Master's Thesis of Business Administration

Analysis of risk factors influencing the semiconductor supply chain: A fuzzy Bayesian Network approach

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Abstract

This study attempts to classify the risk factors for semiconductor industry’ s supply chain and quantify their occurrence probability within the supply chain using the fuzzy Bayesian network methodology. Using the PESTEL classification system, a risk classification system is created for the semiconductor supply chain. In total, 9 experts participated in a survey regarding their opinions on the previously defined risk elements and risk categories. The overall supply chain disruption probability and the figures for each risk category and risk element are derived with the help of f-weighted approach and triangular fuzzy numbers.

It is economic and social risk categories that show relatively high chances to occur, and, namely, such risk elements as volatile demand, fierce competition, or lack of talents are deemed risky by the experts. Still, sensitivity analysis techniques, including causal and diagnostic inference and tornado graphs imply that some of the risk elements with low probability of occurrence but high magnitude of impact, originating from the other categories (e.g. natural disasters from the environmental risk category) are of great interest as well. In compliance with the results, practical implications regarding the risks are made for the management.

Keyword : risk management, risk classification, semiconductor industry, supply chain, fuzzy Bayesian network, disruption
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Chapter 1. Introduction

1.1. Study Background

The importance of semiconductor industry in the 21^{st} century is inevitable: semiconductors serve as a key element of various industries, including healthcare, military, transportation etc. They can be undoubtedly called an integral part of modern life, as they can be easily found in such devices used daily, as mobile phones or laptops; moreover, they are the drivers of the 4^{th} industrial revolution. It is estimated that the total market size of the semiconductor industry reaches USD 580bn (Alsop, 2023), and by 2029 it is projected to reach USD 1380bn (Fortune Business Insights, 2022). One of the leading players in the global market of semiconductor industry is the Republic of Korea: its total production value, export value and global market share are KRW 201tr, USD 129bn and 19.9% respectively (Yoon, 2023).

One of the peculiarities of semiconductor supply chain is its complexity. Many materials are required to produce a single chip; moreover, some of the materials are rare. Besides, there are numerous sub-segment technologies needed to refine materials into finished chips. On average, each segment of semiconductor supply chain spans over 25 countries (Khan et al., 2021). Consequently, complexity of such a supply chain comes together with globality: for instance, largest companies in the market have plants and R&D centers outside of the countries where they are based. Samsung Electronics has a NAND flash plant in Xian, China; SK Hynix has a R&D center in the USA and Italy (Jeong et al., 2023). Possible reasons for globality to be chosen as another specific trait of the semiconductor supply chain include the natural inevitability of outsourcing due to a relatively large number of steps comprising the actual chip manufacturing processes (approximately 600 to 800), as well as the low international trade cost. Since 1996, for the past 30 years tariffs on semiconductors, as well as IT devices, have been constantly decreased by authorities.

However, globality itself may have negative sides to it, as the semiconductor industry is generally assessed as volatile, despite the overall efficiency of the industry. Possible risks for the industry’s supply chain may include the following: demand volatility, pricing volatility, political instability (e.g. USA-China trade war, terror attacks). Aside from those, natural disasters (e.g. Tohoku earthquake, 2011) or global pandemics (COVID-19 pandemic) can also serve as impactful risks for supply chain operations. On a country level, leading players in the market also may face risks tailored to specific conditions: for instance, the Republic of Korea is facing such risks as visible weakness in the non-memory market, possible political issues with the USA, China, and Japan (given the relations with those states), labor force-related issues (e.g. lack of talents), and the need for localization (Daxue, 2023). Still, the preliminary analysis of the previously published literature sources yielded that such risks have not yet been classified for the semiconductor industry supply chain using any classification framework.

Aside from risk classification, this study aims at setting causal relationships between risk elements and risk categories so that the risk elements’ possible impact on the semiconductor supply chain can be assessed in a proper manner. We pursue quantifying the occurrence probabilities for each risk element and risk category, with the goal of obtaining the overall disruption probability figure for the whole supply chain. From the previous literature, Bayesian networks are frequently used as a methodology for assessing risk elements or uncertainties in terms of such a scientific field like risk management, given the causality between observed elements. However, considering the lack of open-source data for the semiconductor industry due to highly protective nature of the industry, we proceed with using the fuzzy Bayesian network methodology, where the data is obtained with the help of industry experts’ opinions on certain matters - risk elements for the supply chain of semiconductor industry in this case.

Thus, the research questions for this study may be as follows:

1) What risk elements can be extracted from the previous literatures for semiconductor supply chain in particular?
2) Can these risk elements be classified in a single framework?
3) Can the probability of the risk elements' occurrence in the semiconductor supply chain be quantified?
4) Can the overall probability of disruption in the semiconductor supply chain be quantified?
5) What are the most impactful risk elements / categories for the semiconductor supply chain?
6) What managerial and theoretical implications can be produced?

Chapter 2. Literature Review

The literature review section can be divided into 3 main topics as shown below: supply chain risk management, semiconductor industry supply chain, and semiconductor industry risk management.

2.1. Supply chain risk management

Before the global pandemic of COVID-19, main developments in the field of supply chain risk management (SCRM) included risk classification or systemization-related studies. Shahbaz et al. (2019) assessed overall supply chain risks for manufacturing in Malaysia with the help of a systematic process and categorized them into 7 constructs. Pournader et al. (2020) attempted to systemize the main topics emerging in the field of SCRM, concluding with promising avenues for the future research.

The impact of pandemic on this field can be characterized by papers mixing the topic of supply chain resilience together with SCRM (El Baz & Ruel, 2021; Bag et al., 2021). Moreover, COVID-19 induced studies on its impact on various industries' supply chains. For instance, McMaster et al. (2020) investigated the fashion industry's supply chain agility and offered several strategies that can be adopted to control for risk elements. Sharma et al. (2020) analyzed the impact of pandemic on the Indian healthcare industry's supply chains, stressing the need for amending policies to help local workforce. Spieske et al. (2022) studied empirically how supply chain networks in the automobile industry contributed to avoiding the worst consequences of the pandemic; Sudan & Taggar (2021) suggested robust strategies for mitigating the automobile industry-associated risks in the post-COVID era.

2.2. Semiconductor industry supply chain

The field of semiconductor industry supply chain has been studied actively since 2000s. Several studies have been conducted on various topics, including simulation techniques, control strategies and supply chain disruptions. For instance, Wang et al. (2007) attempted applying the model predictive control (MPC), originating from the process industries to the semiconductor manufacturing-related problems, and showed that it addresses such distinguishable features of the semiconductor supply chain as high stochasticity, nonlinearity in throughput times and customer demands. Matsuo (2015) focused on a real case of Toyota's supply chain disruption, induced by the 2011 Tohoku earthquake, and tried to identify which functions were missing in the supply chain coordination mechanism in the Toyota Production System (TPS), given that it took 3 months for the company to recover to the pre-earthquake production levels. Results of the analysis imply that direct control functions must be added to the mechanism so that disruption risks can be alleviated.

It is worth noting that among the academic papers published so far, prevailing are the papers of review nature. A notable work is produced by Mönch et al. (2018), who have summarized peculiarities of the semiconductor supply chain models in general. This work is divided into 3 parts and touches upon the following topics: strategic network design, supply chain simulation, demand planning, inventory management, capacity planning, master planning, production planning, and demand fulfillment. Still, this paper has not provided any insights on the field of risk management within the semiconductor supply chain.

Moreover, COVID-19 has impacted studies in this field as well. For instance, Ramani et al. (2022) investigated the impact of semiconductor lack on the automotive industry as a COVID-19 pandemic aftermath and studied the distinction between systematic disruptions impacting entire industries and normal disruptions affecting supply chains of a particular company. Ishak et al. (2022)

attempted to define the relationship between supply chain adaptive strategies and firm performance, given the influence of COVID-19 pandemic, in a conceptual manner. They concluded that adaptive strategies influence the firm performance significantly when robustness, agility, and resilience are combined. Jaenichen et al. (2021) studied the supply chain disruption-related dangers in the semiconductor industry setting using the simulation techniques: a system dynamics simulation was modeled to investigate the response of a multi-echelon supply chain to the various end-market scenarios. Authors note that in case of unforeseen events of a large scale (i.e. global pandemic), a close collaboration among players in the supply chain can contribute to increase of robustness across the whole supply chain and, consecutively, mitigate the corresponding supply chain risks.

2.3. Semiconductor industry risk management

Narrowing the scope of the literature review to the field of risk management within semiconductor industry, we find out that most of the published academic papers are of a holistic nature. Besides, majority of them are not recent and contain only general guidelines for managing the risks in the semiconductor industry. For example, Chelton et al. (1993) assessed the risks related to chemical hazards used frequently in the manufacturing processes in the semiconductor supply chain, thus, touching upon only the production-related risks. Zafra-Cabeza et al. (2007) investigated a stochastic predictive control approach to managing risks in semiconductor manufacturing and optimizing costs and time of a project simultaneously. Effectiveness of the method is supported by a real risk management problem related to the construction of manufacturing facilities, solved with the help of the technique mentioned above.

However, we notice that, to the best of our knowledge, no research on fuzzy Bayesian networks and semiconductor supply chain risk management has been conducted yet. Despite the visible progress in the studies on semiconductor industry supply chain in general, the field of risk management in this industry's settings lacks quantitative studies. In this sense, such a lack of academic work in this field calls for closing a corresponding research gap and the need to define main disruption drivers for this industry. Moreover, given the acceleration of research in this field induced by the occurrence of COVID-19 global pandemic, we suppose that moving towards quantitative studies in this field might bring more promising insights in the future.

Chapter 3. Methodology I: Systematic Literature Analysis

Systematic literature analysis (SLA) is known as a methodology used for selecting certain studies according to specific criteria and forming a cohort of such studies dedicated to a particular topic. In this study, SLA is used for extracting risk elements relevant to the semiconductor industry supply chain and using these risk elements to form a classification of risk elements placed under certain risk categories.

The choice of SLA as a primary methodology for extraction of risk elements can be well justified by a few reasons. One of the advantages of SLA is that it is effective at minimizing possible biases, as it sets prespecified relevance and quality criteria for selecting studies for the final sample and makes such criteria transparent to the readers (Denyer & Tranfield, 2009). Usefulness of SLA can be shown in terms of creating new knowledge (Light and Pillemer, 1984) or critical evaluation of eligible studies (Briner & Denyer, 2012) as well. Moreover, SLA has been frequently used in supply chain-related studies on the wide range of topics, including supply chain resilience (Ali et al., 2017; Hohenstein et al., 2015), blockchain technologies in the supply chains (Wang et al., 2019), or Industry 4.0 for supply chain management (Birkel & Müller, 2021).

The usage of SLA in this study complies with the well-established principles of SLA. These principles include the following:

1) **Replicability**: We are using the protocol and criteria for choosing the papers to form a sample or eliminating them at a later stage for not fitting the established criteria similar to those mentioned in the previously published academic papers (Han et al., 2020).
2) **Exclusiveness**: We are accessing various academic databases

and journals in the paper collection process.

3) **Aggregation**: We are conducting several rounds of adding new academic papers to the final sample. For instance, a few rounds were conducted over January-February 2023.

Thus, the main research questions for SLA align with the research questions for the whole study and concern the following:

1) What are the risk elements that are mentioned most frequently in the papers devoted to the field of supply chain risk management?
2) Upon which criterion(-a) are the risk elements found in the papers to be classified?

Initially, it is required to limit the range of literature sources. In compliance with the protocols used in the previously published sources, it was decided to use such academic databases as INFORMS, Taylor & Francis, and Wiley Online, with the condition of removing overlapping sources from the sample if required. Keywords for searching the papers included the following: supply chain risk management OR disruption OR resilience. As methodologies used in the analysis in the found papers can be different, it was also decided to attempt maintaining the balance between quantitative and qualitative papers (approximately 50% attained to each category). Only papers published between 2010 and 2022 were chosen for SLA, and the minimum quantity of papers for the sample was set at 90.

From the initially formed sample, papers were eliminated step-by-step according to the assessment of their relation to the field of supply chain risk management, semiconductor industry settings, and the language in which papers were written. Elimination protocol composed 3 stages, in which assessment was firstly assessed based on the paper title and its abstract, followed by introduction / conclusion of a paper, and, lastly, paper text itself.

Trend analysis, based on 96 papers in total, yielded the following results.

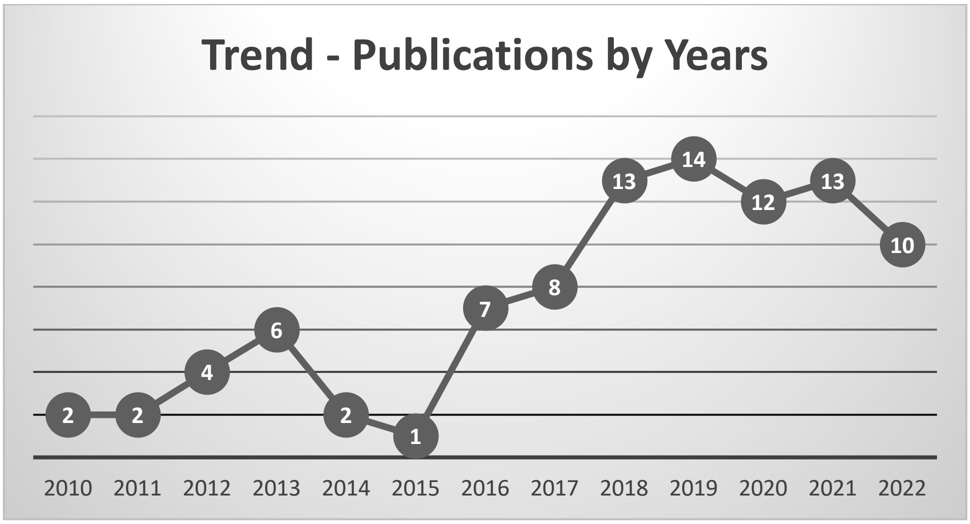

Figure 3-1. Trend analysis: publications by years.

From the Figure 3-1, it is observed that before 2018, the number of papers from our final sample published yearly was lower than 10. However, after 2019, the number increased to 14 in 20 and did not fall behind 10 until 2022. We suppose that this could be explained not only by solely growing interest of academia in supply chain risk management-related studies, but also by COVID-19 pandemic-induced supply chain disruptions that might have induced studies in this direction as well.

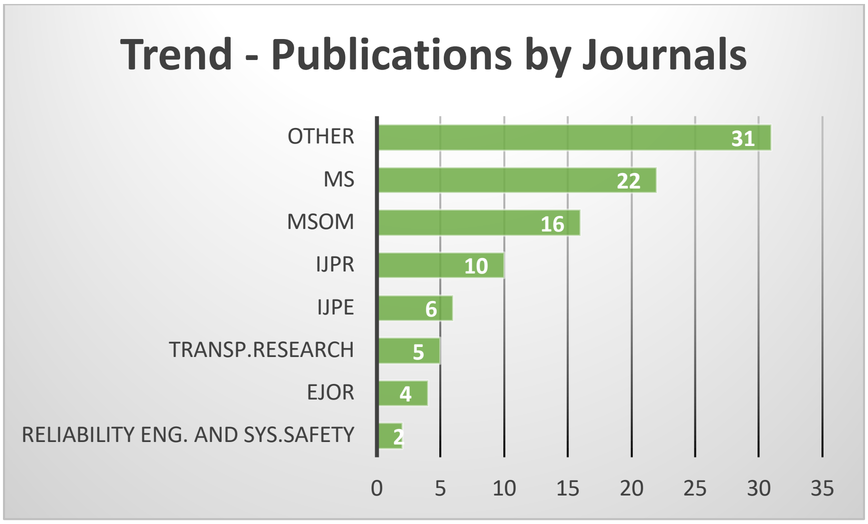

Figure 3-2. Trend analysis: publications by journals.

Figure 3-2 shows the distribution of journals in which the selected papers were published. As we have decided on including INFORMS in the list of academic databases for the paper search, it is inevitable that such journals as Management Science (MS) or Manufacturing & Service Operations Management (MSOM) are in the leading positions. Still, many papers were published in such journals as International Journal of Production Research (IJPR), International Journal of Production Economics (IJPE), Transportation Research, and European Journal of Operational Research (EJOR). Two papers were also published in the journal named Reliability Engineering and System Safety, signaling that risk management-related studies are naturally covered not only by business settings, but also engineering settings as well. For convenience, journals that had only one paper from the sample published in them were placed under the category "Other" with 31 such journals in total.

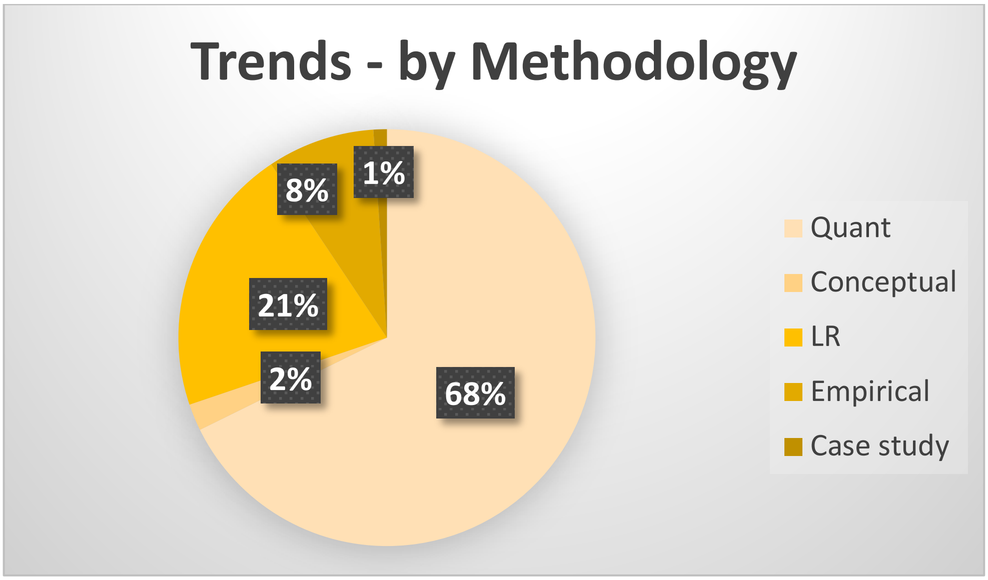

Figure 3-3. Trend analysis: publications by methodology.

Figure 3-3 shows the distribution of papers by the main methodology used for analysis. In contrast with the initially expected balance between quantitative and qualitative papers, the results turned out to be slightly different, with 68% of the papers concentrating on the various quantitative methodologies. 21% of the papers concerned literature reviews, and 8% – empirical studies, which shows a possible lack of empirically oriented research in the area. Conceptual papers, as well as case studies, turned out to be very scarce in the search process.

As for the extraction of risk elements from the papers, it was considered reasonable to investigate papers touching upon the semiconductor supply chain settings separately from the already analyzed 96 papers. This was done with the intention of searching for additional risk elements that might be relevant to our study. A sample of 9 papers led to discovery of 10 new risk elements. The small number of papers aligns well with the fact mentioned in the literature review section that the papers on the semiconductor industry supply chain are relatively scarce.

For building a final version of the risk elements' framework, it was decided to use the PESTEL framework frequently used in the risk management studies (Kilubi, 2016). PESTEL stands for the names of risk categories: political, economic, social, technical, environmental, and legal. Previously found risk elements are to be tailored to semiconductor supply chain settings with some of the risk elements excluded from the classification, where applicable due to a mismatch with the semiconductor supply chain peculiarities. For example, tailoring maritime supply chain risk elements to the semiconductor supply chain settings without prior assessment of how much such risk elements match the settings themselves might be questionable.

The choice of PESTEL framework can also be supported by the nature of risks that we deal with in the study. If we proceed with internal risks only, the number of risk elements will be much higher, inevitably leading to increased analysis complexity. Another alternative is to tailor risk elements to every stage of the semiconductor supply chain; however, given that semiconductor industry is famous for having complex supply chain, this would contribute to analysis complexity as well. Lastly, mixing PESTEL framework with internal risks would only make analysis more complex. Hence, we proceed with exclusively external risks in our framework.

While extracting and grouping the risk elements, we faced an issue of having imbalance between the risk categories in terms of the number of risk elements in each category. For example, political risk category contained 4 risk elements, compared to 16 in the economic risk category. However, previous papers concerning PESTEL framework report no issues with such imbalance. Additionally, it was decided to form sub-categories within the main 6 risk categories, as we expected to use the conditional probability concept in our quantitative analysis; having no sub-categories might lead to combinatorial explosion and serious difficulties with collecting data and opinions from the industry experts. This will be discussed in more detail in the next section.

As a part of SLA, frequency analysis was conducted for all 6 categories to investigate the most frequently found risk elements. The results are shown below.

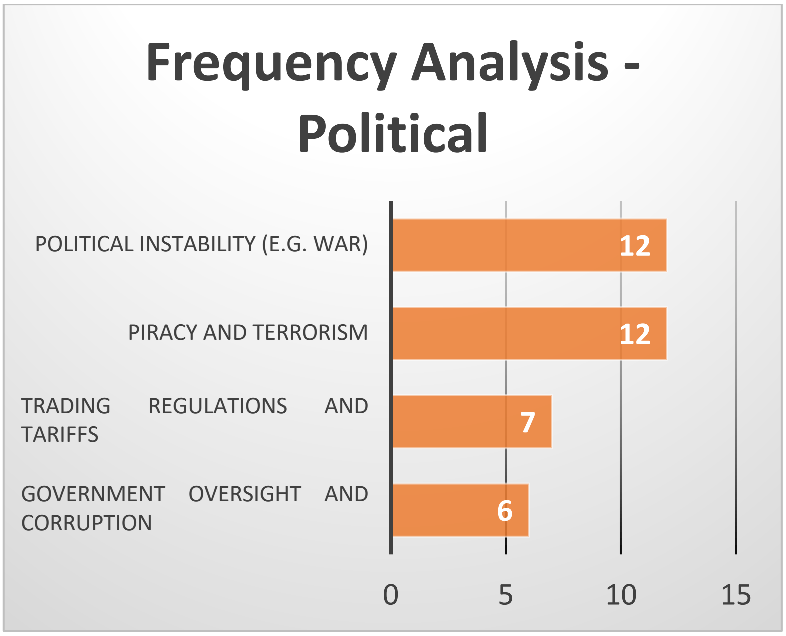

Figure 3-4. Frequency analysis: political risks.

Figure 3-4 shows 4 political risk elements contained in the political risk category. We can observe that political instability and piracy and terrorism were mentioned most frequently in the papers, while government oversight and corruption – least frequently.

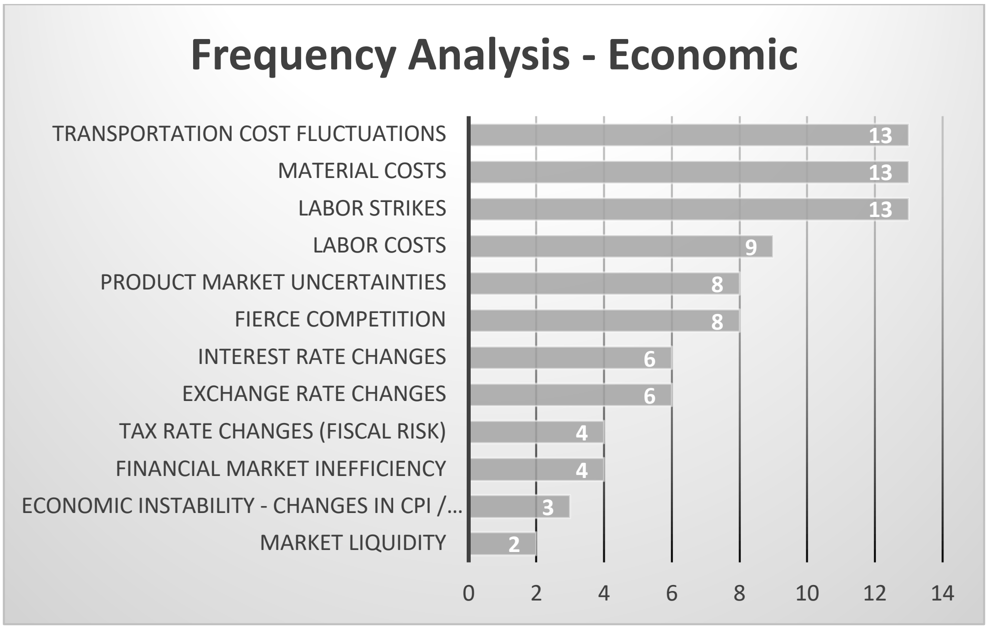

Figure 3-5. Frequency analysis: economic risks.

Figure 3-5 shows the economic risk elements. Among those, fluctuations of transportation cost, material costs, and labor strikes were mentioned most frequently in the papers from the sample. On the other side, such risk elements as market liquidity, economic instabilities (e.g. changes in CPI / GDP), financial market inefficiency, and tax rate changes (or fiscal risk) were mentioned only from 2 to 4 times.

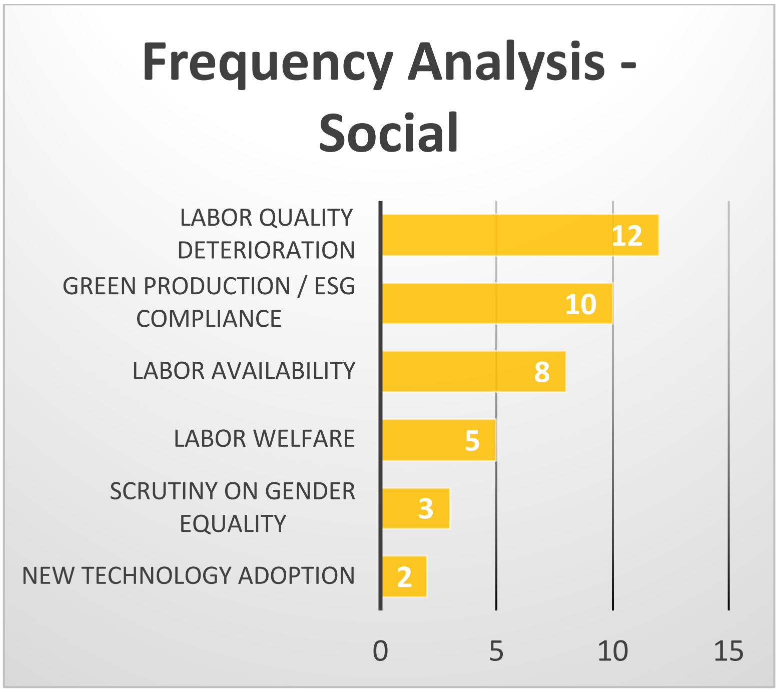

Figure 3-6. Frequency analysis: social risks.

Figure 3-6 shows the social risk elements derived from the papers. New technology adoption was found only in 2 papers, while scrutiny on gender equality – in 3; the most frequent risk elements from the social risk category were green production / ESG compliance (10) and labor quality deterioration (12).

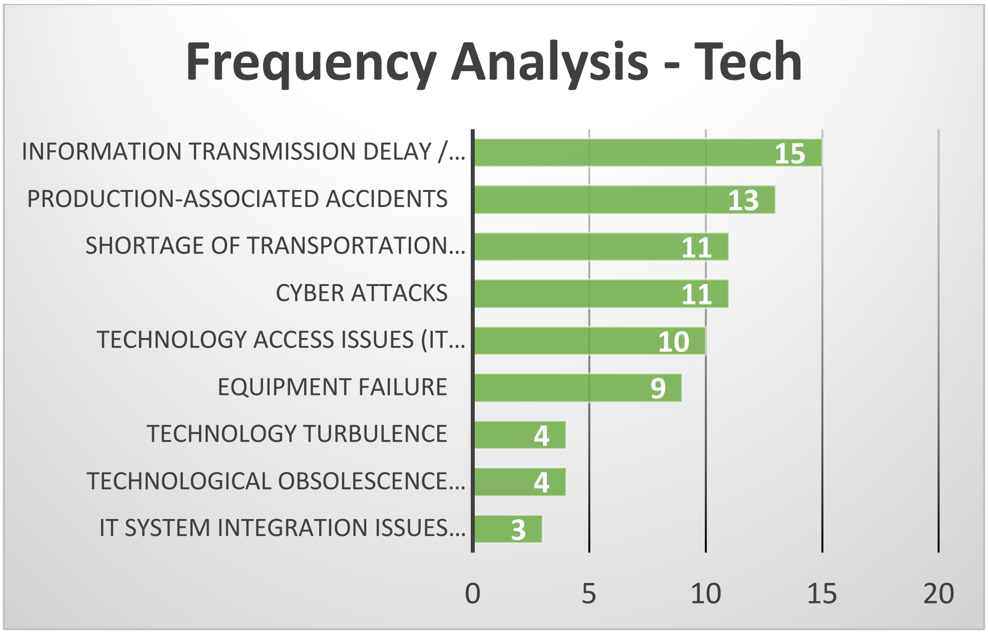

Figure 3-7. Frequency analysis: technical risks.

Figure 3-7 concerns the technical risks, which are 9 in total. While production-associated accidents (human-involved) and information transmission delay / distortion were the most frequently mentioned risk elements (13 and 15 mentions respectively), we can notice that such risk elements related to technology as technology turbulence and technological obsolescence and IT system integration issues are at the bottom of the chart.

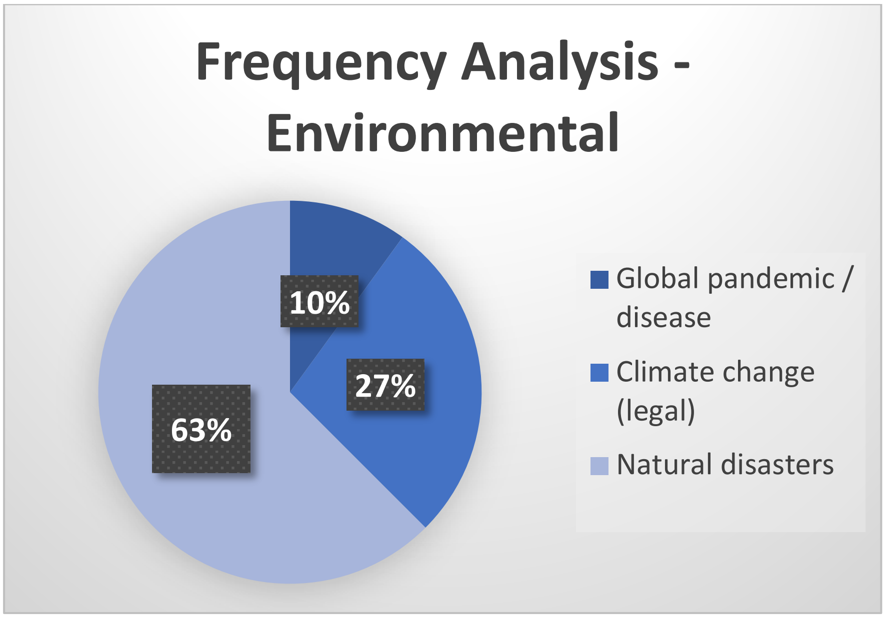

Figure 3-8. Frequency analysis: environmental risks.

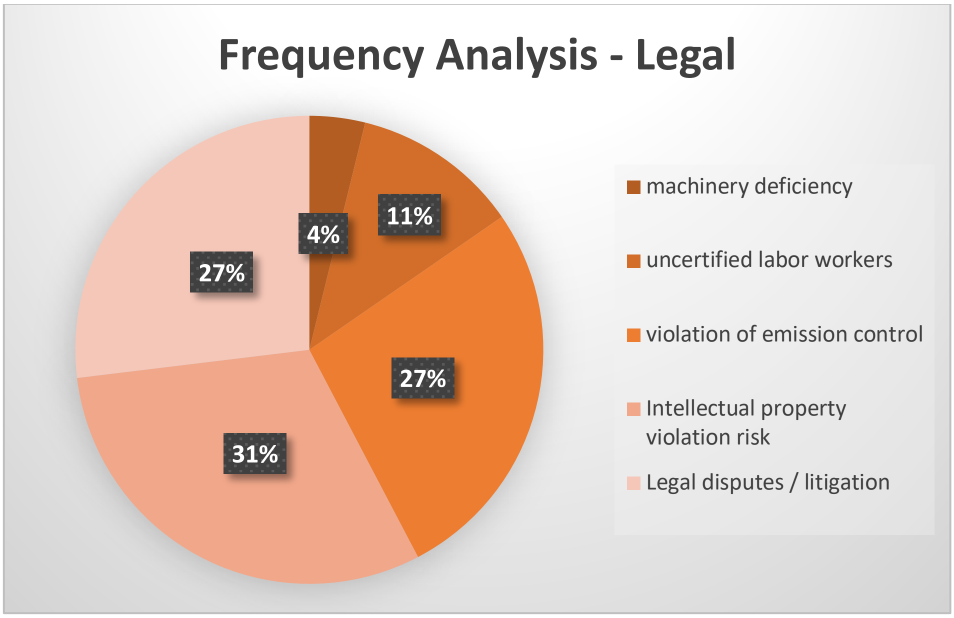

Figure 3-9. Frequency analysis: legal risks.

Figure 3-8 and Figure 3-9 concern the last categories from PESTEL classification: environmental and legal risks. In the environmental risk category, natural disasters as a risk element prevail over the other 2 risk elements: global pandemic / disease and climate change (in legal terms). As for the legal risk elements, the leading position is shared by 3 risk elements: intellectual property violation risk, violation of emission control, and legal disputes / litigation. The least frequently mentioned risk element in this category is the machinery deficiency with only 4% recorded.

The last step of SLA before finalizing the risk classification concerned the process of validating the risk elements, categories, and the classification itself by the industry experts. This was done based on the aforementioned lack of academic papers concerning solely semiconductor supply chain settings – thus, the academic papers as the only judgment basis for matching the found risk elements with the semiconductor industry settings were insufficient. In total, 2 experts from the industry were asked to assess the validity of the framework. Changes in the framework that were induced after consultations include the following examples:

- Volatility in costs was proposed as a risk element comprising 4-sub costs (inventory, production, quality, and procurement), with the procurement cost comprising labor, material, and transportation costs.
- Labor strikes were removed from the economic risk category due to the overlap with the social risk category (namely, labor quality deterioration due to the causal relationship).
- Experts questioned the technological turbulence in the technical risk category as the risk factor, given the nature of the semiconductor industry, as well as the counterfeit as the economic risk factor.

Upon assessment of validity conducted by the experts, we extract the finalized risk classification framework as follows:

1. Political Risks:
    - Political instability (e.g. war)
    - Government oversight and corruption
    - Piracy and terrorism
    - Trading regulations and tariffs

2. Economic Risks:
    - Industry-specific risks
        - Short / long product life cycle
        - Long lead times
        - High capital intensity
        - Volatile demand
    - Financial market inefficiency
        - Interest rate changes
        - Tax rate changes
        - Exchange rate changes
        - Liquidity
    - Cost increase
        - Inventory cost increase
        - Production cost increase
        - Quality cost increase
        - Procurement cost increase
            - Labor cost increase
            - Material cost increase
        - Transportation cost increase
    - Global-scaled risks
        - Economic instability
        - Fierce competition
3. Social Risks:
    - Labor quality deterioration
    - Labor availability
    - Stakeholders' scrutiny on:
        - green production / ESG compliance
        - labor welfare
    - Lack of talents
4. Technical Risks:
    - Technology-related risk elements
        - Technology access issues
        - IT system integration issues
        - Technological obsolescence
    - Equipment failure

- Production-associated accidents

5. Environmental Risks:
   - Natural disasters
   - Global pandemic / disease
   - Regulations related to climate change
6. Legal Risks:
   - Law and regulation changes
   - Intellectual property violation risk
   - Legal disputes / litigation

Chapter 4. Methodology II: Fuzzy Bayesian Network

A fuzzy Bayesian network can be defined as a statistical methodology used for quantifying the probability, with which a certain event might occur. In this study, a risk element is deemed as a certain event that can happen within the risk elements' classification framework, transformed into a network. Naturally, probabilities span from 0 to 1, and fuzzy Bayesian networks help establish causal relationships between the risk elements and observe how those influence the probabilities. We can justify the existence of causal relationships between the risk elements by the fact that given the large number of stages in the semiconductor supply chain and the demand for semiconductors defined by the demand for the finished products, the bullwhip effect might significantly impede the supply chain operations (Mönch et al., 2018). Additionally, such uncertainties of a relatively larger scale as COVID-19 pandemic or the Russia-Ukraine war only add to the reasoning behind the choice of this methodology.

In general, fuzzy Bayesian networks have been actively used in various academic fields. Most notable ones include quality control-related studies and safety management area. For quality control, soft computing of embedded systems in quality control was blended well with fuzzy logic principles and fuzzy Bayesian networks for enhancing the quality levels (Koljonen et al., 2006). Enhancement of product quality can also be supported by using a fuzzy quality feature monitoring model, capable of calculating the operational risks for different stages of production (Jenab & Ahi, 2010). Data mining methods for ensuring the network quality also took advantage of fuzzy logic principles (Athanasiadis et al., 2010). As for the safety management-related studies, risk assessment and quantification studies prevail with implications derived for various industries: especially, those industries with complex dynamic environments show high frequency of implementing fuzzy logic and fuzzy Bayesian networks. For instance, fuzzy Bayesian networks can be successfully used for assessing the risks related to offshore operations in ocean engineering and modeling corresponding causal relationships (Ren et al., 2009). Operational risks can also be calculated, as well as predicted, with the help of fuzzy algorithms and Bayesian networks in terms of building projects of various kind (Guo et al., 2010). In transportation, safety analysis of unmanned aircraft systems can also be supported by usage of fuzzy Bayesian networks contributing to formation of a regulatory-based approach (Luxhøj & Öztekin, 2009).

Another reasoning behind choosing the fuzzy Bayesian network as a primary methodology for this study relates to its established presence in the academic papers dedicated to supply chain management, especially since 2010s. Several topics in this sense include fuzzy optimization for solving the supply chain network design problem (Tabrizi & Razmi, 2013), information risk assessment in supply chains for preventing the issues induced by information distortion (Sharma & Routroy, 2016), or modeling the supplier choice-related decisions via integration of influence diagram and fuzzy logic (Ferreira & Borenstein, 2012). Moreover, the COVID-19 pandemic influenced the growth of research in this field with fuzzy Bayesian networks as a primary methodology, supporting the statement above regarding the influence of major uncertainties on the usefulness of fuzzy Bayesian networks: thus, such methodology can be implemented successfully in terms of risk assessment in various industries, including maritime industry (Sahin et al., 2021), cold chain (Chen et al., 2021), healthcare (Rehman & Ali, 2022) etc.

A Bayesian network is the basis of the fuzzy Bayesian network, as follows from its name, and is also called as a belief network, uniting the Bayes' rule and the network theory to form a directed acyclic graph. A conceptual model of a Bayesian network applied to supply chain settings is shown below and concerns supply chain disruption triggers, supply chain risk events, and supply chain consequences. In our paper, risk elements serve as the triggers, categories from the risk classification framework play the role of risk events, and supply chain disruption is the only consequence we are to have in the network.

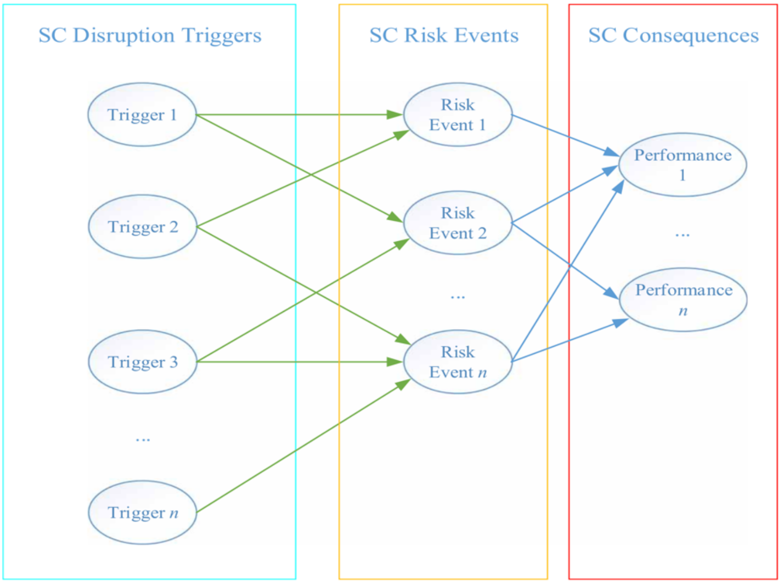

Figure 4-1. Bayesian network for supply chain: conceptual model (Hosseini and Ivanov, 2021).

As an extension added to the original Bayesian network, fuzzy logic is applied to obtain the fuzzy Bayesian network methodology. Fuzzy logic is a form of many-valued logic, within which the value of variables ranges from 0 to 1. However, its peculiarity is that it complies with the principle that decisions are made based on the non-numerical basis. Thus, in this sense, experts that participate in the data collection process with the help of surveys typically express their opinions using a certain linguistic scale rather than choosing a certain value in the range of 0 to 1. Linguistic scales commonly contain an odd number of elements for convenience: most frequently, variations of 5, 7, and 9 elements are met in the literature. For this study, we proceed with a 7-point linguistic scale as shown below in the Table 4-2.

Occurrence probability	Description
Impossible (IM)	The event never occurs.
Nearly impossible (NI)	The event is extremely impossible to occur.
Unlikely (UN)	Even though the event is unlikely, it is possible to occur.
Fair-chance (FC)	The occurrence likelihood of possible events is fair-chance.
Likely (LI)	The event is likely to occur.
Nearly certain (NC)	The event will always occur.
Certain (CE)	The event is to occur with absolute certainty.

Table 4-2. A 7-point linguistic scale for data collection (survey-based).

Linguistic terms selected by experts are then to be quantified. Although many approaches to quantification exist and have been tested in the literature, in this study, we proceed with the triangular fuzzy numbers (TFN) and the f-weighted approach for defuzzification and, consequently, obtaining the final, crisp risk values for risk elements and categories, as well the supply chain disruption as the supply chain consequence. A crisp risk value in this sense stands for the occurrence probability of a certain event.

Typically, TFN is given as [a, b, c], and the notations for the letters are as follows:

- a: lower limit of the occurrence probability
- b: probability that a certain event occurs (most probable figure, on average)
- c: upper limit of the occurrence probability

Thus, in Table 4-3 below we propose the TFNs for the original linguistic scale shown in the Table 4-2.

Linguistic term	Corresponding TFN	Description
Impossible (IM)	[0.00, 0.00, 0.05]	The event never occurs.
Nearly impossible (NI)	[0.00, 0.05, 0.25]	The event is extremely impossible to occur.
Unlikely (UN)	[0.05, 0.25, 0.50]	Even though the event is unlikely, it is possible to occur.
Fair-chance (FC)	[0.25, 0.50, 0.75]	The occurrence likelihood of possible events is fair-chance.
Likely (LI)	[0.50, 0.75, 0.95]	The event is likely to occur.
Nearly certain (NC)	[0.75, 0.95, 1.00]	The event will always occur.
Certain (CE)	[0.95, 1.00, 1.00]	The event is to occur with absolute certainty.

Table 4-3. Triangular fuzzy numbers for the 7-point linguistic scale.

The extraction of crisp risk values, as mentioned before, is conducted with the help of the f-weighted approach (Ramli et al., 2021). Given that a TFN is defined as [a, b, c], the crisp value extracted from a TFN via the f-weighted approach equals:

$$\frac{b+\frac{a+c}{2}}{2}.$$

Figure 4-4. F-weighted approach for extraction of crisp risk values.

Consequently, we can calculate the crisp risk values for all 7 elements of the linguistic scale. The values are shown in the Table 4-5. We note here that the crisp risk values do not equal 0 and 1: they are sufficiently close to the minimum and maximum values of the probability range, but never reach those.

TFN	F-weighted
Impossible (IM)	0,0125
Nearly impossible (NI)	0,0875
Unlikely (UN)	0,2625
Fair-chance (FC)	0,5
Likely (LI)	0,7375
Nearly certain (NC)	0,9125
Certain (CE)	0,9875

Table 4-5. Crisp risk values for the 7-point linguistic scale.

To account for the possible differences between experts in terms of, for instance, years of experience in the industry or their reliability levels (i.e. an expert may be familiar with the economic risks, but very far from the political risks due to peculiarities of his experience etc.), and consequent heterogeneity of the sample, we proceed with applying the weighted approach for aggregation of the experts' opinions (Guan et al., 2020). Figure 4-6 shows the calculations for the weight of a single expert, including such elements as ability (measured in years of experience) and reliability (self-assessed by the experts), while Figure 4-7 shows the calculations for aggregating the opinions of all experts in the cohort for a single risk element.

$$\omega_t = \frac{\theta_t}{\sum_{t=1}\theta_t} = \frac{\zeta_t \times \psi_t}{\sum_{t=1}\zeta_t \times \psi_t}, t = 1, 2, 3, \cdots.$$

Weight of an expert t

Ability of an expert t (y of exp.)

Reliability of an expert t (self-assessed)

Figure 4-6. Calculations for the single expert's weight (Guan et al., 2020).

$$WRF_i = \omega_1 \otimes RF_{i1} \oplus \omega_2 \otimes RF_{i2} \oplus \omega_3 \otimes RF_{i3} \oplus \cdots.$$

Figure 4-7. Calculations for aggregation of experts' opinions regarding a single risk element (Guan et al., 2020).

However, the calculations above may be applied without any additional steps only to the root elements of the network – that is, risk elements that do not depend on any other risk elements. Hence, for those risk elements with dependency relations (i.e. risk categories or the main, leaf node of the network, supply chain disruption) we are to use the conditional probability theory together with defuzzification and extraction of crisp risk values. An example is given in the Figure 4-8 below: if we suppose that a risk element FC depends on the risk elements FK, AC, and VC, then the conditional probability for the risk element FC comprises a sum of 8 elements in total ($2^3 = 8$ combinations in total), where elements themselves represent the products of the probabilities of the root risk elements' occurrence and the experts' opinions (Ramli et al., 2021).

$$
\begin{aligned}
&P(FC = FC_1) \\
&= P(FK = FK_1) \times P(AC = AC_1) \times P(VC = VC_1) \times P(FC = FC_1 | FK = FK_1, AC = AC_1, VC = VC_1) \\
&+ P(FK = FK_1) \times P(AC = AC_1) \times P(VC = VC_2) \times P(FC = FC_1 | FK = FK_1, AC = AC_1, VC = VC_2) \\
&+ P(FK = FK_1) \times P(AC = AC_2) \times P(VC = VC_1) \times P(FC = FC_1 | FK = FK_1, AC = AC_2, VC = VC_1) \\
&+ P(FK = FK_1) \times P(AC = AC_2) \times P(VC = VC_2) \times P(FC = FC_1 | FK = FK_1, AC = AC_2, VC = VC_2) \\
&+ P(FK = FK_1) \times P(AC = AC_1) \times P(VC = VC_1) \times P(FC = FC_1 | FK = FK_1, AC = AC_1, VC = VC_1) \\
&+ P(FK = FK_2) \times P(AC = AC_1) \times P(VC = VC_1) \times P(FC = FC_1 | FK = FK_2, AC = AC_1, VC = VC_1) \\
&+ P(FK = FK_1) \times P(AC = AC_2) \times P(VC = VC_1) \times P(FC = FC_1 | FK = FK_1, AC = AC_2, VC = VC_1) \\
&+ P(FK = FK_2) \times P(AC = AC_2) \times P(VC = VC_2) \times P(FC = FC_1 | FK = FK_2 AC = AC_2, VC = VC_2) \\
&= (0.5 \times 0.37 \times 0.5 \times 0.86) + (0.5 \times 0.37 \times 0.5 \times 0.71) \\
&+ (0.5 \times 0.63 \times 0.5 \times 0.59) + (0.5 \times 0.63 \times 0.5 \times 0.41) \\
&+ (0.5 \times 0.37 \times 0.5 \times 0.41) + (0.5 \times 0.37 \times 0.5 \times 0.25) \\
&+ (0.5 \times 0.63 \times 0.5 \times 0.25) + (0.5 \times 0.63 \times 0.5 \times 0.04) \\
&= 0.387
\end{aligned}
$$

Figure 4-8. An example of conditional probability theory application in the process of extracting the crisp risk values (Ramli et al., 2021).

Therefore, the goal of applying the fuzzy Bayesian network methodology to the previously extracted risk elements united in a single risk classification framework is to obtain the probabilities of occurrence not only for the risk elements and corresponding categories in the supply chain, but also investigate how high the occurrence probability is for the overall disruption in the supply chain as the main consequence for the supply chain. A conceptual version of the fuzzy Bayesian network that we aim at obtaining is shown in Figure 4-9 as an example.

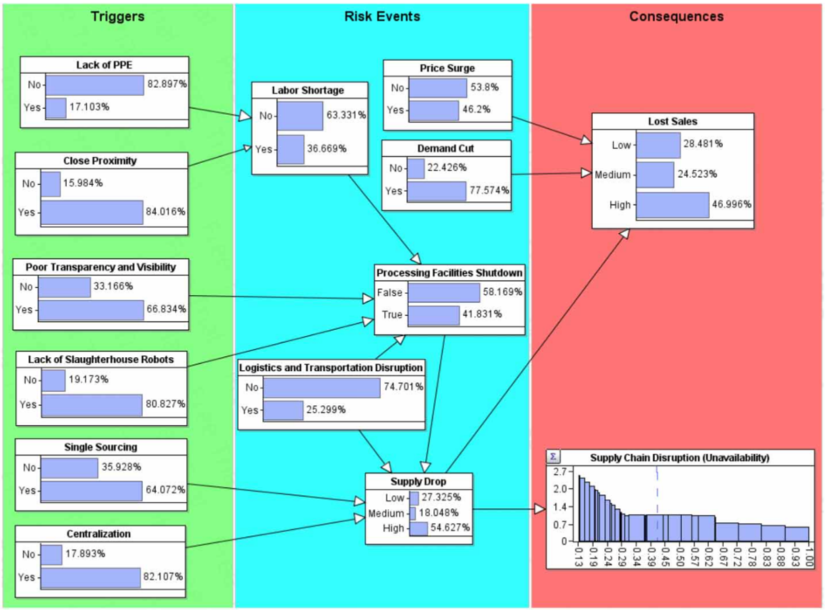

Figure 4-9. Conceptual model of a fuzzy Bayesian network (Hosseini and Ivanov, 2021).

Chapter 5. Data Collection

As mentioned in Chapter 4, the analysis related to fuzzy Bayesian networks strongly depends on collecting responses from the industry experts in the case of this paper. Additionally, as follows from our attempt to control for heterogeneity of the experts in the final sample, it is needed to control for their educational level, work experience measured in years, position in the company etc. Even though the little experience does not critically impede the weighted approach to the experts' cohort, a decision on limiting the minimum experience to 4 years was made prior to searching for experts, given that the responses of experts are of relatively high value for this study; too little experience might not result in producing valuable outcomes for the analysis.

Also, a minimum number of experts for the final sample was of great concern at the initial stage of data collection. Coming back to the analyzed papers from Chapter 3, where fuzzy Bayesian networks are implemented with the help of survey-based data collection, showed that the average number of experts in the sample equaled 5.5 (minimum number of experts: 3; maximum number of experts: 10); hence, our goal was to at least exceed this figure and obtain access to 6 experts. Additionally, no papers limited the sample to a certain country or nationality as well. A survey was produced in English first, then translated into Korean and verified by 4 native speakers for ensuring the clarity of the survey content, as according to our initial expectations, majority of the experts would be from the Republic of Korea and, presumably, native speakers of Korean language.

In total, 9 experts of Korean nationality were found from a company in the semiconductor industry sector based in the Republic of Korea: 5 of them represented the purchasing team, and 4 – the sales team. This secured the homogeneity of sample in terms of nationality and allowed to conduct analysis not only for the whole sample with complete aggregation, but also for separate samples of 5 and 4 experts with partial aggregation within those two samples. Due to data protection and security-related issues, the data on experts is shown in the Table 5-1 in a limited form.

#	Years of exp.	Educational level	Weight
1	25	Undergraduate	15.5%
2	16	Undergraduate	8.4%
3	16	Master's	9.8%
4	22	Undergraduate	11.5%
5	15	Undergraduate	7%
6	18	Master's	10.4%
7	21	Master's	12.6%
8	19	Undergraduate	9.8%
9	26	Undergraduate	15%

Table 5-1. Data on experts.

A survey that experts worked with took approximately 2 hours to be finished completely. Given that we have produced relatively many risk elements in the final version of the risk classification framework with sub-categories and main categories included and the need to use conditional probability theory to quantify the responses of the experts into the crisp risk values, it was decided, opposed to initial plan, to use only 2 states for all risk elements and categories: TRUE (a risk element occurs in the supply chain) and FALSE (a risk element does not occur in the supply chain). Inevitably, more insights can be produced if there are more states to the risk elements (i.e. low /

medium / high risk of occurrence in the supply chain; that is, 3 states); however, given the relatively large size of the network, proceeding with more states would only lead to combinatorial explosion and lower levels of eagerness for the experts to participate in the survey.

Descriptions for the risk elements were also provided for the experts not only for convenience, but also for preventing various approaches to understanding what risk elements mean. Such descriptions were taken from the academic papers mentioned in Chapter 3. An example of descriptions for the technical risk elements are shown below in the Table 5-2.

T1	Technology access	Risks arise due to e-commerce, information delays and data breach in IT systems. Industry 4.0 is built upon cyber-physical systems which increases the risk when controlling information. Vulnerability of IT systems to cyber attacks due to viruses, bugs, and hackers.
T2	IT system integration issues	Incompatibility of IT systems between supply chain elements.
T3	Technological obsolescence	Production inefficiencies or shortfall due to obsolete production technology or equipment.
T4	Equipment failure	Machinery failures in supply chain.
T5	Production-associated accidents	Production-accidents in supply chain (human-related).
T6	Tech-related risk elements	Risk elements related to aspects of technology.

Table 5-2. Example of risk elements' descriptions: technical risk category.

At first, experts were asked to evaluate the probability for the root risk elements not dependent on any other risk elements in the section named prior occurrence probability. An example with 4 risk elements from the political risk category is given in Table 5-3: using the 7-point linguistic scale, experts evaluated how likely the risk elements were to occur in the semiconductor industry supply chain.

No.	Risk factor	Prior occurrence probability						
		IM	NI	UN	FC	LI	NC	CE
P1	Political instability							
P2	Corrupt government							
P3	Piracy and terrorism							
P4	Trade regulation and tariffs							

Table 5-3. Prior occurrence probability section.

As explained previously, prior occurrence probability section is followed by conditional occurrence probability assessment for the risk sub-categories / categories dependent on the root risk elements. An example of evaluating a risk element “Procurement and purchase cost increase”, dependent on such risk elements as “Labor cost increase”, “Material cost increase”, and “Transportation cost increase”, is shown in Table 5-4. In total, given three dependent risk elements, there are 8 possible combinations that experts are to evaluate. For instance, when all three risk elements are deemed TRUE, an expert may consider the occurrence probability of the parent risk element (“Procurement and purchase cost increase”) to be CE (Certain). Another example is when “Labor cost increase” is TRUE, but the other two root risk elements are FALSE: in this case, the answer of an expert can be FC (Fair-chance). Lastly, when all three risk elements are deemed FALSE, it can be stated that the conditional occurrence probability is NI (Nearly impossible).

Labor cost increase (EC12)	Material cost increase (EC13)	Transportation cost increase (EC14)	**Conditional occurrence probability of “Procurement and purchase cost increase” (EC19)**						
			IM	**NI**	**UN**	**FC**	**LI**	**NC**	**CE**
TRUE	TRUE	TRUE							X
		FALSE							
	FALSE	TRUE							
		FALSE				X			
FALSE	TRUE	TRUE							
		FALSE							
	FALSE	TRUE							
		FALSE		X					

Table 5-4. Conditional occurrence probability section.

Lastly, aside from the occurrence probability assessment, experts are to evaluate the magnitude of impact for each risk factor upon their occurrence in the supply chain. This is done with the purpose of conducting sensitivity analyses for the fuzzy Bayesian network. For evaluating the magnitude of impact, a separate 7-point linguistic scale with several changes in the wording is used and shown in the Table 5-5.

Impact	Description
Absolutely low (AL)	Impact on supply chain can be ignored.
Very low (VL)	Potential for causing slight impacts on supply chain.
Low (LO)	Potential for causing minor impacts on supply chain.
Medium (ME)	Potential for causing moderate impacts on supply chain.
High (HI)	Potential for causing substantial impacts on supply chain.
Very high (VH)	Potential for causing critically large impacts on supply chain.
Absolutely high (AH)	Impact on supply chain is disastrous.

Table 5-5. A 7-point linguistic scale for assessment of magnitude of impact.

Thus, experts are to choose a certain element from the linguistic scale when assessing the magnitude of impact, similar to prior occurrence probability section. Besides, in this part of the survey, experts must conduct self-assessment of their own reliability in terms of subjectivity. An example is given in Table 5-6: an expert deems the impact of the risk element “Political instability” to be VH (Very high) but considers subjectivity reliability to be 0.7. For subjectivity reliability self-assessment, we do not use a separate linguistic scale: instead, we use the range of values from 0.6 to 1.0 with a 0.1 step, where 0.6 stands for the lowest level of subjectivity reliability (an expert does not have sufficient experience with this risk element), and 1.0 – for the highest level.

No.	**Risk factor**	**Impact of risk factors**							***Expert subjectivity reliability***				
		AL	VL	LO	ME	HI	VH	AH	*0.6*	*0.7*	*0.8*	*0.9*	*1.0*
P1	Political instability						X			X			

Table 5-6. An example of magnitude of impact and subjectivity reliability assessment.

Chapter 6. Results & Sensitivity Analysis

Upon running the GeNle Modeler 4.0 software (academic version), base network models for the whole sample of 9 experts, purchasing team, and sales team were obtained as follows in the Figures 6-1 to 6-3. Here, the probability of supply chain disruption is located at the center of each network model and noted in green: for the whole sample of experts, such probability equals 67%, while for the purchasing and sales teams – 91% and 44% respectively.

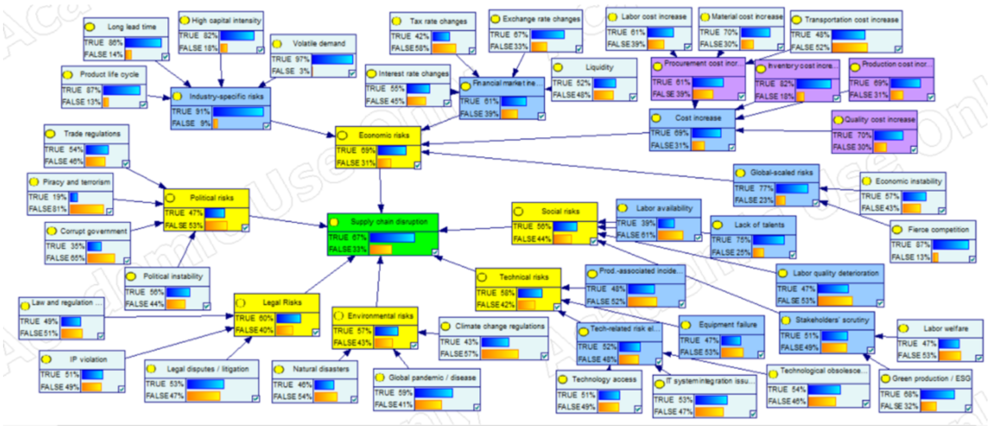

Figure 6-1. Base network model for the whole sample of experts.

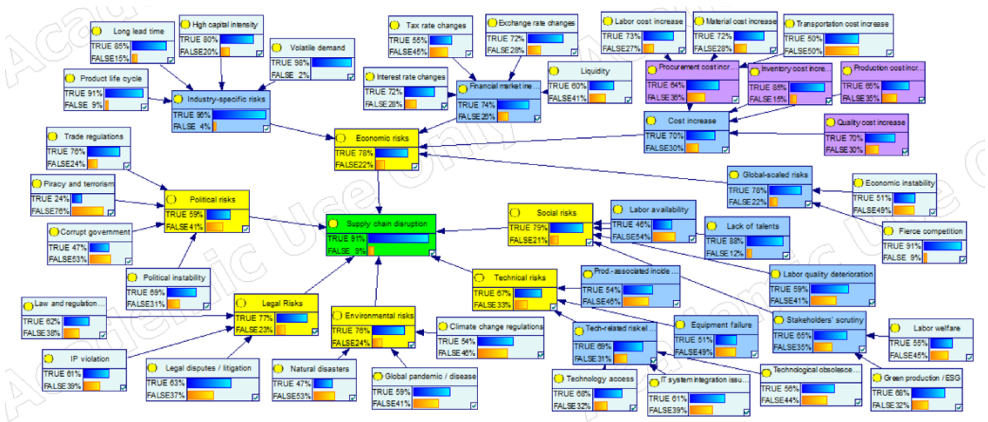

Figure 6-2. Base network model for the purchasing team.

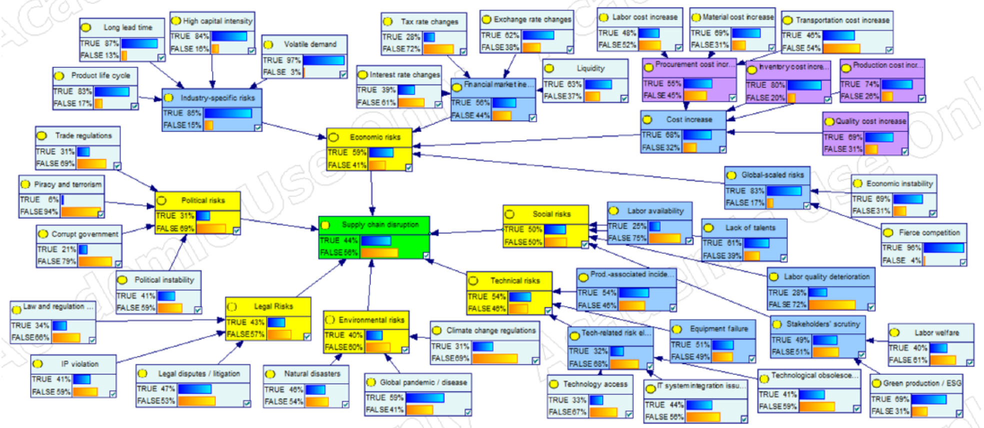

Figure 6-3. Base network model for the sales team.

Table 6-4 summarizes the order of the occurrence probabilities by 6 risk categories originating from the PESTEL for 3 samples.

Order	Whole	Purchasing	Sales
1	Economic (69%)	Social (79%)	Economic (59%)
2	Legal (60%)	Economic (78%)	Technical (54%)
3	Technical (58%)	Legal (77%)	Social (50%)
4	Environmental (57%)	Environmental (76%)	Legal (53%)
5	Social (56%)	Technical (67%)	Environmental (40%)
6	Political (47%)	Political (59%)	Political (31%)

Table 6-4. Order of occurrence probabilities by risk categories.

In Tables 6-5 and 6-6, top-5 risk elements with the highest occurrence probability and the risk elements with the highest occurrence probability for each of the 6 risk categories are noted.

Order	Whole	Purchasing	Sales
1	Volatile demand (97%)	Volatile demand (98%)	Volatile demand (97%)
2	Industry-specific risks (91%)	Industry-specific risks (96%)	Fierce competition (96%)
3	Product life cycle (87%)	Product life cycle (91%)	Long lead times (87%)
4	Fierce competition (87%)	Fierce competition (91%)	Industry-specific risks (85%)
5	Long lead times (86%)	Lack of talents (88%)	High capital intensity (84%)

Table 6-5. Top-5 risk elements with the highest occurrence probability.

Category	Whole	Purchasing	Sales
Political	Political instability (56%)	Trading regulations and tariffs (76%)	Political instability (41%)
Economic	Volatile demand (97%)	Volatile demand (98%)	Volatile demand (97%)
Social	Lack of talents (75%)	Lack of talents (88%)	Scrutiny on green production / ESG (69%)
Technical	Technological obsolescence (54%)	Tech-related risks (69%)	IT system integration issues (44%)
Environmental	Global pandemic / disease (59%)	Global pandemic / disease (59%)	Global pandemic / disease (59%)
Legal	Legal disputes and litigation (53%)	Legal disputes and litigation (63%)	Legal disputes and litigation (48%)

Table 6-6. Risk elements with the highest occurrence probability for each of the 6 risk categories.

Tables 6-7 to 6-12 contain probability figures for all risk elements that belong to a certain risk category. The maximum probability figures for a particular sample are colored in red. We provide detailed implications derived upon these results in the next chapter.

Risk element	Whole	Purchasing	Sales
Political instability	56%	69%	41%
Government oversight and corruption	35%	47%	21%
Piracy and terrorism	19%	24%	6.4%
Trading regulations and tariffs	54%	76%	31%

Table 6-7. Probability figures for political risk elements.

Risk element	Whole	Purchasing	Sales
Product life cycle	87%	91%	83%
Long lead times	86%	85%	87%
High capital intensity	82%	80%	84%
Volatile demand	97%	98%	97%
Interest rate change	55%	72%	39%
Tax rate change	42%	55%	28%
Exchange rate change	67%	72%	62%
Liquidity	52%	60%	63%
Inventory cost increase	82%	85%	80%
Production cost increase	69%	65%	74%

Quality cost increase	70%	70%	69%
Labor cost increase	61%	73%	48%
Material cost increase	70%	72%	69%
Transportation cost increase	48%	50%	46%
Economic instability	57%	51%	69%
Fierce competition	87%	91%	96%
Industry-specific risks	91%	96%	85%
Financial market inefficiency	61%	74%	56%
Procurement cost increase	61%	64%	55%
Cost increase	69%	70%	68%
Global-scaled risks	77%	78%	83%

Table 6-8. Probability figures for economic risk elements.

Risk element	Whole	Purchasing	Sales
Labor quality deterioration	47%	59%	28%
Labor availability	39%	46%	26%
Scrutiny on green production / ESG	68%	68%	69%
Scrutiny on labor welfare	47%	55%	40%
Lack of talents	75%	88%	61%
Stakeholders' scrutiny	51%	65%	49%

Table 6-9. Probability figures for social risk elements.

Risk element	Whole	Purchasing	Sales
Technology access issues	51%	68%	33%
IT system integration issues	53%	61%	44%
Technological obsolescence	54%	56%	41%
Equipment failure	47%	51%	42%
Production-related accidents	48%	54%	41%
Tech-related risks	52%	69%	32%

Table 6-10. Probability figures for technical risk elements.

Risk element	Whole	Purchasing	Sales
Natural disasters	46%	47%	46%
Global pandemic / disease	59%	59%	59%
Regulations related to climate change	43%	54%	31%

Table 6-11. Probability figures for environmental risk elements.

Risk element	Whole	Purchasing	Sales
Law and regulation changes	49%	62%	34%
Intellectual property violation risk	51%	61%	41%
Legal disputes / litigation	53%	63%	47%

Table 6-12. Probability figures for legal risk elements.

An important part of network analysis concerns the sensitivity analysis. In this paper, we investigate two kinds of inference, typical for Bayesian network analysis: causal and diagnostic, as well as tornado graphs for the main node of the network – supply chain disruption - to derive implications useful for the management. The latter ones are explained in detail in the next chapter.

Firstly, causal inference is based on changes in the root nodes (risk elements on the lowest level) and aims at investigating to which extent the main node's (supply chain disruption) probability can change because of these changes. Upon aggregation of magnitude of impact-related answers using the already defined weights, we can obtain a list of top-N risk elements that are deemed impactful by the experts and produce several scenarios with those risk elements' occurrence probability either left as it is or increased to 100%, which implies that they always occur in the supply chain. For 3 samples, we develop 7 scenarios for each (21 scenarios in total), and define the most sensitive risk elements, changes in probabilities of which induce the highest change in the main node – supply chain disruption. Tables 6-13 to 6-15 contain results of causal inference for 3 samples.

Scenario #	1	2	3	4	5	6	7
P4 (Trading regulations and tariffs)	As is	As is	100%	As is	100%	100%	100%
EC16 (Fierce competition)	As is	100%	As is	100%	As is	100%	100%
EN1 (Natural disasters)	100%	As is	As is	100%	100%	As is	100%
Change (in %)	0	0	**3.0%**	1.5%	**3.0%**	1.5%	**3.0%**

Table 6-13. Causal inference for the whole sample.

Scenario #	1	2	3	4	5	6	7
P4 (Trading regulations and tariffs)	As is	As is	100%	As is	100%	100%	100%
EC16 (Fierce competition)	As is	100%	As is	100%	As is	100%	100%
EN1 (Natural disasters)	100%	As is	As is	100%	100%	As is	100%
Change (in %)	0	0	0	0	**1.1%**	0	**1.1%**

Table 6-14. Causal inference for the purchasing team.

Scenario #	1	2	3	4	5	6	7
P4 (Trading regulations and tariffs)	As is	As is	100%	As is	100%	100%	100%
EC16 (Fierce competition)	As is	100%	As is	100%	As is	100%	100%
EN1 (Natural disasters)	100%	As is	As is	100%	100%	As is	100%
Change (in %)	0	4.5%	0	4.5%	4.5%	**9.1%**	**9.1%**

Table 6-15. Causal inference for the sales team.

Diagnostic inference is, to some extent, an opposite of the causal inference in the sense that the probability of the main, leaf node – supply chain disruption – is set to 100% (implying that disruption is to happen inevitably), so that it is possible to observe how much probabilities of 6 risk categories in our classification increase from their initial levels in the base network model. We measure the change in % (i.e. if original probability and probability after inference are 30% and 45% respectively, the change yields 50%). The larger change in %, the more sensitivity pertains to this category. Table 6-16 shows 3 most sensitive categories for each sample with changes in % placed on the right from the categories' names.

Order by change in %	Whole	Purchasing	Sales
TOP 1	Technical (8.6%)	Political (5.2%)	Economic (50%)
TOP 2	Legal (6.7)	Technical (3.0%)	Environmental (15%)
TOP 3	Political (6.3%)	Legal (2.6%)	Technical (14.8%)

Table 6-16. Diagnostic inference results for 3 samples.

Tornado graph is another variation of sensitivity analysis that was tackled in this paper. It shows how much the target node (supply chain disruption) changes due to the changes in the parameter nodes that is, experts' opinions expressed through survey and quantified upon proposed methodology) across the whole network. That is, all opinions of experts are investigated to build the tornado graph. Usefulness of tornado graph in our settings can be supported by the fact that the main node, supply chain disruption, is not the only node that can be chosen as the target node: for instance, a tornado graph can be produced for a risk category and show the sensitive risk elements that belong to this specific category. Commonly, it is considered that parameter nodes change in the range of 10% (both negative and positive changes apply). Figures 6-17 to 6-19 contain tornado graphs for 3 samples.

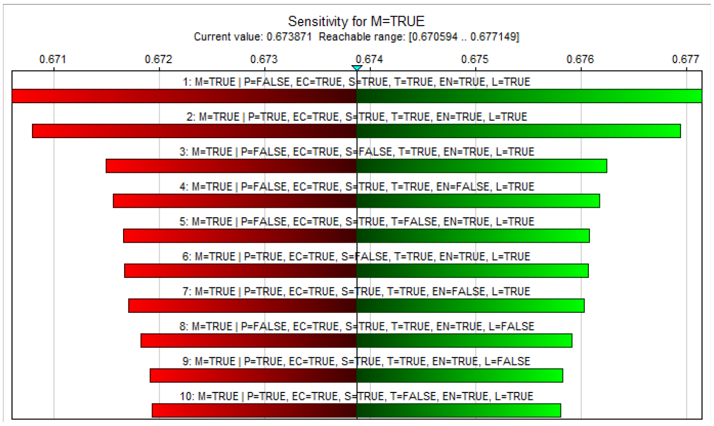

Figure 6-17. Tornado graph for the whole sample.

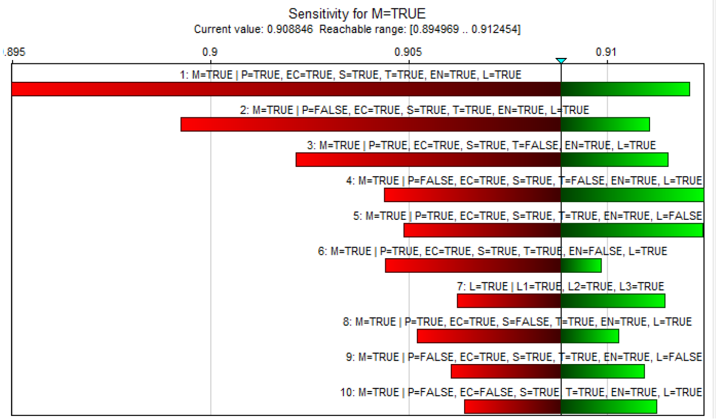

Figure 6-18. Tornado graph for the purchasing team.

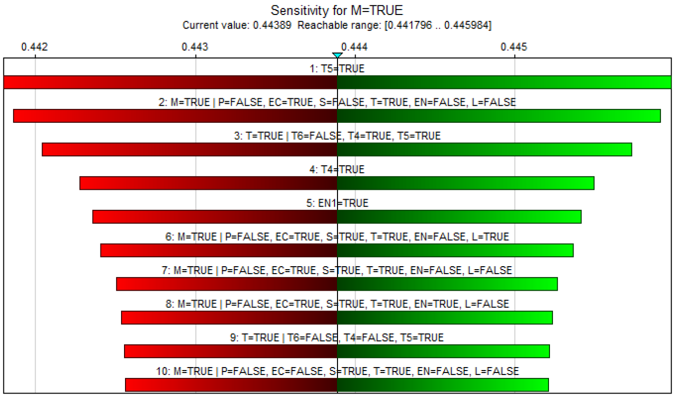

Figure 6-19. Tornado graph for the sales team.

As a sort of extension to sensitivity analysis, we have decided to investigate how different risk elements in the risk classification network differ from each other depending on their occurrence probability and magnitude of impact. Even though we do not incorporate dynamics in the fuzzy Bayesian network in this paper, this analysis could contribute to predicting the risk elements that would be, for instance, marked as sensitive, given that we conducted the analysis using the dynamic fuzzy Bayesian network. Investigations yielded the following observations for the samples:

- Whole sample: Volatile demand showed both high occurrence probability and magnitude of impact. For natural disasters, equipment failures, and regulations related to climate change, the occurrence probability was low, yet the magnitude of impact was deemed high by the experts. For piracy and terrorism, both measures were recorded as low.

- Purchasing team: The results for purchasing team aligned well with the whole sample's results, with a difference in the risk elements with low occurrence probability and high magnitude of impact; instead, natural disasters and labor availability were placed under this category.
- Sales team: Together with volatile demand, fierce competition also showed high figures for occurrence probability and magnitude of impact. Interestingly, results for this sample were different from above in the sense that it was trading regulations and tariffs and tech-related risks (as a sub-category under technical risk category) that showed low occurrence probability, but high magnitude of impact. Lastly, labor availability recorded both low occurrence probability and magnitude of impact, which is different from the results of the purchasing team.

Chapter 7. Implications

In general, this study may be viewed as a certain call for more research conducted in semiconductor supply chain risk management, given relatively high figures of disruption occurrence probability for the whole sample of 9 experts (67%). Moreover, more quantitative research can be demanded upon this paper: to capture the dynamics of the industry, other methodologies apart from fuzzy Bayesian networks can be applied to the same settings.

From a practical point of view, as the disruption may occur with probability equal to almost 70% in case of the whole sample, management should be aware of disruption-related risks in the operations. As expected, economic and legal risks play a great role for the field as of now; yet it does not negate the fact that risk elements from the other categories can be sensitive on their own as well. It is important to consider such risk elements, including trading regulations and tariffs or production-related accidents. Another threat is the risks with low probabilities of occurrence but, presumably, big impact on supply chain operations: those, for instance, include piracy and terrorism, natural disasters, and labor availability. Besides, drastic difference between the occurrence probability of the supply chain disruption for purchasing and sales teams – 91% versus 44% - might imply that to some point, alignment of two teams' efforts can be useful for preventing disruptions in the supply chain.

As for the order of categories in terms of the occurrence probability figures for each sample, it is worth mentioning that the political risk category was deemed by experts from all samples as the least risky category. This may be explained by the fact that semiconductor industry companies, when selecting the outsourcing partners, tend to choose relatively safe countries in which such partners are based, given that the selection process itself might take relatively long time. At the same time, economic risk category was deemed sufficiently prone to occurrence, taking the first place in the order in all samples, except for the purchasing team.

Summarizing the occurrence probability figures among all risk elements for all three samples yielded that volatility in demand is indeed the most likely to occur in the supply chain, as its probability ranges from 97% to 98%. Moreover, in the top-5 risk elements list for each sample, risk elements originating from the economic risk category prevail; examples include industry-specific risks as a sub-category, fierce competition, product life cycle, long lead time etc. Having product life cycle in this list is not surprising: Uzsoy et al. (2018) noted that product life cycle itself impacts the demand prediction process drastically and contributes to complexity of this process.

Among political risk elements, there is a need to pay attention to such risk elements as political instability and trading regulations and tariffs. The first one showed the highest occurrence probability figures for two samples – sales team and the whole sample (41% and 56% respectively); while trading regulations and tariffs were of great concern for the purchasing team (76%). For economic risk elements, even though volatile demand was placed first in all 3 samples, it does not negate the fact that given the large number of risk elements in this category, management still must pay attention to the risk elements located, for instance, in the middle of the risk elements' list by occurrence probabilities. Such elements include, for example, high capital intensity (80%~84%) or inventory cost increase (80%~85%).

As for the social risk category, two risk elements may cause concern for the management: those are the lack of talents and the scrutiny of stakeholders regarding green production or ESG compliance. The lack of talents recorded 75% and 88% of occurrence probability for the whole sample and purchasing team respectively; in this study, the lack of talents can be defined as the lack of mainly engineering talents. However, the sales team had this risk element on the second place: the first one belongs to the scrutiny of stakeholders on green production and ESG. Given that its occurrence probability is sufficiently close to 70%, it may be important for the management to pay attention to this kind of scrutiny as well. Technical risk elements did not show notably large variations in terms of occurrence probability figures: they mainly varied in the range of 40% to 69%. Experts were concerned by IT system integration issues, given the large number of steps involved in the semiconductor industry supply chain, and technological obsolescence for its direct impact on the inventory management.

Environmental risk category showed understandable inclining of experts towards the global pandemic / disease risk element. Clearly, responses of experts could have been affected by recent experiences with the global pandemic of COVID-19: the latter is considered an event of high uncertainty and low frequency at the same time (Hosseini and Ivanov, 2021). Interestingly, the figures for the whole risk category are quite high for the whole sample and the purchasing team, and yet the lack of visible differences between risk elements themselves across 3 samples in terms of their occurrence probability values implies that, to some extent, experts valued all 3 risk elements in this category to be of relatively similar importance for the semiconductor's supply chain operations. Similarly, in the legal risk category, experts assume 3 risk elements in total to be important for the supply chain operations.

Sensitivity analysis results yielded the following:

- For the causal inference, the whole sample showed that trading regulations and tariffs were the most sensitive, as increasing its probability alone to 100% already yields a positive change of 3.0% in the occurrence probability of the supply chain disruption, the main node of the network. For the purchasing team, trading regulations and tariffs were the most sensitive together with production-associated accidents, as sending these two risk elements' probabilities to 100% yielded the maximum change of 1,1%. Lastly, for the sales team, natural disasters and production-associated accidents were deemed the most sensitive, and the maximum change that could be taken by the main node was 9.1%. Thus, management may need to keep in mind the consequences that might come out of these risk elements deemed most sensitive upon the causal inference.

- Diagnostic inference showed that the technical risk category is met in every sample, despite taking different places in every sample. Still, this implies that this risk category might be of great importance for the supply chain operations. For the sales team, we notice the visible gap with the other samples in terms of the magnitude of change measured in %: this might be explained by the fact that the overall disruption probability was lower for this sample, compared to the whole sample of experts or purchasing team only (44% versus 67% or 91%). Additionally, results of the diagnostic inference stress the fact that purchasing and sales teams might indeed have different views on the same issues or questions – in this analysis, except for the technical risk category, the other risk categories for each sample are different and do not overlap with each other: the purchasing team's results consider political and legal risk categories to be of great importance, but the sales team's results stress the importance of economic and environmental risk categories.
- As for the tornado graphs, in the whole sample's results, we can observe that the most sensitive combination for the network model is "P = FALSE, EC, S, T, EN, L = TRUE", implying that all categories, except for the political risk category, matter for the supply chain disruption occurrence. For the purchasing team, all categories are of high importance for the supply chain disruption, while for the sales team it turned out that "T5 = TRUE" (production-related accidents happen in the supply chain) is the most sensitive combination. The supply chain disruption occurrence probability is vulnerable to shifts from

67.3% in the range of 67.06% ~ 67.71%, 90.9% in the range of 89.5% ~ 91.25%, and 44.39% in the range of 44.18% ~ 44.6% for the whole sample, purchasing team, and sales team respectively. The most sensitive combinations are to be considered by the management as well; though tailoring them to the real-life events might be complicated given that a certain risk category cannot be defined by one single event possessing risks for the supply chain, this still can be useful for the management, considering the potential of tornado graph analysis in terms of changing the magnitude of the experts' answers from 10% used in this study to, for instance, 20% or 30%.

- An extension of sensitivity analysis – a search for the risk elements depending on how small or large their occurrence probability and magnitude of impact are – indeed proved the fact that since the risk elements mentioned for multiple times previously in the main results and sensitivity analysis section are met under the groups of risk elements with low or high chance of probability and large magnitude of impact, management must attentively investigate such risk elements as well, especially in the case of incorporating the dynamic settings in such investigations. Examples of such risk elements, about which management must be cautious, include volatile demand, natural disasters, or fierce competition.

Chapter 8. Conclusion

Despite the implications obtained in the previous chapter, this study has several limitations that must be considered when developing research in this direction. Firstly, it can be argued that using risk elements mentioned only in the academic sources may not reflect the nature of the industry fully given the typical gap between research and practice. To investigate whether typical risk elements mentioned in academic papers differ from reality and whether our proposed risk classification system is viable for the future research, it was decided to study industrial reports published between 2021 and 2023 by leading consulting firms. 6 reports showed that the common trends for the semiconductor industry were the visible lack of talents and risks such a lack possesses for the future of industry and a sufficiently big need for enhancing resilience for the supply chains, which is aligned with the key points taken from the results of our study. Legal risk elements were deemed important in such reports for the future 3-5 years as well; however, while our risk classification system, originating from the PESTEL classification principles, maintains generalizability of the risk elements, the industrial reports considered legal risk elements to be more detailed. For instance, our classification has only intellectual property violation risk as a single risk element, but industrial reports deem each intellectual property type as a separate risk element: topography right, patents, trade secrets, designs etc. It was thus deemed viable to consider outcomes of the report analysis for the future studies in this field with a possibility to bring changes to the risk classification system.

For causal inference, the process of developing scenarios can be criticized to some extent for not matching the real-life scenarios or incidents that have already happened across supply chains worldwide. A search for real-life examples in accordance with the obtained most sensitive risk elements would bring us to forming a real disruption induced by the risk combinations. However, one knows that semiconductor industry is not eager to share information related to accidents in a voluntary manner, as the industry is not only protective in terms of information spread, but also aware of how big the impact of negative information disclosure on the stakeholders or company image is. Additionally, capturing the disruption itself and proving that the occurrence of a disruption was due to solely certain risk factors without sufficient background information is a complicated task.

As mentioned previously in Chapter 6, continuous disruptions cannot be captured in our fuzzy Bayesian network as we do not work with dynamic Bayesian networks in our study. This leaves room for future research with dynamic settings incorporated in the network model. Moreover, since the fuzzy Bayesian network used in this study is static, there is a chance that experts expressed their opinion under influence of, for instance, COVID-19 and its current influence on the state of their respective companies.

Based on the limitations mentioned above, we can conclude that there are several directions in which this study could be extended, not limited to incorporation of dynamic settings in the network. Possibly, PESTEL classification could be mixed with the other existing risk classification systems to include, for instance, internal risks. Fuzzy Bayesian network as a methodology can be implemented in the research dedicated to supply chain resilience, and the outcomes of this study could be connected in a natural manner with the studies from the field of supply chain analytics, given the implementation of the newest technologies in practice in many companies.

In general, this study serves as an attempt to classify risk factors for the semiconductor industry supply chain and quantify their possible impact on the supply chain using the fuzzy Bayesian network methodology. It also attempts to close the research gap, characterized by lack of quantitative studies in the field of risk management in the semiconductor supply chain. In total, 6 categories are produced for the whole sample of risk events with the help of PESTEL classification system.

Overall disruption probability figures, as well as figures for each risk category and risk element in all 3 samples, are produced for comparative analysis using the f-weighted approach and triangular fuzzy numbers. It is economic, social, and legal risk categories that pertain to high-risk figures; yet sensitivity analysis techniques implied that some of the risk elements with low probability of occurrence but high magnitude of impact, originating from the other categories (e.g. natural disasters) need special attention from the management as well. In compliance with the results, practical implications are produced for the management, and the latter must consider those to make conclusions regarding their own entities.

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Abstract in Korean

본 연구에서는 퍼지-베이지안 네트워크를 활용하여 반도체 산업의 공급망 리스크 요인을 분류하고, 공급망에 미칠 수 있는 영향을 수치화하고자 한다. PESTEL 분류 시스템을 이용하여 반도체 공급망에 관한 리스크 요인 분류 시스템을 생성한다. 총 9명의 반도체 산업의 전문가가 앞서 정의된 리스크 요인/카테고리에 대한 설문 조사에 참여하여 의견을 제시하였다. 전체적인 공급망 붕괴 확률 수치와 각 리스크 요인/카테고리에 대한 수치는 f-가중치 접근법과 삼각 퍼지 수치를 통하여 도출된다.

붕괴 발생 가능성이 상대적으로 높은 카테고리는 경제적 및 사회적 리스크 카테고리이며, 2 개의 카테고리에 속한 수요 변동의 불확실성, 치열한 경쟁 또는 인재 부족과 같은 리스크 요인은 전문가에 의하여 위험하다고 간주된다. 그러나 인과/진단 추론 및 토네이도 그래프를 포함한 민감도 분석 기법은 발생 가능성은 낮고, 영향의 크기가 높은 리스크 요인 중 일부가 다른 카테고리에 속해도 (예: 자연 재해) 위험할 수도 있음을 증명한다. 마지막으로 본 연구에서 리스크와 관련된 실무적 시사점은 경영진에게 제공된다.

주요어: 리스크 관리, 리스크 분류, 반도체 산업, 공급망, 퍼지-베이시안 네트워크, 붕괴

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