Risk assessment of dynamic interdependencies based of sectoral survey data

Otto Saikkonen

School of Science

Thesis submitted for examination for the degree of Master of Science in Technology.

Espoo 15.1.2021

Supervisor

Prof. Ahti Salo

Advisor

M.Sc. Juho Roponen

Aalto University
School of Science

Aalto University
School of Science

Aalto University, P.O. BOX 11000, 00076 AALTO
www.aalto.fi

Abstract of the master's thesis

Author Otto Saikkonen

Title Risk assessment of dynamic interdependencies based of sectoral survey data

Degree programme Mathematics and Operations Research

Major Systems and Operations Research **Code of major** SCI3055

Supervisor Prof. Ahti Salo

Advisor M.Sc. Juho Roponen

Date 15.1.2021 **Number of pages** 51 **Language** English

Abstract

In this thesis we conduct an exploratory analysis of risk propagation on a network of vital sectors to a National Emergency Supply Agency. The objective of the National Emergency Supply Agency is to secure continuity of production and infrastructure vital to the Finnish society. Mitigating the risk of disruptions and their further propagation in the network can significantly improve the outcomes for vulnerable sectors and for the network as a whole.

The analysis of this thesis is based on a survey conducted on behalf of the National Emergency Supply Agency, in which almost two hundred participants from various sectors estimated their dependence on other sectors. We use the answers from the survey to fit continuous distributions of risk propagation for each sector pairs and simulate the behaviour of the network formed by the sectors in case of disruptions. Moreover, we discuss the survey itself, and propose improvements to similar future surveys to facilitate more comprehensive risk assessments of the sector network.

Our results reveal the sectors that are more prone to propagating disruptions and affect the network the most. Furthermore, we show which disrupted sectors constitute the greatest risks for specific sectors and give examples on how to analyse the riskiest chain of disruptive events. In addition, we demonstrate the importance of sectors to focus their risk prevention strategies also on the least risky sources of propagating disruptions.

Keywords Sector network, disruption, ripple effect, simulation

Aalto University
School of Science

Aalto-yliopisto, PL 11000, 00076 AALTO
www.aalto.fi

Diplomityön tiivistelmä

Tekijä Otto Saikkonen

Työn nimi Riskitarkastelu sektoreiden keskinäisriippuvuuksista kyselytutkimuksen perusteella

Koulutusohjelma Matematiikka ja operaatiotutkimus

Pääaine Systeemi- ja operaatiotutkimus **Pääaineen koodi** SCI3055

Työn valvoja Prof. Ahti Salo

Työn ohjaaja DI Juho Roponen

Päivämäärä 15.1.2021 **Sivumäärä** 51 **Kieli** Englanti

Tiivistelmä

Tässä työssä tutkimme häiriöiden etenemistä Huoltovarmuusorganisaatiossa, joka sisältää elinkeinoelämän eri sektoreita. Huoltovarmuuskeskuksen tehtävä on taata yhteiskunnalle tärkeiden palveluiden ja infrastruktuurin toimivuus vaikeinakin aikoina. Tätä tehtävää varten se muun muassa ohjaa ja fasilitoi Huoltovarmuusorganisaatiota, joka koostuu eri talouden toimialojen kriittisistä yrityksistä. Kun erilaisten häiriöiden etenemisestä tässä verkostossa tiedetään enemmän, haitallisia tapahtumia on helpompi ennaltaehkäistä.

Työn pohjana toimii Huoltovarmuuskeskuksen toimesta teetätetty kysely, johon osallistui lähes 200 eri alojen asiantuntijaa. Kyselyssä kartoitettiin Huoltovarmuusorganisaation eri sektorien riippuvuussuhteita normaalioloissa ja häiriötilanteissa. Vastausten pohjalta sovitimme jokaiselle sektorien välisille riippuvuussuhteelle todennäköisyysjakauman, jonka jälkeen simuloimme toimitusverkostoa eri häiriötilanteissa.

Tulosten avulla voidaan arvioida, millä sektoreilla tapahtuvista häiriöistä voi olla kokonaistasolla eniten haittaa ottaen huomioon myös sen, mistä häiriö saa alkunsa. Lisäksi arvioimme, miten yksittäisillä sektoreilla tapahtuvat häiriöt vaikuttavat toisiin sektoreihin ja ehdotamme parannuksia Huoltovarmuuskeskuksen kyselyyn, jotta vastaavia analyysejä voidaan tehdä jatkossa kattavammin.

Avainsanat Toimitusverkosto, häiriön eteneminen, simulaatio

Preface

I want to thank Professor Ahti Salo and my instructor Juho Roponen for their good and poor guidance. I will beyond doubt miss our easy-going discussions on various thesis and not-so-thesis related topics. Furthermore, I have to give credit to Juho's instant replies to my 4AM emails.

I want also thank Jani, Juho H., Kalle, Rustam and HP for their continuous support on our shared journey in the academic world. What started a as beer refilling mission on the freshmen week transpired to a remarkable fellowship.

Otaniemi, 15.1.2021

Otto Saikkonen

Contents

1 Introduction

Peterson Institute for International Economics defined *globalization* as "the growing interdependence of the world's economies, cultures, and populations" (Kolb, 2018). From 1950, the value of global exports have grown more than thirty-fold as the volume of trade and number of participating countries have skyrocketed (Ortiz-Ospina and Beltekian, 2018). The financial crisis across the banking sector that started in the United States caused a $4.6 billion bailout for Iceland's government (O'Brien, 2015). The US local labor markets rising exposure to Chinese competition from 1990 to 2007 lead to higher unemployment and lowered wages in the US (Autor et al., 2013). Both one-way dependencies and two-way interactions occur in the social-ecological systems as well. Rocha et al. (2018) showed, that on 30 large scale regime shifts in our ecosystems, 45% of the pairwise regime shift combinations present at least one plausible structural interdependence. Thus, the world has become more interconnected than ever before.

A collection of dependencies of a system form a network. Identifying which factors link to dependencies to form the network can be a challenge. For example, the uprisings in Arab Spring were accelerated by a complex network of drivers, including the extent of non-tax hydrocarbon rents, the nature of the ruling elite and whether the incumbent had inherited power (Brownlee et al., 2015). However, not all complex networks are the size of Northern Africa or the Middle East. For example, nuclear power plants and aircrafts have been modeled as a network of components (Celeux et al. (2006), Lee et al. (2015), Banghart et al. (2017)).

In a system which consists of multiple components, component failures can cause distress in other components in the system or even a total system failure. For example, in 2000, a fire destroyed an electronics manufacturer's factory in New Mexico (Latour, 2001). Two European mobile phone giants, Nokia and Ericsson, relied on this supplier for its crucial components. While Nokia had hedged the risk of such an event, Ericsson's lack of preparation cost the company eventually over $400M in lost sales. As a result of this disaster Ericsson had to quit the mobile phone business, leaving Nokia to cement its place as European market leader. Studies show that, on average, if a publicly held company experiences a moderate or higher risk event, it can expect a $7-10\%$ reduction in shareholder value (Schlegel and Trent, 2015).

Identifying the risks in a network before any harmful events occur can be crucial to the functionality of the system, as exemplified by the Nokia & Ericsson case. A common set of *risk importance measures* have been established to describe the risk of components in a network. *Birnbaum's importance* measures the risk in terms of the differences between probabilities of system states where given component either functions or not (Birnbaum, 1968). *Fussell-Vesely* measures the overall contribution of the risk caused by the component to the total risk of the system (Fussell, 1975). *Risk achievement worth* (RAW) is the ratio of the conditional system unreliability if a specific component is known to fail to the actual system reliability, while *risk reduction worth* (RRW) is the ratio of the actual system unreliability to the system reliability if a specific component is known to work (Aven, 2008).

At present, companies are facing tougher competition and less loyal customers. Price wars keep the profit margins low, and operating costs are often already cut to the minimum. As a result, companies are looking to outsource their manufacturing instead of producing components in-house. These external suppliers may have outsourced part of their manufacturing, creating a chain of suppliers for the end product. Supply chains have become an integral part of many business, since a well managed supply chain can give companies the edge over competitors. Multiple supply chains create a web of relationships called supply network, which incorporates indirect relationships and subsidiary organisations in addition to core members (Braziotis et al., 2013). Furthermore, there is a rich scientific literature on the study of risks in supply chain management, which can be applied to other types of networks, e.g., ones formed by sectors. The literature review in Section 2, covers common qualitative and quantitative risk management methods on supply chains and networks, as well as, focuses on literature written on disruption analysis.

In this thesis, we analyze collected data from a cross-sector survey to 1) construct a network formed by sectors, 2) identify the components with highest risk of disruption propagation in the network and 3) recognize how disruptions propagate in the network. It is an exploratory analysis, and the research goal is to present which industries are responsible for the majority of the overall systemic risk, as well as, to specific individual industries. Contrary to the original survey analysis, we will include variance in the answers to model risk propagation in the system. In addition, we discuss the survey itself and propose modifications to the survey so that it can better serve this kind of analyses in the future.

The thesis is structured as follows: first we discuss literature on sector risks and supply chain risk management, second we describe the survey data that was used in the analysis. In Section 4, we explain how survey answers can be used to approximate continuous distributions for the simulation. Next, we introduce the simulation model used for the computations, which is followed by the presentation of simulation results. Finally, Section 8 discusses improvements for similar surveys in the future.

2 Literature review

2.1 Sector risks

The well-being of citizens depends on the infrastructure and services that are provided by the nation. Each sector, with its infrastructure and services, have differing roles for our safety, security and economies, but also depend on other sectors to function and prosper. The consequences caused by a disruption are greater for some infrastructure, depending whether the discomfort caused by disruptions are measured in terms of ecology, economy, national security, among others.

In 2005, the European Union drew attention to the fact the infrastructure of several sectors were significant for today's society, and that failures of these critical infrastructure could have serious impact on national security, the economy and basic vital functions of member states (Rehak et al., 2016). In 2008, European Union issued a directive (of European Union, 2008) that requires member state's to identify the European Critical Infrastructure Elements (EPCIP). Klaver et al. (2008) discussed the results of European Risk Assessment Methodology program, whose objectives were to identify elements for a EU methodology for general risk assessment on a single organization level and for a common methodology for analysis of interdependencies on sector level. A key point of results was that interdependencies should be analyzed bottom-up, meaning that the analysis should start at organisation level, and end at cross-organisation, cross-sector or cross-border level.

Risk management of critical infrastructure across multiple sectors has its own unique problems. Each sector operates in its own way, has its own organizations and may be hesitant to share information to competitors or other external parties, even though sharing information to dependant parties can help others mitigate risks. Schaberreiter et al. (2011) presented an approach to model critical infrastructure, which was divided into three steps: an off-line risk assessment, a measurement aggregation and an on-line monitoring step. In the off-line risk assessment, base measures of the observable entities in the infrastructure were identified. These base measures can be associated with one or more services that the infrastructure provides. Next, the base measures were aggregated to a five step scale for comparability. Finally, in the on-line monitoring step, operators of critical infrastructures receive the base measures of dependant infrastructures to manage the risks they are facing.

Difference in the environments that the sectors operate in, or the different customers and competitors they have, can lead to situations where methods used to assess risks within one sector may not be applicable in another. However, when managing risks of a broader system with cross-sector dependencies, the sector's own abilities to mitigate and control risks are important so that in a event of a disruption inside a sector, the disruption does not propagate to other dependant sectors. For example, the national economy of Australia is largely dependent upon maritime trade, and relies upon the Navy to control the maritime domain and border (Cordner, 2008). Mitigation of the risks in maritime sector serves the greater good for Australia, and decrease the risk facing other dependent sectors of Australia. In the context of maritime sector, Stergiopoulos et al. (2018) proposed a risk-based interdependency analysis method, based on graph theory, which is capable of detecting large-scale traffic congestions between interconnected ports and ship routes in the maritime network and provide suggestions to improve flow. The authors were able to identify that shipping routes or ports that were prone to delays, greatly affect the overall maritime network and got affected the most by delays in previous route legs.

The literature on sector dependencies and cross-sector risk management is not as expansive as the vast body of research on supply chains. Like networks, supply chain is a system which consists of service providers and their dependencies, but the system is acyclic. However, it is worthwhile to discuss the methodologies used to model supply chain risks, because of the similarities that supply chains and system networks share.

2.2 Supply chain risk management

Concept of *risk* has many interpretations, and thus, different measurements, depending on the field of research (Jemison, 1987). For example, in the field of finance, risk is often described as fluctuations around the expected value, and therefore has both *upside* and *downside*. Wagner and Bode (2008) studied risk in supply chains, and described risk as a purely negative event, hence excluded "positive surprises" and situations where supply chain managers intentionally took deliberate risks. This notion of risk is suitable when studying unexpected events in supply chains, such as disruptions. The authors further divided risk into four categories - demand side risk, supply side risk, catastrophic risk and regulatory, legal & bureaucratic risk.

Demand side risks can be caused by discrepancies between company's projections on demand and the actual demand from the customers. Risks arising from product delivery to end-customers, i.e., distribution risks are included on the demand side risk. The demand side risk can have two consequences. First, if the company fails to meet the consumer demand and there is a shortage on a product, consumers cannot purchase this product from the company. Moreover, consumers may purchase this product from a competitor, thus the company loses the sale, and in the worst case, the customer. Second, if the company overestimates the consumer demand, excess inventory may lead to expired and outdated inventory, especially in industries, where customer habits may change quickly. Based on the these two consequences, Sodhi

(2009) proposed two metrics to capture the demand side risk - inventory-at-risk and demand-at-risk, to quantify the unsold excess product on inventory side and the unmet demand on customer side, respectively.

To continue on the four categories of supply chain risks, proposed by Wagner and Bode (2008), supply side risks arise from operations upstream in the supply chain. The key risks that exists with inbound supply are business risk, supplier capacity constrains, quality risk, technological changes and product design changes (Zsidisin et al., 2000). Business risks emerge from the (un)stability of the supplier, both in the financial and management context, while supplier capacity constrains refer to suppliers limited equipment and workforce to produce certain amount of products. Limitations to modify existing products due to changes in the end-product design are considered as an separate risk by Zsidisin et al. (2000).

Over the decades, researches have adopted various methodologies to study supply chain risks. Quantitative, qualitative and mixed methods have all been used to measure risk in many ways. The most adopted approach by researchers is case study, which is mostly used for dealing with problems at strategic management level (Ghadge et al., 2012). Case studies have been made on various industries, including automotive (Salehi et al. (2018), Hudin et al. (2019), Vanalle et al. (2020)), healthcare (Zepeda et al. (2016), Lawrence et al. (2020)) and maritime (Aljabhan (2016), Jeong et al. (2020)), to name a few. Finch (2004) used case studies to determine if large companies increase their exposure to risk by having small- and medium-size enterprises as partners in business critical positions in the supply chain, and to make recommendations concerning best practice. Khan et al. (2008) addressed the impact of product design on supply chain risk management in an era of global supply arrangements. The authors presented empirical evidence providing practical examples of the impact of product design on risk, and argued that design-led risk management offers a novel approach to mitigating supply chain risk.

In addition to case studies, conceptual theory is an another popular methodology in the context of qualitative methods. Conceptual theory is a research methodology describing fundamental concepts on supply chain risk management (Vanany et al., 2009). Ghadge et al. (2012) highlights that for such an constantly evolving field, conceptual theory or framework development are frequently attempted by many supply chain risk management (SCRM) researchers. Shenoi et al. (2016) identified three critical dimensions in SCRM and introduced a framework to understand the relationship between risk and performance measures of manufacturers. The three conceptual dimensions they proposed were risk sources and management commitment, mitigation strategies and risk management processes and performance measures. The framework could be utilised by practising managers to more effectively implement SCRM strategies. However, as the authors point out, researches could validate this framework model empirically. In addition, the framework supposes that the entities in supply chain need to share information transparently across the supply chain. This may not be the case in real life, and many entities in supply chain (SC) have to manage their operations on partial or non-existing information. Schlüter et al. (2017) presented a first approach establishing Smart Supply Chain Risk Management (SSCRM) as sub-research field of SCRM by proposing a specific research framework. SSCRM refers to real data driven SCRM as a result of digitalization of supply chains and Industry 4.0. The authors argue that in the era of Big Data, digitalization and autonomisation, technologies, such as blockchain, will allow more proactive SCRM and create more transparent supply chains.

On the quantitative side, operations research (OR) modeling and simulation are common for assessing supply chain risks (Ghadge et al., 2012). Kırılmaz and Erol (2017) used linear programming in the risk mitigation phase of the supply chain risk management processes. In their model, the first stage in proposed procedure was to minimize the costs, and in the second phase the objective was to maximize the product flow from a risky supplier to a relatively less risky supplier. Another widely used methodology to model supply chain risks is game theory. Qazi et al. (2014) proposed a game theoretic analysis to capture uncertainty of the Tier-1 suppliers about the cost functions of each other and to demonstrate that any uncertainty of information in a supply chain can adversely affect the intended outcome.

Chen et al. (2013) presented various Agent-based modeling and Simulation (ABMS) researches in the field of SCRM. The authors pointed out that even though advances in ABMS and supply chain related topics have been made, a smaller volume of papers have focused in ABMS for supply chain risk management. Colicchia et al. (2011) used Monte Carlo simulation to evaluate the expected impact of supply lead time to compare different SCRM strategies. The simulation-based framework the authors presented was validated with two real-life case studies. Guller et al. (2015) provided a simulation-based decision support framework for assessing supply chain resilience and evaluating the cost and resilience trade-off with different mitigation strategies in an uncertain environment. Their decision framework incorporates the supply chain resilience metrics and argues their relationship to the impacts of those disruptions on the performance and to the time required for recovery. Schlüter et al. (2017) presented a simulation-based approach for evaluating digitalization scenarios prior to realization, whose applicability was demonstrated in a case study of a German steel producer.

According to a recent literature review by Fan and Stevenson (2018), the most dominant research perspective in SCRM, is that of the buyer's. Fan and Stevenson (2018) pointed out that to understand SCRM more broader, research should also focus on SCRM from other perspectives, especially from suppliers. Within the few researches made from suppliers perspective, Ojala and Hallikas (2006) studied partnership relationships in investment decision-making within supply networks with empirical evidence from electronic and metal industries. They found out that risks associated in partnership relationships were mainly related to increasing responsibilities for suppliers and reliability of information. In addition, some proposed future research directions in SCRM include cost-benefit analyses of SCRM, benchmarking of SCRM strategies and implementation of theories (Fan and Stevenson, 2018).

2.3 Disruptions and resilience in supply network

Disruptions are sudden events, which cause total or partial failure to the supply chain. The historical data show that the total number of disasters (both natural and those caused by people) have increased vastly over the last decades, and that the average costs of these disasters have increased 10 fold from the 1960s (Tang, 2006).

The theoretical fundamentals of risk assesment of supply chains, in terms of disruptions and resilience, have been built over the last few decades (Sheffi and Rice (2005), Craighead et al. (2007)). Sheffi and Rice (2005) describe different stages of disruptions in supply chains and give high-level recommendations on how to increase supply chain flexibility, to make supply chains more resilient. The authors argue that potential disruptions should be categorized as a function of likelihood and consequences, instead of a single metric. Craighead et al. (2007) derived six propositions relating the severity of supply chain disruptions to the complexity, density and node critically of the SC.

Today number of suppliers in a single supply chain can be vast, and suppliers may be dependant of one another. This calls for a methodology, where inter-dependencies between entities can be represented as straightforward as possible. Bayesian networks (BNs) have been extensively studied in other domains of research, but in the field of SCRM it is relatively new (Hosseini and Ivanov, 2020). Bayesian networks were first introduces by Pearl and Kim (1983), and they are directed acyclic graphs, where conditional influences are represented. BNs are built on the fundamentals of Bayes' theorem and conditional probability theory, and have been acknowledged as an appropriate methodology for quantification of risks, uncertainty modeling and decision-making (Fenton and Neil, 2012). Use of Bayesian networks have been researched within 'data rich' fields, such as telecommunications (Ezawa and Norton (1996), Hood and Ji (1997)) and finance (Shenoy et al. (1999), Alexander (2000)), but also in fields where nowadays machine learning methods may not be appropriate because of the amount of training data needed, like nuclear power-plants (Kang, 1999). The ability to perform inference makes the BNs especially great for analyzing SC risks and resilience problems, and they work well with partial information and limited data availabilty (Hosseini and Ivanov, 2020).

Ojha et al. (2018) studied risk propagation within a multi-level network. The authors used four echelons (suppliers, manufacturer, distributors and retailer) to construct a BN model for an automotive SC. Different risks were modeled as nodes for stakeholders in the network and disruptions were measured using metrics like service level, fragility, inventory costs and lost sales. The paper further studies the ripple effect of disruptions between echelons, and lays important groundwork for quantitative approaches to measuring supply chain disruptions. Garvey et al. (2015) built risks graphs from supply networks to measure how much disruptions would spread relatively to local losses, the contribution of specific risk in total losses, et cetera. Hosseini and Barker (2016) built BN model for resilience-based supplier selection, accounting for operational and disruption risks that suppliers possess. Their model outputs a probability statement about whether a specific supplier should be selected, based on primary, green and resilience risks. The findings indicate that incorporating and modeling the probability of a disruption is a key issue in resilient supplier selection. They also point out that the benefits of Bayesian network approach are flexibility of different types of variables, capability of inference analysis and accounting for uncertainty. However, BN approach may require extensive resources to build the model, especially if the network is complex.

Käki et al. (2015) used BNs to assess disruption risks of a car manufacturer's SC. The authors introduced an index that measures the change in total risk at disruptions in different entities in the SC. However, the methology was built for BN models, which can only have two system states: fully operational or dysfunctional. Si et al. (2010) developed an importance measure for multi-state Bayesian network systems. This importance measure is more complex than one for binary-state systems, and has not yet been tested on supply chain network. Qazi et al. (2018) combined BNs and expected utility theory to manage supply chain risk. The benefit of having expected utility part of the BN is to be able to take into account different risk appetites of SC managers. Risk acceptance levels vary depending on the managers, ergo should risk mitigation strategies.

Bayesian network comes with its limitations, one of them which is lack of stochastic properties. Dynamic Bayesian Networks (Dagum et al., 1992) and hybrid BN approaches have tried to address the time-dependency limitation. Kao et al. (2005) introduced a dynamic Bayesian network model to represent the cause-and-effect relationship in an industrial supply chain. The authors extended the static Bayesian network to a dynamic Bayesian network by creating relevant temporal dependencies between representations of the static network at different time steps. Hosseini and Ivanov (2019) came up with a model, which combines discrete-time Markov chain and dynamic Bayesian network to model the ripple effect of a supply chain disruption, i.e., the effect that a disruption is not localized and spreads downstream in the supply chain. The authors used Markov chain to model behaviour of the supplier after a disruption, while dynamic bayesian was used to predict the behaviour of the supplier and to model how disruption propagates through the supplier at different time steps. Hybrid BN approaches have been also used in other ways. Qazi et al. (2014) proposed an approach, where BN captures interdependency between risk factors of SC and game theory is utilized to assess risks with conflicting incentives of stakeholders within a SC.

The number of machine learning and artificial intelligence related research in supply chain risk management have risen in the last decade (Baryannis et al., 2019). Many of the BN models use expert knowledge to determine the structure of BNs and estimate conditional probabilities for each entity. The drawback of using experts is that probability estimations are not often precise, because the numbers are very small and do not correspond to events that people can reasonably contemplate (Koller and Friedman (2009), Constantinou et al. (2016)). Moreover, experts views can be biased Johnson et al. (2010)). Accordingly, machine learning techniques can be used to estimate system parameters and learn BN structures. Chen and Chao (2020) used machine learning techniques to learn system-relevant parameters in a inventory control problem. Koller and Friedman (2009) have extensively gone through different algorithms to construct BN structures. Hosseini and Ivanov (2020) proposed a generic framework which integrates BN with machine learning to model SC risks. The framework consists of five steps and uses machine learning techniques to learn conditional probabilities and BN structures. However, especially with parameter estimation, machine learning techniques require high amount of data. In context of supply chains, disruptions are rare events, and therefore there is often not enough data to train ML models.

3 Data

The data used in this thesis was collected via a survey, which was done in 2020. 280 participants from 25 different sectors were asked on their relationship with other sectors. Each participant were asked two questions per sector X with the following possible answers:

1. How much does your sector interact with the sector X in general (in normal situation)?
   (a) Not at all
   (b) A little
   (c) Some
   (d) A lot
   (e) Very much
2. Will the disruptions in the sector X affect the operations of your sector now or possibly in the next 3 months?
   (a) No effect at all

(b) Affects a bit

(c) Moderate effect

(d) Affects a lot

(e) Prevents operations almost completely

From this point on, questions 1 and 2 are referred as Interaction Question and Impact Question, respectively. Answers for Interaction Question and Impact Question were quantified on an ordinal scale from 0 to 4, 0 representing answers “Not at all”/“No effect at all”, and 4 representing answers “Very much”/“Prevents operations almost completely”.

In total, 198 participants from 23 different sectors answered the survey. Moreover, Interaction Question was answered 3925 times and Impact Question was answered 3438 times. Participants were also asked to identify themselves in one of the following expertise categories: Finance and management (Fin), Technology / Infrastructure (Tech), Supply chains (SC), Production (Prod), Security (Sec), Legislation (Leg), Politics (Pol) and Other. Tables 1 and 2 show summary statistics for both question. Finance and management represented the largest area of expertise in the survey, while politics and legislation the smallest. On average, participants from political background estimated the impact of propagating disruption to be much lower than other participants (0.17 vs total of 0.72). Participants from legislation background estimated the risks to be higher than rest of the participants.

Table 1: Summary for Interaction Question.

Expertise	# of answers	Average	Stdev.
Fin	1199	1.33	1.22
Tech	688	1.50	1.20
Sec	626	1.33	1.19
Prod	626	1.64	1.27
SC	494	1.72	1.29
Pol	48	0.73	1.05
Leg	25	1.48	0.82
Other	219	1.11	1.01
Total	3925	1.44	1.23

Table 2: Summary for Impact Question.

Expertise	# of answers	Average	Stdev.
Fin	999	1.17	0.38
Tech	644	0.68	1.02
Sec	546	0.93	1.06
Prod	528	0.73	1.02
SC	442	0.8	1.12
Pol	48	0.17	0.38
Leg	24	1.17	0.82
Other	207	0.79	0.97
Total	3438	0.72	1.06

To conduct a sanity check of the answers, we looked at the distribution of how participants answered to both question (Table 3). In general, if a participant estimated that the interaction between their and the correspondent sector was low (Interaction Question), then the impact of propagating disruption (Interaction Question) should be low as well, because without interaction between the sectors, the disruption should not be able to propagate directly.

From Table 3 that the survey answers are in line with our assumption about the relationship between Interaction and Impact Questions. The share of answers do almost always decrease when going downwards column-wise. Less than 1% of the answers estimated the propagating disruption would prevent operations almost completely, even though they also estimated that there were no interaction between their and the other sector. In those cases, the participants may have considered indirect risks, i.e., disruptions propagating from another sectors than the one which the Impact Question poses it did.

Table 3: Share of answers (%) per questions.

↓ Impact, Interaction →	Not at all	A little	Some	A lot	Very much	Total
No effect at all	20.8	16.4	13.9	4.6	2.3	58.0
Affects a bit	1.4	8.2	8.2	3.4	2.3	23.5
Moderate effect	0.5	1.1	4.5	2.4	1.0	9.5
Affects a lot	0.3	0.7	1.5	3.0	1.3	6.8
Prevents operations a/m completely	0.1	0.2	0.2	0.4	1.2	2.2
Total	23.1	26.6	28.4	13.8	8.1	100.0

It is important to discuss what the survey data does not tell us, in order to clarify what needs to be assumed for later analysis. The data does not tell us marginal or conditional probabilities of disruptions. Premise for Impact Question is that a disruption has already happened, and the formulation of the question does not ask the participant to estimate the probability of the disruption propagating; it only asks participant to estimate the impact of a propagating disruption. Additionally, the survey data does not tell us the resilience of a sector. It is also important to notice that answers for Impact Question are time relevant - the question requests participants to estimate the impact of disruption at the time of the survey and for the next three months. For later use of the data, answers may not be relevant anymore. Moreover, the three-month time frame makes the modeling harder, because we do not know if the propagating disruption affects the sector immediately or sometime in the next three months.

4 Approximating survey answers with beta distributions

Uncertainty in surveys is a results of multiple factors, e.g., the varying comprehension of the wording, personal attitudes, the heterogeneous expertise of the participants and the fact that no one has the definitive answer, which is one of the basis of conducting a survey in the first place. Analyzing the exact answers distributions possess multiple problems. First, in case of few answers, idiosyncratic uncertainty of individual responses is high. Considering one expert's answer as the sole truth, and ignoring other possibilities of the network dependencies can exclude some important scenarios out of the analysis. Second, to conclude that an event has no probability of happening, even in the presence of multiple answers, can lead to restricted results, when severe low-probability events can have devastating effects on the network.

Conceptually, it is better to approach the survey answers as approximations of the network dependencies. Therefore, we need to model the survey answers as probability distributions, where the mean and variance of answers is taken into account.

The beta distribution is a family of continuous probability distributions with finite support in $[0, 1]$, although it can be extended to support $[a, b]$. For parameters $\alpha, \beta > 0$, the beta distribution is

$$f_X(x) = \frac{1}{B(\alpha, \beta)} x^{\alpha-1}(1-x)^{\beta-1}, \tag{1}$$

where B is the normalizing constant

$$B(\alpha, \beta) = \frac{\Gamma(\alpha)\Gamma(\beta)}{\Gamma(\alpha+\beta)}. \tag{2}$$

The beta probability distribution is widely used in simulation studies to model the behaviour of an input that is subject to random variation or that is simply not know with certainty (AbouRizk et al. (1994)). The great value in using beta distribution is that it can generate many shapes with only two parameters, α and β (Touran et al. (2004)). Indeed, it is this reason why we have chosen beta distribution to model distributions of Impact Question.

4.1 Methods of fitting a beta distribution

Various statistical methods have been studies to fit beta distributions on observed data points. By fitting we mean that parameters α and β, which control the shape of the beta probability distribution, are statistically estimated to represent the underlying distribution from which the observed data points come from. Next, we introduce two parameter estimation methods - Maximum likelihood approach and Method of Moments - and go on and show how they can be applied when fitting a beta distribution.

Suppose we have have a collection of n i.i.d. samples $X_1, ..., X_n$ from a population following a pdf $f(x|\theta)$. Because the samples are i.i.d, we define the likelihood function as

$$L(\theta|x_1, ..., x_n) = \prod_{i=1}^{n} f(x_i, \theta). \tag{3}$$

The Maximum likelihood estimator (MLE) is the parameter $\hat{\theta}$, which maximizes the function L, i.e., the likelihood that $X_1, ..., X_n$ is from $f(x|\hat{\theta})$. In case where we want to fit a beta distribution (1) to the sample, the likelihood function L becomes

$$\begin{aligned} L(\alpha, \beta|X) &= \prod_{i=1}^{n} \frac{1}{B(\alpha, \beta)} x_i^{\alpha-1}(1-x_i)^{\beta-1} \\ &= \frac{1}{B(\alpha, \beta)^n} \prod_{i=1}^{n} x_i^{\alpha-1} \prod_{i=1}^{n} (1-x_i)^{\beta-1}. \end{aligned} \tag{4}$$

In many cases, such as this, it is easier to express (4) as a log likelihood function:

$$\log L(\alpha, \beta|X) = -n \log B(\alpha, \beta) + (\alpha - 1) \sum_{i=1}^{n} \log x_i + (\beta - 1) \sum_{i=1}^{n} \log(1 - x_i). \tag{5}$$

Maximizing the log likelihood function leads to the same optimal solution as maximizing likelihood function, because the logarithmic function is an increasing function. To solve the problem and obtain MLEs α and β, partial derivatives with respect to α and β are set to equal zero. Unfortunately, no closed form solutions is possible to obtain to the system of equations. However, there are many solvers available to solve the problem.

Another method of fitting a beta distribution is Method of Moments (MoM). This estimation technique is based on the law of large numbers:

Theorem 4.1. *Let $X_1, X_2, ...$ be independent random variables from the same common distribution with a mean μ_X. Then the sample means converge to the distribution mean as the number of observations increase.*

$$\lim_{n \to \infty} \frac{1}{n} \sum_{i=1}^{n} X_i = \mu_X.$$

Therefore, if number of observations n is large, the sample mean $\overline{X}$ should be a good approximate for the distributional mean. However, beta distribution has two parameters, which requires us to calculate the two first moments, mean and variance.

A beta distributions has mean μ_X and variance σ_X^2 of

$$\mu_X = \frac{\alpha}{\alpha + \beta} \tag{6}$$

$$\sigma_X^2 = \frac{\alpha\beta}{(\alpha + \beta)^2(\alpha + \beta + 1)}. \tag{7}$$

From (6) and (7) we can solve for α and β as a function of μ_X and σ_X^2. In MoMs, we use approximate the distribution mean and variance as the sample mean and variance, calculated from $X_1, ..., X_n$.

As Theorem 4.1 indicates, small number of observations do not necessary produce good results in the approximations of the distribution mean and variance. Therefore in thesis we are going to use MLE to estimate our parameters for the beta distributions.

4.2 Fitting a beta distribution on discrete-valued observations with MLE

As the answers in the survey in hand are on ordinal discrete scale $[0, 4]$ and the support of a beta distribution is $[0, 1]$, we need first to scale the answers to $[0, 1]$. Second, rather than treating the survey answers as continuous variables and estimating MLE α and β for a beta distribution, we are going to use MLE on a discrete probability distribution, which is composed from two cumulative beta probability distributions (CDF). A beta CDF is formulated as follows:

$$F_X(x) = \frac{1}{B(\alpha, \beta)} \int_0^x t^{\alpha-1}(1-t)^{b-1} dt. \tag{8}$$

The discrete probability distributions we are going to use in the parameter estimation is

$$P_X(x|\alpha, \beta) = F_X(x + \delta) - F_X(x - \delta) = \frac{1}{B} \int_{x-\delta}^{x+\delta} t^{\alpha-1}(1-t)^{b-1} dt, \tag{9}$$

where δ is a step size of $1/(2 \cdot 4) = 0.125$. Simply put, we are binning the discrete survey answers, and then calculating the probability with beta CDF within that range.

The intuition in this approach comes from the nature of survey. As participants are given five choices to choose from in the questions, their range of answers reduced to five points in that range. For example, given two participants that answered 1 to the question, one may have pondered over possibilities of answering 0 or 1, while the other one may have had the problem with answering 1 or 2. If both were in the middle, i.e., wanting to give 0.5 and 1.5, respectively, then the difference in their opinion is exactly one answer step away from each other. However, quantifying the answers in bins, as we are doing, takes into account this reduction of information, as answering 1 can be interpreted as answering "between 0.5 and 1.5".

We assume that the survey answers $\boldsymbol{X} = (x_1, ..., x_n)$ are i.i.d. The likelihood function of (9) is

$$
\begin{aligned}
L_P(\alpha, \beta | \boldsymbol{X}) &= \prod_{i=1}^{n} P(x_i | \alpha, \beta) \\
&= \prod_{i=1}^{n} \frac{1}{B(\alpha, \beta)} \int_{x_i - \delta}^{x_i + \delta} t^{\alpha - 1} (1 - t)^{\beta - 1} dt,
\end{aligned}
$$

which yields a log likelihood function of

$$
\log L_P(\alpha, \beta | \boldsymbol{X}) = -n \log B(\alpha, \beta) + \sum_{i=1}^{n} \log \int_{x_i - \delta}^{x_i + \delta} t^{\alpha - 1} (1 - t)^{\beta - 1} dt. \tag{10}
$$

One important constraint for upper and lower bounds in the integral in (10) is that they have to be between zero and one, because the support of beta CDF is $[0, 1]$. Therefore, for upper and lower bounds we set

$$
\begin{aligned}
x_i + \delta &\leftarrow \min\{x_i + \delta, 1\} \\
x_i - \delta &\leftarrow \max\{x_i - \delta, 0\}.
\end{aligned}
$$

We acknowledge that this modification on the integral bounds affects the parameter estimation. The extreme values, 0 and 4 (0 and 1 when scaled), have a stronger impact on the shape of the beta pdf, because the bin range is twice as small. However, this is completely acceptable, because it reflects the survey answer behaviour. For example, if participant answered 0, this is interpreted as an estimation between $[0, 0.5]$, not $[-0.5, 0.5]$.

Another aspect of parameter estimation that needs to be addressed is the number of answers per ordered sector pairs. Some ordered sector pairs have only one answer, which leads to beta distributions where random variables drawn from those distributions are only within the bin of the single answer. Solution for this problem is to use a prior distribution. As beta distribution has no closed-form conjugate prior and we are using MLE approach, the prior is expressed as padded data. Thus, the MLE are estimated from the union of padding data and the observations.

When choosing the padding data, two things have to be taken into consideration: 1) the frequency of values and 2) the size of the padding data. Reflecting back to the Impact Question, the padded data represents our estimation of the impact from propagating disruption if we had no survey answers. In the context of the subject, an uniform distribution, i.e., every outcome would have the same probability, is too pessimistic. Another approach would be to estimate the prior with the mean and variance from all the answers. However, this approach assumes that sector relationships are in some sense comparable. In general, if the sector-to-sector relationship got only few answers, one could argue that relationship is not relative important. Therefore, the padding data should be emphasized on the small values, i.e., creating a prior distribution where small values are more likely than large values.

The size of the padded data has also an impact on the estimated parameters. The more padding values we have, the smaller impact the actual answers will have in the estimation. As the median number of answers per ordered sector pair is X, the number of padding values should in no case be more than that.

Figures 1, 2 and 3 show how different padding vectors affect the fitted PDFs when values 0, 2 and 4, respectively, are observed. From the figures we see that padding vector $(0, 1, 2)$ is best for our model, because the size of the vector is less than the median and the padding vector emphasizes smaller values. Moreover, it also assigns non-zero probabilities for higher values, even when observed data is skewed towards smaller values.

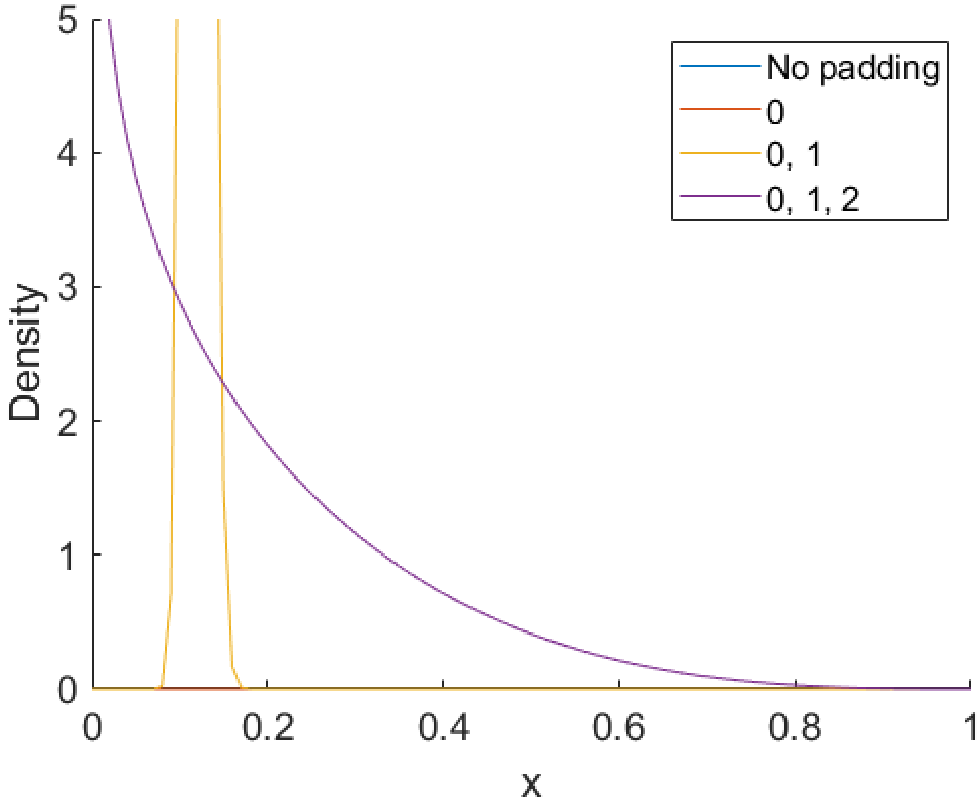

Figure 1: Pdfs of fitted beta distributions with different padding vectors when value 0 is observed.

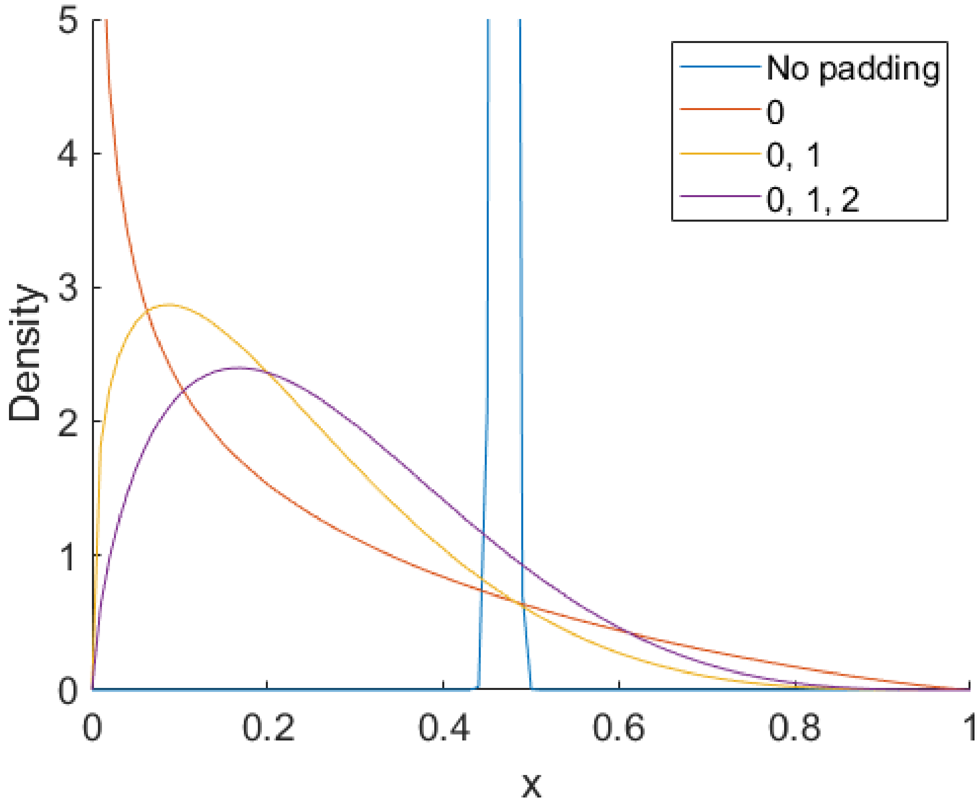

Figure 2: Pdfs of fitted beta distributions with different padding vectors when value 2 is observed.

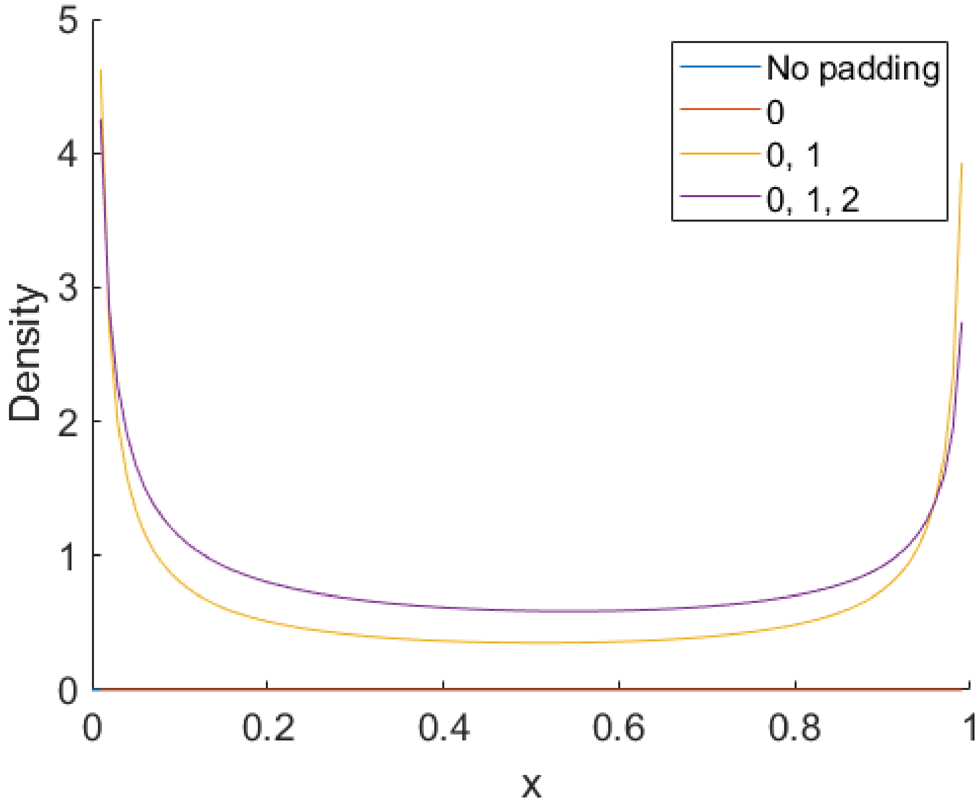

Figure 3: Pdfs of fitted beta distributions with different padding vectors when value 4 is observed.

5 Sector network

5.1 Directed network graph

The sector network is presented as a directed network graph

$$G = (V, E), \tag{11}$$

which consists of set of nodes $V = \{v_i, ..., v_n\}$ and edges $E \subseteq \{(v_i, v_j) \mid (v_i, v_j) \in V^2 \wedge v_i \neq v_j\}$. From this point on, *network* refers to this directed network graph.

The set of nodes represent the sectors that were part of the survey and each sector is connected to every other sector in the network by an edge. 25 sectors participated in the survey, resulting in $25 \times 24 = 600$ edges.

The state of node i at time t is represented as $s_{i,t} \in [0, 1]$. The state of a node is a measure of sector performance loss, where a value of zero indicates that the sector is fully operational, and correspondingly a value of one indicates that the sector is fully disrupted. The performance loss at time t is presented as vector $\boldsymbol{s}_t = (s_{1,t}, ..., s_{|V|,t})$, where $|V|$ is the number of nodes in the graph, i.e., number of sectors in the network. We denote aggregated performance losses as the sum of $\boldsymbol{s_t}$. It is important to remember that the performance loss are closely related to the Impact Question (Section 3), and due to the subjectivity of the question, performance loss may have different interpretations across sectors.

5.2 Ripple effect

The propagation of a disruption in a supply chain and its associated impact on the network is called ripple effect (Ivanov et al. (2019)), and the same definition holds in the context of supply networks. In this thesis, we incorporate similar principles and the ripple effect is modeled based on the survey data (Section 3). For every edge between ordered sector pair (v_i, v_j), a ripple coefficient $r_{ij} \in [0, 1]$ is calculated, based on the fitted beta distribution on Impact Question. The purpose of r_{ij} is to control the magnitude of propagated disruption, and can be interpreted as the edge weight from sector i to sector j in the graph. The ripple coefficients can be represented as matrix R

$$R = \begin{bmatrix} r_{11} & \cdots & r_{1|V|} \\ \vdots & \ddots & \vdots \\ r_{|V|1} & \cdots & r_{|V||V|} \end{bmatrix}. \tag{12}$$

If the sector j only has one parent sector i, i.e., only one parent node in the graph, the propagating disruption is equal to the sector performance loss times the specific ripple coefficient. If there exists multiple parent sectors, simply by summing the product of sector performance losses and ripple coefficients can lead to propagating disruption greater than one, which is unacceptable. Therefore, it is necessary to the aggregate the propagating disruptions with an aggregate function g, that maps to propagating disruptions from parent sector into a single value. Next let's take a look what properties g has to have.

Property 1. If a disruption is to be fully propagated, the aggregated disruption has to be one, i.e., $\exists\ v_i : r_{ij} = 1 \wedge p_{i,t} = 1 \longrightarrow g(r, s) = 1$.

Property 2. If either sector performance loss or ripple coefficient is zero for all parent nodes, the aggregated disruption has to be zero, i.e., $\forall\ v_i\ : r_{ij} = 0 \vee s_{i,t} = 0 \longrightarrow g(r,s) = 0$.

Property 3. Increasing the number of parent nodes cannot decrease the aggregated disruption.

The choice of g impacts the network dynamics greatly, because it dictates how much of the propagating disruptions affects the sector in total, and therefore, must be chosen with care. Equally important is to reflect the interpretation of g in the real world.

We have chosen g for sector j at time t as follows:

$$g(\boldsymbol{r}, \boldsymbol{s}, j, t) = 1 - \prod_i (1 - s_{i,t} \times r_{ij}). \tag{13}$$

Equation 13 satisfies all properties g has to have. Moreover, it takes into account every propagating disruption in an increasing manner, but does not assume that propagating disruptions can be summed. It also has a probabilistic interpretation: if $s_{i,t} r_{i,j}$ is interpreted as the probability that a disrupted sector i disrupts sector j in the next time step, and that all probabilities in g are independent, then g is the probability that sector j is disrupted in the next time step.

Another possible formulation of g is

$$g(\boldsymbol{r}, \boldsymbol{s}, j, t) = \max(s_{1,t} \times r_{1j}, ..., s_{|V|,t} \times r_{|V|j}). \tag{14}$$

In Equation 14, every required property of g is fulfilled, but only the single maximum incoming disruption is taken into account. Conceptually, it assumes that only the most devastating disruption affects a sector, which in many cases is false. Furthermore, g could also be presented as

$$g(\boldsymbol{r}, \boldsymbol{s}, j, t) = \max\left(\sum_i s_{i,t} \times r_{ij}, 1\right). \tag{15}$$

Again, Equation 15 satisfies all three required properties, but assumes that propagating disruptions can be summed. In case where the number of sectors in the network is large, even small disruptions can quickly lead to very high propagating disruptions, which may not reflect the real world, because, in general, sectors can have resilience to absorb small scale disruptions.

The disruption in sector i that carries out to the next time step is defined as

$$s_{i,t+1} = 1 - \prod_{j}(1 - s_{j,t} \times r_{j,i}) - hs_{i,t}, \tag{16}$$

where h is the recovery rate. Recovery rate is the rate at which the sector is able to recover from the disruption with respect to a time step. Instead of assigning $r_{i,i}$ to be the recovery rate for sector i, we want the recovery to only depend on the previous sector performance loss $s_{i,t}$. By choosing the recovery to happen this way, we have to assign $r_{i,i} = 1, i = 1, ..., 25$ in Equation 16.

5.3 Bi-sectoral resilience

In reality, entities within sector can take measures to reduce their dependence from other sectors. These can take form of stockpiling critical supplies or increasing the in-house production. Because disruptions can be propagate from different sectors and affect different parts of sector operations, we define resilience on sector-to-sector level, i.e., what is the ability for sector i to prevent disruptions from sector j to propagate into sector i operations.

As the ripple coefficient r_{ij} is interpreted as the amount of disruption which propagates from sector i to sector j, we define bi-sectoral resilience c_{ij} as the factor which r_{ij} is decreased with. This means that with given c_{ij}, the new ripple coefficient is formulated as

$$r_{ij}^{*} \leftarrow \frac{r_{ij}}{c_{ij}}. \tag{17}$$

The survey itself does not provide any distinct information about sector resilience, but we assume that resilience has been taken into account in the question answers given by participants. Moreover, with the resilience approach we introduced, further analysis can be done on how different sectors should allocate their resources to minimize risks of propagating disruptions in the network. In this thesis, we are going to take an opposite approach, and demonstrate how only focusing on the most important sectors can lead to devastating results.

5.4 Network performance preferences

Depending on the observer, not all sectors are equally important, and some sectors have more critical roles in the functionality of the network. For example importance to society is one way to measure if sector is more critical than other. If some sectors are more preferred to work, *utility functions* can be used to transform the aggregated performance loss $\boldsymbol{s}_t$ to take into account specified preferences:

$$U(\boldsymbol{s}_t) = \Big(U_1(s_{1,t}), ..., U_{|V|}(s_{|V|,t})\Big)\,, \tag{18}$$

where U_i is the utility function of sector i.

If there exists a threshold τ, that the sector performance loss cannot exceed, and values below the threshold are equally preferred, the utility function is as follows:

$$U_i(s_i) = \begin{cases} 1, & \text{if } s \geq \tau \\ \\ 0, & \text{otherwise} \end{cases}\,. \tag{19}$$

Another utility function is an exponential utility function, with parameter a:

$$U_i(s_i) = \frac{a^{s_i} - 1}{a - 1}. \tag{20}$$

The parameter $a \neq 1$ controls the concavity of the utility function; if $a < 1$, smaller disruption values decrease production capabilities relatively more than large disruption values. The smaller the parameter a is, the greater this effect is. On the other hand, if $a > 1$, smaller disruption values decrease production capabilities relatively less.

6 Simulation

6.1 Simulation setup

The simulations consist of K iterations, where each iteration consists of T discrete time steps. For every iteration and time steps, we estimate the ripple coefficients $r_{i,j}$ for all ordered sector pairs based on the answers to the Impact Question. The Impact Question asked participants to estimate how a disruption in other sectors would affect the operations in their sector. Given the five ordinal answer options, which were quantified on a scale from 0 to 4 (0 representing no impact in case of disruption in other sector), we fit a beta distribution for each ordered sector pair.

At each time step in each iteration, we draw a random variable from each 600 beta distributions to create a ripple coefficient matrix R:

$$R = \begin{bmatrix} r_{1,1} & \cdots & r_{1,25} \\ \vdots & \ddots & \vdots \\ r_{25,1} & \cdots & r_{25,25} \end{bmatrix}.$$

Note that R is 25-by-25 matrix with total of 625 elements. The diagonal entries, i.e., $r_{i,i}, i = 1, ..., 25$ are set to 1. The beta random variables are generated with MATLABs `betarnd` function.

Each iteration starts with a predetermined initial performance loss vector $\boldsymbol{s_1} = (s_{1,1}, ..., s_{25,1})$, which is the same for each iteration in the simulation. For our analysis, we are interested in individual sectors and their imposed risk to the network. Therefore, we will run through 25 simulations, in which the initial performance loss vector represents the situation where one sector is fully disrupted and others operate at their normal performance level. Simulations where multiple sectors are disrupted and the magnitude of disruption at start (e.g., 0.5 vs 1) are topics for further research.

After the first time step, the disruption starts to propagate through the network. At the end of each iteration we will have T sectors performance losses from each of the 25 sectors in network.

6.2 Simulation risk measures

After obtaining K performance loss vectors for each time step $t \in T$ from 25 simulations each, we analyse the simulation results from network and sector perspective. The insights that are derived assess which sectors poses the greatest risk to the network in whole and on sector-to-sector level. Different risk measures detailed in the following subsections examine the results in different ways, some taking into account the dynamic nature of the risk propagation and others the performance loss of network and sectors. Measurements about the overall performance loss (average and median) and that consider only the extreme events, e.g., 10th vs 90th percentile, are all incorporated in the assessment of the simulation results.

6.2.1 Risk achievement worth

Risk achievement worth (RAW) is one of the most widely used risk importance measures (Borgonovo and Smith (2012)). RAW measures how the total risk in a system would increase if given component's failure probability was 1, i.e., for component x_i in system y

$$\mathrm{RAW}_{x_i} = \frac{\mathbb{P}(y|x_i = 1)}{\mathbb{P}(y)}, \tag{21}$$

where $\mathbb{P}(y)$ is the probability of system failure. In contrast, risk reduction worth (RRW) measures the amount of decreasing total risk when a component is fully functional:

$$\mathrm{RRW}_{x_i} = \frac{\mathbb{P}(y)}{\mathbb{P}(y|x_i = 0)}. \tag{22}$$

In this thesis, we believe that because the network is fully connected, the RAW measure is not going to differ from sector to sector significantly. However, RRW measure on the other hand can show if excluding some sectors from the network did or did not decrease the performance loss of the network.

We measure the risk reduction worth as the ratio between aggregates performance loss when sector is excluded from the simulation and when the sector is included in the simulation. We consider excluding sector from simulation to represent the situation where a sector is immune to propagating disruption, as well as immune to propagate any disruption it may face. Risk reduction worth is calculated for each sector at each time step, which makes it a dynamic risk measure.

The higher the RRW is, the smaller the aggregated performance loss is when a sector is immune to disruption propagation. This means that smaller RRW measures indicate that the sector does not contribute much in presence of a propagating disruption. A RRW measure of 1 implies that the network is going to face the same amount of performance loss, independent of whether the sector is immune or not.

6.2.2 Bi-sectoral resilience strategies

In addition to the propagating disruption we calculate with the ripple coefficients estimated from beta distributions, we also run the simulations with different investments made into sector-on-sector resilience (see Section 5.3). To demonstrate the importance of bi-sectoral resilience, we analyse on how the network functions when some ripple coefficients are reduced and some not. We start by reducing every ripple coefficient by a factor of 25, which is the number of sectors in the network. This is our baseline case, to which all other scenarios are compared to. Following we give details on the different scenarios we are conduction.

Based on the average answers on the Impact Question, we calculate the ordered sector pairs, to which the participants estimated the impact of propagating disruption to be the smallest. In the first scenario, the ripple coefficient of the least risky ordered sector pair for each sector stays the same as in the original simulations, and all other ripple coefficients r_{ij} for sector j are divided by 25. The second scenario is similar to the first, but instead of keeping only one ripple coefficient per sector at the original value, five of the least risky ripple coefficients are kept at their original values. In the next two scenarios we keep the ripple coefficients of the 75 and 125 least risky ordered sector pairs in the whole at their original value. Compared to the baseline case, each scenario can be thought of as lack of preparation, from the sector and the network in whole.

7 Results

In this section we first show the fitted beta distributions, and then present the simulations results. Simulation results are divided into two subcategories. First we discuss the network risks in whole, and then dive into sector relationships and show the effect of different scenarios where resilience of some sectors is not fully operational. The simulation parameters used is presented in Table 4. The number of simulations is 25, one for each sector, where the disruption starts. The number of iterations within the simulation was chosen to be 1000, so that we get enough data points to construct reliable distributions of performance losses. Initial disruption was set to 1, to model a fully disrupted sector at start of the simulation.

Table 4: Simulation parameters used.

Parameter	Value
# of simulations	25
# of iterations per simulation	1000
# of time stemps per iteration	4
Recovery ratio	0.75
Initial disruption	1.0

7.1 Sector relationships

In the simulation, the ripple coefficients were drawn from fitted beta distributions. The goodness of the estimated parameters for the distributions were visually verified. Figure 4 shows the pdf of fitted beta distributions and survey answer densities for four randomly selected ordered sector pairs. From the figure we can see that the beta distributions do model the survey answers well. For example, comparing upper right and lower right subfigures, the larger ripple coefficient values are more likely to be drawn from upper right than from the lower right beta distribution. Moreover, in the lower left subfigure, some participants estimated the impact of disruption from sector 22 to prevent operations almost completely, which is why the lower left distribution is skewed more to right than distributions on the right side.

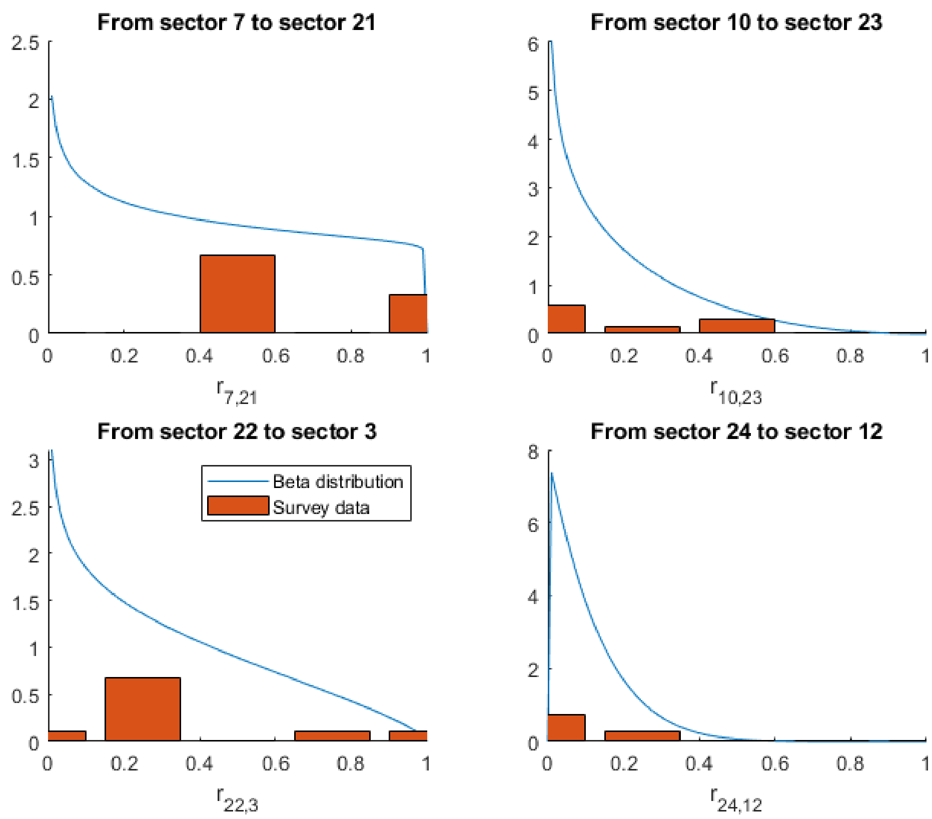

Figure 4: Pdf of fitted beta distribution and survey answer densities for four randomly selected ordered sector pairs.

In addition to visual verification of the beta distributions, we plotted the variance as a function of mean for all 600 fitted beta distributions to check if any distribution showed indication of failed parameter estimation (Figure 5). From the figure, we see that the maximum mean for the distributions was 0.45, that is in line with our expectations, because even though some average scaled survey answers would had been higher, the use of padding values skewed the distribution away from the high averages. The smalles mean is 0.045, which again, is aligned with our expectations.

Figure 5 shows that with lower expected ripple coefficients, the variances also smaller. With larger expected the variance seems to be high where as well. This indicates that the participants tend to agree on a sector having low impact on their operations, but disagree more on sectors where there are higher potential risks.

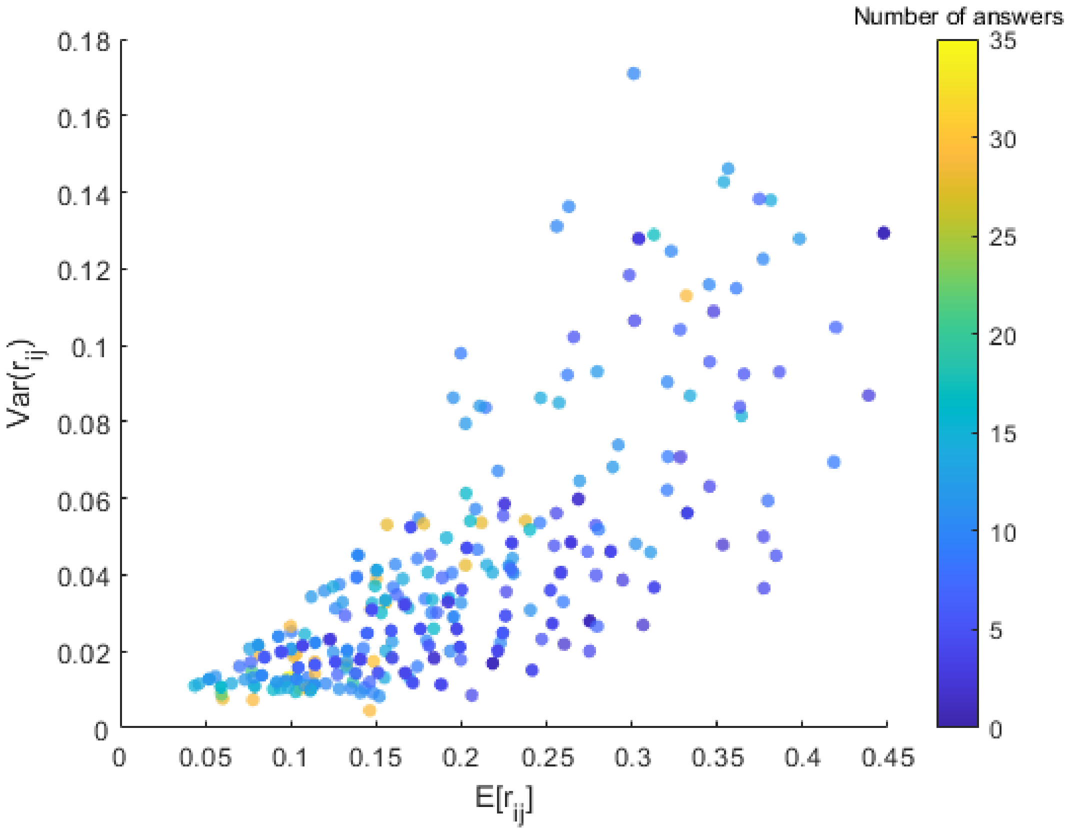

Figure 5: The mean and variance for all 600 fitted beta distributions.

7.2 Impacts on network performance

We start our analysis of simulation results by examining the aggregated performance losses, i.e., the sum of sector performance losses. Figure 6 shows the distributions of the aggregated performance losses w.r.t. time. On each box, the central mark indicates the median, and the bottom and top edges of the box indicate the 25th and 75th percentiles, respectively. The whiskers extend to the most extreme data points, which are 1.5 times the interquartile range away from the 25th and 75th percentiles. Data points outside these boundaries are considered outliers, and are plotted individually using the '+' symbol. Approximately 5% of the data points were outliers.

From the plot we can see that the aggregated performance losses increases each time step. The largest increase happens between time steps 2 and 3, where the increase in median aggregated performance losses is ≈ 7.9. The smallest increase in happens between time steps 3 and 4, where the increase is ≈ 1.4. Moreover, the deviation of aggregated performance losses are similar within time steps 2 and 3. However, the deviation in aggregated performance losses at time step 4 is a lot smaller than for the previous two time steps.

Figure 7 shows the average share of disrupted sectors with respect to the threshold in performance losses for which a sector is considered disrupted. For time step 2, the steepest tangent of the curve is at the beginning, compared to time steps 3 and 4, where the tangent of the curve is the steepest at 0.5 and 0.55, respectively. Furthermore, curves for time steps 3 and 4 intercept at 0.66 threshold. This means that on average there is equally many sectors with greater performance loss than 0.66 for both time steps.

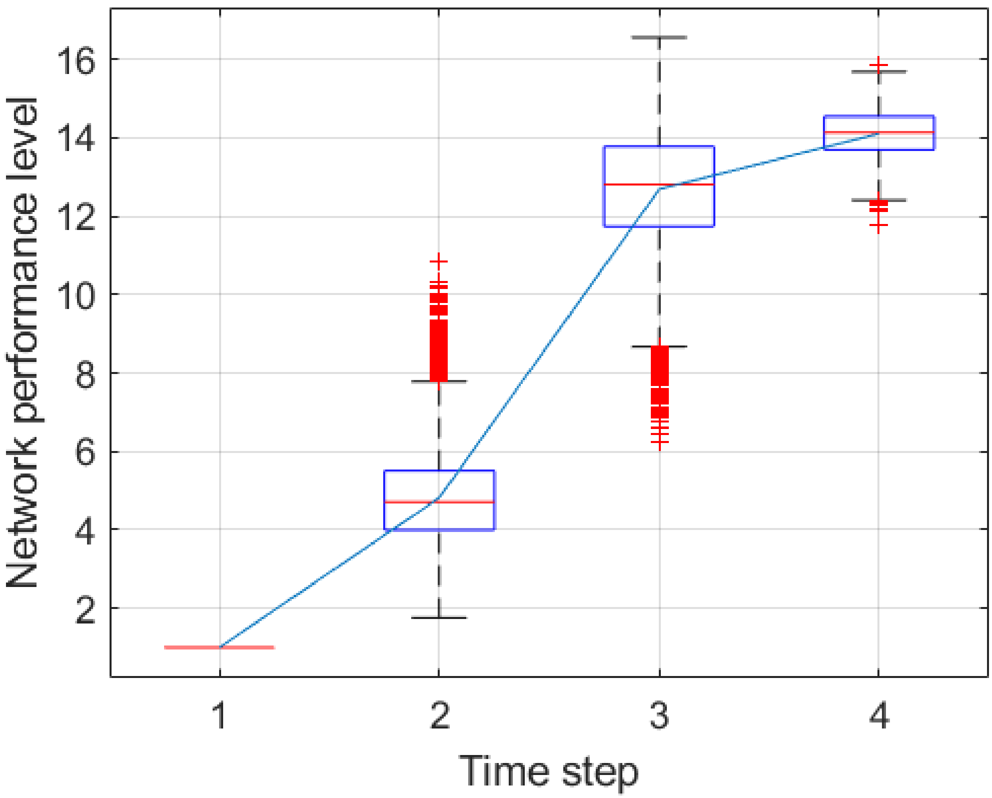

Figure 6: Aggregated performance losses with respect to time.

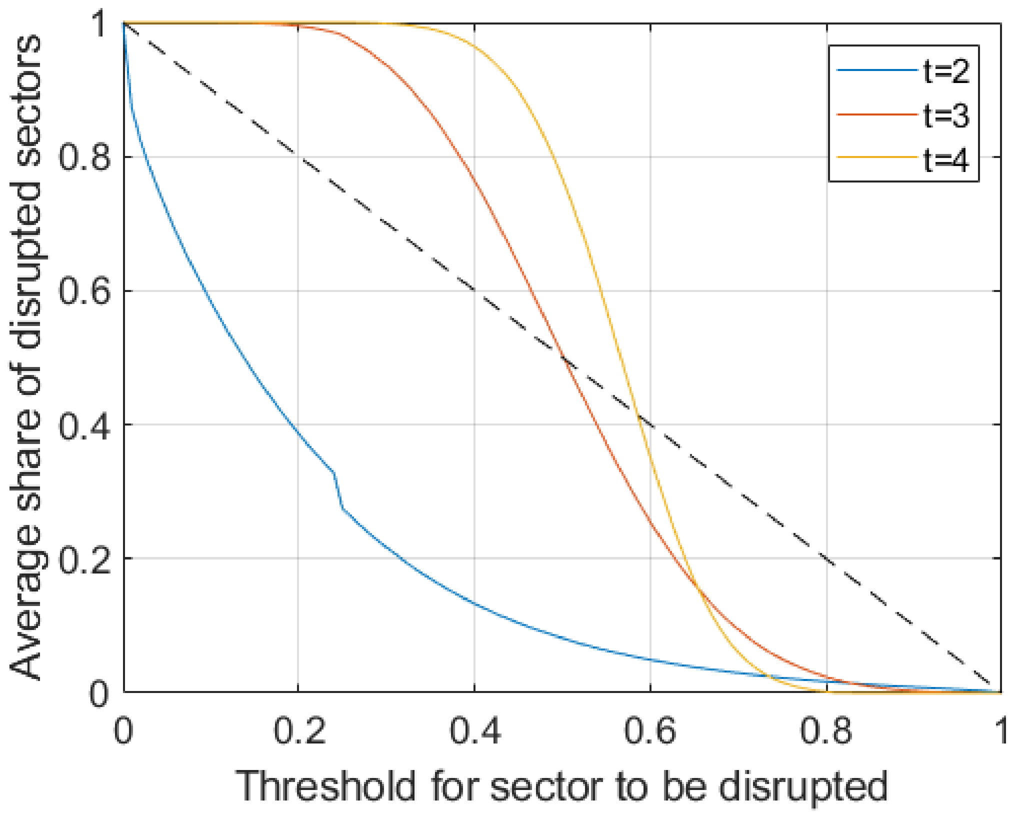

Figure 7: The average share of disrupted sectors in the network with respect to threshold for a disrupted sector.

Figure 8 represents distributions of the aggregated performance losses for each disrupted sector. The interquartile range is more or less the same size for each sector and time step. When the disruption started from sectors 7 or 22, aggregated performance losses were the highest with median above 6.0. This means that the sectors propagated disruption to other sectors the most. These two sectors showed the highest aggregated performance losses for time step 3 as well. However, at time step 4, sectors that had previously caused relative small aggregated performance losses now had the highest losses.

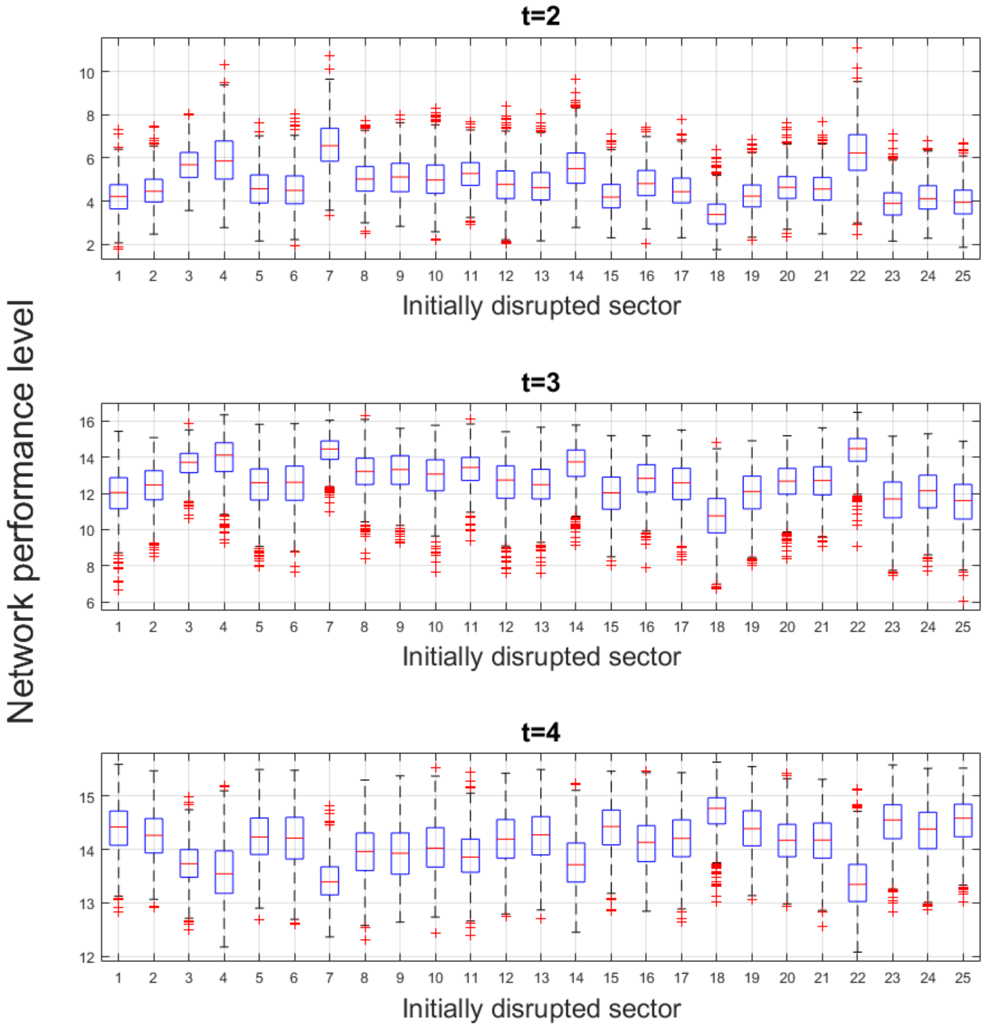

Figure 8: Aggregated performance losses per initially disrupted sector.

Figure 9 shows the risk reduction worth (RRW) values for each sector and time step. RRW values close to 1 indicate that removing the sector from the network had no impact on the overall aggregated performance losses. Including outliers, the RRW values ranged from 1.0 to 1.4. At time step 2, the largest RRW and largest deviation in RRW is associated with sector 18. At time steps 3 and 4, the deviation of RRW decreases for all sectors. The smallest RRW values for at each time step were associated with sectors 2 and 14. Disruptions which started from sectors 4, 7 and 22 were most harmful to the network on short term, but disruptions which started from sectors 1, 15, 18 and 23 at least equally harmful in the long run. Removing sector 18, i.e., making sure that no disruption can propagate in or out of the sector, would achieve the greatest risk reduction for the whole network, in terms of risk reduction worth.

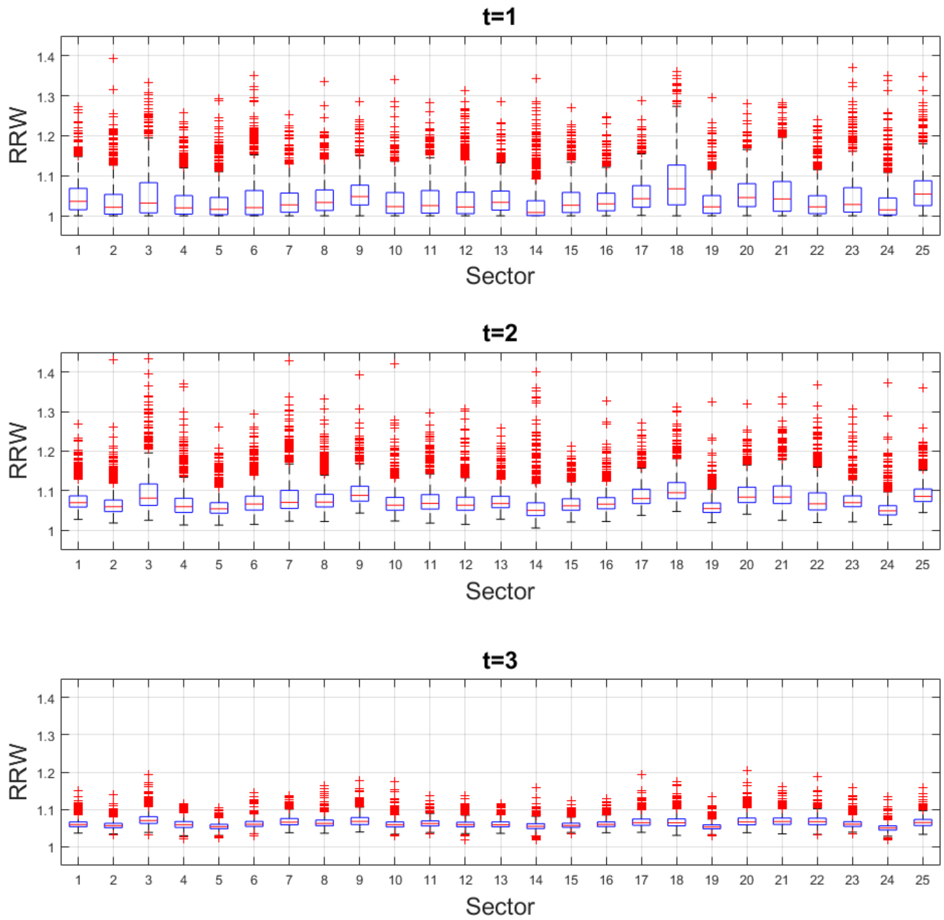

Figure 9: RRW for each sector and time step.

7.3 Sector specific risk and bi-sectoral resilience strategies

Next we analyse the sector performance losses. Table 5 shows the 5th, 25th, 50th, 75th and 95th percentiles of the cumulative performance losses, as well as, the variance of the performance losses. From the table we see that overall sector 18 performance losses were the highest, and sector 14 the lowest. Moreover, the maximum performance losses for each sector were approximately the same. The largest deviation in cumulative performance losses were within sectors 6 and 14.

To analyse sectoral risks in more detail, we plot the average performance loss with respect to the initially disrupted sector for each sector (Figure 10). In the figure, rows indicate the initially disrupted sector and column the sector from which average is calculated, e.g., 7th row and 3rd column is the average of performance loss of sector 3 when the disruption started from sector 7. From Figure 10 several observations can be made: 1) performance loss in sector 18 is relatively high when the disruption starts from sectors 7, 8, 9, 12 or 13, 2) disruption in sector 7 causes high performance losses in sectors 3, 6, 188, 21, 23 and 25 and 3) disruptions in sectors 18, 23, 24, and 25 causes the aggregated performance losses to increase only after third time step.

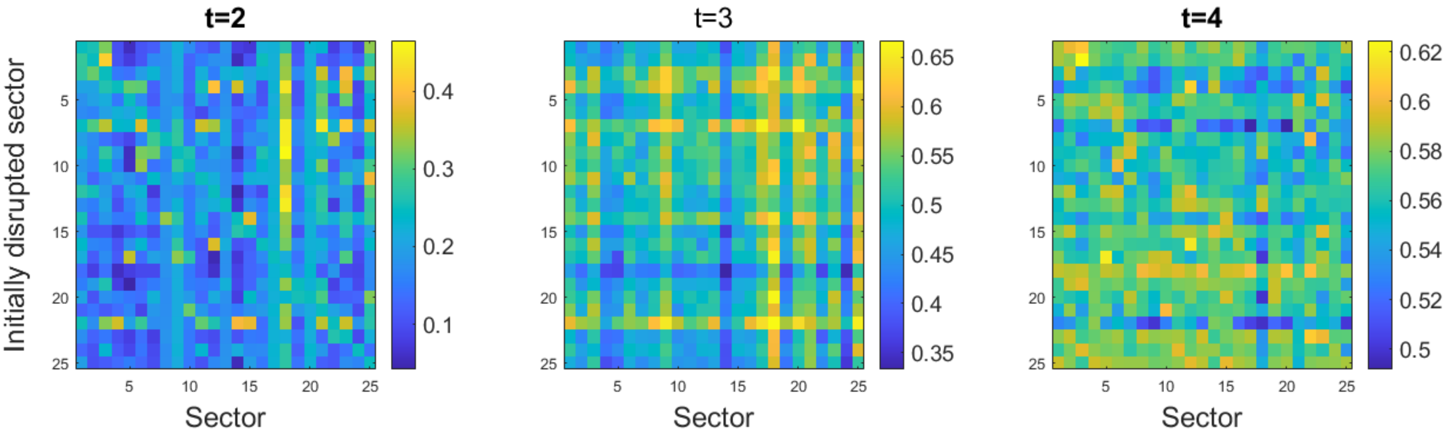

Figure 10: Average performance loss for each sector w.r.t. initially disrupted sector.

Table 5: Minimum, maximum, nth percentiles and variances of the performance losses for each sector.

Sector	Min	5th	25th	50th	75th	95th	Max	Var
1	0.83	1.08	1.18	1.27	1.42	1.78	2.43	0.07
2	0.54	0.98	1.09	1.18	1.33	1.92	2.43	0.08
3	0.73	1.07	1.16	1.26	1.45	1.97	2.44	0.09
4	0.60	0.91	1.04	1.12	1.25	1.84	2.44	0.09
5	0.56	0.93	1.05	1.14	1.27	1.87	2.41	0.08
6	0.62	1.02	1.12	1.20	1.39	2.02	2.43	**0.10**
7	0.71	0.99	1.10	1.18	1.30	1.76	2.43	0.08
8	0.74	1.05	1.15	1.23	1.37	1.73	2.43	0.07
9	0.88	1.16	1.25	1.33	1.45	1.74	2.44	0.06
10	0.67	1.01	1.11	1.19	1.33	1.71	2.43	0.07
11	0.56	1.00	1.11	1.20	1.35	1.90	2.43	0.08
12	0.61	1.01	1.11	1.20	1.36	1.98	2.43	0.09
13	0.83	1.06	1.16	1.25	1.37	1.70	2.42	0.06
14	**0.33**	**0.84**	**0.99**	**1.08**	**1.22**	**1.93**	**2.44**	**0.10**
15	0.78	1.02	1.12	1.21	1.35	1.81	2.43	0.07
16	0.74	1.04	1.14	1.23	1.34	1.65	2.41	0.06
17	0.92	1.14	1.23	1.32	1.45	1.74	2.43	0.06
18	**1.01**	**1.21**	**1.30**	**1.44**	**1.66**	**2.05**	**2.44**	**0.08**
19	0.65	0.97	1.08	1.16	1.28	1.63	2.41	0.07
20	0.92	1.14	1.23	1.32	1.44	1.74	2.43	0.06
21	0.84	1.11	1.20	1.31	1.52	2.02	2.44	0.09
22	0.70	0.98	1.09	1.18	1.31	1.77	2.43	0.08
23	0.70	1.08	1.18	1.27	1.46	2.00	2.43	0.08
24	0.51	0.87	1.01	1.10	1.23	1.69	2.39	0.08
25	0.93	1.16	1.25	1.36	1.52	1.89	2.44	0.07

We choose sector 14 for closer examination because of the high deviation in cumulative performance losses (Table 5). First we calculate two subsets of simulations results: one with simulation iterations where the final performance loss at sector 14 was higher than the 90th percentile (worst case) and another where the final performance loss at sector 14 was lower than the 10th percentile (best case). Figure 11 shows the averages performance losses at time step 2 for both best case iterations (left) and worst case iterations (right). Some properties in worst case iterations are high performance losses in sector 14, 15 and 18 at time step 2. Moreover, some other characteristics in worst case iterations are 1) high performance losses at sector 6 when disruption started from sectors 3, 12 and 16 and 2) high performance losses in sector 21 when disruption started from sector 25.

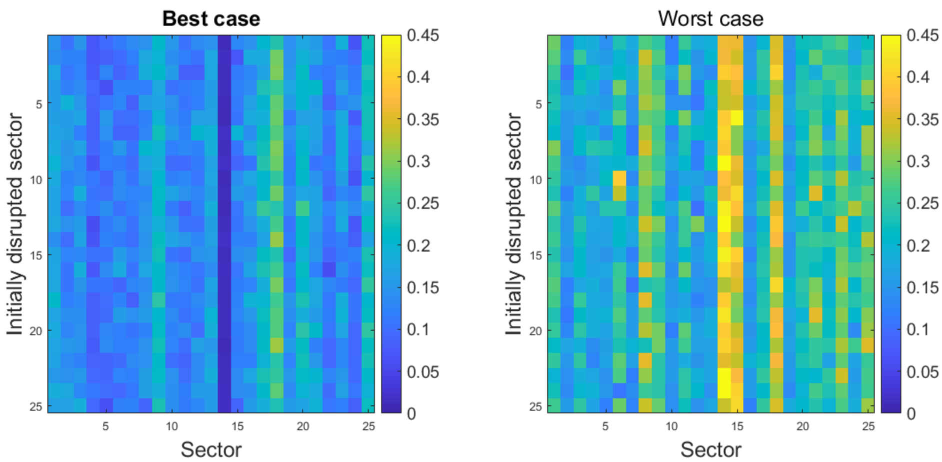

Figure 11: Average performance losses for sector 14 best cases and worst cases at time step 2.

From Figure 12 we see the distributions of cumulative aggregated performance losses for each bi-sectoral resilience strategy (See sub-Section 5.3 and 6.2.2). When each sector focused only on the 23 or 19 most risky bi-sector relationships, the cumulative aggregated performance losses were tremendously higher, compared to strategy where all bi-sector relationships were in focus. The same applied to strategies were the network collectively focused on the 475 and 525 most risky bi-sector relationships.

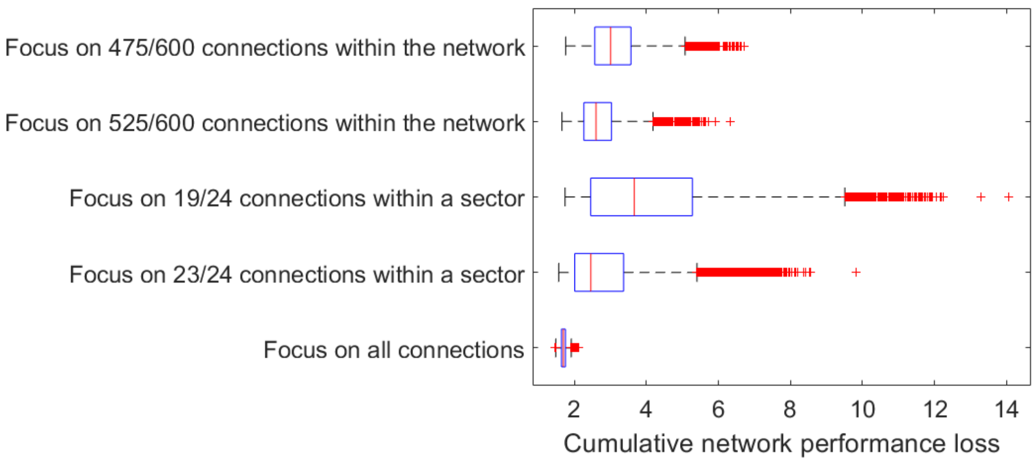

Figure 12: Average performance losses for sector 14 best cases and worst cases at time step 2.

8 Improvements for future surveys

We have shown examples on how network disruption propagation can be analysed with one survey question. To assess the network risks with a more sophisticated model, the survey needs to address more than the impact of propagating disruption. First, rather than using subjective answer options, e.g., "Disruption at sector X would affect our operations a bit", giving participants only quantifiable objective answer options standardizes the answers. New answer options could relate to monetary losses, decreasing production or cuts in labor force. The aspect of the answer options should be comparable to all sectors in the network and in best case in equal importance to all sectors as a performance indicator.

Sticking with the Impact Question, the question could also ask the participant to estimate the impact of the disruption for the institution or company that the participant represents, rather than asking to estimate the impact to the whole sector. The rational behind this is that in general participants have better understanding of their representative institutions or companies rather than of the whole sector. Furthermore, phrasing the question this way eliminates the bias of intra-sector differences. For example, a propagating disruption from sector X may have opposite effects on production for two different institutions within the same sector. One could argue that these opposite effects can affect the way participants estimate the impact for the sector in whole. Phrasing the Impact Question this way requires additional information about the importance of individual institutions and companies intra-sector. In the best case, the relevance would be quantified on the same objective scale as the Impact Question, so that each participants relevance to the whole network could be measured.

In our simulations, the rate at which sectors were able to recover from propagating disruptions was constant. One way to improve the survey could be to address the recovery rate for each sector. The question could be phrased as the time it takes for a sector to fully recover from a disruption. A quantifiable scale, e.g., weeks, would be necessary to make the recovery rates comparable across the network.

Reducing the risk of propagating disruptions is as important as identifying the most riskiest sectors for the network and for specific sectors. Considering the network performance, risk of propagating disruption can be reduced by increasing the number of entities inside a sector. This way, if one of the sector entities become disrupted, other entities can still upkeep the sector performance. In case of a sector wide disruption, it is important to have measures in place which limit the amount of disruption being propagated to other sectors. As seen in simulation, when the number of sectors in the network is 25, even the disruptions happening in sectors which are regarded as less risky, the propagating disruption can cause significant loss of performance. In many cases the network is even larger, which highlights the importance of stopping the disruption from propagating further.

9 Conclusions

The goal of this thesis was to conduct an exploratory analysis on a sector network which was characterized by survey answers. Based on the survey answers, we fitted 600 beta distributions to model all the connections in the network of 25 sectors. Furthermore, we simulated the network with different initial disrupted sectors and measured the propagating disruption for several time steps.

Our results reveal the sectors that are more prone to propagating disruptions and affect the network the most. Furthermore, we show which disrupted sectors constitute the greatest risks for specific sectors and give examples on how to analyse the most risky chain of disruptive events for sectors. In addition, we exhibit the importance of sectors to focus their risk prevention strategies also on the least risky sources of propagating disruptions.

In our research, we did not analyse the speed of the propagation. In reality, some sectors may propagate the disruption faster, which is something to consider in future research. On one hand, sectors which propagate disruptions faster are more riskier to the sector network, because the amount of propagating disruption is higher within a time frame. On the other hand, sectors which propagate disruptions slower may get overlooked because no immediate propagating disruption can be seen. Furthermore, the behaviour of the propagating disruption under different recovery ratios and initial disruptions, both in terms of the amount and number of sectors that are disrupted, was left outside of this thesis.

We also propose improvements for a more through survey (see Section 8), which opens up potential for a more broader analysis on this topic. Moreover, limiting the scope to a specific sector allows for a more detailed analysis of risk propagation. Furthermore, instead of having sector performance losses being represented by a scalar variable, modeling those performance losses as distributions expands the robustness of the analysis. As an optimization problem, finding the optimal allocation for risk reducing strategies would be beneficiary for the sector entities and the institution responsible for the network.

References

S. AbouRizk, D. Halpin, and J. Wilson. Fitting beta distributions based on sample data. *Journal of Construction Engineering and Management*, 120(2):288–305, 1994.

C. Alexander. Bayesian Methods for Measuring Operational Risk. ICMA Centre Discussion Papers in Finance icma-dp2000-02, Henley Business School, Reading University, 2000.

B. Aljabhan. *Supply Chain Risk Management: A Case Study of Maritime Firms in the Kingdom of Saudi Arabia*. PhD thesis, Anglia Ruskin University, 2016.

D. Autor, D. Dorn, and G. Hanson. The China syndrome: local labor market effects of import competition in the United States. *American Economic Review*, 103(6): 2121–2168, 2013.

T. Aven. *Risk analysis: assessing uncertainties beyond expected values and probabilities*, pages 161–162. Wiley, Chichester, England; Hoboken, NJ, 2008.

M. Banghart, L. Bian, L. Strawderman, and K. Babski-Reeves. Risk assessment on the EA-6B aircraft utilizing Bayesian networks. *Quality Engineering*, 29(3): 499–511, 2017.

G. Baryannis, S. Validi, S. Dani, and G. Antoniou. Supply chain risk management and artificial intelligence: state of the art and future research directions. *International Journal of Production Research*, 57(7):2179–2202, 2019.

Z. W. Birnbaum. On the importance of different components in a multicomponent system:. Technical report, Defense Technical Information Center, Fort Belvoir, VA, 1968.

E. Borgonovo and C. L. Smith. Composite multilinearity, epistemic uncertainty and risk achievement worth. *European Journal of Operational Research*, 222(2):301 – 311, 2012.

C. Braziotis, M. Bourlakis, H. Rogers, and J. Tannock. Supply chains and supply networks: distinctions and overlaps. *Supply Chain Management: An International Journal*, 18(6):644–652, 2013.

J. Brownlee, T. Masoud, and A. Reynolds. From dynamic events to deep causes: outcomes and explanations of the arab spring. *Middle East Law and Governance*, 7(1):3–15, 2015.

G. Celeux, F. Corset, A. Lannoy, and B. Ricard. Designing a Bayesian network for preventive maintenance from expert opinions in a rapid and reliable way. *Reliability Engineering & System Safety*, 91(7):849–856, 2006.

B. Chen and X. Chao. Dynamic inventory control with stockout substitution and demand learning. *Management Science*, 66(1):5108–5127, 2020.

X. Chen, Y. Ong, P. Tan, N. Zhang, and Z. Li. Agent-Based Modeling and Simulation for Supply Chain Risk Management – A Survey of the State-of-the-Art. Proceedings - 2013 IEEE International Conference on Systems, Man, and Cybernetics, SMC 2013, pages 1–6, 2013.

C. Colicchia, F. Dallari, and M. Melacini. A simulation-based framework to evaluate strategies for managing global inbound supply risk. *International Journal of Logistics Research and Applications*, 14(6):371–384, 2011.

A. C. Constantinou, N. Fenton, and M. Neil. Integrating expert knowledge with data in Bayesian networks: Preserving data-driven expectations when the expert variables remain unobserved. *Expert Systems with Applications*, 56(1):197–208, 2016.

L. Cordner. ARPA: Securing australia's maritime domain. *Australian Review of Public Affairs*, 2008.

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

P. Dagum, A. Galper, and E. Horvitz. Dynamic Network Models for Forecasting. In *Proceedings of the Eighth International Conference on Uncertainty in Artificial Intelligence*, pages 41–48. Morgan Kaufmann Publishers Inc., 1992.

K.J. Ezawa and S.W. Norton. Constructing Bayesian networks to predict uncollectible telecommunications accounts. *IEEE Expert*, 11(5):45–51, 1996.

Y. Fan and M. Stevenson. A review of supply chain risk management: definition, theory, and research agenda. *International Journal of Physical Distribution & Logistics Management*, 48(3):205–230, 2018.

N. E. Fenton and M. Neil. *Risk assessment and decision analysis with Bayesian networks*, pages 20–25. Taylor & Francis, Boca Raton, 2012.

P. Finch. Supply chain risk management. *Supply Chain Management: An International Journal*, 9(2):183–196, 2004.

J.B. Fussell. How to hand-calculate system reliability and safety characteristics. *IEEE Transactions on Reliability*, R-24(3):169–174, 1975.

M.. Garvey, S. Carnovale, and S. Yeniyurt. An analytical framework for supply network risk propagation: A Bayesian network approach. *European Journal of Operational Research*, 243(2):618–627, 2015.

A. Ghadge, S. Dani, and R. Kalawsky. Supply chain risk management: present and future scope. *The International Journal of Logistics Management*, 23(3):313–339, 2012.

M. Guller, E. Koc, M. Henke, B. Noche, and L. Hingst. A Simulation-based Analysis of Supply Chain Resilience. volume 20 of *Proceedings of the Hamburg International Conference of Logistics (HICL)*, pages 533–556, 2015.

C. S. Hood and C. Ji. Proactive network-fault detection telecommunications. *IEEE Transactions on Reliability*, 46(3):333–341, 1997.

S. Hosseini and K. Barker. A Bayesian network model for resilience-based supplier selection. *International Journal of Production Economics*, 180(1):68–87, 2016.

S. Hosseini and D. Ivanov. A new resilience measure for supply networks with the ripple effect considerations: a bayesian network approach. *Annals of Operations Research*, pages 1–27, 2019.

S. Hosseini and D. Ivanov. Bayesian networks for supply chain risk, resilience and ripple effect analysis: A literature review. *Expert Systems with Applications*, 161 (1):113649, 2020.

No. S. Hudin, A. B. A. Hamid, N. F. Habidin, and W. S. W. Mustaffa. Barrier analysis of supply chain risk management adoption in automotive companies. *International Journal of Academic Research in Accounting, Finance and Management Sciences*, 9(3):Pages 295–299, 2019.

D. Ivanov, A. Dolgui, and B. Sokolov. Ripple effect in the supply chain: definitions, frameworks and future research perspectives. In *Handbook of Ripple Effects in the Supply Chain*, pages 1–33. Springer International Publishing, Cham, 2019.

D. Jemison. Risk and the relationship among strategy, organizational processes, and performance. *Management Science*, 33(9):1087–1101, 1987.

K. Jeong, J. Cha, and Y. Kim. Scrm awareness in the shipbuilding and marine equipment market: empirical evidence from South Korea, China, and Singapore. *Sustainability*, 12(1):5115, 2020.

S. R. Johnson, G. A. Tomlinson, G. A. Hawker, J. T. Granton, and B. M. Feldman. Methods to elicit beliefs for Bayesian priors: a systematic review. *Journal of Clinical Epidemiology*, 63(4):355–369, 2010.

C. Kang. A Bayesian belief network-based advisory system for operational availability focused diagnosis of complex nuclear power systems. *Expert Systems with Applications*, 17(1):21–32, 1999.

H.G Kao, C. Huang, and H. Li. Supply chain diagnostics with dynamic Bayesian networks. *Computers & Industrial Engineering*, 49(2):339–347, 2005.

O. Khan, M. Christopher, and B. Burnes. The impact of product design on supply chain risk: a case study. *International Journal of Physical Distribution & Logistics Management*, 38(5):412–432, 2008.

M. H. A. Klaver, H. A. M. Luiijf, A. H. Nieuwenhuijs, F. Cavenne, A. Ulisse, and G. Bridegeman. European risk assessment methodology for critical infrastructures. In *2008 First International Conference on Infrastructure Systems and Services: Building Networks for a Brighter Future (INFRA)*, pages 1–5, 2008.

M. Kolb. What is globalization? *Peterson Institute for International Economics*, 2018. URL https://www.piie.com/microsites/globalization/what-is-globalization. [accessed 13-September-2020].

D. Koller and N. Friedman. *Probabilistic graphical models: principles and techniques*, pages 783–849. MIT Press, Cambridge, MA, 2009.

A. Käki, A. Salo, and S. Talluri. Disruptions in supply networks: a probabilistic risk assessment approach. *Journal of Business Logistics*, 36(3):273–287, 2015.

O. Kırılmaz and S. Erol. A proactive approach to supply chain risk management: Shifting orders among suppliers to mitigate the supply side risks. *Journal of Purchasing and Supply Management*, 23(1):54–65, 2017.

A. Latour. A fire in albuquerque sparks crisis for european cell-phone giants. *Wall Street Journal*, 2001. URL https://www.wsj.com/articles/SB980720939804883010. [accessed 10-October-2020].

J. M. Lawrence, Niamat U. Ibne H., R. Jaradat, and M. Hamilton. Leveraging a bayesian network approach to model and analyze supplier vulnerability to severe weather risk: A case study of the u.s. pharmaceutical supply chain following hurricane maria. *International Journal of Disaster Risk Reduction*, 49(1):101607, 2020.

S. Lee, H. Kim, K. Son, S. Shin, S. Lee, and H. Kang. Reliability modeling of safety-critical network communication in a digitalized nuclear power plant. *Reliability Engineering & System Safety*, 144(1):285–295, 2015.

M. O'Brien. The miraculous story of iceland. *Washington Post*, 2015. URL https://www.washingtonpost.com/news/wonk/wp/2015/06/17/the-miraculous-story-of-iceland/. [accessed 10-October-2020].

Council of European Union. Council directive 2008/114/ec of 8 december 2008 on the identification and designation of european critical infrastructures and the assessment of the need to improve their protection. *Official Journal of the European Union*, L 354:75–82, 2008.

M. Ojala and J. Hallikas. Investment decision-making in supplier networks: Management of risk. *International Journal of Production Economics*, 104(1):201–213, 2006.

R. Ojha, A. Ghadge, M. Tiwari, and U. S. Bititci. Bayesian network modelling for supply chain risk propagation. *International Journal of Production Research*, 56 (17):5795–5819, 2018.

E. Ortiz-Ospina and D. Beltekian. Trade and globalization. *Our World in Data*, 2018. URL https://ourworldindata.org/trade-and-globalization. [accessed 13-September-2020].

J. Pearl and J. Kim. A computational model for causal and diagnostic reasoning in inference systems. *Proceedings of the Eighth International Joint Conference on Artificial Intelligence*, 1(1):190–193, 1983.

A. Qazi, J. Quigley, and A. Dickson. Interdependency Modeling of Supply Chain Risks incorporating Game Theoretic Risks. pages 1–15, University of Bologna, Italy, 2014.

A. Qazi, A. Dickson, J. Quigley, and B. Gaudenzi. Supply chain risk network management: A Bayesian belief network and expected utility based approach for managing supply chain risks. *International Journal of Production Economics*, 196 (1):24–42, 2018.

D. Rehak, M. Hromada, and P. Novotny. European critical infrastructure risk and safety management: directive implementation in practice. *Chemical Engineering Transactions*, 48(1):943–948, 2016.

J. C. Rocha, G. Peterson, Ö. Bodin, and S. Levin. Cascading regime shifts within and across scales. *Science*, 362(6421):1379–1383, 2018.

S. Salehi, M. Khanbabaei, and M. Sabzehparvar. A model for supply chain risk management in the automotive industry using fuzzy analytic hierarchy process and fuzzy TOPSIS. *Benchmarking: An International Journal*, 25(9):3831–3857, 2018.

T. Schaberreiter, J. Aubert, and D. Khadraoui. Critical infrastructure security modelling and RESCI-MONITOR: A risk based critical infrastructure model. In *2011 IST-Africa Conference Proceedings*, pages 1–8, 2011.

G. Schlegel and R. Trent. *Supply chain risk management: an emerging discipline*, page Preface. CRC Press, Boca Raton, FL, 2015.

F. F. Schlüter, E. Hetterscheid, and M. Henke. A simulation-based evaluation approachfor digitalization scenarios in smart supplychain risk management. *Journal of Industrial Engineering and Management Science*, 2017(1):179–206, 2017.

Y. Sheffi and J. Rice. A Supply Chain View of the Resilient Enterprise. *MIT Sloan Management review*, 47(1):41–48, 2005.

V. Shenoi, S. Dath, and C. Rajendran. Supply chain risk management in the Indian manufacturing context: a conceptual framework. *International Journal of Logistics Systems and Management*, 25(3):313, 2016.

C. Shenoy, P. Shenoy, B. LeBaron, A. W. Lo, and A. S. Weigend. Bayesian Network Models of Portfolio Risk and Return. In Y. S. Abu-Mostafa, editor, *Computational Finance*, pages 87–106. MIT Press, Cambridge, MA, 1999.

S. Si, Z. Cai, S. Sun, and S. Zhang. Integrated importance measures of multi-state systems under uncertainty. *Computers & Industrial Engineering*, 59(4):921–928, 2010.

M. S. Sodhi. Managing demand risk in tactical supply chain planning for a global consumer electronics company. *Production and Operations Management*, 14(1): 69–79, 2009.

G. Stergiopoulos, E. Valvis, D. Mitrodimas, D. Lekkas, and D. Gritzalis. Analyzing congestion interdependencies of ports and container ship routes in the maritime network infrastructure. *IEEE Access*, 6(1):63823–63832, 2018.

C. S. Tang. Robust strategies for mitigating supply chain disruptions. *International Journal of Logistics Research and Applications*, 9(1):33–45, 2006.

A. Touran, M. Atgun, and I. Bhurisith. Analysis of the united states department of transportation prompt pay provisions. *Journal of Construction Engineering and Management*, 130(5):719–725, 2004.

R. M. Vanalle, W.C. Lucato, G.M.D. Ganga, and A.G. Alves Filho. Risk management in the automotive supply chain: an exploratory study in Brazil. *International Journal of Production Research*, 58(3):783–799, 2020.

I. Vanany, S. Zailani, and N. Pujawan. Supply chain risk management: literature review and future research. *International Journal of Information Systems and Supply Chain Management*, 2(1):16–33, 2009.

S. Wagner and C. Bode. An empirical examination of supply chain performance along several dimensions of risk. *Journal of Business Logistics*, 29(1):307–325, 2008.

E. D. Zepeda, G. N. Nyaga, and G. J. Young. Supply chain risk management and hospital inventory: Effects of system affiliation. *Journal of Operations Management*, 44(1):30–47, 2016.

G. Zsidisin, A. Panelli, and R. Upton. Purchasing organization involvement in risk assessments, contingency plans, and risk management: an exploratory study. *Supply Chain Management: An International Journal*, 5(4):187–198, 2000.