Bottleneck identification in supply chain networks

Article *in* International Journal of Production Research · January 2012

DOI: 10.1080/00207543.2012.695878

Stephan M. Wagner
ETH Zurich

Bottleneck identification in supply chain networks

Kamil J. Mizgier[*] Matthias P. Jüttner[†] Stephan M. Wagner[‡]

Abstract

In supply chain risk management, it is essential to identify firms that induce high losses due to supply chain disruptions in a focal firm or the supply chain network as a whole (bottlenecks). In this article, we describe supply chain networks as complex systems of firms and their suppliers. We revisit some established network measures and compare their predictions with a new methodology for detecting bottlenecks. In this bottom-up approach, production disruptions on the firm level are modelled with stochastic point processes, and a mechanism for the propagation of losses through the network is defined. The individual firms' emerging loss contributions to the total losses of the focal firm provide, then, an alternative risk-adjusted measure. Our methodology and findings enable more informed and transparent decisions to be made for optimal supply chain network design.

Please cite this article as Mizgier, Kamil J./Jüttner, Matthias P./Wagner, Stephan M. (2013): Bottleneck Identification in Supply Chain Networks, *International Journal of Production Research*, Vol. 51, No. 5, March, pp. 1477-1490.

Keywords: Supply chain risk management, Network theory, Disruption management

[*]Chair of Logistics Management, Department of Management, Technology, and Economics, Swiss Federal Institute of Technology Zurich, Weinbergstrasse 56/58, CH-8092 Zurich, Switzerland; `mailto: kmizgier@ethz.ch`

[†]Swiss Finance Institute and University of Zurich, Plattenstrasse 14, CH-8032 Zurich, Switzerland;

[‡]Chair of Logistics Management, Department of Management, Technology, and Economics, Swiss Federal Institute of Technology Zurich, Weinbergstrasse 56/58, CH-8092 Zurich, Switzerland;

1 Introduction

Supply chain networks (SCNs) are becoming larger and more densely interconnected, which increases the inherent complexity and uncertainty of production. The pressure of increasing competition and the possibilities of globalised markets have driven firms to outsource manufacturing globally to reduce inventories or economise the supply base. Although production processes are becoming more efficient, for example, through technological advances (Brynjolfsson and Hitt 2000), the complexity of these networks makes it difficult to predict losses due to production breakdowns in the supply chain. On the other hand, many of the lean initiatives undertaken by manufacturers (e.g., in the automotive industry) in the last two decades have striven to simplify supply network structures and reduce both the number of stages (also called 'tiers') and the number of entities at each stage. Indeed, much of the evident risk involves reduced diversification, albeit with a simplified structure. The correct assessment of the firm's risk exposure embedded in the actual network design is still a highly debated issue. Due to insufficient knowledge regarding the impact or correlation of hazard events and the dispersion of losses through the network, it is unclear whether certain network structures are more resilient or more susceptible to supply chain disruptions in single or multiple nodes in the SCN (Wagner and Neshat 2010). In particular, it is essential that focal firms identify their high-risk suppliers. Supply chain risk managers are then able to reconfigure the network structure or improve resilience by introducing additional inventories to mitigate or prevent contagious effects.

This article compares a set of measures for the identification of bottlenecks in SCNs. First, we revisit some established measures from social network theory, e.g., degree centrality or betweenness, and analyse them in the SCN context. Second, we introduce a new methodology for an efficient and accurate detection of firms in a SCN that potentially generate high losses for a focal firm in the case of a disruption. We use a simple bottom-up approach, in which supply chain disruptions are modelled on the firm level with stochastic point processes. A mechanism for the loss propagation through the network is defined. We determine via Monte Carlo (MC) simulation the aggregate loss distribution for the focal firm. The loss contribution of the individual firms and hazard events to total losses for the focal firm provide, then, a risk-adjusted measure. These measures aim to condense the complex informational content of a given network topology. However, it is crucial to our interpretation to consider the nature of the network connections. In SCNs, these connections occur on different interaction levels, including information channels, the flow of physical goods or, in our case, the loss dispersion induced by supply chain disruptions. We interpret and compare the results of these measures in the context of loss dispersion. Our findings support the need for an accurate methodology to identify firms in the SCN that greatly impact the losses of the focal firm.

The article is organised as follows: Section 2 discusses the relevant literature. The SCN under consideration is introduced in Section 3. In Section 4, we revisit centrality measures from network theory and discuss their applicability in the supply chain risk management context. We present our approach in Section 5. We discuss the results of both approaches in Section 6 and conclude in Section 7.

2 Literature review

Network theory has been widely applied in many research areas, spanning fields from the natural sciences (Dorogovtsev and Mendes 2003) to finance (Boss et al. 2004), banking (Mistrulli 2011), economics (Allen and Gale 2000) and the social sciences (Granovetter 2005). The network paradigm developed in the aforementioned areas is fairly new to supply chain management (SCM). Nevertheless, we have observed a rapid growth in interest and applications in this domain. One of the initial studies of supply chains as complex systems was conducted by Macal (2003). He employs the network version of the beer game simulation to optimize the inventory and information acquisition costs in a supply chain. Pathak et al. (2007) propose the Complex Adaptive System (CAS) perspective to study the interrelations that are often inherent in SCNs. They highlight the advantages of using the CAS approach to support decision making at the SCN level. Mizgier et al. (2012) develop an agent-based model to examine the defaults of companies in a SCN. They show how the dynamics of the relations among the supply chain members affect the system's performance. Yang and Yang (2010) study the role of postponement in supply chain risk management from a complexity perspective. Building on the normal accident theory, they conclude that in some circumstances the introduction of postponement may add to the complexity of a system and, thus, make the system inherently infeasible. Kumar et al. (2010) analyse a mathematical model for SCN design under uncertainty. Considering the problem's complexity, they apply various computational techniques to offer potential solutions to robust supply chain design.

A thorough overview of the social network approach to SCM is provided by Borgatti and Li (2009). They state, that network theory has the potential to enrich SCM research with new tools and that network theory supports the creation of a coherent management science perspective. Choi and Kim (2008) and Choi and Wu (2009) use examples to show how to manage suppliers based on their embeddedness in the network and the strategic formation of triads. Such a view of the supplier base encourages buying firms to develop more realistic policies and strategies when managing their suppliers. An empirical investigation of a SCN has been carried out by Kim et al. (2011). Their framework relates key social network analysis metrics to SCNs and proposes SCM-specific implications. They also provide a comprehensive literature review of topics related to social networks.

Several measures for bottleneck identification are proposed in the literature. Craighead et al. (2007) derive six propositions relating the severity of supply chain disruptions to supply chain characteristics, such as density, complexity and node criticality. Their underlying theory involves identifying the most important nodes based on the measurement of information and the material flows between them. In this article, we will concentrate on some basic definitions of node importance. Degree centrality and betweenness centrality are discussed by Freeman (1977). Opsahl et al. (2010) propose modified algorithms and definitions, including the weighted connections. The use of these measures has many applications in social and natural sciences, such as scientific collaboration networks (Newman 2001) or biological metabolic networks (Ravasz et al. 2002). Algorithms used for the calculation of the centrality measures can be found in Brandes (2008).

3 Supply chain network structure

A SCN is a complex system of interconnected firms. The SCN under consideration consists of N agents – divided into suppliers, focal firms and customers – who operate on different stages in the SCN. We are interested in the stage of the focal firms, and we calculate the loss distribution of a focal firm that arises from disruptions downstream in its supply chain (flow of production). The relationships in the network are described by a directed graph $(\mathcal{G}_t)_{t\in[0,T]} = (V, A_t)_{t\in[0,T]}$, where V is the set of nodes representing the agents and $(A_t)_{t\in[0,T]}$ describes the evolution of edges, representing the purchasing volumes between suppliers and buying firms. We assume that the composition of the SCN V is constant, while the business relations can vary over time. The graph is associated with the adjacency matrix $\boldsymbol{\Xi}_t = (\xi^t_{ij})_{i,j=1,\ldots,N}$. The entry ξ^t_{ij} describes the maximum percentage loss of the daily turnover of the firm j if the disruption occurs in the downstream production firm i. Therefore, these entries represent the exposure of j to i, because once a supplier suffers a production interruption or defaults, the ordered products cannot be delivered, and the focal firm will be negatively affected.

We use the following stylised example throughout this article. We study a SCN with six agents: one focal firm F_{01} with three suppliers in the first stage S_{11}, S_{12}, S_{13} and two second stage suppliers S_{21}, S_{22}. The network structure is depicted in Figure 1. At time $t \in [0, T]$ the matrix $\boldsymbol{\Xi}_t$ is given by

$$\boldsymbol{\Xi}_t = \begin{pmatrix} 0 & 0 & 1 & 0.8 & 0.6 & 0 \\ 0 & 0 & 0 & 0.2 & 0.4 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0.7 \\ 0 & 0 & 0 & 0 & 0 & 0.2 \\ 0 & 0 & 0 & 0 & 0 & 0.1 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{pmatrix} . \tag{1}$$

[Figure 1 about here.]

First, in the last row of $\boldsymbol{\Xi}_t$, we see that the focal firm F_{01} does not sell any products to agents within the network. To study the downstream risk for this focal firm all connections to possible clients to F_{01} are naturally not considered. F_{01} herself receives all products or necessary components from all three direct suppliers, where, for instance, $\xi^t_{S_{11}F_{01}} = 0.7$ or $\xi^t_{S_{13}F_{01}} = 0.1$ (fifth row). A disruption in the production process of firm S_{11} (S_{13}) can induce a 70% (10%) reduction of the delivery volume of F_{01}. On the other hand, for S_{11}, all the necessary components are sourced from supplier S_{21}, and for S_{12}, components are sourced 80%, 20% from supplier S_{21}, S_{22} respectively. We assume the total disruptions (indirect costs of 100%). This stylised example has been discussed in several meetings with our industry partners to ensure the feasibility of our approach.

4 Network theory-based measures for bottleneck identification

In graph theory and related applications, measures exist to determine the rank or centrality of nodes according to their positions in the network (see, for example, Freeman 1977, Brandes 2008, Opsahl et al. 2010). A thorough overview of centrality metrics and applications in SCM can be found in Kim et al. (2011). Though these measures help identify the relative importance of nodes in a network, the context of the application is important. We apply the centrality measures to our simple example and describe some of the shortcomings when using the respective measure for risk management purposes. For the calculation and visualisation of these measures, we use Visone, a freeware software developed at the University of Konstanz.[1]

For the SCN, $G = (V, A)$ one of the simplest measures is the *degree centrality* $C_D(a)$ (outdegree) for vertex $v \in V$. V (with $|V| = N$) is the set of nodes representing the firms and A describes the edges representing the business weightings between the firms. $C_D(v)$ is defined as follows:

$$C_D(v) = \frac{deg(v)}{N-1}, \tag{2}$$

where $deg(v)$ is the number of links node v directs to others (downstream), i.e., these firms are directly affected by a disruption of the production process in v. Several shortcomings exist: first, the network topology is only partially anticipated because only direct links are relevant; second, the weightings of the edges are not considered; third, the risk of a disruption in each node is not included. The results are depicted in Figure 2. Not surprisingly, supplier S_{21} is the most important node for our sample SCN, due to its high connectivity with other suppliers.

[Figure 2 about here.]

Following Freeman (1977), the *betweenness centrality* counts the fraction of shortest paths between each pair of vertices that are passing through a given node $v \in V$, in the following formula:

$$C_b(v) = \sum_{s \neq v \neq t \in V} \frac{\sigma_{st}(v)}{\sigma_{st}}, \tag{3}$$

where σ_{st} is the number of shortest paths from s to t, and $\sigma_{st}(v)$ is the number of shortest paths from s to t that pass through a vertex v. The result is standardised by dividing it through the term $(N-1)(N-2)$, which corresponds to the maximum number of edges in a directed graph. The theory behind this concept is that nodes between others are central because they can influence the flow of information. In the case using weighted links, Brandes (2001) proposes to invert the weights while computing the betweenness centrality. He also introduces several computationally efficient algorithms. In the case of the propagation of losses in a SCN, this measure appears misleading because firms on the outermost stage of the SCN are not identified as risk sources. The information flow, in contrast to the loss dispersion, should be sustained, and, therefore, disruptions in the nodes present between other nodes are central. For the area of loss propagation in SCNs, these disruptions can have a positive effect because the contagious effects are absorbed. On the other hand, if the losses are not absorbed, these nodes in the network appear to be central for loss propagation. In Figure 3, we see that the group of suppliers S_{12}, S_{13} is marked with the highest values of centrality. For a supply chain manager, this result indicates that this group of suppliers is highly clustered and is, therefore, vulnerable to collective disruptions. The results of the calculations of the weighted betweenness centrality are depicted in Figure 4. The next measure, which can be used to support the identification of the most critical suppliers is called *radiality* (Valente and Foreman 1998). Radiality is the degree of a supplier's connectivity when reaching out into the network. It is defined as follows:

$$R(k) = \frac{\sum_{j \neq k} RD_{jk}}{N-1}, \tag{4}$$

[1] For more information, see `www.visone.info`.

where RD_{jk} is the reverse distance computed from the geodesic between suppliers j and k, measured on outdegree ties and N is the network size. High radiality means that fewer steps, on average, are necessary for that supplier to deliver goods to everyone else in the network through her distribution channels (outdegree ties). In terms of supply chain disruptions, a supplier with high radiality would affect more firms in the network if a disruption occurred. The results of analysis based on node radiality are depicted in Figure 5.

[Figure 3 about here.]

[Figure 4 about here.]

[Figure 5 about here.]

5 Alternative method for bottleneck identification

In this section, we first model the frequency and severity of disruptions on each firm's production process. In the second subsection, we define loss propagation through the network. In the last subsection, we implement the model for the exemplary SCN, generate via MC simulation a loss distribution for the focal firm and study the impact (loss contribution) of single nodes to the total average loss of the focal firm. In performing these measures, we are able to identify potential bottlenecks in the focal firm's supplier structure, i.e., the suppliers with the highest loss contributions.

5.1 Disruption risk: frequency and severity

We model disruption risks (frequency and severity) on the firm level using renewal-reward processes. We first identify potentially disruptive supply chain events for each node in the network. The finite set $\mathcal{E} = \{e_1, \dots, e_E\}$ collects all the possible events of all the nodes in the network; $\mathcal{E}_j$ then denotes the set of possible hazard events for firm j. We can distinguish two types of disruptions: firm-specific and systematic hazard events. The term systematic is only used for the simultaneous dependence of different firms in the network on the same hazard event and not to describe the simultaneous impact due to interfirm links (contagion). The variable $(N_t^{e_i})_{t>0} \in \mathbb{N}_0$ is the random number of disruption event e_i that occur during the period $[0, t]$. The probability function is denoted by $p_{e_i,t}(k) = \mathbf{P}[N_t^{e_i} = k]$. The cumulative density function (cdf) for the loss frequency is then obtained by

$$\mathbf{P}[N_t^{e_i} \leq n] = \sum_{k=0}^{n} p_{e_i,t}(k). \tag{5}$$

It is necessary to determine the theoretical distribution and parameters that best fit the empirical distribution of documented historical occurrences. The disruption frequency is often modelled by a Poisson or negative binomial distribution. In contrast, the impact of a disruption differs across firms because firms have different approaches to organisation and business continuity management. The required time for firm j to resolve the disruption due to event $e_i \in \mathcal{E}_j$ is described by the sequence of independent and identically distributed (i.i.d.) and positive random variables $(R_{j,n}^{e_i})_{n\in\mathbb{N}}$. The production losses for connected nodes are denoted by $(IC_{j,n}^{e_i})_{n\in\mathbb{N}}$. These indirect costs represent reductions in production in percentage terms and per time unit. After a disruption occurs, the firm requires a random amount of time to resume the production process. As soon as production restarts, it is exposed to new disruptions. The entire time structure for a hazard event e_i is depicted in Figure 6. In the simulations in Section 5.3, we will assume that production times are exponentially distributed (Poisson process) and are independent across hazard events. According to this assumption, it is possible to aggregate these processes. We also impose the assumption that recovery times are non-stochastic and identical across hazard events, i.e., $R^{e_i} = r$ for $i = 1, \ldots E$.

[Figure 6 about here.]

The total indirect costs in terms of an exposure to hazard event e_i, with respect to direct neighbouring firms in the deterministic[2] network $\mathcal{G}$ up to time t are given by

$$IC^{e_i}(t) := \sum_{\{j \in \{1,\ldots,N\} | e_i \in \mathcal{E}_j\}} \left(\sum_{k=1}^{N_t^{e_i}} IC_{j,k}^{e_i} \, R_{j,k}^{e_i} \Big(\sum_{l>j} \xi_{jl} \Big) \right). \tag{6}$$

In equation (6), all firms with an exposure regarding hazard event e_i are collected. The result is given in relative terms, i.e., the entries of $\boldsymbol{\Xi}$ are given as percentages of purchasing volume.

5.2 Correlated supply chain disruptions

We have previously described the effects on the hazard event- and firm-specific levels. The complete hazard model for one firm j is consequently given by aggregating the events within the set $\mathcal{E}_j$. The correlation across the nodes in the network is established by two channels: first, the intersection of firm-specific hazard event sets is not necessarily empty, i.e., $\mathcal{E}_j \cap \mathcal{E}_i \neq \{\}$ (systematic risk) and second, the network $\mathcal{G}$ naturally produces a dependency structure across the firms. Therefore, idiosyncratic disruptions also propagate through the network and affect other firms (contagion). For the second aspect of correlated losses we must describe how disruptions that occur in the farther stages propagate and affect other firms in the network. In this way, they also affect the focal firm through the existing connections. As mentioned previously, $\boldsymbol{\Xi}$ describes the business weightings between the firms. The indirect costs describe the percentage production reduction and can be translated into losses for the neighbouring nodes by anticipating the weighting matrices. We adjust the notation to $\boldsymbol{\Xi}^1$ to express that the entries represent the downstream risk between direct neighbouring nodes (distance of one stage). The loss propagation through network connections can also be described by efficient matrix algebra. The $n-$th power of the matrix $\boldsymbol{\Xi}^1$ describes the impact on the different firms from respective suppliers on the n-th stage exclusively (without disruptions on intermediate stages). We assume that there is no inventory to absorb even part of the potential supplier disruptions. This implies that losses are transferred without any friction. The simultaneous occurrence of disruption events is also important: we anticipate the effects of each disruption event and the associated losses separately, but we must impose the constraint that aggregated losses will not exceed the indirect losses of direct neighbours, i.e., we follow the complete path of each disruption through the network. Hence, the propagation of losses from one stage to the next stage is restricted to the maximum loss of the 'nearer' (or next) stage.

[2] The business relations are fixed; therefore, we eliminate the time index for the entries of $\boldsymbol{\Xi}$.

5.3 Simulation setting and loss contribution

The SCN is given by the adjacency matrix in equation (1). The time horizon is set to 180 days, and we perform 1000 MC iterations. First, we assume that two idiosyncratic hazard events exist for each firm. Therefore, we simulate two independent Poisson processes with corresponding intensities[3] on each node. The intensities can be found in the first column of Table 1. Later, we also incorporate an event e^h (third column) that can have an impact on more firms in the network. In our case, e^h has an impact on node S_{13} and S_{21}, i.e., here we simulate one Poisson process with intensity 0.001. Therefore, the time structure $(T_m^{e_h})_m$ of this event is the same for both firms. We keep the 'initial' average recovery time $r_j^{e_i}$ of 3 days for hazard events 1 and 2 (HE1 and HE2) and 14 days for hazard events of type 3 (HE3).

[Table 1 about here.]

We calculate the relative contributions to the total losses of the focal firm by each node. We identify their impact on the focal firm in two ways. First, we simulate disruptions for only the single nodes and assume that losses propagate through the network unhindered (not mitigated or amplified), i.e., all other firms in the SCN are operating without disruption in their own production facilities. An efficient computation of these losses is made possible by using the squared business weighting matrix. Second, we simulate the actual hazard events in all the nodes and separate the contributions from the different nodes from the total losses of the focal firm. It is possible that disruptions from second stage suppliers do not affect the focal firm because simultaneous disruptions on the first stage prevent the loss propagation. This computation enables us to evaluate each supplier's contribution to the risk exposure and its impact on the focal firm, which is not isolated but embedded in the risk environment of the whole SCN. In the following figures, the blue (green) bars depict the first 'isolated' (second 'embedded') case.

We start by simulating only the idiosyncratic events HE1 and HE2, thus neglecting the correlation effects induced by HE3. In Figure 7 we summarise the mean percentage value of losses coming from a given supplier as the measure of the nodes' importance. We can see that independent of the way we map the losses to separate nodes, the supplier S_{21} accounts for approximately 36% of the losses, followed by nodes S_{11} (28%) and S_{12} (27%). If we look more closely at the values of suppliers' hazard event intensities, we observe that the network structure is the crucial factor in bottleneck identification. Although the intensities of the hazard events are comparable, the business volumes and the interconnectedness of a given node play the most important roles. Our approach clearly shows that supplier S_{21} has the highest relevance in terms of generated losses and its impact on the focal firm's risk exposure, although its hazard intensities are not much higher than the other suppliers' intensities.

Next, we add the systematic hazard event HE3 to analyse the influence of the correlated disruptions. As Figure 8 shows, the distribution of the blue bars representing the first case does not change much. This is obvious because the effect of HE3 is only observable when hazard events of different firms interact which is assumed not to occur in the isolated case. Instead, the difference in the distributions of the green bars is very clear. Suppliers S_{21} and S_{11} are now nearly equal. It comes from the fact that the losses generated on the second stage are not

[3] Note that the intensities refer to days as time units. A value of 0.01 corresponds to a mean arrival rate during 180 days of 1.8 malfunctions.

propagated when disruptions occur on both stages simultaneously, which is always the case for HE3.

[Figure 7 about here.]

[Figure 8 about here.]

In a third step, we demonstrate the impact of a changed network structure. We can imagine that a focal firm influences the first stage of suppliers. The firm decides to switch purchasing volumes. In this setup, the network structure remains as it was, but purchasing volumes from suppliers S_{11}, S_{12} and S_{13} are adjusted to 20%, 70% and 10%, respectively. We present the results for HE1 and HE2 in Figure 9 and with the additional systematic hazard event in Figure 10.

[Figure 9 about here.]

[Figure 10 about here.]

In both settings, the supplier's S_{12} loss contribution surges and it becomes the only bottleneck with approximately 66%. The impact of an additional systematic hazard event is similar to the results of the previous analysis. The technique presented above can be applied to any given network structure, providing managers with a risk-based optimisation support tool for decisions about SCN design.

5.4 Comparison of results

First, as presented in Tables 2, 3 and 4, we observe that the results for bottlenecks in the SCN can vary massively depending on the centrality measure or risk structure. Node S_{21} is identified as the most important production facility using degree centrality or the first case (two independent hazard events) of our approach. Betweenness centrality predicts that the nodes on the first stage S_{12} and S_{13} are the prominent facilities in the SCN. For the management of SCNs, this variety of results is not desirable. As previously noted, the concrete context, interpretation and application are essential to using these measures without being misled. Second, a change in the risk structure does not change the results of these established measures.[4] Adding the third hazard event to each node, which represents a correlated disruption, changes the picture dramatically. The impact in the embedded case of S_{21} and S_{11} is now almost identical. The real inherent SCN risk changed, but it can only be identified using our advanced approach. Although the isolated case is superior in its computational simplicity, it does capture important aspects of the SCN risk.

[Table 2 about here.]

[Table 3 about here.]

[Table 4 about here.]

[4] To incorporate this feature, it may be necessary to adjust the weightings according to the risk of hazard events.

6 Discussion and implications

6.1 Discussion

From our results, we infer that each of the measures presented in this article has both advantages and limitations, as summarised in Table 5. Simple network theory-based measures can be helpful in obtaining first indications regarding possible bottlenecks in a SCN, but these are definitely not conclusive. The more advanced concepts, such as radiality, are capable of including the entire network structure and following complete geodesic paths. Therefore, they contain more information about the global network design. They are also superior in terms of computational efficiency, as they do not require heavy numerical calculations. The main drawback of these methods is that they do not capture the dynamic properties of the supply chain disruptions and their propagation across the network. Here, our approach adds the most value, as it correctly captures the risk exposure to different hazards and includes the topological features of the SCN. Naturally, these improvements come at a cost. The performance of our method depends on the complexity of the network and the number of hazard events that must be included in the MC simulation. As we assume that waiting times between successive disruptions are exponentially distributed, the running time of our algorithm depends heavily on the quality and efficiency of the random number generators. Moreover, because the algorithms used to sort the graphs depend on the number of nodes and edges in the network, the time complexity of the algorithms will increase with the size of the network. After considering all these factors, we believe that combining our proposed method with the network measures will achieve accurate bottleneck identification to support supply chain risk management decisions. As computational power rises, the running time of our algorithms should be acceptable, even when applied to large-scale networks.

[Table 5 about here.]

6.2 Practical implications

Our study has several practical implications. First, the direct consequence of the presented comparison between the established network measures and our proposed loss contribution approach (5.4) is the careful use of all measures. In particular, the data requirements for the established network measures are relatively low, and efficient algorithms already exist, which lends a great advantage to our new approach. Firms are tempted to apply these approximate and sometimes misleading indicators. Managers must always be aware of the respective purposes of each measure and operate with a set of different measures.

Second, the implementation of the appropriate approach necessitates the establishment of a detailed loss database. Therefore, guidelines for reporting and documenting losses from supply chain disruptions within the SCN (also across different firms) are required. The firm needs to have sufficient data about hazard events, respective frequencies, recovery times and corresponding losses to calibrate the model. The fulfilment of this requirement is certainly ambitious. The documentation and analysis of such a loss database is very helpful for sensibilising the workforce regarding inherent risks in the SCN and optimising production and supply chain operations.

Third, our new method provides operations and supply chain managers with an efficient tool for the quantification of losses due to supply chain disruptions from single suppliers, both in isolation and when embedded in the network structure. They can both identify the most critical suppliers and estimate the potential impact of disruptions in absolute terms. These evaluations may have two consequences. On the one hand, managers may monitor these firms accurately to avoid the negative impacts caused by disruptions. They learn more about their business model, the risks of their suppliers' operations and locations and potentially have the ability to change some of the parameters. On the other hand, the quantification of losses based on the model input parameters allows managers to study the impact of reconfigured networks (as Figures 9 and 10 show). Our model can, therefore, be developed further, allowing for the automatisation and optimisation of risk-weighted allocations of purchasing volume. Using a stepwise comparison of purchasing volumes sourced from each supplier, supply chain managers can optimise the risk exposure of the entire SCN. A comparative statics analysis for all the input variables may also be helpful in identifying both important nodes and their risk exposure.

7 Conclusion and outlook

In this article, we present a set of methods for identifying bottlenecks in a SCN. By incorporating the risk-specific features of the SCNs, we extend the set of measures proposed by Kim et al. (2011). We demonstrate that some methods based on network theory may support the bottleneck identification process. However, they can also be misleading because they often focus only on a small part of the network or have been developed for a particular application, not for supply chain risk management. Therefore, we propose an alternative method of bottleneck identification that considers the features of modern SCNs. Moreover, we show that the reconfiguration of the SCN can offer substantial benefits regarding the reduction of the company's risk exposure in absolute terms. Using our bottleneck identification scheme, supply chain risk managers can easily discover which suppliers are strongly interconnected (critical) and pose the greatest threat to the focal firm.

Our study is not without its limitations. We run simulations on a simplistic and stylised SCN structure. It would be desirable to test the measures on a real-world example and then to backtest the simulation results. To circumvent this shortcoming, we discussed the network structure with industry representatives to confirm the validity of the proposed model, and it is sufficiently complex for illustrative purposes. For a similar network setup, please refer to the study by Cossin and Schellhorn (2007). Nevertheless, we are aware of this limitation.

Both the investigation of the network theory measures and the loss contribution method are research paths that can be explored in the future. It would be interesting from the network perspective to observe how the model behaves when the network under investigation increases in size and complexity. As noted by Brandes (2001), the fastest algorithms to compute the betweenness centrality and radiality measures require $O(N + A)$ space and $O(NA + N^2 logN)$ time, where N is the number of nodes and A the number of edges in the network. Therefore, the computational complexity and efficiency of the methods presented in this article also present an interesting research avenue. We previously assumed in the simulation that the connections are deterministic and fixed. The incorporation of a more realistic, random graph may provide additional insight. Furthermore, the assumption of fixed values of hazard event intensities may be relaxed to incorporate seasonal effects. In stressed market phases, these intensities could increase, causing the picture to change fundamentally. The analysis of SCNs under stress –

including strongly increased intensities – should be considered as an additional valuation tool. Another aspect that has potential for improvement is the integration of the risk structures of hazard events into existing network measures. One could modify the business weightings by the corresponding values of risk parameters and obtain the risk-adjusted network measures.

As our model presents a novel method for the computation of losses in a SCN, it may be of interest to researchers and managers of social and financial networks to further explore our modelling approach.

References

Allen, F. and Gale, D. (2000). Financial contagion. *Journal of Political Economy*, 108(1):1–33.

Borgatti, S. P. and Li, X. (2009). On social network analysis in a supply chain context. *Journal of Supply Chain Management*, 45(2):5–22.

Boss, M., Elsinger, H., Summer, M., and Thurner, S. (2004). Network topology of the interbank market. *Quantitative Finance*, 4(6):677–684.

Brandes, U. (2001). A faster algorithm for betweenness centrality. *Journal of Mathematical Sociology*, 25(2):163–177.

Brandes, U. (2008). On variants of shortest-path betweenness centrality and their generic computation. *Social Networks*, 30(2):136–145.

Brynjolfsson, E. and Hitt, L. M. (2000). Beyond computation: information technology, organizational transformation and business performance. *Journal of Economic Perspectives*, 14(4):23–48.

Choi, T. Y. and Kim, Y. (2008). Structural embededness and supplier management: a network perspective. *Journal of Supply Chain Management*, 44(4):5–13.

Choi, T. Y. and Wu, Z. (2009). Taking the leap from dyads to triads: buyer-supplier relationships in supply networks. *Journal of Purchasing and Supply Management*, 15(4):263–266.

Cossin, D. and Schellhorn, H. (2007). Credit risk in a network economy. *Management Science*, 53(10):1604–1617.

Craighead, C. W., Blackhurst, J., Rungtusanatham, M. J., and Handfield, R. B. (2007). The severity of supply chain disruptions: design characteristics and mitigation capabilities. *Decision Sciences*, 38(1):131–156.

Dorogovtsev, S. N. and Mendes, J. F. F. (2003). *Evolution of Networks: From Biological Nets to the Internet and WWW*. Oxford: Oxford University Press.

Freeman, L. (1977). A set of measures of centrality based on betweenness. *Sociometry*, 40(1):35–41.

Granovetter, M. (2005). The impact of social structure on economic outcomes. *Journal of Economic Perspectives*, 19(1):33–50.

Kim, Y., Choi, T. Y., Yan, T., and Dooley, K. (2011). Structural investigation of supply networks: a social network analysis approach. *Journal of Operations Management*, 29(3):194–211.

Kumar, S. K., Tiwari, M., and Babiceanu, R. F. (2010). Minimisation of supply chain cost with embedded risk using computational intelligence approaches. *International Journal of Production Research*, 48(13):3717–3739.

Macal, C. M. (2003). *Supply Chains as Complex Adaptive Systems*. Santa Fe, NM: Santa Fe Institute.

Mistrulli, P. (2011). Assessing financial contagion in the interbank market: maximum entropy versus observed interbank lending patterns. *Journal of Banking & Finance*, 35(5):1114–1127.

Mizgier, K. J., Wagner, S. M., and Holyst, J. A. (2012). Modeling defaults of companies in multi-stage supply chain networks. *International Journal of Production Economics*, 135(1):14–23.

Newman, M. E. J. (2001). Scientific collaboration networks. I. Network construction and fundamental results. *Phys. Rev. E*, 64(1):016131.

Opsahl, T., Agneessens, F., and Skvoretz, J. (2010). Node centrality in weighted networks: generalizing degree and shortest paths. *Social Networks*, 32(3):245–251.

Pathak, S., Day, J. M., Nair, A., Sawaya, W. J., and Kristal, M. M. (2007). Complexity and adaptivity in supply networks: building supply network theory using a complex adaptive systems perspective. *Decision Sciences*, 38(4):547–580.

Ravasz, E., Somera, A. L., Mongru, D. A., Oltvai, Z. N., and Barabási, A.-L. (2002). Hierarchical organization of modularity in metabolic networks. *Science*, 297(5586):1551–1555.

Valente, T. W. and Foreman, R. K. (1998). Integration and radiality: measuring the extent of an individual's connectedness and reachability in a network. *Social Networks*, 20(1):89–105.

Wagner, S. M. and Neshat, N. (2010). Assessing the vulnerability of supply chains using graph theory. *International Journal of Production Economics*, 126(1):121–129.

Yang, B. and Yang, Y. (2010). Postponement in supply chain risk management: a complexity perspective. *International Journal of Production Research*, 48(7):1901–1912.

Table 1: Intensities of hazard events.

Hazard Event 1	**Hazard Event 2**	**Hazard Event 3**
$\lambda^{e^1_{S_{11}}} = 0.01$	$\lambda^{e^2_{S_{21}}} = 0.01$	$\lambda^{e^h_{S_{21}}} = 0.001$
$\lambda^{e^1_{S_{12}}} = 0.015$	$\lambda^{e^2_{S_{22}}} = 0.005$	$\lambda^{e^h_{S_{22}}} = 0.001$
$\lambda^{e^1_{S_{13}}} = 0.01$	$\lambda^{e^2_{S_{11}}} = 0.01$	$\lambda^{e^h_{S_{11}}} = 0.001$
$\lambda^{e^1_{S_{21}}} = 0.02$	$\lambda^{e^2_{S_{12}}} = 0.05$	$\lambda^{e^h_{S_{12}}} = 0.001$
$\lambda^{e^1_{S_{22}}} = 0.01$	$\lambda^{e^2_{S_{13}}} = 0.01$	$\lambda^{e^h_{S_{13}}} = 0.001$

Table 2: Comparison of bottleneck measures – benchmark case: $C_D(v)$ ($C_b(v)$) denotes the outdegree centrality (betweenness centrality) measure introduced in equation (2) ((3)). Bold letters indicate the node with the highest importance according to the respective measure. Loss contribution (LC) is the loss for the focal firm F_{01} induced by node v relative to total losses.

Node v	$C_D(v)$	$C_b(v)$ (uniform)	$C_b(v)$ (weighted)	Radiality	Loss Contribution (LC) (isolated)	LC (embedded)
F_{01}	0	0.00	0.00	0.00	-	-
S_{11}	0.2	0.017	0.54	0.20	28.18%	29.17%
S_{12}	0.2	**0.042**	1.68	0.20	26.84%	27.77%
S_{13}	0.2	**0.042**	**2.83**	0.20	4.06%	4.20%
S_{21}	**0.6**	0.00	0.00	**2.80**	**37.62%**	**35.87%**
S_{22}	0.4	0.00	0.00	1.50	3.30%	2.98%

Table 3: Comparison of bottleneck measures – benchmark case with a systematic hazard event: Isolated (embedded) loss contribution (LC) if all nodes in the SCN are additionally exposed to a systematic hazard event HE3.

Node	LC (with HE3) (isolated)	LC (with HE3) (embeddeed)
F_{01}	-	-
S_{11}	29.04%	32.49%
S_{12}	23.60%	26.40%
S_{13}	4.24%	4.75%
S_{21}	**39.78%**	**33.68%**
S_{22}	3.34%	2.68%

Table 4: Comparison of bottleneck measures – modified SCN without and with a systematic hazard event: The first two columns contain the loss contribution when the nodes are dependent on firm-specific hazard events, the last two columns when an additional systematic hazard event is introduced.

Node	LC (isolated)	LC (embedded)	LC (with HE3) (isolated)	LC (with HE3) (embedded)
F_{01}	-	-	-	-
S_{11}	5.48%	5.72%	6.01%	6.64%
S_{12}	**63.89%**	**66.73%**	**59.80%**	**66.10%**
S_{13}	2.76%	2.89%	3.07%	3.40%
S_{21}	22.81%	20.24%	25.67%	19.72%
S_{22}	5.06%	4.42%	5.44%	4.15%

Table 5: Summary of measures for bottleneck identification.

Centrality measure	**Conceptual definition**	**Advantages**	**Disadvantages**
Out-degree centrality	The supplier is critical when it is connected to a large number of other suppliers	Easy to compute, can be used as a first measure of supplier's criticality	Measures only the impact on the directly connected firms
Betweenness centrality	The supplier is critical when it lies between many other suppliers	Includes the whole network structure	Raw material providers are not penalized even if critical due to their position in the network
Weighted betweenness centrality	The supplier is critical when it lies between many other suppliers	Includes the whole network structure and business weightings	Raw material providers are not penalized even if critical due to their position in the network
Radiality	The supplier is critical when its reachability to other suppliers is high	Includes the whole network structure	Raw material providers are penalized even if not critical due to their position in the network
Loss contribution approach	The supplier is critical when it generates the highest expected losses	Includes the whole network structure and all parameters of disruption risk	Computational complexity and high data requirements

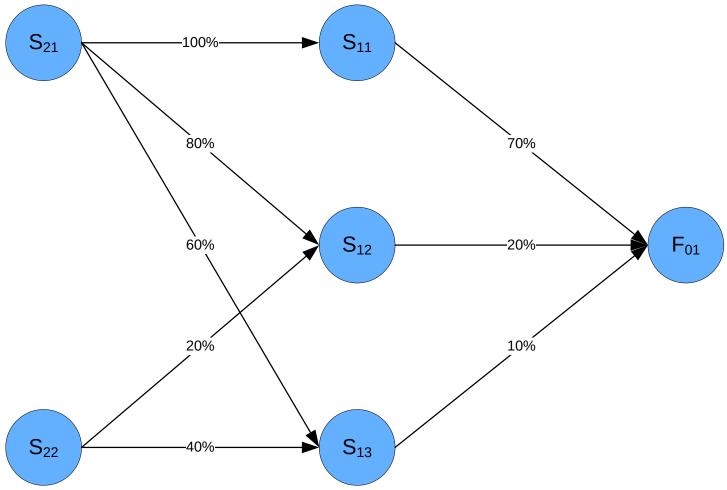

Figure 1: A sample supply chain network with two stages of suppliers.

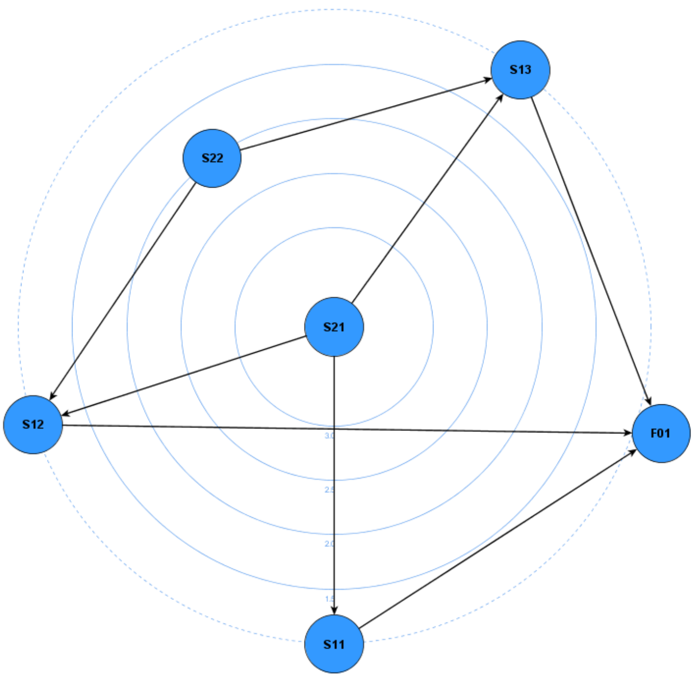

Figure 2: The relative importance of the suppliers, based on the outdegree.

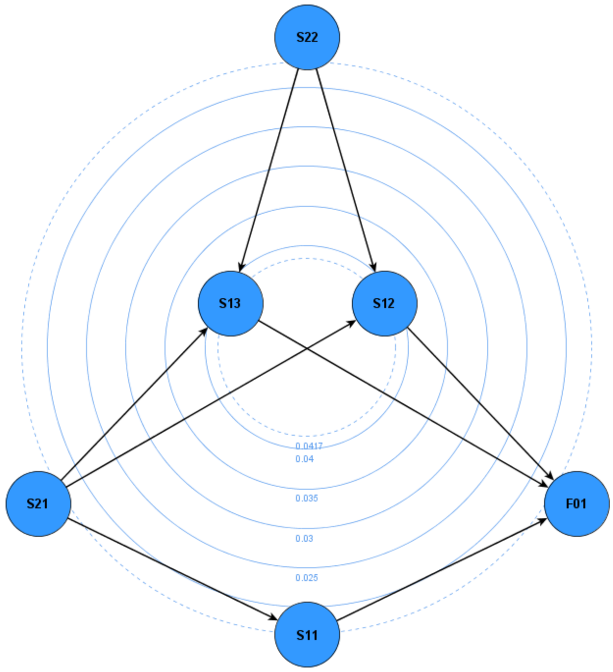

Figure 3: The relative importance of the suppliers, based on the betweenness centrality measure.

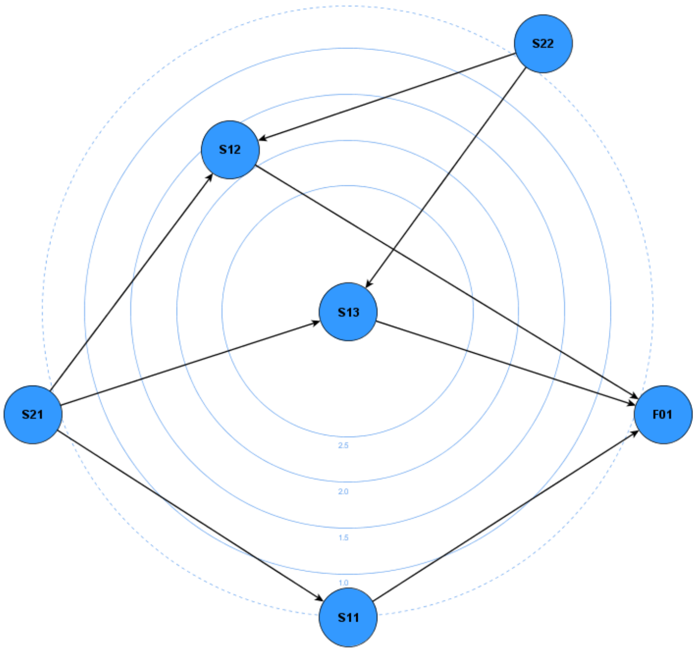

Figure 4: The relative importance of the suppliers, based on the weighted betweenness centrality measure.

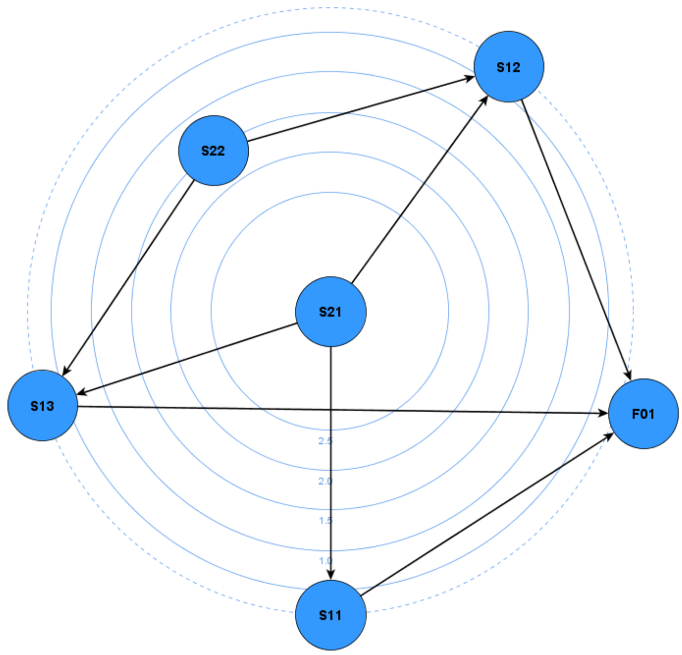

Figure 5: The relative importance of the suppliers, based on the radiality measure.

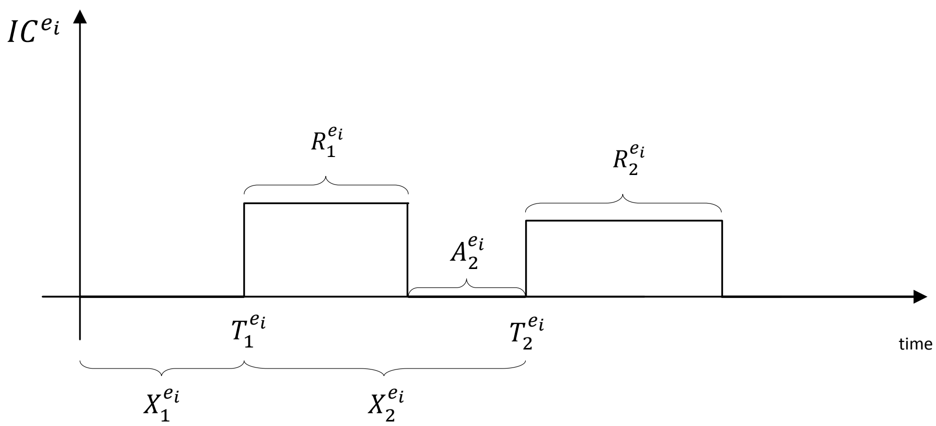

Figure 6: Basic disruption time structure of event e_i with costs IC^{e_i}, recovery time R^{e_i}, disruption time T^{e_i}, active time A^{e_i} and interarrival time X^{e_i}.

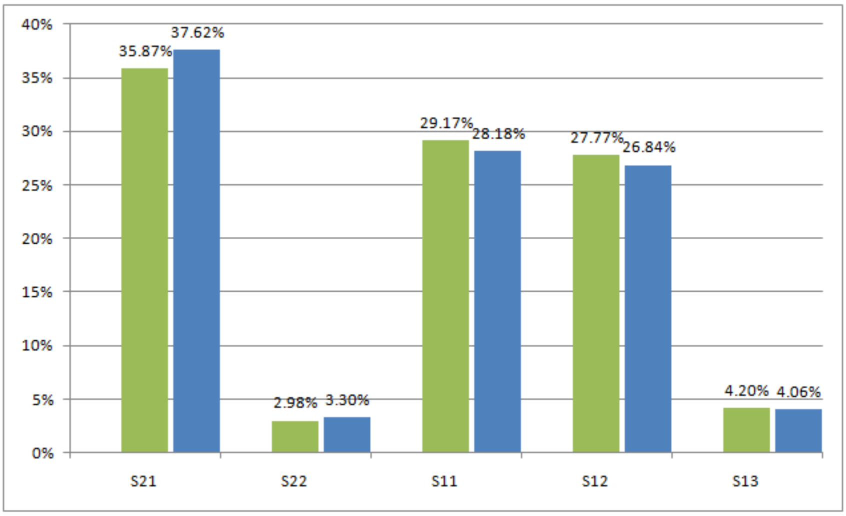

Figure 7: The relative importance of the suppliers, based on the percentage loss contribution (green bars: embedded, blue bars: isolated).

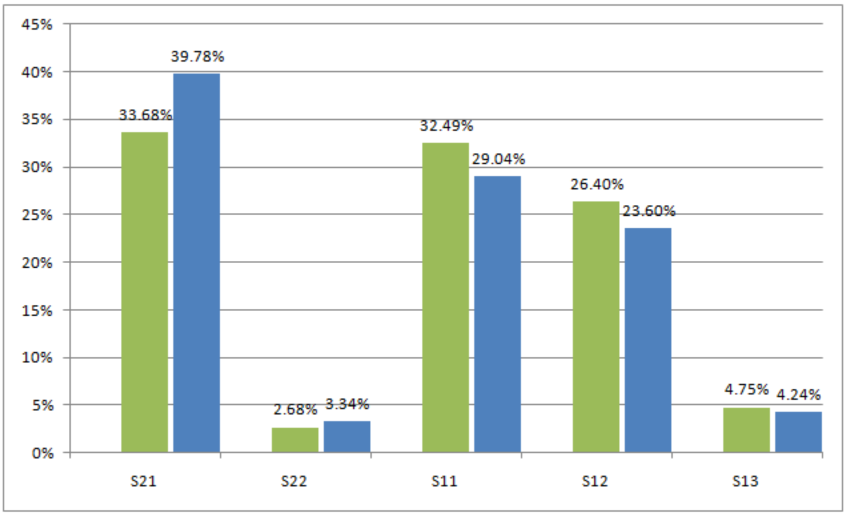

Figure 8: The relative importance of the suppliers, based on the percentage loss contribution with correlated hazard event (green bars: embedded, blue bars: isolated).

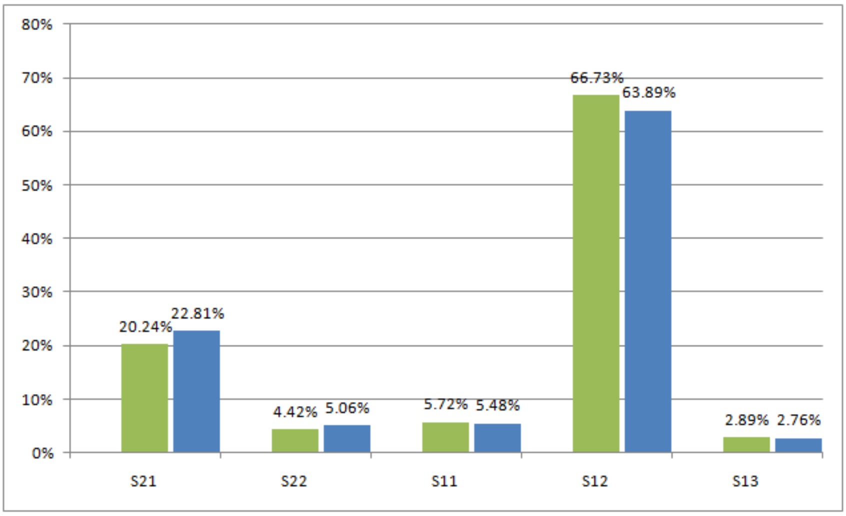

Figure 9: The relative importance of the suppliers, based on the percentage loss contribution with modified business weightings (green bars: embedded, blue bars: isolated).

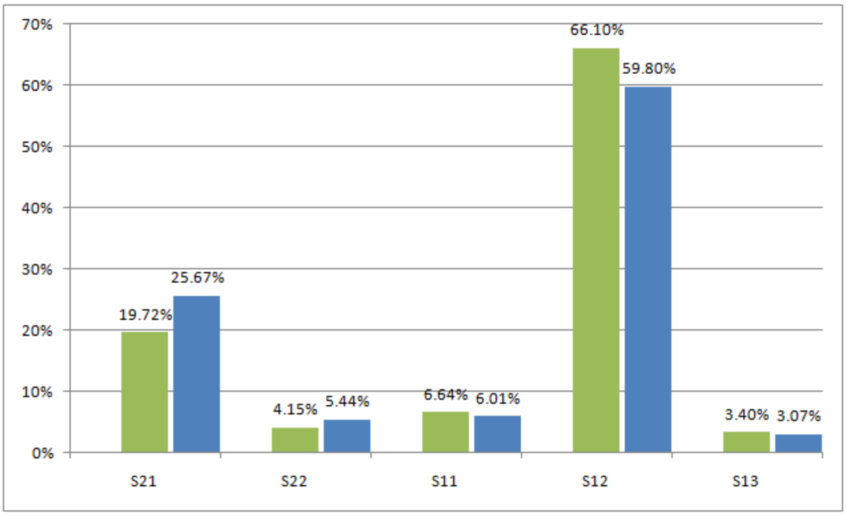

Figure 10: The relative importance of the suppliers, based on the percentage loss contribution with correlated hazard event and modified business weightings (green bars: embedded, blue bars: isolated).