risks within a different node. Material flows always are considered to have an informational element to it since information flows from a node to the particular agent on the flow in a moment in time. Now, let $s_i \in S$ be an element from the supply network (these can be either nodes or directed edges in the supply network). We let $R_{s_i} = \{r_1^{s_i}, \ldots, r_{N(R_{s_i})}^{s_i}\}$ be the binary random variables representing the risks at the element s_i. Now let

$$N_R = \bigcup_{i=1}^{N(N_S)+N(E_S)} R_{s_i} \tag{6}$$

be the set of nodes representing all the random variables representing the risks at each element of the supply network. Now we must construct the causal relationships between these risks. To do so, let

$$\Im(s_i) = \begin{cases} \text{set of all edges and nodes that are neighbors} \\ \quad \text{of } s_i \text{ if } s_i \text{ is a node} \\ \text{set of nodes connected to } s_i \text{ if } s_i \text{ is an edge} \end{cases} \tag{7}$$

The casual relationships are determined using the following procedure: Let CAUSE(x, y) be a procedure where x, y belong to a probability dependency model and returns 1 if x causes y, 2 if y causes x and 0 if x and y are not causally linked. We assume this procedure will keep a memory of the relationships so as to not result in a directed cycle. Then:

Algorithm 1 Determining edge set of risk graph.

procedure EDGECONSTRUCT
 for $i \in \{1, \ldots, N(S)\}$ **do**
  for $r_j^{s_i}, r_k^{s_i} \in R_{s_i}$ **do**
   if CAUSE$(r_j^{s_i}, r_k^{s_i}) == 1$ **then**
    $E_R \leftarrow \{r_j^{s_i}, r_k^{s_i}\}$
   if CAUSE$(r_j^{s_i}, r_k^{s_i}) == 2$ **then**
    $E_R \leftarrow \{r_k^{s_i}, r_j^{s_i}\}$
  for $x \in \Im(s_i)$ **do**
   for $r_j^{s_i} \in R_{s_i}, r_k^x \in R_x$ **do**
    if CAUSE$(r_j^{s_i}, r_k^x) == 1$ **then**
     $E_R \leftarrow \{r_j^{s_i}, r_k^x\}$
    if CAUSE$(r_j^{s_i}, r_k^x) == 2$ **then**
     $E_R \leftarrow \{r_k^x, r_j^{s_i}\}$

Let E_R be the set of directed edges representing the causal relationships as determined by the above procedure. Then the acyclic directed graph $R_S = N_E \cup E_R$ is called the risk graph of the supply network S (see Fig. 3).

Note how the node set in the risk graph are random variables representing the risks at particular locations in the supply network. They represent two important pieces of information that when considered together have been overlooked in the extant literature. Also note that based on our assumptions, we must have an acyclic directed graph. The next step in the model construction is developing the conditional probability tables or distributions. Once constructed, we will have the capability to perform probabilistic inference.

4.3. Measures of risk

Now that we have a risk dependency model for supply networks, we seek to develop measures that will allow for managerial insight in terms of the propagation of risk in a network. Risk in the network can be viewed from three perspectives: the belief that a single risk will occur and the cost of occurrence, the propagated effects assuming the risk occurred, or the combination of both. Our measures are based off of a scenario analysis where we assume that for each combination of risks that can occur at a location in the supply network we seek to measure the propagated effects. Given the supply network in Fig. 3, we can see that risk can propagate in one of two directions: either inbound to or outbound from a location as well as upstream and downstream in the supply network. It is of importance to note that risk may flow through the descendants of a particular node in the risk graph but may not necessarily do so sequentially. These sort of outcomes are very likely to be low in probability but must also be considered. We begin with the average impact of a particular location in the supply network where we consider all the possible outcomes, each termed a scenario, of the various risks that can occur there. We can develop fruitful measures by considering (1) the cost of the scenario occurring and (2) the expected propagated cost given that the scenario occurred. Multiplying this number by the scenario's probability will give the expected total loss, including the loss at the location together with the expected propagated loss. As a foundation for the first measure, we seek to find: P(scenario)(scenario loss + expected propagation loss).

Let $s_i \in S$ be an element of the supply network and let $r_j^{s_i} \in R_{s_i}$ be a risk that can occur at s_i. If we assume that the event $r_j^{s_i}$ has occurred, this changes the beliefs of the entire risk graph. We seek, however, to only incorporate the pure descendants of $r_j^{s_i}$ that will lead to the creation of causal risk measures rather than using any ancestors, which will conversely lead to the creation of diagnostic measures. In order to develop these causal risk measures, we begin by defining a cost function $U(r_j^{s_i})$ for each node. The cost function is dependent on what we are trying to measure (i.e. financial cost of damage) and can be any measurable quantity that represents some sort of consequence if $r_j^{s_i}$ were to occur. For simplicity, we assign the random variable $r_j^{s_i}$ to one of two outcomes: 0 if the event does not occur or $U(r_j^{s_i})$ if the event does occur.

We now develop a measure in order to find the propagated effects of a scenario occurring. We assume that each scenario is a complete instantiation of all the risks $r_j^{s_i} \in R_{s_i}$. Since all the risks are binary, they are either set to 0 or their cost $U(r_j^{s_i})$. Since the instantiation of the risks changes the beliefs in the risk graph, we can take them into consideration by finding a conditional expectation of all the pure descendants, denoted as $\Gamma(R_{s_i})$, of the risks R_{s_i}. Intuitively, this gives us a sense for how much the propagated loss we can expect if this particular scenario were to occur. We hence define the expected risk contribution factor (ERCF) of a scenario $I = \{r_1^{s_i} = a_1, \ldots, r_{N(R_{s_i})}^{s_i} = a_{N(R_{s_i})}\}, a_j \in \{0, U(r_j^{s_i})\}$ as:

$$\mathrm{ERCF(I, s_i)} = \mathrm{E}\left[\left(\sum_{\mathrm{y} \in \blacksquare(\mathrm{R}_{\mathrm{s_i}})} \mathrm{y}\right) |\mathrm{I}\right] \tag{8}$$

The expectation is taken with respect the conditional joint distribution of the variables in the pure descendants of R_{s_i} given the scenario. In order to measure the overall risk of a location in the supply network, we can add together to the total losses of the scenario together with its ERCF and lastly multiply it by its probability. Let I_{s_i}

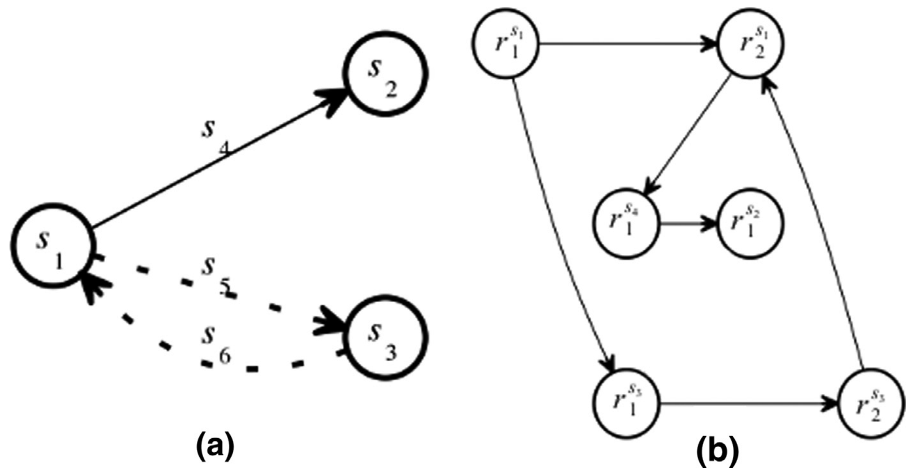

Fig. 3. (a) A supply network. (b) The supply network's risk graph.

be the set of scenarios at s_i. We thus define the expected location risk contribution factor (ELRCF) of a location $s_i \in S$ as

$$\mathrm{ELRCF(s_i)} = \sum_{\mathrm{I} \in \mathrm{I}_{s_i}} \left(\sum_{\mathrm{x} \in \mathrm{I}} \mathrm{x} + \mathrm{ERCF(I, s_i)} \right) \mathrm{P(I)} \tag{9}$$

Now that we have a score of the expected loss at each location in the supply network, we can develop a measure that puts the scores on a relative scale from 0 to 1. We seek to see how much total loss is accounted for in each location in the supply network. We can do so by adding all the cost functions for each risk in the risk graph:

$$U_{\mathrm{T}} = \sum_{s_i \in S} \left(\sum_{r_j^{s_i} \in R_{s_i}} U(r_j^{s_i}) \right) \tag{10}$$

We now can define the relative expected location risk contribution factor (RELRCF) of a location s_i as:

$$\mathrm{RELRCF(s_i)} = \frac{\mathrm{ELRCF(s_i)}}{\mathrm{U_T}} \tag{11}$$

We propose another measure of risk that depends on what we define as a risk equilibrium point. This point is the mean of the ELRCF in the supply network, that is, the average total loss at each location of a scenario occurring in the network. After establishing this point, we can determine how much our ELRCF scores deviate from the equilibrium. The reasoning around this measure is that all of the risk scores may be clustered on the established relative scale and we seek to find deviations from the "average loss" originating at a particular location. These measures can also be used to determine subjective thresholds in terms of deviations from the equilibrium. Those that fall on the upper portion can be classified as "extremely risky" and those that fall on the lower portion can be classified as "extremely safe". While the expected location risk contribution factor measures a location's risk, taking into account both the loss at the location and its propagated effects, to know how its propagated effects compare to the actual loss at the location is also of interest. That is, assuming a scenario occurs, how much of the total loss is attributed to propagation effects relative to the location loss? We define the propagation ratio as a solution to this problem. This can be defined as the total amount of propagation loss for all scenarios at a location divided by the total amount of loss for all scenarios:

$$\gamma_{\mathrm{prop}}(s_i) = \frac{\sum_{I \in I_{s_i}} \mathrm{ERCF(I)P(I)}}{\sum_{I \in I_{s_i}} \left(\sum_{x \in I} U(x) \right) P(I)} \tag{12}$$

The propagation ratio may be high while the ELRCF may be low. That is, while a location in the supply network may be deemed "low risk", its propagated effects may be high and hence may be considered critical in certain circumstances. Ratios above 1 can be interpreted as having more propagated effects while those of less than 1 may be deemed as having most of the damage occur solely at that particular location. This ratio gives us an idea for how much risk spreads relative to its own loss at the location.

Table 1
Risks identified in the supply network.

Risks		
Risk location	Risk number	Risk description
W	1	Flood
W	2	Overburdened employee
W	3	Damage to inventory
W	4	Delay in shipment
R	5	Inventory shortage
M1	6	Machine failure
M1	7	Delay in shipment
M2	8	Machine failure
M2	9	Delay in shipment
RM	10	Delay in shipment
RM	11	Contamination
W-R	12	Truck accident

5. A demonstration of the supply chain risk propagation model

In this section we illustrate the use of our model and measures with a small example generated by developing a simple supply network as well as considering a small number of risks, shown above in Table 1. Suppose we have a raw materials source (RM) that has a materials/information flow to two distinct manufacturing locations (M_1, M_2) both of whom have a materials/information flow to a wholesaler (W) who in turn delivers products to a retailer (R) (Fig. 4).

The risks in Table 1 are associated with a particular location in the supply network. By construction, our example satisfies all of the assumptions listed above. The risk graph was constructed using our model procedure as well as the basic characteristics and nature of the given risks. The probabilities in the conditional probability table were randomly sampled from a constrained uniform distribution. The table is shown in Table 2. After determination of the structure of the risk graph, the network was inputted into JavaBayes (Cozman, 2004), which is an open source software used for Bayesian network interference and analysis. Individually feeding JavaBayes the appropriate evidence and then querying the appropriate variables allowed us to compute the proposed measures above. The results of our measures are shown in Table 3.

Table 2
Conditional probability table for the risks in the constructed risk graph.

Conditional probability table for the risk graph																																			
												P(risk|parents)																							
Parents												1		2		3		4		5		6		7		8		9		10		11		12	
1	2	3	4	5	6	7	8	9	10	11	12	T	F	T	F	T	F	T	F	T	F	T	F	T	F	T	F	T	F	T	F	T	F	T	F
–	–	–	–	–	–	–	–	–	–	–	–	0.2	0.8	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–
–	–	–	–	–	–	–	–	–	–	–	–	–	–	0.4	0.6	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–
T	T	–	–	–	–	–	–	–	–	–	–	–	–	–	–	0.8	0.2	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–
T	F	–	–	–	–	–	–	–	–	–	–	–	–	–	–	0.6	0.4	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–
F	T	–	–	–	–	–	–	–	–	–	–	–	–	–	–	0.3	0.7	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–
F	F	–	–	–	–	–	–	–	–	–	–	–	–	–	–	0.4	0.6	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–
–	–	T	–	–	–	T	–	T	–	–	–	–	–	–	–	–	–	0.9	0.1	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–
–	–	T	–	–	–	T	–	F	–	–	–	–	–	–	–	–	–	0.6	0.4	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–
–	–	T	–	–	–	F	–	T	–	–	–	–	–	–	–	–	–	0.4	0.6	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–
–	–	T	–	–	–	F	–	F	–	–	–	–	–	–	–	–	–	0.7	0.3	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–
–	–	F	–	–	–	T	–	T	–	–	–	–	–	–	–	–	–	0.5	0.5	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–
–	–	F	–	–	–	T	–	F	–	–	–	–	–	–	–	–	–	0.3	0.7	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–
–	–	F	–	–	–	F	–	T	–	–	–	–	–	–	–	–	–	0.4	0.6	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–
–	–	F	–	–	–	F	–	F	–	–	–	–	–	–	–	–	–	0.2	0.8	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–
–	–	–	T	–	–	–	–	–	–	–	T	–	–	–	–	–	–	–	–	0.9	0.1	–	–	–	–	–	–	–	–	–	–	–	–	–	–
–	–	–	T	–	–	–	–	–	–	–	F	–	–	–	–	–	–	–	–	0.6	0.4	–	–	–	–	–	–	–	–	–	–	–	–	–	–
–	–	–	F	–	–	–	–	–	–	–	T	–	–	–	–	–	–	–	–	0.7	0.3	–	–	–	–	–	–	–	–	–	–	–	–	–	–
–	–	–	F	–	–	–	–	–	–	–	F	–	–	–	–	–	–	–	–	0.2	0.8	–	–	–	–	–	–	–	–	–	–	–	–	–	–
–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	0.3	0.7	–	–	–	–	–	–	–	–	–	–	–	–
–	–	–	–	–	T	–	–	–	T	–	–	–	–	–	–	–	–	–	–	–	–	–	–	0.7	0.3	–	–	–	–	–	–	–	–	–	–
–	–	–	–	–	T	–	–	–	F	–	–	–	–	–	–	–	–	–	–	–	–	–	–	0.8	0.2	–	–	–	–	–	–	–	–	–	–
–	–	–	–	–	F	–	–	–	T	–	–	–	–	–	–	–	–	–	–	–	–	–	–	0.4	0.6	–	–	–	–	–	–	–	–	–	–
–	–	–	–	–	F	–	–	–	F	–	–	–	–	–	–	–	–	–	–	–	–	–	–	0.1	0.9	–	–	–	–	–	–	–	–	–	–
–	–	–	–	–	–	–	–	–		–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	0.2	0.8	–	–	–	–	–	–	–	–
–	–	–	–	–	–	–	T	–	T	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	0.9	0.1	–	–	–	–	–	–
–	–	–	–	–	–	–	T	–	F	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	0.5	0.5	–	–	–	–	–	–
–	–	–	–	–	–	–	F	–	T	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	0.6	0.4	–	–	–	–	–	–
–	–	–	–	–	–	–	F	–	F	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	0.2	0.8	–	–	–	–	–	–
–	–	–	–	–	–	–	–	–	–	T	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	0.8	0.2	–	–	–	–
–	–	–	–	–	–	–	–	–	–	F	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	0.3	0.7	–	–	–	–
–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	0.4	0.6	–	–
–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	0.4	0.6
											Loss:	200		40		500		940		30		340		100		200		220		500		600		340	

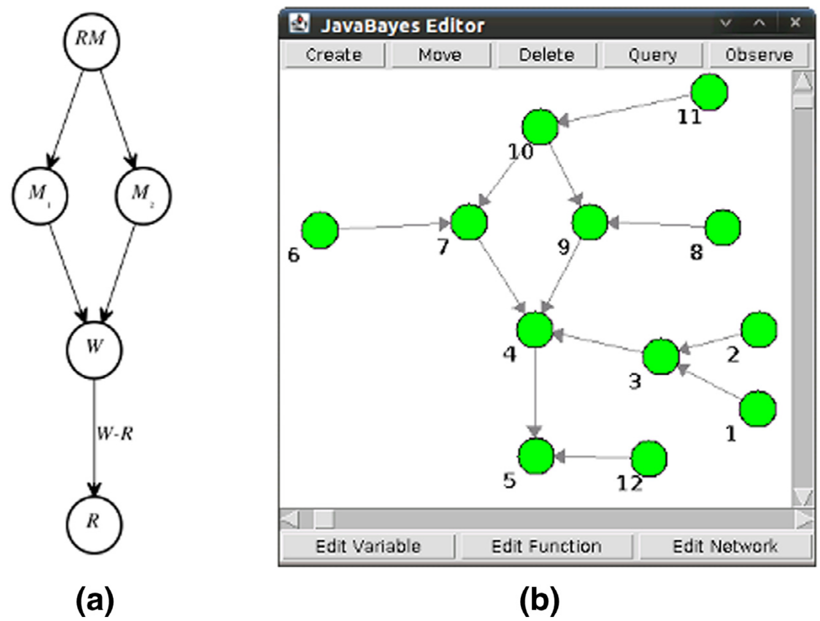

Fig. 4. (a) The supply network for the example. (b) The resulting risk graph in the Java Bayes editor.

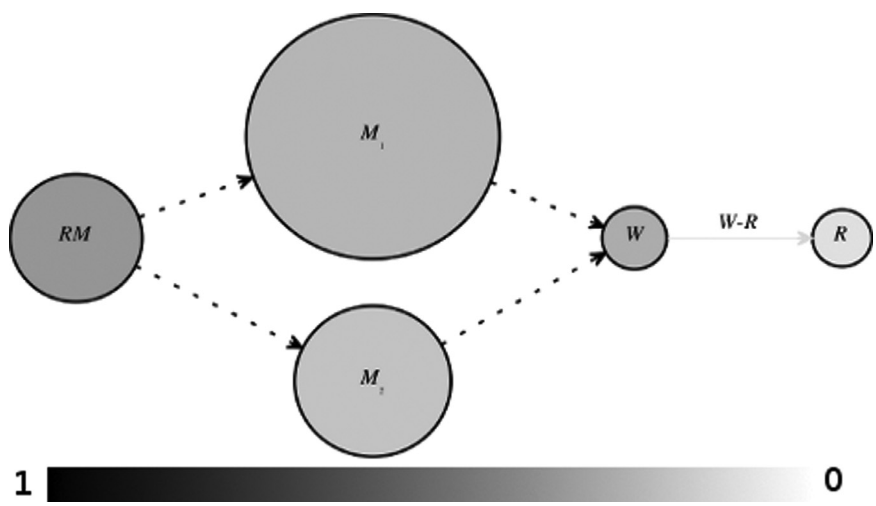

Fig. 5. The propagation heat map. The dotted lines represent edges with no risks found. The shade of the nodes and solid edges represent the RELRCF. The size (weight) of the nodes (edges) represents the propagation ratio.

Table 3
Summary of the various risk measures of the supply network.

Location	Risks	Expected location risk contribution factor	Relative expected risk contribution factor	Propagation ratio	Risk equilibrium point	Risk SD
RM	10, 11	1093.2223	0.2726	1.0968	508.952	397.828
M1	6, 7	597.4632	0.149	2.1275	508.952	397.828
M2	8, 9	427.8933	0.1067	1.0315	508.952	397.828
W	1, 2, 3, 4	766.0223	0.191	0.02	508.952	397.828
W-R	5	152.56	0.038	0.1046	508.952	397.828
R	12	16.551	0.0041	0	508.952	397.828

In addition to the table above, we can develop a propagation heat map, which gives a visual representation of both the propagation ratio and the RELRCF. The node size represents the propagation ratio and the shade represents the RELRCF:

For the results, we were able to compute the ELRCF, the risk equilibrium, the deviations of the ELRCF, the RELRCF and the propagation ratio. As intuition may dictate, the RM source is high in risk and accounts for a good portion of the total possible loss in the network. This is so since RM has many dependents and hence has room for risk to flow. However, we note that the propagation ratio, albeit high, is not as high as the first manufacturer. We can interpret this by saying that while the RM has a higher level of total risk, the first manufacturer has a higher propagation loss relative to its own loss when compared with the RM (Fig. 5).

We also observe that the only edge that was considered has a relatively low loss. Dotted edges were considered to have no risks present. The retailer also poses a low risk to the network. It is interesting to also note that the wholesaler has a higher RELRCF than the first two manufacturers. This is counterintuitive since one would predict that the higher up the supply network, the more potential for higher total losses to occur. It is worthwhile to note, however, that while the RELRCF on the manufacturers are respectively relatively low, the propagation ratio is relatively high. This indicates that while total losses at the manufacturers are low, the potential for risk to propagate is higher compared to its own costs than those of any other node in the network. All ratios were less than 1, however, indicating that for all locations in the network, the loss occurs mostly at the node in which a scenario occurs rather than through propagation. Nonetheless, the risk propagation ratio offers an insight into how risk is spreading through the given network.

6. Conclusions

The primary goal of this paper was to introduce a framework to measure risk propagation in a supply network. As indicated previously, previous models of supply chain risk have either been specific to a particular problem or lacked a set of standard measures to be used for other scenarios. Many had disregarded the structure of the network itself. Also lacking was the measurement of risk propagation through a network. We argue that Bayesian networks lend themselves as a natural fit for the goal of measuring risks within a supply chain. If constructed according to the structure of the supply network, Bayesian networks represent a snapshot of a firms supply chain risk profile. The measures we developed as a result of the construction of the risk graph are general enough to adapt to nearly any situation involving a consequence to a particular event happening. These need not be solely financial loss but can be easily extended to other measures of loss such as damage to the environment, characteristics of the underlying supply network, economical measures of loss, psychological measures and so on. Furthermore, our measures can be used to solve for global optimality using previous models such as newsvendor and other inventory models (Eeckhoudt et al., 1995; Kass & Raftery, 1995; Lai, Debo, & Sycara, 2009), transportation problems involving risk (Erkut & Verter, 1998), network configuration and facility location (Blackhurst et al., 2011; Kulkarni, Magazine, & Raturi, 2004) and many more (Vakharia & Yenipazarli, 2008). They also could be used to develop mitigation and contingency plans that will increase a supply chain's resiliency efforts (Hu, Gurnani, & Wang, 2013) by performing scenario analysis and integrating our measures in existing petri-net models (Wu et al., 2007; Zegordi & Davarzani, 2012). While we strongly advance the idea that our model is a solution to the problem of measuring risk in a supply network as well as its propagated effects, we must be weary of the limitations. First, the assumptions we have placed on the model are very specific and only account for a limited number of simple supply networks. Future work would be to loosen the assumptions and develop extensions on our model to solve the issues with the restrictive assumptions. Second, our measures are based heavily on the expectation operator, which for large networks could be computationally burdensome. Appropriate heuristics may need to be developed to solve these issues. The measures are also reliant on probabilistic inference, which itself becomes NP-Hard when the network grows beyond a certain point, however, there exist many algorithms to efficiently perform inference.

While these limitations are restrictive, we must note that our proposed model has potential for many future research topics. Now that we have developed a model for measuring risks it is important to see the effects on current operational and logistical problems that were previously solved for locally optimal solutions. Additionally, given that our model is based on BN, we can query the network with simple or even complex problems. Such an ability allows for scenario analysis to be more prudently taken. Risk management strategies and contingency plans can also be developed around these measures since the underlying model allows for complex queries to be posed. Also of importance is the structure of the risk graph itself which is heavily reliant on the construction of a Bayesian network, and if the distributions are represented by the beta distributions, the networks have an ability to learn. Such flexibility allows for reduced effort in risk analysis and if implemented correctly can lead to a live "snapshot" of the firm's risk profile, which itself may lend to information as to where the risk will next spread.

Other measures can be further developed such as the aforementioned diagnostic measures. Rather than discovering how risky a location is within a supply network, it may be of interest to see the causes of a particular risk that had been observed. Also of importance to note is that our model assumes binary events: either the event happened or it failed to occur. An interesting extension would be to use continuous or discrete distributions in order to gauge to what extent can the risk occur.

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